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總體金融資產定價的實證研究

Stock market alphas help predict macroeconomic innovations.

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中文摘要

我們運用新型遞歸多變量濾波〔recursive multivariate filter〕，順利萃取好動態條件基本面解釋成因的風險溢酬〔dynamic conditional factor premiums〕，實證計量解析顯示此項新型計量模型成功解釋許多資產訂價領域的異常現象〔size, value, momentum, asset growth, and operating profitability〕。同時，自我向量迴歸解析實證確認總經衝擊與動態條件溢酬兩者的雙向因果連動關係〔mutual causation in vector autoregressions〕，我們將其雙向因果連動關係，確立成為基本面解釋成因選擇的科學理據條件，由於動態條件溢酬顯著反映總經衝擊風險，此雙向因果連動關係自然展現投資人的基本面總經預期資產報酬，這項經濟見解可以幫助有效區分衡量金融領域當中的理性預期均衡訂價模型與行為財務失衡訂價模型。

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Abstract

We extract dynamic conditional factor premiums from the Fama-French factor model and find that most anomalies disappear after one accounts for time variation in these premiums. Vector autoregression evidence shows that mutual causation between dynamic conditional alphas and macroeconomic surprises serves as a core qualifying condition for fundamental factor selection. This economic insight is an incremental step toward drawing a distinction between rational risk and behavioral mispricing models. To the extent that dynamic conditional alphas can reveal the marginal investor's fundamental news and expectations about the cross-section of average asset returns, our economic insight helps enrich macroeconomic asset return prediction.

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Keywords: Fama-French multi-factor models; vector autoregressions; Granger causation tests; dynamic conditional alphas; macroeconomic innovations; asset return anomalies.

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Abstract

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1. Introduction

Fama and French's (1992, 1993, 1996, 1998, 2015, 2016) seminal contributions shed skeptical light on the empirical performance of the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965). The subsequent search for a better asset return model has been a hot pursuit for many financial economists (Fama and French, 1993, 1995, 1996, 1998, 2006b, 2008, 2015; Hou, Xue, and Zhang, 2014). Financial economists engage in the relentless debate over whether dramatic movements in market valuation such as the Global Financial Crisis reflect a "rational" fair-value price correction or a lack of compensation for risk. The debate has left many financial economists at a time-worn impasse (Fama and French, 2004). Empiricists continue to discover new asset anomalies (e.g. Titman, Wei, and Xie (2004); Fama and French (2006b, 2008); Cooper, Gulen, and Schill (2008); Li, Livdan, and Zhang (2009); Novy-Marx (2013)).

Kozak, Nagel, and Santosh's (2017; 2018) recent studies show that many recent empirical horse races cannot draw a distinction between both rational and behavioral theories of average return evolution. Kozak et al (2018) report that a factor model with a small number of statistical principal-components (PCs) performs as well as the prior factor models (e.g. Fama and French (1993); Hou, Xue, and Zhang (2014); Fama and French (2015); Novy-Marx and Velikov (2016); Barillas and Shanken (2018)). For typical portfolios, these few factors dominate the covariance matrix of returns. In the absence of near-arbitrage investment opportunities, these factor models include only a few dominant factors, which can be fundamental characteristics such as size and book-to-market or purely statistical PCs. Because these models exhibit few conceptual links to investor beliefs and preferences, the *q*-theoretic factor models are as much "behavioral models" as the models are "rational models" (cf. Berk, Green, and Naik (1999); Johnson (2002); Gomes, Kogan, and Zhang (2003); Liu, Whited, and Zhang (2011); Liu and Zhang (2008); Lin, and Zhang (2013); Liu and Zhang (2014)). In a similar vein, the prior tests of characteristics-versus-

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covariances inform us little of whether and how behavioral barriers such as investor sentiment and overconfidence affect asset returns (e.g. Daniel and Titman (1997); Brennan, Chordia, and Subramanyam (1998); Davis, Fama, and, French (2000); Stambaugh and Yuan (2017)). Overall, it seems futile to implement these horseraces to assess the complex convolution of both investor sentiment and rationality in most asset return tests.

In the current study, we carry out an alternative approach to tackling this important issue in finance. We first extract all dynamic conditional factor premiums from the Fama-French (2015) model and then find that most anomalies disappear after one accounts for time variation in these premiums. Granger-causality tests suggest new mutual causation between dynamic conditional alpha spreads and macroeconomic innovations. This mutual causation therefore serves as a core qualifying condition for factor selection with sound economic motivation. In the current study, our economic insight is an incremental step toward drawing a distinction between both rational risk and behavioral models in response to Kozak, Nagel, and Santosh (2017; 2018). To the extent that macroeconomic surprises manifest in the form of dynamic conditional alphas, this causation can reveal the marginal investor's fundamental news and expectations about the cross-section of average returns. Hence, our evidence contributes to macroeconomic asset return prediction.

Kozak, Nagel, and Santosh (2018) point out that the presence of arbitrageurs will connect the covariance structure to the cross-section of average returns. Insofar as this cross-section at least partially reflects investor sentiments such as overconfidence, salience of recent experience, and other cognitive biases, behavioral mispricing factors can help price assets with reasonable bounds on the Sharpe ratios. In this context, these behavioral factors load reasonable premiums to correctly price assets. However, these behavioral factors and premiums "will not necessarily covary with ***aggregate macroeconomic risks***, as the [fundamental factors] would…" (cf. Kozak, Nagel, and Santosh (2017, 2018); Daniel et al (2017); Daniel, Hirshleifer, and Sun (2017)). In fact, Kozak, Nagel, and Santosh (2018) suggest several alternative routes to design asset return tests that are more informative about investor beliefs, behaviors, and preferences:

"To devise tests that are more informative about investor beliefs, researchers must exploit additional predictions of a factor model that relate returns to other data such as ***macroeconomic variables***, information on portfolio holdings, or data on investor beliefs" (cf. Kozak, Nagel, and Santosh (2018): Section III.C first paragraph with our own bold italic emphasis).

In the current study, we pick the low-hanging fruit through an empirical analysis of mutual causation between macroeconomic innovations and dynamic conditional factor premiums. To the extent that macroeconomic innovations manifest in the form of dynamic conditional alphas and betas, the conditional moments of returns and factors convey information about the cross-section of average returns. This causation can thus serve as a core qualifying condition for valid and sound factor selection in macroeconomic asset return prediction. In particular, our evidence lends credence to the ubiquitous use of Fama-French (2015) factors that can reveal the marginal investor's response to fundamental expectations about the cross-section of average returns. At

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the same time, however, our econometric tests support Fama and French's (1996, 2008, 2015, 2016) perennial reluctance to consider the Carhart (1997) momentum factor in their factor model. We connect our dynamic conditional factor model results to recent advances in the intertemporal CAPM context (Merton, 1973; Campbell, 1993; Campbell and Vuolteenaho, 2004; Campbell et al, 2017). On balance, our current study represents an incremental step toward better deciphering a distinction between the rational risk paradigm and the behavioral mispricing conjecture.

We acknowledge the fact that some recent studies replicate a broader basket of anomalies (cf. Fama and French (2016); Harvey et al (2016); Harvey (2017); Hou, Xue, and Zhang (2017); Chordia, Goyal, and Saretto (2017)). Our primary and ultimate goal is not to compete with these prominent authors with more empirical replication. Instead, we establish new Granger causation between dynamic conditional alpha spreads and macroeconomic innovations as a core qualifying condition for fundamental factor selection in macro asset return prediction. This condition adds sound economic rigor and intuition to macroeconomic asset return prediction. So this condition contributes to our fresh insight that bilateral causation between macroeconomic surprises and dynamic conditional alpha spreads reflects the marginal investor's fundamental news and macro expectations about the cross-section of average returns. This fresh insight can help demystify the empirical puzzle that Kozak, Nagel, and Santosh (2018) suggest in their recent research.

Macroeconomic innovations move in tandem with dynamic conditional factor premiums that provide unique economic insights into the implicit nexus between state-dependent alphas and betas across fundamental factors. This nexus reveals rich information about the conditional factor covariance matrix in contrast to the unconditional counterpart, the latter of which omits informative restrictions across the conditional moments of both asset returns and factors from the empirical assessment of goodness-of-fit (Nagel and Singleton, 2011). Not only do dynamic conditional alpha spreads change over time, but these alpha spreads also exhibit a robust causal relation with macroeconomic surprises in a standard vector autoregressive system (Sims, 1980). Macroeconomic innovations *Granger-cause* most dynamic conditional alpha spreads except for momentum and partial value. Granger causation runs in a bilateral direction such that dynamic conditional alpha spreads both lead and convey material information about macro innovations (cf. our subsequent explanatory text on **Section 4** and **Tables 6 to 8**).

This evidence enriches our key interpretation of the intertemporal CAPM that macroeconomic gyrations both lead and vary with the conditional expectations of terminal payoffs in the marginal investor's intertemporal selection (Merton, 1973; Campbell, 1993; Fama, 1996; Campbell and Vuolteenaho, 2004; Campbell et al, 2017). Macro innovations manifest in the form of dynamic conditional alpha spreads that persist as abnormal returns. Therefore, mutual Granger causation between macro surprises and dynamic conditional alpha spreads becomes an informative piece of evidence that we can apply to help resolve some long prevalent asset anomalies.

With this theoretical justification of the intertemporal CAPM, we contribute to the empirical design of a workhorse asset return model by qualifying specific fundamental factors as useful

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and reasonable state variables. Our core qualifying condition is equivalent to mutual causation between macro surprises and alpha spreads that reflect changes in the conditional expectations of structural shifts in terminal wealth for the marginal investor. To the extent that many residual macroeconomic fluctuations lead dynamic conditional alpha spreads and vice versa, this causal relation becomes a necessary condition for valid and effective factor selection in empirical asset return research. For this pivotal purpose, sound theoretical justification of fundamental factors with respect to *causal* macroeconomic innovations should precede pure empirical motivation in macroeconomic asset return prediction (Harvey, 2017; Harvey, Liu, and Zhu, 2016).

Our current study also contributes to the conditional multifactor model literature. It is well-known that a dynamic conditional mean-variance efficient return need not unconditionally price the static portfolios with constant weights (cf. Cochrane (2005: 140)). Specifically, if a portfolio return is on the conditional mean-variance efficient frontier, this return may or may not land on the unconditional mean-variance efficient frontier. Cochrane (2005: 168) describes this issue in a succinct statement: "Whether the [multifactor model] can be rescued by more careful treatment of conditioning information remains an empirical question". In the current study, we attempt to fill this theoretical void by conditioning the main prediction of average returns on Fama-French (2015) factors up to each time increment. Subsequent work substantiates our economic insight that reconciles a reasonable array of anomalies within the dynamic conditional factor model.

Our unique use of fresh econometric tools serves as another empirical contribution to the asset return literature. Both the conditional specification test and recursive multivariate filter help extract dynamic conditional factor premiums that covary with macro surprises substantially over time. This important econometric innovation extends and generalizes the Fama-French multiple-regression approach and therefore can become part of the standard toolkit for subsequent asset pricing analysis. This application reconciles a baseline array of anomalies with the central theme of "dynamic" multifactor mean-variance efficiency (cf. dynamic MMVE in Fama (1996) and Merton (1973)). Further, the concomitant tests provide evidence in support of this notion. As a result, dynamic MMVE can serve as an informative benchmark for the empirical assessment of pervasive anomalies or portfolio strategies that generate persistent abnormal returns in a static context. Overall, our dynamic conditional factor model thus has key implications for equity cost estimation, risk management, fund performance evaluation, and corporate event assessment.

Applying the recursive multivariate filter adds value to the notion of dynamic multifactor mean variance efficiency (MMVE) in the intertemporal asset pricing context (cf. Merton (1973); Campbell (1993); Fama (1996); Campbell and Vuolteenaho (2004); Campbell et al (2017)). In this context, investors care about not only their terminal wealth but also state variables such as human capital, labor income, consumption, and hedging investment opportunities that covary with their terminal wealth (Fama and French, 2004). For instance, several studies suggest that inter-industry heterogeneity in both human capital and labor mobility can help explain the cross-section of average returns (Eiling, 2013; Donangelo, 2014). An international factor model with

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Epstein-Zin (1989) recursive investor preferences explains the high correlation of stock market indices despite the low correlation of fundamental factors (Colacito and Croce, 2011). A twin-country model can demystify both the carry trade puzzle and low correlation between exchange rate movements and cross-country differences in total consumption in the intertemporal context (Colacito and Croce, 2013). Hence, the Fama-French (2015) factors serve as valid and relevant empirical hedging instruments for the marginal investor's intertemporal selection between his or her current and future investment opportunities. Our current work suggests that the exclusion of Fama-French factors leads the econometrician to reject the null hypothesis of a correct factor model specification (Fama and French, 2016). Specifically, we find mutual Granger causation between macroeconomic surprises and dynamic conditional alphas for the Fama-French (2015) fundamental factors, except for momentum and partial value. This latter falsification provides empirical justification of Fama and French's (1993, 1996, 2015, 2016) perennial reluctance to encompass Carhart (1997) momentum as a new fundamental factor in the rational risk paradigm. All of this evidence thus bolsters our intertemporal CAPM interpretation of fundamental factors for the dynamic conditional factor model.

To the extent that macroeconomic surprises manifest in the form of dynamic conditional alphas, this causation reveals the marginal investor's fundamental news and expectations about the cross-section of average returns. Our evidence enriches and contributes to the intertemporal CAPM interpretation of dynamic conditional factor models. In this context, macro innovations serve as fundamental news and expectations that induce cash-flow and future-risk betas as "bad betas" or negative discount-rate betas as "good betas". In accordance with this intertemporal CAPM thesis, we expect assets with positive cash-flow shocks, future-risk spillovers, or subpar discount-rate news to yield low average returns. Conversely, we would expect other assets with negative cash-flow shocks, volatility declines, or optimistic discount-rate news to generate high average returns. Therefore, mutual causation between macroeconomic innovations and dynamic conditional alpha spreads serves as a core qualifying condition for fundamental factor selection with sound economic rigor and intuition. This economic insight is one of our main contributions to macroeconomic asset return prediction.

In addition to the use of a recursive multivariate filter for dynamic conditional alpha and beta estimation, the conditional specification test helps draw a crucial distinction between both the static and dynamic conditional factor models. This conditional specification test examines whether the core distance between the static and dynamic conditional estimators turns out to be significant so that there is sufficient evidence for one to reject the null hypothesis of a consistent and efficient static specification. Under the alternative hypothesis, only the dynamic conditional estimator is consistent although this more generic alternative specification may or may not be efficient in the econometric sense. In our empirical analysis of 100 decile returns on the major anomalies plus their respective 10 long-short stock portfolio strategies that focus on the extreme deciles, about 95% of the stock portfolio tilts point to the statistically reliable rejection of the

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null hypothesis that the static factor model is a correct specification. The key preponderance of empirical results thus supports our chosen dynamic conditional factor model in contrast to the static baseline factor model.

The remainder of our current study follows the structure below. Section 2 discusses the use of a recursive multivariate filter for estimating dynamic conditional factor premiums from the baseline Fama-French (2015) factor model. Section 3.1 describes the key datasets on the Fama-French factors and anomalies. Section 3.2 discusses the core empirical evidence in support of dynamic conditional factor premiums. Section 3.3 empirically analyzes each factor premium as a typical financial time series that we extract from recursive multivariate filtration. Section 3.4 lists the conditional specification test evidence in favor of the dynamic conditional factor model. Section 4 finds Granger causation between macroeconomic surprises and dynamic conditional alpha spreads as the core qualifying condition for fundamental factor selection in modern asset pricing model design. Section 5 concludes our study and offers new avenues for future research, especially structural factor models with an economically intuitive and meaningful specification of both investor beliefs and preferences.

The appendices offer supplementary evidence for our work. In particular, Appendix 1 helps the reader visualize top-to-bottom-decile dynamic conditional alphas across several anomalies. Appendix 2 presents the econometric test details for the canonical treatment of each dynamic conditional factor premium as a unique typical financial time-series. Appendix 3 provides a list of macroeconomic variable definitions and their data sources for our core vector autoregression (VAR) empirical analysis of Granger bilateral causation between fundamental macro surprises and dynamic conditional factor premiums. Appendix 4 encapsulates some elaborate discussions on the conceptual nexus between our current study and several recent studies of empirical asset return prediction. Appendix 5 presents the empirical results for dynamic conditional betas.

2. Methodology

In this section, we discuss our application of recursive multivariate filtration as an econometric innovation. This filter helps extract major dynamic conditional factor premiums from Fama and French's (2015) factor model. We offer an intuitive explanation for connecting this filter to the core notion of dynamic multifactor mean-variance efficiency (MMVE) (e.g. Merton (1973) and Fama (1996)). Our intuitive explanation contributes to the empirical asset-pricing literature by reconciling ubiquitous anomalies with dynamic multifactor portfolio efficiency.

An advantage of this unique econometric method is that we can assess whether the pervasive asset pricing anomalies persist after one accounts for time variation in these dynamic conditional factor premiums. We propose an alternative test of dynamic multifactor mean-variance efficiency to complement Gibbons, Ross, and Shanken's (1989) *F*-test. Our central evidence suggests that the pervasive anomalies of size, value, momentum, asset growth, operating profitability, and short-term and long-term return reversals, are not robust after we account for the dynamic nature of conditional

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factor premiums.[1] A unique core implication of our empirical evidence is that dynamic MMVE is essential to the design of a workhorse factor model for modern investment analysis. The prior static factor models can be viewed as special cases of the more generalized dynamic conditional factor model.

The vast majority of earlier studies of factor models rest upon the implicit assumption that factor premiums are constant over time. Under this key assumption, the resultant static analysis cannot account for the adverse effect of measurement noise that might be present in each state variable. To the extent that conditional factor premiums vary over time, this measurement noise can persist even in long-term data. Hence, the emergence and persistence of anomalous returns may arise from the fact that the conventional static baseline model cannot adequately take into account time variation in dynamic conditional factor premiums.

It is important for us to point out that our chosen use of a recursive multivariate filter differs from the recent attempts by numerous proponents of the conditional CAPM or other conditional factor model to allow each factor premium to change in short-window regressions, to move in tandem with economic variables, or to co-vary in accordance with some specific structure of autoregressive mean reversion (Lewellen and Nagel, 2006; Fama and French, 2006; Adrian and Franzoni, 2009; Ang and Kristensen, 2012).[2] In contrast, the recursive multivariate filter can allow conditional factor premiums to jointly covary in each time increment. This covariation is not conditional on particular macroeconomic fluctuations. Neither does this covariation strictly follow any arbitrary structure. As the recursive multivariate filter and conditional specification test evidence both bolster the case for dynamic MMVE, these main results lend credence to the empirical plausibility of dynamic conditional factor premiums. As dynamic conditional factor

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1 In our current empirical assessment, we consider a reasonably wide array of ubiquitous asset pricing anomalies such as size (Banz, 1981), value (Basu, 1977; Rosenberg, Reid, and Lanstein, 1985; Fama and French, 1992; Fama and French, 1998; Lakonishok, Shleifer, and Vishny, 1994), medium-term return momentum (Jegadeesh and Titman, 1993, 2001; Chan, Jegadeesh, Lakonishok, 1996), asset investment growth (Titman, Wei, and Xie, 2004; Cooper, Gulen, and Schill, 2008), operating profitability (Haugen and Baker, 1996; Collins and Hribar, 2000; Dechow, Hutton, and Sloan, 2000; Richardson, Sloan, Soliman, and Tuna, 2005; Fama and French, 2006b; Novy-Marx, 2013), and contrarian long-term return reversal (DeBondt and Thaler, 1985; Lakonishok, Shleifer, and Vishny, 1994; Fama and French, 1996, 1998). Fama and French (2004) provide a meticulous survey of the main anomalies that point to the empirical embarrassment of the CAPM. Fama and French (2008) revisit the empirical assessment of these key anomalies and in turn suggest that these anomalies tend to concentrate in the extreme deciles or in the microcap portfolio. Some more recent studies replicate a broader basket of anomalies (cf. Fama and French (2016); Harvey et al (2016); Harvey (2017); Hou, Xue, and Zhang (2017); Chordia, Goyal, and Saretto (2017)). Our primary and ultimate goal is not to compete with these prominent authors with more replication. Instead, the current study seeks to establish "mutual causation" between dynamic conditional alphas and macro surprises as a core qualifying condition for relevant and effective factor selection in subsequent asset pricing model design.

2 The conditional asset pricing literature can be traced back to the econometric contributions of Harvey (1989), Shanken (1990), Jagannathan and Wang (1996), Lettau and Ludvigson (2001). Ferson and Harvey (1991, 1993, 1999) empirically link multifactor betas to economic fluctuations. Several studies point out the importance of identifying the correct and relevant set of state variables (Harvey, 1989; Shanken, 1990; Jagannathan and Wang, 1996; Cochrane, 2001: 145). Lewellen and Nagel (2006) avoid this problem by using short-window regressions. Furthermore, Ang and Chen (2007) and Fama and French (2006) both assume some particular structure of auto-regressive mean reversion or structural breaks in the time-series behavior of market beta. Adrian and Franzoni (2009) allow market beta to vary over time with a univariate version of the recursive filter that the current paper proposes in the multivariate context. Ang and Kristensen (2012) test the conditional CAPM and the conditional Fama-French three-factor model and report evidence in favor of the alternative hypothesis that the pricing errors are too large for the conditional model to be correctly specified.

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premiums are highly volatile over time, this high volatility suggests a lack of statistical evidence against the hypothesis that our chosen dynamic conditional factor model is correctly specified.[3]

Nagel and Singleton (2010) design a test of conditional moments of asset returns in a high-dimensional context. It is well-known that it is more difficult to handle the multi-variate kernel regressions as the number of dimensions increases in the Nagel-Singleton (2010) framework. Thus, our chosen use of both recursive multivariate filtration and conditional specification test evidence helps resolve this important issue in modern asset pricing model design. Not only do we apply recursive multivariate filtration to extract informative time-varying conditional factor premiums, but we also devise a new dynamic conditional specification test to empirically verify factor premiums as dynamic financial time-series in the form of ARMA-EGARCH and ARMA-GJR-GARCH stochastic processes. Appendix 1 provides the complete time-series visualization of our dynamic conditional alphas over time.

The Fama-French (2015) five-factor model follows the canonical representation of **Eq(1)** with static point estimates of factor premiums on the respective factors. This model embeds the excess return on the CRSP value-weighted market portfolio. Each factor is the spread between the average returns on the top 30% and bottom 30% stock deciles that the econometrician sorts on size, book-to-market, asset growth, and operating profitability. Specifically, (R_{kt}–R_{ft}) and (R_{mt}–R_{ft}) denote the excess returns on the respective individual and market stock portfolios; SMB_t or Small-Minus-Big is the mean return spread between the top 30% and bottom 30% size deciles; HML_t or High-Minus-Low is the mean return spread between the top 30% and bottom 30% book-to-market deciles; CMA_t or Conservative-Minus-Aggressive equates the mean return

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[3] There are several main differences between the current paper and the previous studies of conditional factor models. First, we consider all of Fama-French's (2015) fundamental factors in the recursive estimation of dynamic conditional factor premiums in contrast to the narrower focus on the single-beta CAPM (Lewellen and Nagel, 2006; Fama and French, 2006a; Petkova and Zhang, 2005; Ang and Chen, 2007; Adrian and Franzoni, 2009) and the prior Fama-French factor model (Ang and Kristensen, 2012). Should the model exclude some relevant state variables, the incorrect specification would lead to an inconsistent estimator and also would produce significant alphas. In effect, each alpha absorbs the sum product of each dynamic factor premium and the corresponding state variable that one excludes from the model. Therefore, the inclusion of all of the Fama-French (2015) return spreads captures a broader gamut of state variables. This information set can more accurately span the mean-variance space. In turn, the consistent estimation of dynamic conditional factor premiums minimizes the likelihood of omitted-variables bias. Second, the current study uses a dynamic version of the Fama-French (2015) factor model to assess the persistence of anomalies such as size, value, momentum, asset investment growth, operating profitability, short-run return reversal, and long-term return reversal. Unlike Petkova and Zhang (2005), Lewellen and Nagel (2006), Fama and French (2006a), and Ang and Kristensen (2012), we find evidence in favor of the null hypothesis that a dynamic multifactor model adequately explains the long-short return spreads from portfolio tilts that consistently generate static anomalous returns. All of these anomalies are not robust after we consider the dynamic nature of conditional factor premiums. Third, our dynamic application is simple, requires no stringent time-series structure, and retains parsimony and flexibility in econometric usage. Unlike Ang and Chen (2006), we specify no highly parameterized latent-variable process to characterize the evolution of conditional factor premiums (Fama and French, 2006a: 2177). Unlike Lewellen and Nagel (2006), Fama and French (2006a), and Ang and Kristensen (2012), we set no particular time interval for updating the estimation of conditional factor premiums. Neither do we apply any specific kernel method or bandwidth choice to estimate smooth conditional factor premiums (Ang and Kristensen, 2012). Time variation in factor premiums is not conditional on macroeconomic fluctuations. The current study differs from the prior studies that assess time variation in macroeconomic factor premiums (cf. Ferson and Harvey, 1991, 1993, 1999; Lewellen and Nagel, 2006; Ang and Kristensen, 2012). However, each recursively fit dynamic factor premium can be generalized as a common financial time series that contains rich and meaningful economic content. It is plausible for conditional factor premiums to convey useful information about macroeconomic trends and cycles.

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spread between the top 30% and bottom 30% investment deciles; and RMW_t or Robust-Minus-Weak is the average return spread between the top 30% and bottom 30% profitability deciles. In comparison, we attempt to gauge the "dynamic estimates" of conditional factor premiums as unique individual time-series in the alternative representation of **Eq(2)**. A primary comparison between **Eq(1)** and **Eq(2)** suggests that the former entails the static estimation of point estimates of factor premiums, α, β_m, β_s, β_h, β_r, and β_c, on the Fama-French (2015) five-factors while the latter involves the dynamic estimation of time-series trajectories of conditional factor premiums, α_t, β_{mt}, β_{st}, β_{ht}, β_{rt}, and β_{ct}, on the Fama-French (2015) five-factors. For the practical purpose of our current analysis, the point estimates of static factor premiums in **Eq(1)** differ from the long-term mean values of dynamic conditional factor premiums in **Eq(2)** where these equations carry the Gaussian normal error terms ε_t and e_t:

$$R_{kt} - R_{ft} = \alpha + \beta_m (R_{mt} - R_{ft}) + \beta_s SMB_t + \beta_h HML_t + \beta_r RMW_t + \beta_c CMA_t + \varepsilon_t \quad \textbf{Eq(1)}$$

$$R_{kt} - R_{ft} = \alpha_t + \beta_{mt} (R_{mt} - R_{ft}) + \beta_{st} SMB_t + \beta_{ht} HML_t + \beta_{rt} RMW_t + \beta_{ct} CMA_t + e_t \quad \textbf{Eq(2)}$$

Our recursive multivariate filter follows the dynamic multifactor representation below (Kalman, 1960; Harvey and Shephard, 1993: 267-270; Lai and Xing, 2008: 130-133; Tsay, 2010: 591):

$$\boldsymbol{\beta}_{t+1} = \boldsymbol{A}_t \boldsymbol{\beta}_t + \boldsymbol{u}_{t+1} \quad \textbf{Eq(3)}$$

$$\boldsymbol{r}_t = \boldsymbol{F}_t \boldsymbol{\beta}_t + \boldsymbol{v}_t \quad \textbf{Eq(4)}$$

where $\boldsymbol{\beta}_t$ is a $(k+1)\times 1$ vector of conditional factor premiums at each time increment; $\boldsymbol{A}_t$ is a $(k+1)\times(k+1)$ identity matrix of linear dynamic variation in the state equation **Eq(3)**; $\boldsymbol{r}_t$ is a vector of excess returns on each portfolio; $\boldsymbol{F}_t$ is a $T\times(k+1)$ matrix of Fama-French factors plus an intercept in the measurement equation **Eq(4)**; and $\boldsymbol{u}_t$ and $\boldsymbol{v}_t$ are independent random vectors with $E(\boldsymbol{u}_t)=0$, $\text{cov}(\boldsymbol{u}_t)=\boldsymbol{\Sigma}_u$, $E(\boldsymbol{v}_t)=0$, and $\text{cov}(\boldsymbol{v}_t)=\boldsymbol{\Sigma}_v$. The dynamic states $\boldsymbol{\beta}_t$ are unobservable. The observations are the excess returns $\boldsymbol{r}_t$ that are linear transformations of time-varying factor premiums $\boldsymbol{\beta}_t$ via the matrix $\boldsymbol{F}_t$ plus the unobservable random disturbances $\boldsymbol{u}_t$. The recursive multivariate filter is the recursive minimum-variance linear estimator of $\boldsymbol{\beta}_t$ based on the observations up to each time increment. We can define $\boldsymbol{P}_{t|t-1}$ as the covariance estimator of the unobservable state $\boldsymbol{\beta}_t$, as well as the filter for the previous state $\boldsymbol{\beta}_{t|t-1}$. The gain matrix follows the form $\boldsymbol{\kappa}_t$ below:

$$\boldsymbol{\kappa}_t = \boldsymbol{A}_t \boldsymbol{P}_{t|t-1} \boldsymbol{F}_t^T \left(\boldsymbol{F}_t \boldsymbol{P}_{t|t-1} \boldsymbol{F}_t^T + \boldsymbol{\Sigma}_v \right)^{-1} \quad \textbf{Eq(5)}$$

For better exposition, we summarize the recursive formula for the filter in **Eq(6)-Eq(9)**:

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$$\hat{\boldsymbol{\beta}}_{t+1|t} = \boldsymbol{A}_t\hat{\boldsymbol{\beta}}_{t|t-1} + \boldsymbol{\kappa}_t\left(\boldsymbol{r}_t - \boldsymbol{F}_t\hat{\boldsymbol{\beta}}_{t|t-1}\right) \qquad \textbf{Eq(6)}$$

$$\boldsymbol{P}_{t+1|t} = \left(\boldsymbol{A}_t - \boldsymbol{\kappa}_t\boldsymbol{F}_t\right)\boldsymbol{P}_{t|t-1}\left(\boldsymbol{A}_t - \boldsymbol{\kappa}_t\boldsymbol{F}_t\right)^T + \boldsymbol{\Sigma}_u + \boldsymbol{\kappa}_t\boldsymbol{\Sigma}_v\boldsymbol{\kappa}_t^T \qquad \textbf{Eq(7)}$$

$$\hat{\boldsymbol{\beta}}_{t|t} = \hat{\boldsymbol{\beta}}_{t|t-1} + \boldsymbol{P}_{t|t-1}\boldsymbol{F}_t\left(\boldsymbol{F}_t\boldsymbol{P}_{t|t-1}\boldsymbol{F}_t^T + \boldsymbol{\Sigma}_v\right)^{-1}\left(\boldsymbol{r}_t - \boldsymbol{F}_t\hat{\boldsymbol{\beta}}_{t|t-1}\right) \qquad \textbf{Eq(8)}$$

$$\boldsymbol{P}_{t|t} = \boldsymbol{P}_{t|t-1} - \boldsymbol{P}_{t|t-1}\boldsymbol{F}_t^T\left(\boldsymbol{F}_t\boldsymbol{P}_{t|t-1}\boldsymbol{F}_t^T + \boldsymbol{\Sigma}_v\right)^{-1}\boldsymbol{F}_t\boldsymbol{P}_{t|t-1} \qquad \textbf{Eq(9)}$$

where we can initialize recursions at $\boldsymbol{\beta}_{1|0}=E(\boldsymbol{\beta}_1)$ and $\boldsymbol{P}_{1|0}=\text{cov}(\boldsymbol{\beta}_1)$. Lai and Xing (2008: 130-133) provide a complete derivation of the recursive formula for the filter. Due to its recursive nature, the filter ensures that the measurement noise between the real-time state and its most up-to-date dynamic estimator is nil on average (i.e. the expectation of the last term in **Eq(8)** equates zero).

To compare each stock portfolio to the market portfolio or the dynamic MMVE *Q*-portfolio, we can compute the quadratic Sharp-ratio square as $\boldsymbol{\alpha}^T\boldsymbol{V}^{-1}\boldsymbol{\alpha}$ where $\boldsymbol{\alpha}$ is a vector of alphas on the deciles and $\boldsymbol{V}$ is the residual variance-covariance matrix. In accordance with the prior treatment of Gibbons, Ross, and Shanken's *F*-test (1989) (Campbell, Lo, and MacKinlay, 1997: 192-193; Cochrane, 2005: 230-233), we present this test statistic in **Eq(10)**:

$$GRS = \left(\frac{T-N-1}{N}\right)\left(\frac{\hat{\boldsymbol{\alpha}}^T\hat{\boldsymbol{V}}^{-1}\hat{\boldsymbol{\alpha}}}{1+SR_m^2}\right) \sim F\left(N, T-N-1\right) \qquad \textbf{Eq(10)}$$

where k=5 is the number of regressors in the Fama-French (2015) factor model; N=10 denotes the number of deciles; and SR_{m} denotes the Sharpe ratio for the mean-variance efficient market portfolio in the Sharpe-Lintner CAPM. This GRS *F*-test examines whether a vector of average alphas is jointly zero in a static sense. Several comments can be made on the GRS *F*-test. First, the test assumes away the fact that conditional factor premiums can exhibit substantial variation over time. There can be non-trivial measurement noise in the estimation of unknown parameters in the multifactor model (Merton, 1980; Black, 1986). Second, the test only investigates a static version of portfolio efficiency with a single mean-variance efficient portfolio (Markowitz, 1952; Merton, 1973; Fama, 1996; Fama and French, 1996). The test may thus call for some adjustment in the more plausible case where several assets span the mean-variance space and then address the hedging concerns for the investors who care about their intertemporal portfolio choices. In this light, the optimal benchmark portfolio should include the relevant state variables that yield the largest possible Sharpe ratio over a sufficiently long time horizon. Third, the test rests on the implicit assumption that the alpha spread is constant over time. In this case, the GRS *F*-test may reject the correctly-specified multifactor model more often than one otherwise would in a dynamic context. The subsequent analysis demonstrates the opposite case that there is pervasive time variation in conditional factor premiums. Each dynamic alpha spread varies substantially

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at different historical junctures and exhibits the well-known properties of a financial time series. To the extent that the GRS F-test cannot take into account dynamic heterogeneity in conditional factor premiums, it is important for the econometrician to design a more suitable test of dynamic portfolio efficiency.

When the econometrician applies the recursive multivariate filter to extract the time-series of dynamic conditional factor premiums, alpha spreads should enter the GRS-equivalent F-test formula. Over each time increment the recursion is an independent estimation of dynamic factor premiums. This estimation makes use of all the return data up to the point in time. It is important to assess the joint significance of α_t over each time increment. For this reason, we have to adjust the degrees of freedom for the numerator of the GRS-equivalent F-test statistic:

$$AGRS = \left(\frac{T-N-1}{T-N-k}\right)\left(\frac{\hat{\boldsymbol{\alpha}}^T\hat{\mathbf{V}}^{-1}\hat{\boldsymbol{\alpha}}}{1+SR_m^2}\right) \sim F(T-N-k, T-N-1) \qquad \textbf{Eq(11)}$$

We dub **Eq(11)** the adjusted-GRS F-test. Cochrane (2005: 230-235) offers a GMM-equivalent χ^2-test that yields robust consistent standard errors to safeguard against both heteroskedasticity and serial correlation. In a similar vein, we run the adjusted-GMM χ^2-test to account for the key dynamic nature of each conditional alpha spread:

$$AGMM = \left(\frac{T-N-1}{1}\right)\left(\frac{\hat{\boldsymbol{\alpha}}^T\hat{\mathbf{V}}^{-1}\hat{\boldsymbol{\alpha}}}{1+SR_m^2}\right) \sim \chi^2(T-N-k) \qquad \textbf{Eq(12)}$$

Our chosen use of a recursive multivariate filter adds value to the notion of dynamic MMVE in the intertemporal asset-pricing context of Merton (1973), Campbell (1993), and Fama (1996). In this dynamic context, investors care about not only their terminal wealth but also investment opportunities that these investors expect to face before they achieve their terminal wealth. These marginal investors consider how their current wealth might co-vary with several state variables such as human capital, labor income, consumption, and hedging investment opportunities that remain available after the present period (Fama and French, 2004). For instance, inter-industry heterogeneity in human capital and labor mobility affects the cross-section of average returns (Eiling, 2013; Donangelo, 2014). In addition, an international factor model with Epstein-Zin (1989) recursive investor preferences helps explain the high correlation of global market indices despite the low correlation of fundamental factors (Colacito and Croce, 2011). A similar cross-country model helps demystify the carry-trade puzzle and the low correlation between exchange rate gyrations and international differences in aggregate consumption in an intertemporal asset-pricing context (Colacito and Croce, 2013). In this light, the Fama-French (2015) factors serve as valid and relevant empirical hedging instruments for the marginal investor's intertemporal substitution between the current and future investment opportunities. A subsequent strand of falsification tests suggests that the main exclusion of any one of the Fama-French (2015) factors would lead the econometrician to reject the null hypothesis of our correct dynamic conditional

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factor model specification. All of this evidence thus shines fresh light on a dynamic conditional interpretation of economic intuition behind the intertemporal CAPM (Merton, 1973; Campbell, 1993; Fama, 1996; Campbell and Vuolteenaho, 2004; Campbell et al, 2017).

Fama and French's (2015) five-factor model includes a unique set of fundamental factors (e.g. Fama and French (1993, 1995, 1996, 1998, 2006b, 2012, 2015); Vassalou and Xing (2004); Petkova (2006)). Our empirical study extends their "static" model to encapsulate time variation in conditional factor premiums. This time variation suggests that each dynamic alpha oscillates too much around nil so that the pervasive anomalies vanish. Once the econometrician accounts for the dynamic nature of conditional factor premiums, each alpha spread between the extreme deciles eventually disappears. A pivotal comparison hence has to be made against the dynamic MMVE portfolio. For easier exposition, we dub this dynamic MMVE portfolio the "*Q*-portfolio" that generates the largest possible average returns for each given set of asset return covariances and variances with the valid fundamental factors (Fama, 1996). Without reinventing the wheel, we use the Fama-French (2015) five-factors as state variables in our dynamic conditional factor analysis. Moreover, we propose an alternative *Q*-test of dynamic mean-variance efficiency by comparing the Sharpe ratios for each long-short decile alpha-spread and the MMVE *Q*-portfolio. A reasonable choice is to assume each Sharpe ratio to follow an independent normal distribution, then the *Q*-test statistic conforms to the χ^2 distribution:

$$Q = \left(\frac{T-N-1}{1}\right)\left(\frac{\hat{\boldsymbol{\alpha}}^T\hat{\boldsymbol{V}}^{-1}\hat{\boldsymbol{\alpha}}}{1+\hat{\boldsymbol{q}}^T\hat{\boldsymbol{W}}^{-1}\hat{\boldsymbol{q}}}\right) \sim \chi^2\left(T-N-k\right) \qquad \textbf{Eq(13)}$$

where $\boldsymbol{q}$ denotes a vector of Fama-French return spreads and $\boldsymbol{W}$ is the variance-covariance of these return spreads. In effect, our chosen omnibus *Q*-test verifies whether the Sharpe ratio for a particular portfolio tilt is so large that dynamic conditional alphas cannot be readily explained by the Fama-French (2015) factor model. The *Q*-test statistic is asymptotically analogous to the Wald test statistic of Ang and Kristensen (2012: 138-139) except here we regard the dynamic MMVE *Q*-portfolio as the benchmark portfolio. In this latter case, the *Q*-test helps measure the wedge between the Sharpe-ratio squares for the *Q*-portfolio and each stock portfolio tilt. In our subsequent analysis, we use the *Q*-test to complement the AGRS *F*-test and the AGMM χ^2-test (aka the AGMM *C*-test).

3. Evidence

3.1 Data description

We retrieve the U.S. stock portfolio return data from Professor Ken French's online data library. The monthly stock dataset spans the 50-year period from January 1964 to December 2013. For applying the recursive multivariate filter to this dataset, we run the filter on a training period of 60 months. This technical choice allows the filter to adapt dynamic conditional factor premiums

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by recursively learning from a sufficient set of prior information. The Fama-French factors are the market risk premium (MRP), the return spread between the small-versus-big size portfolios (SMB), the return spread between the high-versus-low book-to-market portfolios (HML), the return spread between the robust-versus-weak portfolios in terms of their operating profitability (RMW), and the return spread between the conservative-and-aggressive asset-growth portfolios (CMA). For the practical purposes of this empirical analysis, we consider the value-weighted deciles for the pervasive portfolio sorts of size, value (i.e. book-to-market, cash-flow-to-price, dividend-to-price, and earnings-to-price), momentum, asset growth, operating profitability, and short-term and long-term return reversals. For each of these sorts, we apply the recursive multivariate filter to extract dynamic conditional factor premiums on the Fama-French (2015) factors and intercept term. This dynamic factor analysis focuses on whether the alpha spread between the extreme deciles for each of the pervasive portfolio sorts is sufficiently large for us to reject the null hypothesis of a correct factor model specification.

Table 1 shows the descriptive statistics for the Fama-French factors and return spreads that generate anomalous patterns in several prior studies (e.g. Fama and French (1996, 2015, 2016)). For the size, asset investment growth, short-run return reversal, and long-run reversal sorts, the portfolio strategy that involves both a long position in the top decile and a short position in the bottom decile produces a negative average return spread. This evidence echoes the descriptive statistics for the other decile sorts that yield positive mean return spreads. Because these time-series are leptokurtic and exhibit fat tails, it is reasonable to conjecture that each factor premium may be similar to a financial time series in the dynamic conditional factor context. Specifically, conditional factor premiums vary much over time and exhibit pervasive autoregressive patterns in the conditional mean specification and volatility clusters and asymmetries in the conditional variance specification. Subsequent analysis provides a deeper exploration of these new patterns.

Table 2 lists the Sharpe ratios for the market benchmark portfolio, the Fama-French MMVE *Q*-portfolio, and the portfolio sorts of size, value, momentum, profitability, investment growth, and short-term and long-term return reversals. While the market portfolio attains a Sharpe ratio of 0.1006, the MMVE *Q*-portfolio achieves a superior Sharpe ratio of 0.3006. The vast majority of portfolio sorts generate Sharpe ratios that land within these bounds. A notable exception is the short-term return reversal sort. The best Sharpe-ratio performers are the portfolio strategies that exploit the return spreads between the top and bottom deciles of momentum, dividend-to-price, asset growth, and short-term reversal with the respective Sharpe ratios of 0.2574, 0.2935, 0.2551, and 0.3362. In light of this evidence, most of the anomalies offer greater rewards that are commensurate with their exposure to systematic risk in comparison to the CAPM. However, the results also suggest that the anomalies largely lead to smaller mean excess returns per unit of risk relative to the MMVE *Q*-portfolio. Table 2 thus resonates with the *Q*-test evidence below that the relative distance between the Sharpe-ratio squares for the dynamic MMVE *Q*-portfolio

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and each of the stock portfolio tilts is not sufficiently large for one to reject the null hypothesis of a correct dynamic conditional factor model specification.

3.2 Time-varying dynamic conditional alphas

Table 3 presents the time-varying Fama-French (2015) alphas across the deciles for each of the portfolio sorts, *t*-tests of these alpha spreads between the extreme deciles with the Newey-West (1987) standard-error correction that safeguards against potential heteroskedasticity and serial correlation, *F*-tests of mean-variance efficiency (Gibbons, Ross, and Shanken, 1989), and *Q*-tests that we propose as the appropriate test of dynamic portfolio efficiency to complement the filter. A first glance at Table 3 indicates that most dynamic conditional alphas are statistically close to nil. Out of these portfolio tilts, only the momentum, short-term reversal, and long-term reversal tilts yield significant alpha spreads between the top and bottom deciles in the range of 0.989, –1.180, and 0.426 (p-values<0.001). Yet, the positive sign of the average alpha spread for long-term return reversal is counter-intuitive and therefore instead suggests long-term return momentum. This evidence contradicts the prior studies in support of long-term return reversal that can arise from the typical investor's naïve extrapolation of past superior stock performance (DeBondt and Thaler, 1985; Lakonishok, Shleifer, and Vishny, 1994; Fama and French, 1996). With respect to return momentum (Jegadeesh and Titman, 1993, 2001; Chan, Jegadeesh, and Lakonishok, 1996), the long-term average dynamic conditional alpha is significant only for the extreme deciles. In this case, the top and bottom deciles produce significant average conditional alphas of –0.569 and 0.42 respectively (p-values<0.005). The resultant alpha spread is therefore significant at the conventional statistical confidence level. Also, the dynamic conditional alpha spread between the extreme short-term reversal deciles is significant in econometric terms (p-value<0.001). Whether these results are a statistical aberration calls for more formal hypothesis tests on the short-term reversal and momentum phenomena.

In Table 3, all the AGRS *F*-tests, the AGMM *C*-tests, and the *Q*-tests unanimously suggest that dynamic conditional alphas are jointly indistinguishable from zero for all the portfolio tilts. The *p*-values are substantially near unity across the board. Hence, there is minimal evidence in support of the alternative hypothesis that our dynamic factor model is incorrectly specified. The main economic intuition is that the wedge between the Sharpe-ratio squares for the benchmark portfolio and the long-short decile strategy is not large enough to justify the statistical rejection of a dynamic variant of the Fama-French (2015) factor model. The conditional factor premiums are too volatile for the econometrician to affirm the consistent outperformance of each portfolio tilt once he or she takes into account the dynamic nature of these conditional factor premiums. In Appendix 1, the time-series visualization of dynamic conditional alpha spreads between both the top and bottom deciles corroborates this empirical fact. A falsification test suggests that the highest *F*-test, *C*-test, and *Q*-test *p*-value is 0.04 (not shown in the tables and charts) when we exclude any one of the Fama-French (2015) explanatory factors from the recursive estimation. This falsification test evidence supports the joint insignificant of dynamic conditional alphas.

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Harvey, Liu, and Zhu (2015) introduce a multiple testing framework (e.g. Harvey and Liu (2014a, 2014b, 2014c, 2014d)) and provide a unique variety of historical significance cut-offs from the first empirical tests in the 1960s to the present. This new strand of investment literature suggests that we should raise the test hurdle substantially from a *t*-ratio of 2.0 to a *t*-ratio of 3.0 for most cross-sectional asset-pricing tests. Specifically, Harvey, Liu, and Zhu (2015) find that this higher hurdle reduces the number of cross-sectional anomalies from 316 to only 2 i.e. value and momentum (cf. Asness et al (2013); Fama and French (2016); Hou, Xue, and Zhang (2017)). In addition, Harvey, Liu, and Zhu (2015) propose that a theoretically-derived factor should have a lower hurdle than an empirically-discovered factor. Their central thesis suggests that a factor can be important in some economic environments but unimportant in some other environments.

While our econometric innovation complements Harvey, Liu, and Zhu's (2015) multiple testing analysis, our work serves as a time-series equivalent to their cross-sectional adjustment for asset-pricing tests. Back-of-the-envelope calculations show that the typical stock portfolio's Sharpe ratio has to increase by at least 3 to 8.2 times for most dynamic conditional alphas to be jointly significant at the conventional confidence level. The critical values for the χ^2-test with 525 degrees of freedom are 603.31, 579.43, and 566.91 at the respective 99%, 95%, and 90% confidence levels. Table 3 demonstrates that the highest *C*-test or *Q*-test statistic is 59.29 while the lowest *C*-test or *Q*-test statistic is 8.97. Therefore, the smallest Sharpe ratio multiplier can be calculated as $(566.932/59.29)^{1/2}$=3.092 while the largest Sharpe ratio multiplier can then be calculated as $(603.31/8.97)^{1/2}$=8.201. As a result, the econometrician has to specify a higher test hurdle for each anomaly. Across the deciles, most dynamic conditional alphas need to be larger on average with significantly less variability for the Sharpe ratio to increase by at least 3 to 8 times. The equivalent Sharpe ratio would be in the approximate range of 1.15 to 2.4 (cf. Kozak, Nagel, and Santosh (2017)). In other words, our unique dynamic analysis of conditional factor premiums proposes raising the bar for the econometric asset pricing test. This recommendation echoes the cross-sectional counterpart of Harvey, Liu, and Zhu (2015).

3.3 ARMA-GARCH representation of each dynamic conditional factor premium

In this section, we demonstrate that each dynamic conditional factor premium can be modeled as a financial time-series. We apply both ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) conditional-mean-and-variance models to fit each conditional factor premium that the econometrician extracts from a dynamic variant of the Fama-French (2015) multifactor model. Although it is possible to identify a better time-series representation for each conditional factor premium, our goal here is more straight-forward. In fact, our primary objective is to apply the standard toolkit in time-series econometrics to establish the empirical fact that each dynamic alpha or beta spread exhibits the major properties of most financial time series. Each conditional factor premium embeds autoregressive mean reversion in the conditional mean specification of ARMA(1,1), and volatility clusters and asymmetries in the conditional volatility specification

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of EGARCH(1,1,1) or GJR GARCH(1,1,1) (cf. Engle (1982); Bollerslev (1986); Nelson (1991); Glosten et al, 1993):

ARMA(1,1) conditional mean specification

$$m_t = a + bm_{t-1} + cw_{t-1} + w_t \qquad \textbf{Eq(14)}$$

$$w_t = \sqrt{h_t}\,\varepsilon_t \qquad \textbf{Eq(15)}$$

EGARCH(1,1,1) and GJR-GARCH (1,1,1) conditional variance specifications

$$h_t = \exp\left\{d + e\left(\frac{w_t}{\sqrt{h_{t-1}}}\right) + f\ln h_{t-1} + g\left(\left|\frac{w_t}{\sqrt{h_{t-1}}}\right| - \left|\frac{E(w_t)}{\sqrt{h_{t-1}}}\right|\right)\right\} \qquad \textbf{Eq(16)}$$

$$h_t = d + ew_{t-1}^2 + fh_{t-1} + gD_{t-1}w_{t-1}^2 \qquad \textbf{Eq(17)}$$

where m_t is the dynamic conditional alpha or beta spread; w_t is the residual error term; h_t is the conditional variance process; ε_t is a Gaussian white noise; D_t denotes a binary variable with a numerical value of unity if w_t is negative or zero if w_t is positive; *a*, *b*, *c*, *d*, *e*, *f*, and *g* are the parameters for quasi-maximum likelihood estimation. The canonical ARMA model serves as the conditional mean specification to capture any autoregressive mean reversion in the dynamic conditional alpha or beta spread between the extreme deciles, while EGARCH or GJR-GARCH fits the conditional variance specification to encapsulate any volatility clusters and asymmetries in the current factor premium time-series under study.

It is important to draw a distinction between this time-series analysis and the prior studies of multiple conditional factor models (Ferson and Harvey, 1991, 1999; Fama and French, 2006; Ang and Chen, 2007; Ang and Kristensen, 2012). In the current study, we need not impose any *a priori* assumption about the dynamic evolution of conditional alpha or beta spreads, whereas, the earlier studies of conditional factor models make specific assumptions about the time-series behaviors of dynamic conditional factor premiums (such as structural breaks in autoregressive mean reversion). Yet, the econometrician can readily fit an ARMA-EGARCH or ARMA-GJR-GARCH model to characterize the dynamic evolution of each conditional alpha or beta spread over time. This characterization entails both reasonable and flexible assumptions about the true conditional mean and variance processes for each dynamic conditional factor premium.

This time-series analysis also differs from several earlier studies that exclusively focus on the CAPM (cf. Adrian and Franzoni (2009); Ang and Chen (2007); Lewellen and Nagel (2006)). The recursive multivariate filter helps extract dynamic conditional alphas and betas from the Fama-French (2015) multifactor model, and then the econometrician can apply **Eq(14)-Eq(17)**

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to model each dynamic conditional alpha or beta spread as a typical financial time series. While it is reasonable to identify the "best" ARMA-GARCH representation for each conditional alpha or beta spread, we aim to establish the empirical fact that each conditional alpha or beta spread exhibits most prevalent properties of a typical financial time series. In turn, this empirical fact defies the conventional wisdom of point estimates of factor premiums in most static time-series ordinary least-squares regressions. Table 4 summarizes the empirical results in Appendix 2 (cf. Tables A2.1 to A2.6).

We summarize several bullet points from Appendix 2 and the tabular results therein:

1. These results allow us to establish the empirical fact that almost all the dynamic conditional factor premiums exhibit the key properties of most financial time-series. Specifically, these dynamic conditional alpha and beta spreads exhibit autoregressive mean reversion in the conditional mean specification, and volatility clusters and asymmetries in the conditional variance specification. Therefore, the conditional moments of factors and returns manifest in the form of state-dependent alphas and betas, or dynamic conditional factor premiums, across Fama and French's (2015; 2016) fundamental factors (Nagel and Singleton, 2011). Our subsequent analysis suggests bilateral causation between macroeconomic surprises and conditional alpha spreads. Overall, the evidence enriches our chosen interpretation of the intertemporal CAPM that most macroeconomic gyrations both lead and covary with the conditional expectations of terminal wealth in the investor's investment opportunity set (cf. Merton (1973); Campbell (1993); Fama (1996); Campbell and Vuolteenaho (2004, 2010); Campbell et al (2017)). To the extent that macroeconomic shocks manifest in the form of persistent dynamic conditional alpha spreads, mutual causation between macro surprises and alpha spreads hence becomes an informative piece of evidence that we can exploit in order to resolve at least some of the prevalent abnormal returns or stock market anomalies.
2. To the extent that stock market information serves as a useful indicator of macro surprises, each dynamic conditional factor premium conveys rich information about macroeconomic growth, market valuation, financial stress, cyclical variation, or forecast combination. This inference calls for more corroboration in the core spirit of several recent studies (Liew and Vassalou, 2000; Vassalou, 2003; Vassalou and Xing, 2004; Petkova, 2006; Campbell and Vuolteenho, 2010; Campbell, Giglio, Polk, and Turley, 2017).
3. Most of the average conditional alpha spreads are insignificant while the exceptions are momentum and short-term reversal (with absolute *t*-ratios more than 2.9). For the latter portfolio tilts, the respective conditional average alpha spreads are 1.03 and –1.12. These conditional mean alpha spreads are close to the corresponding average dynamic conditional alpha spreads for momentum and short-term return reversal of 0.989 and –1.18 in Table 3. Although these average alpha spreads seem to persist in the extreme deciles (cf. Fama and French (2008; 2016)), it is key to recall the more formal Sharpe ratio test evidence that the average alphas do not jointly differ from nil across all the momentum and short-term return

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reversal deciles. In other words, these dynamic conditional alphas are too volatile for one to reject the hypothesis that our chosen dynamic version of the Fama-French (2015) factor model is a correct specification. The logic leads the econometrician to infer that the average alpha spreads are consistent between Table 3 and Table A2.1.

4. Table A2.3 shows that each dynamic conditional HML beta exhibits much variability over time for the original Fama-French value factor to be economically meaningful in explaining time variation in average stock returns. In conjunction with the evidence of significant long-term average HML betas in Table A5.3, the ARMA-GARCH results support the use of HML as a relevant state variable that helps better span the investor's mean-variance space. Thus, HML conveys non-negligible information about at least some variation in average returns for a wide variety of stock portfolio tilts. This major inference reconciles with some recent independent empirical contributions of Fama and French (2015, 2016) and Hou, Xue, and Zhang (2014): HML appears to be redundant once the econometrician incorporates RMW and CMA into the factor model for the U.S. stock market, whereas, the hefty value premium persists both in the U.S. and several other stock markets (Asness, Moskowitz, and Pedersen, 2013; Fama and French, 2016). In turn, the economic content and substance of HML and even SMB may help explain whether these state variables serve as useful empirical proxies for macroeconomic innovations (Liew and Vassalou, 2000, Vassalou, 2003; Petkova, 2006; Hahn and Lee, 2006), distress risk (Griffin and Lemmon, 2002; Vassalou and Xing, 2004), or some other behavioral mispricing reasons (Campbell, Hilscher, and Szilagyi, 2008). Our subsequent evidence generalizes the key empirical inference that mutual causation between macroeconomic surprises and dynamic conditional alpha spreads can be an informative and plausible economic explanation for most anomalies in the fundamental evolution of average returns and factors.

3.4 Conditional specification test evidence

In this section, we follow the recent dynamic conditional specification test from the U.S. patent literature (Yeh, 2017 and 2021) to assess whether the static and dynamic conditional alphas are econometrically different. Table 5 offers the complete empirical results and discussions on this important part of our econometric analysis.

Yeh, A.J.Y. (October 2017 and March 2021). Algorithmic system for dynamic conditional asset return prediction and fintech network platform automation. USPTO patent specification (Patent Application Number #17192059; Publication Number: US20210192628).

Table 5 lists the conditional specification test evidence in favor of the dynamic conditional multifactor asset pricing model. In our empirical analysis of 100 monthly decile returns on the major anomalies plus their respective 10 long-short portfolios that focus on the extreme deciles,

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95% of the portfolio tilts suggest the statistical rejection of the null hypothesis that the static factor model is a correctly specification. The preponderance of empirical results supports the dynamic conditional factor model in stark contrast to the static baseline model for good reasons. First, the vast majority of dynamic conditional alphas are statistically insignificant so that most of the pricing errors are close to zero in the alternative dynamic conditional model specification. Second, the conditional specification test results prevail in favor of the alternative hypothesis that only the dynamic conditional estimator is consistent. This latter point highlights the power of measurement error minimization that the recursive multivariate filter achieves for consistent statistical estimation. Overall, the dynamic conditional factor model can outperform its static counterpart in light of the conditional specification test evidence and dynamic conditional alpha insignificance.[4]

Therefore, both the recursive multivariate filter and dynamic conditional specification test add value to the econometric toolkit for subsequent asset-pricing analysis. Not only does this econometric advancement pose a core conceptual challenge to the conventional use of ordinary least-squares (OLS) regressions for factor model design, but this econometric innovation also suggests that dynamic conditional alpha estimation serves as a useful quantitative method for financial applications such as mutual fund performance evaluation, corporate event assessment, equity cost estimation, and financial risk management.

4. Mutual causation between macroeconomic innovations and alpha spreads

In this section, we delve into the main crux of the current study and empirically ascertain mutual causation between macroeconomic innovations and dynamic conditional alpha spreads. To the extent that macroeconomic innovations manifest in the form of these dynamic conditional alpha spreads, this causality reveals the marginal investor's fundamental news and expectations about the cross-section of average returns. We interpret this Granger-causality evidence in the broader context of the intertemporal CAPM with cash-flow news, discount-rate news, as well as future-risk news (cf. Merton (1973); Campbell (1993); Campbell and Vuolteenaho (2004); Campbell, Giglio, Polk, and Turley (2017)). Campbell and Vuolteenaho (2004) develop the intertemporal CAPM with cash-flow and discount-rate betas. Campbell et al (2017) extend and generalize the

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4 There are a couple of reasons for this model comparison. First, the vast majority of dynamic conditional alphas are statistically insignificant so that most of the pricing errors or alphas are near zero in the alternative dynamic conditional specification. Second, the new conditional specification test results prevail in favor of the alternative hypothesis that only the dynamic conditional estimator is consistent. This latter reason highlights the power of measurement error minimization that the recursive multivariate filter attains for consistent estimation. Overall, the dynamic conditional factor model outperforms its static counterpart in light of the conditional specification test evidence and dynamic conditional alpha insignificance. In effect, both the recursive multivariate filter and conditional specification test contribute to the econometric toolkit for empirical asset pricing analysis. Not only does this advancement pose a new conceptual challenge to the conventional use of ordinary least-squares (OLS) Fama-French time-series regressions for empirical asset pricing analysis, but this econometric innovation also suggests that dynamic conditional alpha estimation serves as a novel and useful quantitative method for a broad variety of financial applications such as cost-of-equity-capital estimation, corporate event study, financial risk management, and mutual fund performance evaluation.

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intertemporal CAPM with stochastic volatility to capture future-risk news. The price of risk for cash-flow news is the marginal investor's relative risk aversion coefficient times more than the unit price of risk for negative discount-rate news. Therefore, cash-flow news carries "bad betas", whereas, negative discount-rate news carries "good betas". Also, an asset that provides positive returns when future risk expectations increase tends to generate low average returns. Thus, the marginal investor's stochastic discount factor is high when he or she anticipates high stochastic volatility in the future. In essence, these fundamental news and expectations reflect the marginal investor's rational response to different kinds of macroeconomic surprises with respect to cash flows, discount rates, and stochastic volatilities. Vector autoregressions (VAR) and Granger-causality tests below accord with the main theme of bilateral causation between macroeconomic innovations and dynamic conditional alphas. This causation reinforces the intertemporal asset-pricing interpretation that macroeconomic shocks manifest in the form of dynamic conditional factor premiums and vice versa such that this nexus reveals the marginal investor's fundamental news and macroeconomic expectations about the cross-section of average returns. To the extent that these causal relations reflect the marginal investor's rational response to changes in his or her intertemporal choice and conditional expectation of terminal wealth, the resultant dynamic conditional factor model differentiates itself from most behavioral mispricing models. This key conceptual distinction resonates with the primary thesis of Kozak, Nagel, and Santosh's (2018) recent critique of numerous horseraces for empirically-driven factor models.

We use 15 main monthly time-series in a macroeconometric vector autoregression (VAR) (Sims, 1980; Campbell, 1993). There are 12 macro time-series, 2 financial uncertainty metrics, and 2 investor sentiment proxies. The resultant dataset spans the 285-month sample period from April 1990 to December 2013. These macrofinancial time-series include first differences in the national economic activity index, Treasury bill rate, unemployment rate, term spread, default spread, prime bank loan rate, aggregate equity market dividend yield, as well as percent changes in industrial production, non-farm payroll, house price index, consumer price index, exchange rate, financial stress index, economic policy uncertainty, and investor sentiment. For the Baker-Wurgler capital market investor sentiment index, we use the first principal component as a main empirical proxy. This variable choice has no impact on our subsequent inferences. Appendix 3 lists and describes these macroeconomic variable definitions and their data sources.

We develop a medium macroeconometric vector autoregressive system in order to gauge macroeconomic innovations or fundamental surprises that the typical investor would face in his or her investment journey. Insofar as we can gauge macroeconomic surprises, we establish the empirical fact of mutual Granger causation between macroeconomic innovations and dynamic conditional alpha spreads. Granger-causality tests help us assess this mutual causation as a core qualifying condition for fundamental factor selection.

Table 6 shows the vector autoregression (VAR) coefficient estimates and *t*-statistics. This VAR model explains most of the time variation in fundamental macroeconomic news. The only

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exception is the macro VAR model of percent changes in the economic policy uncertainty index (Baker, Bloom, and Davis, 2012), which seems to contain peculiar information in its own right. Due to its unique lag structure, the Baker-Wurgler (2006) financial market investor sentiment VAR model generates the highest R^2 of 94.9%. This macroeconometric VAR system captures reasonably well time variation in U.S. national economic activity, prime bank loan interest rate, non-farm payroll, and residential house price index with intermediate R^2s from 40% to 68%.

This macroeconometric VAR system explains about 20%-30% of time variation in each of the other key macroeconomic time-series such as the Treasury 3-month bill rate, unemployment rate, term spread, default spread, aggregate dividend yield, industrial production, dollar strength, CPI inflation, and systemic stress within the U.S. financial sector. Overall, this medium macro VAR system allows us to extract macroeconomic innovations (or fundamental surprises) as the residual disturbances from each of the resultant macro equations.

Tables 7 and 8 list the pairwise Granger causality tests with *p*-values for us to see whether there is mutual causation between macroeconomic surprises and dynamic conditional alphas. Indeed, these test results suggest the affirmative case for Granger causation in both directions. Table 7 shows that at least 1 to 4 macroeconomic innovations Granger-cause each dynamic conditional alpha spread for size, value (B/M, CF/P, and Div/P), operating profitability, asset growth, short-term return reversal, and long-run return reversal. Only momentum and partial value (E/P) turn out to be the exceptions that defy this rule of thumb.

Table 8 shows that reverse causality runs from several dynamic conditional alpha spreads to macroeconomic innovations. Key conditional alpha spreads represent rich and valuable stock market signals about macroeconomic surprises. However, this evidence is less conclusive since only partial value (Div/P and E/P), asset investment growth, operating profitability, short-term return reversal, and long-term return reversal exhibit this reverse causation. In fact, the primary conditional alpha spreads for size, value (B/M and CF/P), and momentum convey little causal information about macroeconomic innovations.

On balance, these results suggest mutual Granger causation from macroeconomic surprises to most dynamic conditional alpha spreads and vice versa (except momentum and partial value). Within the intertemporal CAPM context, we interpret this evidence in support of the prevalent use of Fama-French (2015) factors in a dynamic conditional model. Mutual causation between macroeconomic innovations and dynamic conditional alpha spreads serves as a core qualifying condition for "shrinking the factor zoo", whereas, there is minimal or no sufficient evidence in favor of viewing momentum as a conceptually sound factor in the dynamic conditional context. To the extent that the marginal investor cannot decipher fundamental news nor macroeconomic surprises from momentum, it is difficult to rationalize momentum apart from a unique statistical aberration. Insofar as momentum profits persist as an anomaly, we need a more plausible reason than behavioral mispricing disequilibrium before we view momentum as an extra fundamental factor in the dynamic conditional model.

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Tables 7 and 8 demonstrate bilateral causation between most macroeconomic shocks and dynamic conditional alpha spreads. To the extent that macroeconomic innovations manifest in the form of these dynamic conditional alpha spreads, this critical channel of Granger causation reveals the marginal investor's fundamental news and expectations about the cross-section of average returns. This core evidence enriches and contributes to our chosen intertemporal asset-pricing interpretation of dynamic conditional factor models. In this intertemporal asset-pricing context, macroeconomic innovations serve as fundamental news and surprises that induce cash-flow betas and future-risk betas as "bad betas" or negative discount-rate betas as "good betas". In accordance with this intertemporal CAPM thesis, we would expect assets with positive cash-flow shocks, future-risk spillovers, or subpar discount-rate news to generate low average returns. Conversely, we would expect other assets with negative cash-flow surprises, volatility declines, or optimistic discount-rate news to generate high average returns. Therefore, mutual causation between macroeconomic innovations and dynamic conditional alpha spreads serves as a core qualifying condition for more effective factor selection with sound economic rigor and intuition. This new economic insight is one of our key contributions to modern asset pricing model design. Appendix 4 discusses the main similarities and differences between our current study and some concurrent contributions.

In accordance with the core thesis of Kozak, Nagel, and Santosh (2018), both fundamental and behavioral factors can help price the cross-section of average returns. In order to determine whether a specific factor is fundamental, the econometrician can measure factor covariances or factor premiums with macroeconomic risk innovations. Vector autoregression (VAR) evidence confirms bilateral Granger causation between dynamic conditional alphas and macroeconomic risk innovations. VAR evidence further supports this mutual causation for Fama-French (2015) fundamental factors with the plausible exceptions of both momentum and partial value. In light of this evidence, it would be informative to analyze the dynamic conditional alpha time-series (cf. Appendix 1 time-series visualization of dynamic conditional alphas). When each dynamic conditional alpha is nil on average but can be persistently positive and negative during different phases of the real business cycle, the conditional moments and factor premiums can help inform empirical asset pricing model design and performance.

Our dynamic analysis of core conditional factor premiums from the Fama-French (2015) model proposes raising the hurdle for the conventional asset-pricing test. This recommendation serves as the time-series equivalent to the cross-sectional thesis of Harvey, Liu, and Zhu (2015). Also, our prime empirical analysis contradicts McLean and Pontiff's (2016) recent conjecture that academic research partially erodes stock return predictability because investors are able to learn from a variety of anomalies. To the extent that the dynamic conditional factor premiums exhibit substantial volatility over time, the vast majority of dynamic conditional alphas are not significantly far from zero while there is no sufficient evidence to reject the hypothesis that our conditional factor model carries a correct specification. For this reason, we can reconcile most

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ubiquitous anomalies with a dynamic variant of the Fama-French factor model. Also, our study offers a mild refutation of Berk and Van Binsbergen's (2016) and Barber, Huang, and Odean's (2016) overall qualitative conclusion that the CAPM is the clear victor in the horserace against the other dynamic-equilibrium and factor models. In contrast, our work shows that the dynamic conditional factor model provides progress toward a positive portrayal of the quantitative nexus between average return and risk. Our dynamic conditional factor model helps draw a distinction between both rational-risk and behavioral theories of average return evolution because bilateral causation between macroeconomic innovations and dynamic conditional alpha spreads shines unique light on the marginal investor's fundamental news and economic expectations about the cross-section of average returns. This insight offers economic logic, rigor, and intuition for our empirical analysis in response to the recent landmark statistical discovery of Kozak, Nagel, and Santosh's (2018). As a consequence, the myriad contributions of our current study help address at least part of the concern and suspicion in the recent reappraisals of asset pricing model tests (cf. Lewellen et al (2010); Berk and van Binsbergen (2016); Barber et al (2016); Harvey et al (2016); Fama and French (2015, 2016); Kozak et al (2017, 2018)).

5. Conclusion

In response to Kozak, Nagel, and Santosh's (2018) recent critique of many horseraces among factor models, we apply a new approach to addressing at least part of the concern and suspicion in several reappraisals of asset pricing tests (cf. Lewellen et al (2010); Berk and van Binsbergen (2016); Barber et al (2016); Harvey et al (2016); Fama and French (2015, 2016); Kozak et al (2017, 2018)). We extract dynamic conditional factor premiums from the Fama-French (2015) model and then find that most anomalies disappear after one accounts for time variation in these premiums. Mutual causation between dynamic conditional alpha spreads and macroeconomic surprises serves as a core qualifying condition for relevant fundamental factor selection with sound economic rigor and motivation. To the extent that macroeconomic innovations manifest in the form of dynamic conditional alphas, this causation reveals the marginal investor's fundamental news and macroeconomic expectations about the cross-section of average returns.

Specifically, our evidence bolsters the ubiquitous use of Fama-French (2015) factors that reflect the marginal investor's response to fundamental news about the cross-section of average returns. Our econometric results lend credence to Fama and French's (1996, 2004, 2008, 2015, 2016) perennial reluctance to encompass Carhart (1997) momentum in their factor model. In a conceptual domain, we link the dynamic conditional factor model results to recent advances in the intertemporal CAPM context (Merton (1973); Campbell (1993); Campbell and Vuolteenaho (2004); Campbell et al (2017)). Overall, our current study serves as an incremental step toward better deciphering a distinction between the rational risk and behavioral mispricing paradigms.

We agree with Kozak, Nagel, and Santosh's (2018) qualitative conclusion on "observational equivalence between most rational risk factor models and behavioral mispricing factor models".

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As we have discussed in the introduction of the current study, this consensus resonates with the relentless debate and elusive quest of a factor model for our profession. These advances shed new light on the major essential need for financial economists to "[develop-and-test] structural asset-pricing models with specific assumptions about investor beliefs and preferences that can deliver testable predictions about (1) the fundamental factors that should be in the [stochastic discount factor] (SDF), and (2) the probability distributions under which this SDF prices assets" (Kozak, Nagel, and Santosh, 2018).

A concurrent contribution moves in this direction. Yeh (2021) derives and estimates the SDF from financial intermediary capital strength and then uses the Euler, asset return prediction, and price multiple valuation equations to test stock market anomaly persistence over a broad basket of long-short extreme decile strategies. Yeh (2021) further tests the empirical predictions of the dynamic stochastic general equilibrium (DSGE) structural model to find evidence in support of his permanent capital hypothesis. This new frontier shows some promise in applying "structural macrofinance models" of both investor beliefs and preferences for economists to make progress in macroeconomic asset return prediction.

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Table 1: Descriptive statistics for various stock return spreads

This table summarizes the descriptive statistics for the various stock portfolio tilts. The first panel encapsulates the summary statistics for the Fama-French (2015) return spreads such as the excess return on the CRSP value-weighted market portfolio (MRP), the return spread between the top 30% small and bottom 30% big stocks (SMB), the return spread between the top 30% high book-to-market and bottom 30% low book-to-market stocks (HML), the return spread between the top 30% robust and bottom 30% weak stocks in terms of their relative profitability (RMW), and the return spread between the top 30% conservative investment and bottom 30% aggressive investment stocks (CMA) in developing the multifactor mean-variance efficient (MMVE) tangency portfolio. The second panel sums up the descriptive statistics for the long-short trading strategy that involves both a long position in the top decile and a short position in the bottom decile for the pervasive asset pricing anomalies such as size, value (book-to-market, cashflow-to-price, dividend-to-price, and earnings-to-price), momentum, investment, profitability, short-term return reversal, and long-term return reversal. The descriptive statistics include each return spread's mean value, standard deviation, skewness, kurtosis, minimum, median, and maximum.

Stock return spread	Mean	Stdev	Skew	Kurt	Min	Med	Max
Market risk premium (MRP)	0.49	4.50	-0.53	1.86	-23.24	0.86	16.10
Small-minus-big (SMB)	0.31	2.92	0.37	3.50	-14.32	0.24	18.05
High-minus-low (HML)	0.29	2.17	-0.14	3.26	-10.85	0.25	9.82
Robust-minus-weak (RMW)	0.25	1.52	-0.83	11.64	-12.76	0.26	7.60
Conservative-minus-aggressive (CMA)	0.15	1.18	0.32	1.08	-3.54	0.10	5.10
Size	-0.37	4.87	-0.73	4.17	-32.21	-0.16	21.10
Momentum	1.32	7.01	-1.49	8.04	-45.89	1.67	26.18
Book-to-market	0.53	4.67	0.54	2.31	-13.58	0.44	26.73
Cashflow-to-price	0.49	4.22	0.03	1.74	-20.27	0.39	16.02
Dividend-to-price	0.08	5.38	0.03	2.55	-26.22	0.27	22.11
Earnings-to-price	0.47	4.30	-0.02	1.57	-20.13	0.54	16.75
Investment	-0.48	3.26	-0.32	1.22	-15.47	-0.48	10.12
Profitability	0.19	3.96	0.23	2.93	-19.68	0.35	22.46
Short-term return reversal	-0.36	5.35	-0.24	3.99	-26.65	-0.30	25.23
Long-term return reversal	-0.48	5.07	-0.98	4.67	-33.79	-0.16	18.94

Table 2: Sharpe ratios for the market portfolio, the *Q*-portfolio, and the anomalies

This table summarizes the long-term Sharpe ratio for each stock portfolio strategy in the period from January 1964 to December 2013. The Sharpe ratio is the ratio of excess stock return to its standard deviation. The basket of stock portfolio strategies encompasses the CRSP value-weighted market portfolio, the multifactor mean-variance efficient (MMVE) tangency stock portfolio from the Fama-French (2015) joint return spreads for size, value, investment, and profitability, as well as the ubiquitous asset pricing anomalies such as size, value (book-to-market, cashflow-to-price, dividend-to-price, and earnings-to-price), momentum, investment, profitability, short-term return reversal, and long-term return reversal. The Sharpe ratios land in the range of 0.1006 for the CRSP value-weighted market portfolio to 0.3006 for the multifactor MVE tangency portfolio and 0.3362 for the short-term return reversal strategy. The other Sharpe ratios land within this intermediate range.

Stock portfolio sort	Sharpe ratio
Market risk premium	0.1006
Multifactor MVE Q -portfolio	0.3006
Size	0.2084
Momentum	0.2574
Book-to-market	0.2016
Cashflow-to-price	0.2172
Dividend-to-price	0.2935
Earnings-to-price	0.1358
Investment	0.2551
Profitability	0.1918
Short-term return reversal	0.3362
Long-term return reversal	0.2271

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Table 3: Average dynamic alphas, dynamic alpha spreads, NW *t*-tests, AGRS *F*-tests, AGMM χ^2 tests, and MMVE *Q*-tests

Over the 50-year period from January 1964 to December 2013, the econometrician applies the recursive multivariate Filter to extract dynamic factor premiums from the Fama-French (2015) five-factor asset pricing model. At each time increment, the econometrician takes into account the Fama-French (2015) factors such as the excess return on the market portfolio (MRP), the return spread between the top 30% small and bottom 30% big stocks (SMB), the return spread between the top 30% high book-to-market and bottom 30% low book-to-market stocks (HML), the return spread between the top 30% robust and bottom 30% weak stocks in terms of their relative profitability (RMW), and the return spread between the top 30% conservative investment and bottom 30% aggressive investment stocks (CMA) to explain the variation in the excess return on each stock decile for size, momentum, value (cf. book-to-market, cashflow-to-price, dividend-to-price, and earnings-to-price), investment, profitability, short-term return reversal, and long-term return reversal. The econometrician presents the mathematical time-series representation below:

$$R_{kt} - R_{ft} = \alpha_t + \beta_{mt}\left(R_{mt} - R_{ft}\right) + \beta_{st} SMB_t + \beta_{ht} HML_t + \beta_{rt} RMW_t + \beta_{ct} CMA_t + \varepsilon_t$$

Table 3 sums up the long-run average alpha for each stock decile sorted on size, value, momentum, investment, profitability, short-term return reversal, and long-term return reversal. The first 10 columns summarize each long-run average alpha and its corresponding *p*-value for the null hypothesis of zero dynamic alpha. The next column encapsulates the long-run average alpha spread for the long-short trading strategy that involves both a long position in the top decile and a short position in the bottom decile throughout the 50-year period from January 1964 to December 2013. The last three columns summarize the Gibbons, Ross, and Shanken (1989) AGRS *F*-test, AGMM *C*-test, and AGMM *Q*-test results on each long-short trading strategy across the ubiquitous asset pricing anomalies such as size, value, momentum, investment, profitability, short-term return reversal, and long-term return reversal. This evidence reports each test statistic and its corresponding *p*-value. For each hypothesis test, the econometrician applies the Newey-West (1987) method with quadratic spectral kernel estimation to correct the standard errors to safeguard against any serial correlation and heteroskedasticity. The appendix depicts the time-series dynamic alphas for each of the stock portfolio tilts that yield anomalous excess returns in static asset pricing analysis (i.e. size, value, momentum, investment, profitability, short-term return reversal, and long-term return reversal).

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Table 3: Average dynamic alphas, dynamic alpha spreads, NW *t*-tests, AGRS *F*-tests, AGMM χ^2 tests, and MMVE *Q*-tests

Portfolio	Low	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	High	Spread	*F* -test	*C* -test	*Q* -test
Size														
Alpha (test statistic)	-0.076	-0.112	0.001	-0.092	0.080	0.104	0.090	0.104	0.053	-0.014	0.062	0.043	22.799	21.121
p-value	0.438	0.101	0.983	0.070	0.185	0.258	0.216	0.080	0.344	0.659	0.505	0.999	0.999	0.999
Momentum														
Alpha (test statistic)	-0.569	-0.171	0.016	-0.135	0.063	0.008	-0.021	0.039	0.164	0.420	0.989	0.051	34.776	32.216
p-value	0.005	0.215	0.857	0.072	0.392	0.879	0.722	0.635	0.038	0.001	0.000	0.999	0.999	0.999
Book-to-market														
Alpha (test statistic)	-0.001	0.067	-0.043	0.136	0.015	-0.126	-0.163	0.052	0.128	-0.042	-0.041	0.041	21.318	19.749
p-value	0.988	0.446	0.518	0.093	0.877	0.065	0.008	0.374	0.084	0.664	0.752	0.999	0.999	0.999
Cashflow-to-price														
Alpha (test statistic)	0.050	-0.025	0.106	-0.064	-0.012	-0.012	-0.014	-0.226	-0.021	0.195	0.144	0.038	24.746	22.924
p-value	0.611	0.744	0.155	0.331	0.906	0.855	0.891	0.012	0.820	0.102	0.385	0.999	0.999	0.999
Dividend-to-price														
Alpha (test statistic)	0.031	0.182	0.269	0.193	-0.231	0.015	-0.004	-0.049	-0.116	0.080	0.049	0.070	45.204	41.877
p-value	0.720	0.005	0.009	0.018	0.022	0.851	0.962	0.513	0.279	0.541	0.790	0.999	0.999	0.999
Earnings-to-price														
Alpha (test statistic)	0.100	0.113	0.060	-0.020	0.048	-0.027	0.054	-0.032	-0.122	0.099	-0.001	0.016	9.683	8.970
p-value	0.256	0.048	0.472	0.803	0.610	0.783	0.434	0.709	0.052	0.396	0.995	0.999	0.999	0.999
Investment														
Alpha (test statistic)	-0.229	0.082	-0.104	-0.065	-0.005	-0.008	0.206	0.041	0.137	-0.086	0.143	0.049	34.142	31.629
p-value	0.029	0.223	0.187	0.307	0.948	0.888	0.044	0.358	0.039	0.328	0.310	0.999	0.999	0.999
Profitability														
Alpha (test statistic)	-0.108	0.122	-0.050	0.036	0.039	-0.148	0.045	-0.069	0.105	0.110	0.219	0.031	19.307	17.886
p-value	0.218	0.043	0.571	0.630	0.556	0.115	0.490	0.252	0.044	0.100	0.088	0.999	0.999	0.999
Short-term reversal														
Alpha (test statistic)	0.565	0.571	0.435	0.202	0.156	-0.147	-0.114	-0.262	-0.357	-0.615	-1.180	0.100	59.290	54.927
p-value	0.000	0.000	0.000	0.005	0.015	0.086	0.051	0.001	0.000	0.000	0.000	0.999	0.999	0.999
Long-term reversal														
Alpha (test statistic)	-0.339	0.034	-0.214	-0.124	-0.112	-0.055	0.100	0.254	0.144	0.088	0.426	0.052	27.063	25.071
p-value	0.003	0.748	0.019	0.195	0.040	0.400	0.152	0.000	0.018	0.345	0.001	0.999	0.999	0.999

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Table 4: ARMA-GARCH time-series representation of each dynamic conditional alpha and beta spread

This table summarizes the empirical results in Appendix 2 (cf. Tables A2.1 to A2.6). We demonstrate that each dynamic conditional factor premium can be modeled as a typical financial time-series. We apply both ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) conditional-mean-and-variance models to fit each factor premium that the econometrician extracts from a “dynamic” variant of the Fama-French (2015) factor model. Although it is possible to identify a more precise time-series representation for each factor premium, our goal here is more straight-forward. In fact, our primary and ultimate goal is to use the standard toolkit in time-series econometrics to establish the empirical fact that each dynamic conditional alpha or beta spread exhibits the major properties of most financial time series. Each factor premium embeds autoregressive mean reversion in the conditional mean specification of ARMA(1,1), as well as volatility clusters and asymmetries in the conditional volatility specification of EGARCH(1,1,1) or GJR-GARCH(1,1,1) (cf. Engle (1982); Bollerslev (1986); Nelson (1991); Glosten et al (1993)).

Panel A	**ARMA(1,1)-EGARCH(1,1,1)**					**ARMA(1,1)-GJR-GARCH(1,1,1)**				
Factor premium spread	AR	MA	ARCH	GARCH	Expo	AR	MA	ARCH	GARCH	GJR
Conditional alpha spread										
Size	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Momentum	✓		✓	✓	✓	✓		✓	✓	✓
Book-to-market	✓		✓		✓	✓	✓		✓	✓
Cashflow-to-price	✓			✓	✓	✓			✓	
Dividend-to-price	✓		✓	✓	✓	✓		✓	✓	✓
Earnings-to-price	✓		✓	✓	✓	✓		✓	✓	✓
Investment	✓		✓	✓	✓	✓			✓	✓
Profitability	✓			✓	✓	✓			✓	✓
Short-term reversal	✓			✓	✓	✓			✓	✓
Long-term reversal	✓		✓	✓	✓	✓		✓	✓	✓
Conditional MRP beta spread										
Size	✓			✓	✓	✓		✓	✓	
Momentum	✓		✓	✓	✓	✓		✓		
Book-to-market	✓		✓	✓	✓	✓		✓	✓	✓
Cashflow-to-price	✓			✓	✓	✓		✓	✓	
Dividend-to-price	✓			✓	✓	✓		✓	✓	
Earnings-to-price	✓			✓	✓	✓			✓	
Investment	✓			✓	✓	✓			✓	✓
Profitability	✓			✓	✓	✓		✓	✓	
Short-term reversal	✓	✓		✓	✓	✓	✓	✓	✓	
Long-term reversal	✓			✓	✓	✓			✓	

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Table 4: ARMA-GARCH time-series representation of each dynamic conditional alpha and beta spread

This table summarizes the empirical results in Appendix 2 (cf. Tables A2.1 to A2.6). We demonstrate that each dynamic conditional factor premium can be modeled as a typical financial time-series. We apply both ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) conditional-mean-and-variance models to fit each factor premium that the econometrician extracts from a "dynamic" variant of the Fama-French (2015) factor model. Although it is possible to identify a more precise time-series representation for each factor premium, our goal here is more straight-forward. In fact, our primary and ultimate goal is to use the standard toolkit in time-series econometrics to establish the empirical fact that each dynamic conditional alpha or beta spread exhibits the major properties of most financial time series. Each factor premium embeds autoregressive mean reversion in the conditional mean specification of ARMA(1,1), as well as volatility clusters and asymmetries in the conditional volatility specification of EGARCH(1,1,1) or GJR-GARCH(1,1,1) (cf. Engle (1982); Bollerslev (1986); Nelson (1991); Glosten et al (1993)).

Panel B	**ARMA(1,1)-EGARCH(1,1,1)**					**ARMA(1,1)-GJR-GARCH(1,1,1)**				
Factor premium spread	AR	MA	ARCH	GARCH	Expo	AR	MA	ARCH	GARCH	GJR
Conditional SMB beta spread										
Size	✓		✓	✓	✓	✓		✓	✓	✓
Momentum	✓		✓	✓	✓	✓		✓	✓	✓
Book-to-market	✓		✓	✓	✓	✓		✓	✓	✓
Cashflow-to-price	✓		✓	✓	✓	✓			✓	
Dividend-to-price	✓			✓	✓	✓			✓	✓
Earnings-to-price	✓			✓		✓			✓	✓
Investment	✓		✓	✓		✓			✓	✓
Profitability	✓			✓	✓	✓		✓	✓	
Short-term reversal	✓		✓	✓	✓	✓		✓	✓	✓
Long-term reversal	✓		✓	✓	✓	✓			✓	✓
Conditional HML beta spread										
Size	✓			✓	✓	✓		✓	✓	
Momentum	✓	✓		✓	✓	✓		✓	✓	✓
Book-to-market	✓		✓		✓	✓			✓	✓
Cashflow-to-price	✓			✓	✓	✓		✓	✓	
Dividend-to-price	✓		✓	✓	✓	✓			✓	
Earnings-to-price	✓	✓		✓	✓	✓			✓	
Investment	✓		✓	✓	✓	✓		✓	✓	✓
Profitability	✓			✓		✓			✓	
Short-term reversal	✓			✓	✓	✓			✓	✓
Long-term reversal	✓			✓	✓	✓			✓	

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Table 4: ARMA-GARCH time-series representation of each dynamic conditional alpha and beta spread

This table summarizes the empirical results in Appendix 2 (cf. Tables A2.1 to A2.6). We demonstrate that each dynamic conditional factor premium can be modeled as a typical financial time-series. We apply both ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) conditional-mean-and-variance models to fit each factor premium that the econometrician extracts from a "dynamic" variant of the Fama-French (2015) factor model. Although it is possible to identify a more precise time-series representation for each factor premium, our goal here is more straightforward. In fact, our primary and ultimate goal is to use the standard toolkit in time-series econometrics to establish the empirical fact that each dynamic conditional alpha or beta spread exhibits the major properties of most financial time series. Each factor premium embeds autoregressive mean reversion in the conditional mean specification of ARMA(1,1), as well as volatility clusters and asymmetries in the conditional volatility specification of EGARCH(1,1,1) or GJR-GARCH(1,1,1) (cf. Engle (1982); Bollerslev (1986); Nelson (1991); Glosten et al (1993)).

Panel C	**ARMA(1,1)-EGARCH(1,1,1)**					**ARMA(1,1)-GJR-GARCH(1,1,1)**				
Factor premium spread	AR	MA	ARCH	GARCH	Expo	AR	MA	ARCH	GARCH	GJR
Conditional RMW beta spread										
Size	✓		✓	✓	✓	✓		✓	✓	✓
Momentum	✓			✓	✓	✓			✓	
Book-to-market	✓	✓	✓	✓	✓	✓		✓	✓	✓
Cashflow-to-price	✓			✓	✓	✓		✓	✓	✓
Dividend-to-price	✓			✓	✓	✓		✓	✓	
Earnings-to-price	✓			✓	✓	✓		✓	✓	
Investment	✓			✓		✓	✓		✓	✓
Profitability	✓	✓		✓	✓	✓	✓	✓	✓	✓
Short-term reversal	✓				✓	✓				
Long-term reversal	✓			✓	✓	✓			✓	
Conditional CMA beta spread										
Size	✓	✓	✓	✓	✓	✓			✓	✓
Momentum	✓		✓	✓		✓			✓	✓
Book-to-market	✓		✓	✓	✓	✓		✓	✓	✓
Cashflow-to-price	✓	✓	✓	✓	✓	✓	✓		✓	✓
Dividend-to-price	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Earnings-to-price	✓	✓		✓	✓	✓			✓	✓
Investment	✓	✓		✓	✓	✓	✓	✓		
Profitability	✓	✓	✓	✓	✓	✓			✓	✓
Short-term reversal	✓		✓			✓		✓	✓	✓
Long-term reversal	✓			✓	✓	✓			✓	

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Table 5: Conditional specification test of the static versus dynamic conditional multifactor asset pricing models

Over the 50-year period from January 1964 to December 2013, one applies the recursive multivariate Filter to extract dynamic multifactor factor premiums from the Fama-French (2015) five-factor asset pricing model. At each time increment, the econometrician takes into account the Fama-French (2015) factors such as the excess return on the market portfolio (MRP), the return spread between the top 30% small and bottom 30% big stocks (SMB), the return spread between the top 30% high book-to-market and bottom 30% low book-to-market stocks (HML), the return spread between the top 30% robust and bottom 30% weak stocks in terms of their relative profitability (RMW), and the return spread between the top 30% conservative investment and bottom 30% aggressive investment stocks (CMA) to explain the variation in the excess return on each stock decile for size, momentum, value (cf. book-to-market, cashflow-to-price, dividend-to-price, and earnings-to-price), investment, profitability, short-term return reversal, and long-term return reversal. The econometrician presents the mathematical time-series representation below:

$$R_{kt} - R_{ft} = \alpha_t + \beta_{mt}\left(R_{mt} - R_{ft}\right) + \beta_{st} SMB_t + \beta_{ht} HML_t + \beta_{rt} RMW_t + \beta_{ct} CMA_t + \varepsilon_t$$

Table 5 presents the conditional specification test evidence for each stock decile sorted on size, value, momentum, asset investment, operating profitability, short-term return reversal, and long-term return reversal. The first 10 columns summarize the χ^2-statistic for each stock decile and its corresponding *p*-value for the null hypothesis of a consistent and efficient static estimator against the alternative hypothesis of a correct consistent dynamic conditional estimator. The next column shows the χ^2-statistic for each long-short top-bottom stock decile and its corresponding *p*-value. About 95% of the χ^2-statistics are econometrically significant with at least 90%+ confidence. The appendix depicts the dynamic conditional alpha time-series for each of the stock portfolio tilts that yield anomalous excess returns in static asset pricing analysis (i.e. size, value, momentum, asset investment, operating profitability, short-term return reversal, and long-term return reversal).

$$\hat{\boldsymbol{\xi}} = \hat{\boldsymbol{\theta}}_d - \hat{\boldsymbol{\theta}}_s \Rightarrow H_0 : \boldsymbol{\theta}_d = \boldsymbol{\theta}_s \Rightarrow H_0 : \boldsymbol{\xi} = 0$$

$$N^{1/2} \cdot \left(\hat{\boldsymbol{\theta}}_s - \boldsymbol{\theta}_s\right) \sim N\left(0, \boldsymbol{V}_s\right) \qquad N^{1/2} \cdot \left(\hat{\boldsymbol{\theta}}_d - \boldsymbol{\theta}_d\right) \sim N\left(0, \boldsymbol{V}_d\right)$$

$$\hat{\boldsymbol{\xi}} = \hat{\boldsymbol{\theta}}_d - \hat{\boldsymbol{\theta}}_s \Rightarrow \hat{\boldsymbol{\xi}} + \hat{\boldsymbol{\theta}}_s = \hat{\boldsymbol{\theta}}_d \Rightarrow \boldsymbol{V}\left(\hat{\boldsymbol{\xi}}\right) + \boldsymbol{V}\left(\hat{\boldsymbol{\theta}}_s\right) = \boldsymbol{V}\left(\hat{\boldsymbol{\theta}}_d\right) \Rightarrow \boldsymbol{V}\left(\hat{\boldsymbol{\xi}}\right) = \boldsymbol{V}\left(\hat{\boldsymbol{\theta}}_d\right) - \boldsymbol{V}\left(\hat{\boldsymbol{\theta}}_s\right)$$

$$\kappa = \hat{\boldsymbol{\xi}}^T \left(T^{-1} \hat{\boldsymbol{V}}\left(\hat{\boldsymbol{\xi}}\right)\right)^{-1} \hat{\boldsymbol{\xi}} = T \cdot \hat{\boldsymbol{\xi}}^T \left(\boldsymbol{V}\left(\hat{\boldsymbol{\theta}}_d\right) - \boldsymbol{V}\left(\hat{\boldsymbol{\theta}}_s\right)\right)^{-1} \hat{\boldsymbol{\xi}} \sim \chi^2(q)$$

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Table 5: Conditional specification test of the static versus dynamic conditional multifactor asset pricing models

Portfolio	Low	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	High	Spread
Size											
κ test statistic	32.0	178.8	42.2	46.8	257.5	4092.7	166.9	164.4	13200.4	0.0	31.8
p -value	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.999	0.001
Momentum											
κ test statistic	33.0	42.0	41.0	13.2	829.6	0.0	20.4	11327.4	49.5	61.4	3.1
p -value	0.001	0.001	0.001	0.067	0.001	0.999	0.005	0.001	0.001	0.001	0.876
Book-to-market											
κ test statistic	18.5	47.3	191.6	247.1	160.6	1371.7	710.3	477.8	580.3	462.0	14.6
p -value	0.0097	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.042
Cashflow-to-price											
κ test statistic	24.2	11.9	324.3	220.1	345.3	189.0	214.6	553.9	1111.8	407.2	223.0
p -value	0.001	0.104	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Dividend-to-price											
κ test statistic	59.0	108.3	102.3	53.2	440.0	1623.9	262.1	1655.0	512.9	254.7	222.5
p -value	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Earnings-to-price											
κ test statistic	10.3	26.6	169.0	821.0	149.8	200.3	385.0	495.1	748.0	339.8	87.0
p -value	0.171	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Investment											
κ test statistic	15.6	206.4	33.5	2417.7	867.0	1017.3	1452.1	683.6	1102.5	521.7	23.9
p -value	0.029	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Profitability											
κ test statistic	20.5	398.8	209.1	162.2	203.8	4215.2	743.9	830.9	1938.1	4744.2	23.0
p -value	0.005	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002
Short-term reversal											
κ test statistic	28.4	744.3	168.8	93.2	76.0	2.3	1331.4	60.8	1047.9	319.1	221.4
p -value	0.001	0.001	0.001	0.001	0.001	0.940	0.001	0.001	0.001	0.001	0.001
Long-term reversal											
κ test statistic	20.4	156.6	455.9	899.0	10916.2	598.9	344.1	844.1	4923.1	2151.9	27.5
p -value	0.005	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001

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Table 6: Vector AutoRegression (VAR) of macroeconomic fluctuations with consistent coefficient estimates and *t*-statistics

This table summarizes the macroeconometric vector autoregression (VAR) results. The upper panel presents the consistent coefficient estimates, and the lower panel shows the corresponding *t*-statistics. We use 15 main monthly time-series in a macroeconometric vector autoregressive system (Sims, 1980; Campbell, 1993). There are 12 macro time-series, 2 financial uncertainty metrics, and 2 investor sentiment proxies. The resultant dataset spans the 285-month sample period from April 1990 to December 2013. These macro time-series encompass first differences in the national economic activity index, Treasury bill rate, unemployment rate, term spread, default spread, prime bank loan rate, aggregate dividend yield, and percent changes in industrial production, non-farm payroll, house price index, consumer price index, exchange rate, financial stress index, economic policy uncertainty, and investor sentiment. Appendix 3 presents and describes the macroeconomic variable definitions and their data sources.

Macroeconomic variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	-45.809	13.923	-52.542	-3.716	7.332	12.378	-0.037	0.029	-0.376	0.509	-0.565	-0.094	-1.009	29.052	23.922
National activity index change	-0.447	-0.002	0.033	0.027	0.003	-0.008	0.018	-0.002	0.000	0.001	-0.001	0.002	0.006	0.011	-0.013
Treasury 3-month bill rate change	0.218	0.210	0.032	-0.251	-0.057	0.450	0.098	0.002	0.001	0.001	0.000	-0.001	-0.068	-0.045	-0.014
Unemployment rate change	0.034	-0.035	-0.152	0.135	-0.113	-0.035	-0.048	-0.005	-0.002	0.000	0.001	-0.003	-0.022	-0.262	-0.012
Term spread (10-year minus 1-year)	0.269	-0.046	-0.065	0.123	-0.121	0.006	-0.004	0.000	0.000	0.002	-0.001	-0.015	-0.075	-0.331	0.052
Default spread (Baa minus 10-year)	-0.589	-0.207	0.080	0.036	0.155	-0.103	-0.108	-0.009	0.000	0.001	-0.001	-0.023	-0.005	0.007	-0.052
Prime bank loan rate change	0.261	0.117	-0.106	0.065	0.014	0.203	-0.069	0.002	0.000	0.000	0.000	-0.014	0.087	0.006	0.007
Aggregate S&P 500 dividend yield	-1.318	-0.119	-0.041	-0.415	0.617	-0.046	0.255	-0.014	-0.002	0.000	-0.001	-0.013	0.118	0.396	0.101
Industrial production index change	-27.389	2.535	-3.206	-5.961	-5.808	2.264	-4.374	0.128	0.045	-0.080	0.052	-0.600	-0.313	-20.078	-1.524
Non-farm payroll percent change	-39.774	11.453	-47.308	-2.925	10.034	9.044	2.895	0.691	0.554	0.184	0.100	1.065	-4.478	35.224	16.951
House price index percent change	5.901	1.205	-1.330	-1.440	-1.066	1.067	0.408	0.051	0.006	0.870	-0.018	0.002	1.846	-0.471	1.211
Consumer price index percent change	14.084	-0.937	-0.426	6.208	3.044	0.443	0.988	0.158	0.022	0.509	0.333	0.051	3.344	12.995	6.599
Dollar trade index percent change	1.104	-0.347	-0.400	0.519	1.117	-0.397	0.034	-0.003	-0.003	0.028	-0.033	0.392	-0.172	1.299	0.704
Economic uncertainty percent change	0.214	0.037	0.081	-0.111	0.014	-0.027	0.012	0.003	0.000	-0.001	0.000	-0.004	-0.218	0.107	0.001
Financial stress index change	0.219	0.056	0.009	0.075	0.073	0.030	0.102	0.005	0.000	0.001	-0.002	0.017	-0.010	0.048	-0.060
Baker-Wurgler investor sentiment	-0.007	-0.042	0.022	0.015	0.021	-0.023	0.009	0.000	0.000	0.000	0.000	0.001	0.008	0.025	0.963

Macroeconomic variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Intercept	**-1.68**	**1.67**	**-7.41**	-0.54	0.85	**2.00**	-0.19	0.07	**-7.18**	**2.31**	**-4.68**	-0.16	-0.14	**1.69**	**2.58**
National activity index change	**-7.97**	-0.11	**2.35**	1.55	0.17	-0.62	**2.22**	**-3.08**	**-3.69**	**1.68**	**-2.70**	**2.06**	0.34	0.36	-0.43
Treasury 3-month bill rate change	0.80	**2.41**	0.41	**-2.82**	-0.71	**7.20**	**2.44**	0.61	1.61	0.53	0.25	-0.14	-0.81	-0.26	-0.57
Unemployment rate change	0.14	-0.53	**-2.53**	1.83	-1.62	-0.71	-1.37	**-1.94**	**-3.65**	0.21	1.12	-0.65	-0.30	**-1.92**	-0.08
Term spread (10-year minus 1-year)	1.21	-0.65	-1.19	1.75	-1.87	0.14	-0.11	-0.05	-0.50	1.24	-0.87	**-3.33**	-1.12	**-2.57**	-0.09
Default spread (Baa minus 10-year)	**-1.99**	**-2.25**	1.10	0.39	1.82	-1.58	**-2.49**	**-2.91**	0.28	0.25	-0.65	**-3.94**	-0.05	0.04	-1.11
Prime bank loan rate change	1.02	1.46	-1.71	0.80	0.15	**3.49**	-1.76	0.58	0.39	0.21	-0.22	**-2.72**	1.09	0.05	0.32
Aggregate S&P 500 dividend yield	**-2.62**	-0.72	-0.32	**-2.64**	**4.21**	-0.38	**3.41**	**-2.63**	**-2.25**	0.09	-0.59	-1.33	0.77	1.34	0.71
Industrial production index change	**-3.93**	1.14	**-1.86**	**-2.70**	**-2.88**	1.44	**-4.27**	1.73	**3.46**	-1.48	**1.75**	**-4.38**	-0.14	**-5.01**	-0.89
Non-farm payroll percent change	-1.49	1.41	**-6.90**	-0.42	1.23	1.51	0.60	**2.34**	**10.57**	0.87	0.90	**1.98**	-0.56	**2.17**	**2.02**
House price index percent change	1.14	0.78	-1.01	-0.95	-0.74	0.94	0.49	0.94	0.59	**22.10**	-0.79	0.04	1.21	-0.20	0.82
Consumer price index percent change	0.91	-0.14	-0.09	1.26	0.68	0.16	0.36	0.98	0.69	**4.36**	**5.30**	0.17	0.73	1.46	1.25
Dollar trade index percent change	0.35	-0.45	-0.46	0.56	1.39	-0.68	0.04	-0.13	-0.57	1.27	**-2.69**	**7.04**	-0.19	0.78	0.28
Economic uncertainty percent change	0.99	0.53	1.51	-1.63	0.24	-0.58	0.40	1.20	0.14	-0.89	0.45	-0.88	**-3.36**	0.87	-0.41
Financial stress index change	1.44	1.19	0.20	1.56	1.63	0.91	**4.59**	**3.27**	0.11	0.86	**-3.16**	**5.63**	-0.22	0.54	**-1.82**
Baker-Wurgler investor sentiment	0.06	**-2.50**	1.29	1.14	1.31	**-1.86**	1.48	-0.22	1.64	-0.34	0.58	1.10	0.50	0.99	**54.63**

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Table 7: Granger causation from macroeconomic innovations to dynamic conditional alpha spreads

This table shows the pairwise Granger-causality test *p*-values for the econometrician to assess whether Granger causation runs from macroeconometric innovations to dynamic conditional alphas. The columns indicate the respective asset pricing anomalies such as size, momentum, value (B/M, CF/P, Div/P, and E/P), asset growth, operating profitability, short-run return reversal, and long-run return reversal. This tables demonstrates that at least a few macro innovations Granger-cause each dynamic conditional alpha spread with at least 90% statistical confidence (*p*-values<0.10) for most anomalies such as size, value (B/M, CF/P, and Div/P), asset growth, operating profitability, short-run return reversal, and long-term reversal. Only momentum and partial value (E/P) turn out to be the exceptions that defy this rule of thumb. Within the intertemporal CAPM context, we interpret this evidence in support of the prevalent use of Fama-French (2015) factors in a dynamic conditional model. Granger causation between macroeconomic innovations and dynamic conditional alphas serves as a core qualifying condition for "shrinking the factor zoo", whereas, there is minimal evidence in favor of viewing momentum as a conceptually sound fundamental factor in the dynamic conditional context. To the extent that the investor cannot decipher fundamental news nor macroeconomic surprises from momentum, it remains hard to rationalize momentum apart from a unique statistical aberration. Insofar as momentum returns persist as an anomaly, we need a more plausible explanation than behavioral mispricing disequilibrium before we view momentum as an extra fundamental factor in the dynamic conditional model.

Macroeconomic variable	Size	Momen	B/M	CF/P	Div/P	E/P	AG	OP	SR Rev	LR Rev
National activity index change	0.65	0.13	0.43	0.40	**0.067**	0.18	0.21	0.73	0.82	0.70
Treasury 3-month bill rate change	0.105	0.90	0.54	0.72	0.15	0.94	**0.021**	0.98	0.38	**0.026**
Unemployment rate change	0.64	0.62	0.33	**0.075**	0.35	0.79	**0.034**	0.56	0.13	0.98
Term spread (10-year minus 1-year)	0.78	0.96	0.29	0.61	0.63	0.64	0.12	0.44	0.41	**0.0317**
Default spread (Baa minus 10-year)	0.16	0.52	0.32	0.15	0.14	0.18	**0.027**	0.64	0.88	**0.0321**
Prime bank loan rate change	0.19	0.43	0.59	0.95	0.46	0.86	0.21	0.86	0.16	0.84
Aggregate S&P 500 dividend yield	0.25	0.56	0.52	0.32	0.19	0.21	0.49	0.81	**0.072**	0.54
Industrial production index change	0.52	0.88	0.72	0.98	0.58	0.27	0.78	0.35	0.92	0.16
Non-farm payroll percent change	**0.098**	0.69	0.86	0.35	0.99	0.31	0.40	0.48	0.11	0.64
House price index percent change	0.23	0.14	0.14	0.47	0.78	0.99	0.78	0.26	0.40	0.25
Consumer price index percent change	**0.029**	0.63	**0.073**	0.15	0.14	0.55	0.86	0.63	0.23	0.93
Dollar trade index percent change	0.60	0.88	0.45	0.98	0.11	0.69	0.35	0.35	0.70	0.51
Economic uncertainty percent change	0.98	0.79	0.21	0.66	0.62	0.61	0.33	0.61	**0.084**	0.47
Financial stress index change	0.86	0.16	0.32	0.1002	**0.013**	0.44	**0.037**	0.57	0.65	**0.005**
Baker-Wurgler investor sentiment	0.73	0.57	0.67	0.27	0.68	0.40	0.12	**0.056**	0.76	0.55
		*				*				

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Table 8: Granger causation from dynamic conditional alpha spreads to macroeconomic innovations

This table shows the pairwise Granger-causality test p-values for the econometrician to assess whether Granger causation runs from dynamic conditional alphas to macroeconometric innovations. The columns indicate the respective asset pricing anomalies such as size, momentum, value (B/M, CF/P, Div/P, and E/P), asset growth, operating profitability, short-run return reversal, and long-run return reversal. Only partial value (Div/P and E/P), asset growth, operating profitability, short-run return reversal, and long-run reversal exhibit this reverse causation (*p*-values<0.10). In fact, the primary conditional alpha spreads for size, value (B/M and CF/P), and momentum convey little causal information about macroeconomic innovations (*p*-values>0.10). Within the intertemporal CAPM context, we interpret this evidence in support of the prevalent use of Fama-French (2015) fundamental factors in a dynamic conditional model. Granger causation between macroeconomic innovations and dynamic conditional alphas serves as a core qualifying condition for “shrinking the factor zoo”, whereas, there is minimal evidence in favor of viewing momentum as a conceptually sound fundamental factor in the dynamic conditional context. To the extent that the investor cannot decipher fundamental news nor macroeconomic surprises from momentum, it remains hard to rationalize momentum apart from a unique statistical aberration. Insofar as momentum profits persist as an anomaly, we need a more plausible explanation than behavioral mispricing disequilibrium before we view momentum as an extra fundamental factor in the dynamic conditional model.

Macroeconomic variable	Size	Momen	B/M	CF/P	Div/P	E/P	AG	OP	SR Rev	LR Rev	
National activity index change	0.32	0.52	0.31	0.20	0.64	**0.087**	0.80	0.66	0.91	0.28	*
Treasury 3-month bill rate change	0.87	0.34	0.46	0.96	**0.016**	0.72	0.47	0.63	0.92	0.44	*
Unemployment rate change	0.22	0.35	0.27	0.28	**0.008**	**0.017**	0.49	0.44	0.98	0.70	*
Term spread (10-year minus 1-year)	0.16	0.24	0.28	0.71	0.57	0.20	0.27	0.22	0.43	0.54	
Default spread (Baa minus 10-year)	0.70	0.80	0.73	0.81	0.46	0.88	0.37	0.98	0.35	0.83	
Prime bank loan rate change	0.22	0.20	0.68	0.83	0.31	0.34	0.50	**0.0963**	0.82	**0.0916**	*
Aggregate S&P 500 dividend yield	0.15	0.80	0.64	0.72	0.61	0.77	0.74	0.87	0.62	0.86	
Industrial production index change	0.14	0.16	0.31	0.11	0.95	**0.06**	0.86	0.82	0.87	0.37	*
Non-farm payroll percent change	0.93	0.57	0.42	0.11	**0.04**	**0.08**	0.58	0.22	0.28	0.54	*
House price index percent change	0.41	0.20	0.52	0.34	0.29	0.84	0.75	0.64	0.12	0.39	
Consumer price index percent change	0.50	0.30	0.46	0.97	0.90	0.73	0.51	0.81	**0.022**	0.98	*
Dollar trade index percent change	0.61	0.52	0.70	0.71	0.54	0.67	0.82	0.43	0.30	0.96	
Economic uncertainty percent change	0.54	0.30	0.99	0.23	0.52	0.43	0.18	0.32	0.97	0.45	
Financial stress index change	0.20	0.91	0.41	0.92	0.61	0.60	0.96	0.52	0.26	0.56	
Baker-Wurgler investor sentiment	0.11	0.52	0.33	0.71	0.97	0.63	**0.035**	**0.029**	**0.001**	0.98	*

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Online Appendix to the PhD dissertation

Stock market alphas help predict macroeconomic innovations.

Abstract

We extract dynamic conditional factor premiums from the Fama-French factor model and find that most anomalies disappear after one accounts for time variation in these premiums. Vector autoregression evidence shows that mutual causation between dynamic conditional alphas and macroeconomic surprises serves as a core qualifying condition for fundamental factor selection. This economic insight is an incremental step toward drawing a distinction between rational risk and behavioral mispricing models. To the extent that dynamic conditional alphas can reveal the marginal investor's fundamental news and expectations about the cross-section of average asset returns, our economic insight helps enrich macroeconomic asset return prediction.

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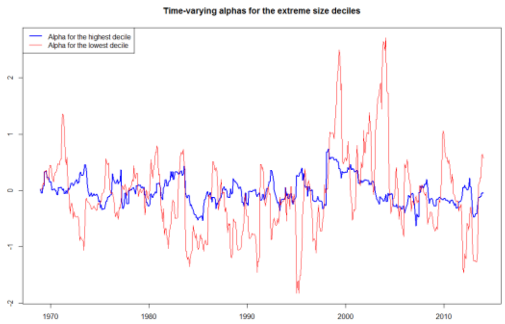
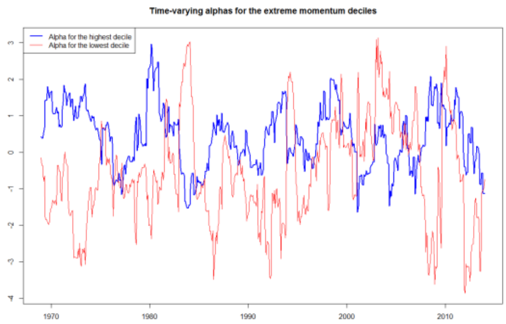
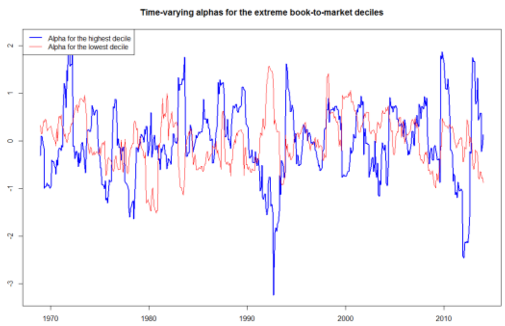
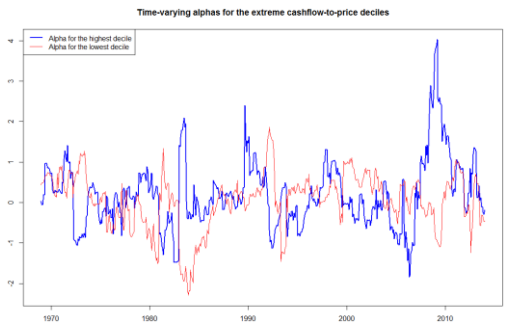
Appendix 1: Dynamic conditional alpha visualization for the extreme deciles

This appendix shows the time-series charts of the dynamic alphas for the extreme deciles based on the stock portfolio tilts such as size, value, momentum, profitability, investment, short-run return reversal, and long-run return reversal. These dynamic factor premiums exhibit wide variation for the top and bottom deciles. Some large comovements tend to influence the central tendency of the alpha spread between the extreme deciles. Each alpha spread often switches its sign and becomes econometrically insignificant. In addition to Gibbons, Ross, and Shanken's (1989) AGRS *F*-test, the AGMM *C*-test and AGMM *Q*-test of dynamic multifactor mean-variance efficiency (MMVE) suggests that the average alpha spreads are not different from zero. The distance between the squared Sharpe ratios for each individual stock portfolio and the MMVE tangency portfolio is not large enough for one to reject the null hypothesis of a correct asset pricing model specification. This inference accords with the spirit of the intertemporal context of Merton (1973), Campbell (1993), and Fama (1996). Investors care about not only their terminal wealth but also several behavioral considerations such as human capital, labor income, consumption, and hedging investment opportunities that covary with the conditional expectations of their terminal wealth. In this light, the Fama-French (2015) factors serve as valid and relevant state variables that reflect these comovements in response to the typical investor's demand for hedging instruments. To the extent that the dynamic factor premiums on each Fama-French (2015) state variable is econometrically significant across the entire data span (i.e. each dynamic multifactor beta consistently differs from zero), the resultant dynamic alpha exhibits too much variability for the pricing error to be significant enough for the econometrician to reject the null hypothesis that the dynamic multifactor model is correctly specified.









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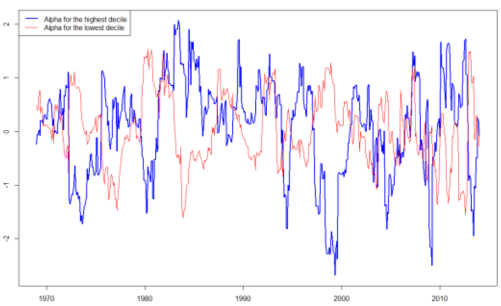
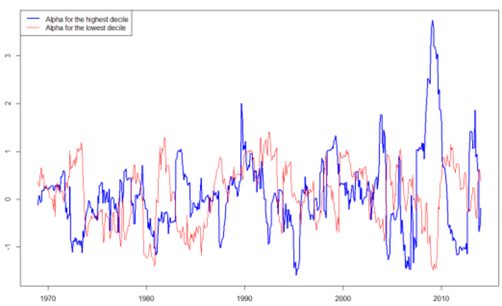
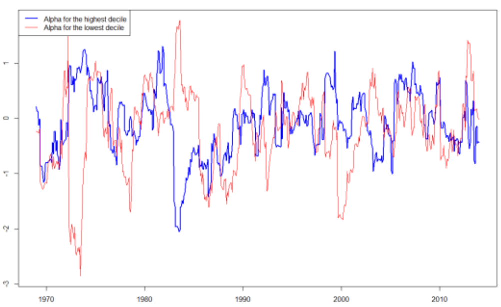
Time-varying alphas for the extreme dividend-to-price deciles



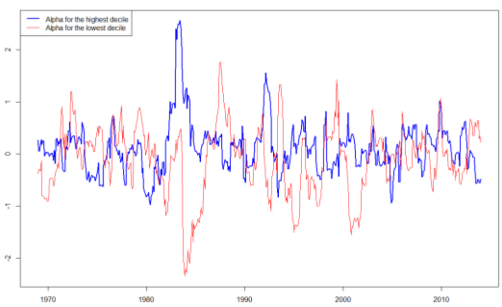
Time-varying alphas for the extreme earnings-to-price deciles



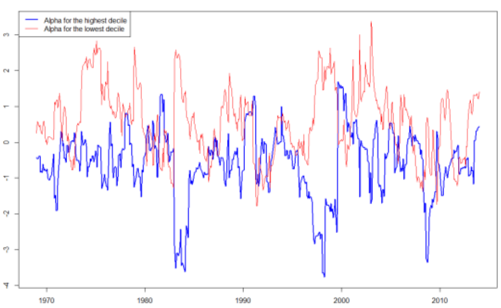
Time-varying alphas for the extreme investment deciles



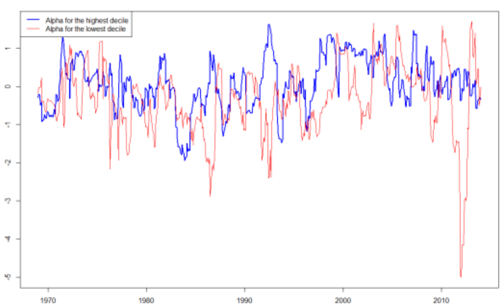
Time-varying alphas for the extreme profitability deciles



Time-varying alphas for the extreme short-term return reversal deciles



Time-varying alphas for the extreme long-term return reversal deciles



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Appendix 2: ARMA-GARCH representation for each dynamic factor premium

We show that each dynamic conditional factor premium can be modeled as a typical financial time-series. We apply both ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) conditional-mean-and-variance models to fit each factor premium that the econometrician extracts from a "dynamic" variant of the Fama-French (2015) factor model. Although it is possible to identify a more precise time-series representation for each factor premium, our goal here is more straight-forward. In fact, our primary goal is to use the standard toolkit in time-series econometrics to establish the empirical fact that each dynamic alpha or beta spread exhibits the major properties of most financial time series. Each factor premium embeds autoregressive mean reversion in the conditional mean specification of ARMA(1,1), and volatility clusters and asymmetries in the conditional volatility specification of EGARCH(1,1,1) or GJR-GARCH(1,1,1) (cf Engle (1982); Bollerslev (1986); Nelson (1991); Glosten et al (1993)). One can readily fit an ARMA-EGARCH or ARMA-GJR-GARCH model to characterize the dynamic evolution of each conditional alpha or beta spread over time. This characterization entails both reasonable and flexible assumptions about the true conditional mean and variance processes for each dynamic conditional factor premium.

This time-series analysis also differs from several earlier studies that exclusively focus on the single-beta CAPM (cf. Adrian and Franzoni (2009); Ang and Chen (2007); Lewellen and Nagel (2006)). The recursive multivariate filter helps extract dynamic conditional alphas and betas from the Fama-French (2015) multi-factor model, and then the econometrician can apply **Eq(14)-Eq(17)** to model each dynamic conditional alpha or beta spread as a financial time series. While it is reasonable to identify the "best" ARMA-GARCH representation for each conditional alpha or beta spread, we establish the empirical fact that each dynamic conditional alpha or beta spread exhibits the most prevalent properties of a typical financial time series. In turn, this empirical fact defies the conventional wisdom of pure point estimates of factor premiums in most static time-series ordinary least-squares regressions.

Table A2.1 presents the ARMA-GARCH results for each dynamic alpha spread between the extreme deciles. While there is substantive evidence in support of autoregressive dynamic alpha spreads across all of the portfolio tilts (*t*-ratios>33), only the size portfolio tilt demonstrates some trace of a moving average alpha spread (*t*-ratio>2.6). Across the EGARCH and GJR-GARCH panels, there is strong evidence in support of both volatility clusters and asymmetries across all of the portfolio tilts (|*t*-ratios|>2). In this light, it is reasonable to infer that each dynamic alpha spread exhibits the common properties of a typical financial time series. Subsequent analysis can shine new light on both the economic content and predictive power of each dynamic alpha spread. To the extent that stock market information serves as a leading indicator of economic activity, each alpha spread can convey material information about economic growth, market valuation, financial stress, cyclical variation, or forecast combination. This conjecture calls for some further empirical confirmation in the spirit of several recent studies (Liew and Vassalou, 2000; Vassalou, 2003; Vassalou and Xing, 2004; Petkova, 2006; Hahn and Lee, 2006).

Only the momentum and short-term reversal portfolio tilts produce significant average alpha spreads (|*t*-ratios|>2.9). The respective intercepts are 1.028 and –1.122. These average conditional alpha spreads are reasonably close to the corresponding average alpha spreads for momentum and short-term return reversal of 0.989 and –1.180 in Table 3. Although these average alpha spreads seem to persist in the extreme deciles (Fama and French, 2008), it is key to recall the more formal Sharpe ratio test evidence that the average alphas do not jointly differ from zero across all the momentum and short-term reversal deciles. This logic leads the econometrician to infer that the average alpha spreads are consistent between Table 3 and Table A2.1.

Table A2.2 encapsulates the ARMA-GARCH results for each dynamic MRP beta spread between the top and bottom deciles. This conditional beta spread represents the relative sensitivity of the excess return on each stock portfolio tilt to changes in the market risk premium. All of the AR(1) coefficients are highly significant across the board (*t*-ratios>9), but only the short-term reversal portfolio tilt carries a significant MA(1) coefficient (*t*-ratio>2). Thus, the conditional mean specification is largely autoregressive in nature. In regard to the conditional variance specification, the GARCH effect is significant for the momentum, book-to-market, cashflow-to-price, profitability, and short-term reversal portfolio tilts. Among these tilts, only the MRP beta spreads for momentum and book-to-market exhibit significant volatility asymmetries in both the EGARCH and GJR-GARCH models. In comparison, the cashflow-to-price, profitability, and short-term reversal tilts exhibit significant volatility asymmetries only in the EGARCH model. Similar to the case for the dynamic alpha spreads, the MRP beta spreads can be further synthesized to offer new insights into a better prediction of economic or financial variables. The time variation in each MRP beta spread reflects shifts in the response of the excess return on a given portfolio strategy to changes in the market risk premium. As a result, this variation indicates changes in the investor's exposure to systematic risk after the econometrician controls for the other Fama-French (2015) state variables. A deeper analysis of MRP beta spread gyrations shows promise beyond the asset pricing literature.

Table A2.3 presents the ARMA-GARCH results for each dynamic SMB beta spread between the extreme deciles. The dynamic SMB beta spread reflects the relative sensitivity of the excess return on each stock portfolio tilt to changes in the return spread between the small and big stock portfolios. With respect to the conditional mean specification, the AR(1) coefficients are significant across the board (*t*-ratios>20), whereas, the MA(1) coefficients are insignificant at any reasonable confidence level. The conditional mean specification is first-order autoregressive. With respect to the conditional variance specification, the GARCH effect is prevalent across the EGARCH and GJR-

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GARCH models for the size, momentum, book-to-market, profitability, and short-term reversal portfolio tilts (|*t*-ratios|>2.1). With the EGARCH model, the GARCH effect of volatility clusters is also evident for the cashflow-to-price, investment, and long-term reversal portfolio tilts (|*t*-ratios|>2.1). Moreover, the presence of volatility asymmetries is real for the size, momentum, book-to-market, cashflow-to-price, investment, profitability, short-term reversal, and long-run reversal portfolio tilts (|*t*-ratios|>2.1). In sum, the SMB beta spread exhibits large variability over time. It is reasonable to infer that the SMB beta spread gyrates sufficiently to capture shifts in the relative response of the excess return on a given portfolio strategy to changes in the return spread between the small and big stock portfolios.

Table A2.4 summarizes the ARMA-GARCH results for each HML beta spread between the extreme deciles. The HML beta spread throws light on the sensitivity of the excess return on a given portfolio strategy to changes in the return spread between the high and low book-to-market stock portfolios. With respect to the conditional mean specification, the AR(1) coefficients are significant (*t*-ratios>25.8). Moreover, the MA(1) coefficients for momentum and earnings-to-price are significant (*t*-ratios>2) in the ARMA-EGARCH model. Thus, there is substantial serial correlation in the conditional mean specification of the dynamic HML beta spread. With respect to the conditional variance specification, the EGARCH model suggests significant volatility clusters for the dividend-to-price, investment, and short-term reversal portfolio tilts while the GJR-GARCH model suggests significant volatility clusters for the size, momentum, cashflow-to-price, and investment portfolio tilts. In this light, the GJR-GARCH seems to better pick up the GARCH effect for the HML beta spread. Among these portfolio tilts, volatility asymmetries prevail in the GJR-GARCH model for both momentum and investment tilts. All this evidence supports the view that the dynamic HML beta spread exhibits the common properties of a typical financial time series.

The above results are informative in the sense that each HML beta spread exhibits much variability over time for the original Fama-French HML factor to be economically meaningful in explaining the variation in stock returns. In conjunction with the evidence of significant mean HML betas in Table A5.3, the ARMA-GARCH results support the use of HML as a relevant state variable that helps better span the investor's mean-variance space. Thus, HML conveys non-trivial information about at least some of the variation in excess returns for a variety of stock portfolio tilts. This inference is inconsistent with the recent claim of Fama and French (2015) and Hou, Xue, and Zhang (2014) that HML becomes redundant after the econometrician incorporates RMW and CMA into the multifactor asset pricing model. The economic content of HML and even SMB relates to whether these state variables serve as proxies for financial distress risk (Griffin and Lemmon, 2002; Vassalou and Xing, 2004), macroeconomic innovations (Liew and Vassalou, 2000; Vassalou, 2003; Petkova, 2006; Hahn and Lee, 2006), or some other behavioral considerations (Campbell, Hilscher, and Szilagyi, 2008).

Table A2.5 presents the ARMA-GARCH results for each dynamic RMW beta spread between the extreme deciles. The RMW beta spread reflects the relative sensitivity of the excess return on a given portfolio to changes in the return spread between the robust and weak stock portfolios in terms of their profitability. With respect to the conditional mean specification, the AR(1) coefficients are highly significant across the board (*t*-ratios>34). Also, the ARMA-EGARCH model yields significant MA(1) coefficients for the book-to-market and profitability portfolio tilts (*t*-ratios>2), whilst the alternative ARMA-GJR-GARCH model yields significant MA(1) coefficients for the investment and profitability tilts (*t*-ratios>2.9). Thus, there is substantial serial correlation in the conditional mean specification of each dynamic RMW beta spread. With respect to the conditional variance specification, the GJR-GARCH model seems to better pick up the GARCH effect than the EGARCH model. Specifically, the GJR-GARCH model suggests a significant GARCH effect for the size, momentum, book-to-market, cashflow-to-price, dividend-to-price, earnings-to-price, and profitability portfolio tilts (*t*-ratios>1.8), whereas, the EGARCH model picks up a large GARCH effect only for the size, book-to-market, cashflow-to-price, and investment portfolio tilts (*t*-ratios>1.7). In addition, the presence of volatility asymmetries prevails in the GJR-GARCH model for the size, book-to-market, cashflow-to-price, investment, and profitability portfolio tilts (|*t*-ratios|>2.3). In light of the above evidence, the RMW beta spread exhibits much variability over time. Similar to the case for the other state variables, RMW carries informative dynamic beta spreads that are analogous to a typical financial time series. To the extent that RMW captures the return spread between profitable stocks and less profitable stocks, this state variable adds value to the explanatory power of a dynamic variant of the Fama-French (2015) multifactor model.

Table A2.6 summarizes the ARMA-GARCH results for each CMA beta spread between the top and bottom deciles. The CMA beta spread describes the sensitivity of the excess return on a given stock portfolio to changes in the return spread that reflects differences in a firm's capital investment or asset growth. With respect to the conditional mean specification, the AR(1) coefficients are significant across the board (*t*-ratios>36). Some of the MA(1) coefficients are also significant for the size, cashflow-to-price, dividend-to-price, investment, profitability, and short-term reversal portfolio tilts (*t*-ratios>1.6). Similar to the case for the other Fama-French beta spreads, the CMA beta spread exhibits serial correlation in its conditional mean. With respect to the conditional variance specification, the EGARCH model appears to better pick up the prevalence of volatility clusters than the GJR-GARCH model. Specifically, the EGARCH model finds a substantial GARCH effect for the size, momentum, book-to-market, cashflow-to-price, dividend-to-price, profitability, and short-term reversal portfolio tilts (|*t*-ratios|>2), while the GJR-GARCH model does so only for the book-to-market, dividend-to-price, and short-term reversal portfolio tilts (*t*-ratios>2). However, the evidence of volatility asymmetries is less conclusive. In sum, CMA seems to be a useful state variable that yields wide time-series heterogeneity in its beta spread between the extreme deciles.

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Table A2.1: ARMA-GARCH representation of each dynamic conditional alpha spread

The econometrician demonstrates that each dynamic factor premium can be modeled as a typical financial time-series. The econometrician can use the canonical ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) models to fit each dynamic factor premiums that one extracts from the dynamic multifactor variant of the Fama-French (2015) asset pricing model. The conditional mean specification is ARMA(1,1) while the conditional variance specification can take the form of EGARCH(1,1,1) or GJR-GARCH(1,1,1). For simple and intuitive exposition, the econometrician describes the ARMA(1,1) conditional mean specification and EGARCH(1,1,1) and GJR-GARCH(1,1,1) conditional variance specifications below (Engle, 1982; Bollerslev, 1986; Nelson, 1991; Glosten, Jagannathan, and Runkle, 1993):

$$m_t = a + b m_{t-1} + c w_{t-1} + w_t \qquad w_t = \sqrt{h_t}\,\varepsilon_t$$

$$h_t = \exp\left\{ d + e\left(\frac{w_t}{\sqrt{h_{t-1}}}\right) + f \ln h_{t-1} + g\left(\left|\frac{w_t}{\sqrt{h_{t-1}}}\right| - \left|\frac{E(w_t)}{\sqrt{h_{t-1}}}\right|\right)\right\}$$

$$h_t = d + e w_{t-1}^2 + f h_{t-1} + g D_{t-1} w_{t-1}^2$$

where m_t is the dynamic alpha or beta spread; w_t is the residual error; h_t is the conditional variance process; ε_t is a Gaussian white noise; D_t is a binary variable with a numerical value of unity if w_t is negative or zero if w_t is positive; *a*, *b*, *c*, *d*, *e*, *f*, and *g* are the parameters for quasi-maximum likelihood estimation. While the ARMA model serves as the conditional mean specification to capture any serial correlation in the dynamic alpha or beta spread between the extreme deciles, the EGARCH or GJR-GARCH model fits the conditional variance specification to encapsulate any volatility clusters and asymmetries in the above time-series under study.

Table 9 summarizes the quantitative estimates of the main parameters for each dynamic alpha in the ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) conditional mean-variance specifications. The main parameters *a*, *b*, *c*, *d*, *e*, *f*, and *g* correspond to the key coefficients in the above time-series representation. This table reports each coefficient estimate and its corresponding *t*-statistic across the pervasive asset pricing anomalies such as size, value, momentum, investment, profitability, short-term return reversal, and long-term return reversal. Each *t*-test statistic helps examine statistical significance. On this basis, the econometrician can assess the presence or absence of the common properties of a typical financial time-series (cf. autoregressive mean reversion in the conditional mean specification and both volatility clusters and asymmetries in the conditional variance specification).

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Table A2.1: ARMA-GARCH representation of each dynamic conditional alpha spread

Asset pricing puzzle	ARMA(1,1)-EGARCH(1,1,1)							ARMA(1,1)-GJR-GARCH(1,1,1)						
Stock portfolio sort	a	b	c	d	e	f	g	a	b	c	d	e	f	g
Size														
Coefficient	0.084	0.887	0.114	0.008	0.035	1.000	0.042	0.087	0.889	0.116	0.000	0.033	0.984	-0.037
t-ratio	0.9	48.6	2.7	2.9	10.1	41597	3.1	0.8	45.5	2.6	3.3	3.6	170.4	-2.5
Momentum														
Coefficient	1.028	0.918	0.041	-0.016	0.078	0.959	0.057	0.987	0.915	0.031	0.013	0.071	0.951	-0.076
t-ratio	2.9	54.6	0.8	-1.0	3.6	50.4	2.3	2.9	49.0	0.6	1.9	3.4	66.7	-3.4
Book-to-market														
Coefficient	-0.195	0.906	0.047	-1.430	0.187	0.170	0.283	-0.173	0.914	0.075	0.003	0.000	1.000	-0.029
t-ratio	-1.0	46.0	0.8	-5.2	2.5	1.1	2.5	-6.2	65.3	4.7	180.6	0.0	380425	-205.7
Cashflow-to-price														
Coefficient	-0.047	0.909	0.012	-0.017	-0.007	0.980	0.068	0.021	0.912	0.022	0.004	0.000	0.979	0.012
t-ratio	-0.2	60.8	0.3	-3.1	-0.4	341	14.3	0.1	47.3	0.5	6.0	0.0	217.4	1.8
Dividend-to-price														
Coefficient	-0.142	0.932	0.002	0.010	0.037	1.000	0.059	-0.239	0.922	0.047	0.007	0.063	0.958	-0.082
t-ratio	-0.6	50.8	0.0	3.3	2.4	2309	10.1	-3.0	56.9	1.3	12.8	208.6	1764	-203.5
Earnings-to-price														
Coefficient	-0.082	0.904	0.031	-0.083	0.068	0.944	0.048	-0.095	0.897	0.043	0.013	0.071	0.910	-0.086
t-ratio	-0.5	46.0	0.7	-11.7	3.8	255	3.4	-0.5	45.5	1.0	3.0	3.4	36.5	-3.7
Investment														
Coefficient	0.056	0.938	0.062	-1.074	-0.403	0.465	0.127	0.051	0.907	0.063	0.062	0.000	0.409	0.351
t-ratio	0.3	59.2	1.7	-5.1	-6.5	4.6	2.0	0.3	51.2	1.2	4.4	0.0	3.7	4.1
Profitability														
Coefficient	0.304	0.928	0.024	-0.227	0.017	0.898	0.034	0.329	0.931	0.032	0.001	0.000	1.000	-0.011
t-ratio	1.9	53.6	0.5	-2.9	0.7	24.2	3.6	2.2	55.4	0.8	1.9	0.0	294824	-2.0
Short-term reversal														
Coefficient	-1.122	0.858	0.079	0.001	0.003	0.980	0.098	-1.076	0.901	0.066	0.004	0.000	1.000	-0.015
t-ratio	-4.8	41.1	1.5	0.1	0.2	98.8	4.1	-2.6	49.9	1.6	7.6	0.0	214006	-9.0
Long-term reversal														
Coefficient	0.378	0.854	0.065	-0.092	0.093	0.928	0.070	0.380	0.860	0.072	0.023	0.062	0.881	-0.065
t-ratio	2.6	38.2	1.4	-2.3	4.3	39.0	2.2	2.4	33.6	1.5	3.3	2.4	27.6	-2.0

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Table A2.2: ARMA-GARCH representation of each dynamic conditional MRP beta spread

The econometrician demonstrates that each dynamic factor premium can be modeled as a typical financial time-series. The econometrician can use the canonical ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) models to fit each dynamic factor premiums that one extracts from the dynamic multifactor variant of the Fama-French (2015) asset pricing model. The conditional mean specification is ARMA(1,1) while the conditional variance specification can take the form of EGARCH(1,1,1) or GJR-GARCH(1,1,1). For simple and intuitive exposition, the econometrician describes the ARMA(1,1) conditional mean specification and EGARCH(1,1,1) and GJR-GARCH(1,1,1) conditional variance specifications below (Engle, 1982; Bollerslev, 1986; Nelson, 1991; Glosten, Jagannathan, and Runkle, 1993):

$$m_t = a + bm_{t-1} + cw_{t-1} + w_t \qquad w_t = \sqrt{h_t}\,\varepsilon_t$$

$$h_t = \exp\left\{d + e\left(\frac{w_t}{\sqrt{h_{t-1}}}\right) + f\ln h_{t-1} + g\left(\left|\frac{w_t}{\sqrt{h_{t-1}}}\right| - \left|\frac{E(w_t)}{\sqrt{h_{t-1}}}\right|\right)\right\}$$

$$h_t = d + ew_{t-1}^2 + fh_{t-1} + gD_{t-1}w_{t-1}^2$$

where m_t is the dynamic alpha or beta spread; w_t is the residual error; h_t is the conditional variance process; ε_t is a Gaussian white noise; D_t is a binary variable with a numerical value of unity if w_t is negative or zero if w_t is positive; *a*, *b*, *c*, *d*, *e*, *f*, and *g* are the parameters for quasi-maximum likelihood estimation. While the ARMA model serves as the conditional mean specification to capture any serial correlation in the dynamic alpha or beta spread between the extreme deciles, the EGARCH or GJR-GARCH model fits the conditional variance specification to encapsulate any volatility clusters and asymmetries in the above time-series under study.

Table 10 shows the quantitative estimates of the key parameters for each dynamic MRP beta in the ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) conditional mean-variance specifications. The main parameters *a*, *b*, *c*, *d*, *e*, *f*, and *g* correspond to the key coefficients in the above time-series representation. This table reports each coefficient estimate and its corresponding *t*-statistic across the pervasive asset pricing anomalies such as size, value, momentum, investment, profitability, short-term return reversal, and long-term return reversal. Each *t*-test statistic helps examine statistical significance. On this basis, the econometrician can assess the presence or absence of the common properties of a typical financial time-series (cf. autoregressive mean reversion in the conditional mean specification and both volatility clusters and asymmetries in the conditional variance specification).

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Table A2.2: ARMA-GARCH representation of each dynamic conditional MRP beta spread

Asset pricing puzzle	ARMA(1,1)-EGARCH(1,1,1)							ARMA(1,1)-GJR-GARCH(1,1,1)						
Stock portfolio sort	a	b	c	d	e	f	g	a	b	c	d	e	f	g
Size														
Coefficient	0.048	0.700	0.012	-0.017	0.023	0.993	0.071	0.047	0.697	0.010	0.000	0.035	0.962	-0.006
t-ratio	1.8	18.8	0.2	-1.0	1.5	176.9	3.8	1.6	15.7	0.2	1.2	2.4	88.2	-0.3
Momentum														
Coefficient	-0.083	0.699	0.021	-0.563	-0.130	0.462	0.454	-0.065	0.701	0.024	0.225	0.178	0.090	0.271
t-ratio	-1.0	12.1	0.2	-2.8	-2.3	2.6	5.1	-0.8	17.4	0.3	4.3	2.5	0.6	1.9
Book-to-market														
Coefficient	0.213	0.708	-0.021	-0.125	0.079	0.941	0.062	0.216	0.711	-0.035	0.005	0.066	0.933	-0.099
t-ratio	6.1	18.1	-0.4	-9.3	4.9	144.6	2.8	4.6	16.0	-0.5	2.8	3.6	32.5	-11.7
Cashflow-to-price														
Coefficient	0.108	0.682	-0.023	-0.336	-0.064	0.822	0.350	0.102	0.670	-0.016	0.040	0.243	0.465	0.119
t-ratio	3.0	22.3	-1.2	-2.2	-1.6	11.0	3.9	2.4	14.6	-0.2	3.7	2.4	4.0	1.1
Dividend-to-price														
Coefficient	-0.254	0.699	-0.010	-0.020	0.002	0.982	0.174	-0.249	0.700	-0.012	0.003	0.072	0.913	0.011
t-ratio	-6.5	23.1	-0.8	-0.8	0.1	68.2	4.1	-4.7	15.8	-0.2	1.5	3.1	37.2	0.3
Earnings-to-price														
Coefficient	0.177	0.713	-0.018	-0.392	-0.072	0.800	0.157	0.169	0.730	-0.024	0.000	0.005	0.988	0.011
t-ratio	2.4	9.0	-0.1	-1.6	-1.8	6.7	2.4	3.0	15.3	-0.4	0.6	0.6	455.4	0.6
Investment														
Coefficient	-0.025	0.665	0.011	-0.278	-0.012	0.885	0.114	-0.021	0.678	-0.006	0.000	0.000	0.991	0.015
t-ratio	-0.7	14.1	0.2	-1.3	-0.4	9.9	2.0	-0.6	14.7	-0.1	0.5	0.0	837.4	2.4
Profitability														
Coefficient	-0.285	0.733	-0.021	-0.138	0.012	0.937	0.184	-0.275	0.735	-0.011	0.006	0.088	0.857	-0.015
t-ratio	-7.2	16.8	-0.3	-2.6	0.4	43.0	4.6	-6.0	16.5	-0.2	2.9	2.4	29.9	-0.3
Short-term reversal														
Coefficient	-0.199	0.661	0.134	-0.044	-0.012	0.956	0.153	-0.185	0.662	0.121	0.015	0.067	0.887	-0.003
t-ratio	-2.6	15.0	2.3	-1.7	-0.5	43.5	3.9	-2.5	14.4	2.0	1.7	2.6	20.2	-0.1
Long-term reversal														
Coefficient	-0.186	0.637	0.109	-0.272	-0.003	0.833	0.205	-0.169	0.642	0.130	0.001	0.008	1.000	-0.024
t-ratio	-4.0	14.5	1.6	-1.9	-0.1	10.0	3.2	-1.8	9.2	1.3	3.8	0.9	213718	-0.9

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Table A2.3: ARMA-GARCH representation of each dynamic conditional SMB beta spread

The econometrician demonstrates that each dynamic factor premium can be modeled as a typical financial time-series. The econometrician can use the canonical ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) models to fit each dynamic factor premiums that one extracts from the dynamic multifactor variant of the Fama-French (2015) asset pricing model. The conditional mean specification is ARMA(1,1) while the conditional variance specification can take the form of EGARCH(1,1,1) or GJR-GARCH(1,1,1). For simple and intuitive exposition, the econometrician describes the ARMA(1,1) conditional mean specification and EGARCH(1,1,1) and GJR-GARCH(1,1,1) conditional variance specifications below (Engle, 1982; Bollerslev, 1986; Nelson, 1991; Glosten, Jagannathan, and Runkle, 1993):

$$m_t = a + b m_{t-1} + c w_{t-1} + w_t \qquad w_t = \sqrt{h_t}\,\varepsilon_t$$

$$h_t = \exp\left\{ d + e\left(\frac{w_t}{\sqrt{h_{t-1}}}\right) + f \ln h_{t-1} + g\left(\left|\frac{w_t}{\sqrt{h_{t-1}}}\right| - \left|\frac{E(w_t)}{\sqrt{h_{t-1}}}\right|\right)\right\}$$

$$h_t = d + e w_{t-1}^2 + f h_{t-1} + g D_{t-1} w_{t-1}^2$$

where m_t is the dynamic alpha or beta spread; w_t is the residual error; h_t is the conditional variance process; ε_t is a Gaussian white noise; D_t is a binary variable with a numerical value of unity if w_t is negative or zero if w_t is positive; *a*, *b*, *c*, *d*, *e*, *f*, and *g* are the parameters for quasi-maximum likelihood estimation. While the ARMA model serves as the conditional mean specification to capture any serial correlation in the dynamic alpha or beta spread between the extreme deciles, the EGARCH or GJR-GARCH model fits the conditional variance specification to encapsulate any volatility clusters and asymmetries in the above time-series under study.

Table 11 shows the quantitative estimates of the key parameters for each dynamic SMB beta in the ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) conditional mean-variance specifications. The main parameters *a*, *b*, *c*, *d*, *e*, *f*, and *g* correspond to the key coefficients in the above time-series representation. This table reports each coefficient estimate and its corresponding *t*-statistic across the pervasive asset pricing anomalies such as size, value, momentum, investment, profitability, short-term return reversal, and long-term return reversal. Each *t*-test statistic helps examine statistical significance. On this basis, the econometrician can assess the presence or absence of the common properties of a typical financial time-series (cf. autoregressive mean reversion in the conditional mean specification and both volatility clusters and asymmetries in the conditional variance specification).

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Table A2.3: ARMA-GARCH representation of each dynamic conditional SMB beta spread

Asset pricing puzzle	ARMA(1,1)-EGARCH(1,1,1)							ARMA(1,1)-GJR-GARCH(1,1,1)						
Stock portfolio sort	a	b	c	d	e	f	g	a	b	c	d	e	f	g
Size														
Coefficient	-1.419	0.844	0.007	-0.050	0.050	0.979	0.061	-1.436	0.845	0.003	0.001	0.042	0.965	-0.046
t-ratio	-24.5	38.0	0.8	-12.4	3.8	4260	12.0	-22.6	30.0	0.0	3.4	4.4	124.6	-3.1
Momentum														
Coefficient	0.034	0.845	0.014	-0.043	0.082	0.939	0.104	0.002	0.840	0.011	0.023	0.099	0.900	-0.094
t-ratio	0.2	31.7	0.3	-1.6	3.0	31.1	2.8	0.0	29.9	0.2	1.7	2.8	20.6	-2.6
Book-to-market														
Coefficient	0.403	0.828	0.066	-0.031	0.038	0.986	-0.024	0.409	0.797	0.080	0.001	0.007	0.996	-0.026
t-ratio	4.4	27.7	1.3	-15.7	3.9	5170	-5.2	5.2	27.8	1.6	2.9	3.4	553289	-4.4
Cashflow-to-price														
Coefficient	0.109	0.797	0.034	-0.329	-0.077	0.827	0.166	0.086	0.788	0.047	0.023	0.041	0.751	0.100
t-ratio	1.7	24.4	0.7	-2.2	-2.1	11.0	2.9	1.1	22.9	0.8	2.5	1.4	9.1	1.8
Dividend-to-price														
Coefficient	-0.317	0.790	0.033	-0.071	-0.043	0.947	0.162	-0.308	0.784	0.052	0.011	0.023	0.875	0.098
t-ratio	-4.5	21.0	0.5	-1.9	-1.5	42.2	4.4	-3.6	21.9	0.8	2.4	1.1	23.6	2.4
Earnings-to-price														
Coefficient	0.168	0.813	0.058	-0.265	0.002	0.858	0.066	0.165	0.824	0.055	0.000	0.000	0.994	0.011
t-ratio	1.8	25.7	1.1	-1.0	0.0	5.9	1.3	1.7	28.7	1.1	0.6	0.0	1046	2.0
Investment														
Coefficient	-0.092	0.871	-0.003	-0.196	0.053	0.918	-0.053	-0.081	0.838	0.012	0.001	0.000	1.000	-0.018
t-ratio	-1.0	30.1	-0.1	-55.1	2.9	18417	-1.8	-1.0	31.7	0.2	25.0	0.0	952657	-25.1
Profitability														
Coefficient	-0.482	0.750	0.084	-0.175	-0.002	0.918	0.132	-0.462	0.754	0.092	0.008	0.045	0.871	0.012
t-ratio	-7.7	20.7	1.3	-2.4	-0.1	29.8	3.1	-8.0	20.6	1.5	2.7	2.1	23.3	0.4
Short-term reversal														
Coefficient	-0.138	0.813	0.035	-0.044	0.077	0.948	0.103	-0.137	0.812	0.026	0.022	0.118	0.880	-0.106
t-ratio	-1.0	25.5	0.6	-1.9	3.0	42.3	3.5	-1.0	25.6	0.5	2.5	3.4	28.9	-2.6
Long-term reversal														
Coefficient	-0.577	0.860	0.025	-0.036	-0.042	0.969	0.097	-0.567	0.857	0.049	0.005	0.010	0.946	0.044
t-ratio	-5.1	34.6	0.6	-1.4	-2.1	62.1	2.9	-4.3	32.4	0.9	2.0	0.6	49.0	2.1

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Table A2.4: ARMA-GARCH representation of each dynamic conditional HML beta spread

The econometrician demonstrates that each dynamic factor premium can be modeled as a typical financial time-series. The econometrician can use the canonical ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) models to fit each dynamic factor premiums that one extracts from the dynamic multifactor variant of the Fama-French (2015) asset pricing model. The conditional mean specification is ARMA(1,1) while the conditional variance specification can take the form of EGARCH(1,1,1) or GJR-GARCH(1,1,1). For simple and intuitive exposition, the econometrician describes the ARMA(1,1) conditional mean specification and EGARCH(1,1,1) and GJR-GARCH(1,1,1) conditional variance specifications below (Engle, 1982; Bollerslev, 1986; Nelson, 1991; Glosten, Jagannathan, and Runkle, 1993):

$$m_t = a + bm_{t-1} + cw_{t-1} + w_t \qquad w_t = \sqrt{h_t}\,\varepsilon_t$$

$$h_t = \exp\left\{ d + e\left(\frac{w_t}{\sqrt{h_{t-1}}}\right) + f \ln h_{t-1} + g\left(\left|\frac{w_t}{\sqrt{h_{t-1}}}\right| - \left|\frac{E(w_t)}{\sqrt{h_{t-1}}}\right|\right)\right\}$$

$$h_t = d + ew_{t-1}^2 + fh_{t-1} + gD_{t-1}w_{t-1}^2$$

where m_t is the dynamic alpha or beta spread; w_t is the residual error; h_t is the conditional variance process; ε_t is a Gaussian white noise; D_t is a binary variable with a numerical value of unity if w_t is negative or zero if w_t is positive; *a*, *b*, *c*, *d*, *e*, *f*, and *g* are the parameters for quasi-maximum likelihood estimation. While the ARMA model serves as the conditional mean specification to capture any serial correlation in the dynamic alpha or beta spread between the extreme deciles, the EGARCH or GJR-GARCH model fits the conditional variance specification to encapsulate any volatility clusters and asymmetries in the above time-series under study.

Table 12 shows the quantitative estimates of the key parameters for each dynamic HML beta in the ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) conditional mean-variance specifications. The main parameters *a*, *b*, *c*, *d*, *e*, *f*, and *g* correspond to the key coefficients in the above time-series representation. This table reports each coefficient estimate and its corresponding *t*-statistic across the pervasive asset pricing anomalies such as size, value, momentum, investment, profitability, short-term return reversal, and long-term return reversal. Each *t*-test statistic helps examine statistical significance. On this basis, the econometrician can assess the presence or absence of the common properties of a typical financial time-series (cf. autoregressive mean reversion in the conditional mean specification and both volatility clusters and asymmetries in the conditional variance specification).

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Table A2.4: ARMA-GARCH representation of each dynamic conditional HML beta spread

Asset pricing puzzle	ARMA(1,1)-EGARCH(1,1,1)							ARMA(1,1)-GJR-GARCH(1,1,1)						
Stock portfolio sort	a	b	c	d	e	f	g	a	b	c	d	e	f	g
Size														
Coefficient	-0.593	0.808	0.026	-0.013	0.005	0.992	0.070	-0.591	0.841	-0.009	0.001	0.040	0.965	-0.028
t-ratio	-12.9	39.0	1.0	-4.4	0.4	1732	28.0	-9.4	25.8	-0.2	2.3	2.6	126.5	-1.3
Momentum														
Coefficient	-0.452	0.920	0.060	0.006	0.021	0.988	0.087	-0.409	0.929	0.064	0.009	0.057	0.961	-0.065
t-ratio	-2.1	53.8	4.5	0.7	1.0	77.8	2.9	-1.1	51.1	1.4	1.6	3.3	54.3	-2.9
Book-to-market														
Coefficient	1.933	0.877	-0.009	-1.518	-0.127	0.259	0.385	1.972	0.877	-0.005	0.004	0.000	0.947	0.047
t-ratio	17.6	39.8	-0.1	-4.1	-2.2	1.49	4.4	17.3	37.9	-0.1	1.8	0.0	42	2.7
Cashflow-to-price														
Coefficient	1.642	0.860	0.059	-0.316	0.065	0.817	0.261	1.620	0.852	0.084	0.035	0.194	0.646	-0.096
t-ratio	15.0	33.4	1.0	-2.3	1.3	10.8	3.5	14.4	32.7	1.4	3.6	2.2	7.8	-1.1
Dividend-to-price														
Coefficient	1.587	0.867	0.063	0.006	-0.037	1.000	0.026	1.633	0.863	0.068	0.001	0.009	0.979	0.022
t-ratio	11.8	46.4	1.4	3.2	-3.7	400458	4.9	11.7	35.4	1.4	1.7	1.2	233.5	1.8
Earnings-to-price														
Coefficient	1.739	0.854	0.057	0.005	0.000	1.000	0.031	1.742	0.856	0.037	0.000	0.004	0.992	0.006
t-ratio	14.7	35.4	2.0	6.7	0.0	105492	97.8	14.4	32.7	0.7	0.7	0.4	981	0.5
Investment														
Coefficient	-0.686	0.888	-0.010	-0.603	0.128	0.716	0.235	-0.725	0.894	0.024	0.001	0.000	1.000	-0.025
t-ratio	-6.5	41.2	-0.2	-3.1	3.2	8.28	3.7	-7.1	49.3	0.5	52.7	4.7	9274919	-41.7
Profitability														
Coefficient	-0.873	0.854	0.076	-0.468	-0.052	0.792	0.075	-0.874	0.851	0.085	0.021	0.017	0.757	0.042
t-ratio	-9.0	33.1	1.6	-1.3	-1.3	5.0	1.4	-9.2	32.9	1.7	1.5	0.7	5.0	0.8
Short-term reversal														
Coefficient	-0.087	0.840	0.012	-0.030	-0.059	0.967	0.068	-0.055	0.844	0.015	0.009	0.000	0.944	0.060
t-ratio	-0.8	40.1	0.7	-7.1	-4.5	260.6	9.3	-0.4	33.1	0.3	1.9	0.0	50.6	3.3
Long-term reversal														
Coefficient	-1.089	0.907	0.018	0.004	-0.026	1.000	0.022	-1.031	0.907	0.018	0.000	0.004	0.992	0.005
t-ratio	-5.8	46.0	0.4	2.8	-1.7	194322	5.99	-5.4	42.4	0.4	0.6	0.4	947.4	0.3

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Table A2.5: ARMA-GARCH representation of each dynamic conditional RMW beta spread

The econometrician demonstrates that each dynamic factor premium can be modeled as a typical financial time-series. The econometrician can use the canonical ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) models to fit each dynamic factor premiums that one extracts from the dynamic multifactor variant of the Fama-French (2015) asset pricing model. The conditional mean specification is ARMA(1,1) while the conditional variance specification can take the form of EGARCH(1,1,1) or GJR-GARCH(1,1,1). For simple and intuitive exposition, the econometrician describes the ARMA(1,1) conditional mean specification and EGARCH(1,1,1) and GJR-GARCH(1,1,1) conditional variance specifications below (Engle, 1982; Bollerslev, 1986; Nelson, 1991; Glosten, Jagannathan, and Runkle, 1993):

$$m_t = a + bm_{t-1} + cw_{t-1} + w_t \qquad w_t = \sqrt{h_t}\,\varepsilon_t$$

$$h_t = \exp\left\{d + e\left(\frac{w_t}{\sqrt{h_{t-1}}}\right) + f\ln h_{t-1} + g\left(\left|\frac{w_t}{\sqrt{h_{t-1}}}\right| - \left|\frac{E(w_t)}{\sqrt{h_{t-1}}}\right|\right)\right\}$$

$$h_t = d + ew_{t-1}^2 + fh_{t-1} + gD_{t-1}w_{t-1}^2$$

where m_t is the dynamic alpha or beta spread; w_t is the residual error; h_t is the conditional variance process; ε_t is a Gaussian white noise; D_t is a binary variable with a numerical value of unity if w_t is negative or zero if w_t is positive; *a*, *b*, *c*, *d*, *e*, *f*, and *g* are the parameters for quasi-maximum likelihood estimation. While the ARMA model serves as the conditional mean specification to capture any serial correlation in the dynamic alpha or beta spread between the extreme deciles, the EGARCH or GJR-GARCH model fits the conditional variance specification to encapsulate any volatility clusters and asymmetries in the above time-series under study.

Table 13 shows the quantitative estimates of the key parameters for each dynamic RMW beta in the ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) conditional mean-variance specifications. The main parameters *a*, *b*, *c*, *d*, *e*, *f*, and *g* correspond to the key coefficients in the above time-series representation. This table reports each coefficient estimate and its corresponding *t*-statistic across the pervasive asset pricing anomalies such as size, value, momentum, investment, profitability, short-term return reversal, and long-term return reversal. Each *t*-test statistic helps examine statistical significance. On this basis, the econometrician can assess the presence or absence of the common properties of a typical financial time-series (cf. autoregressive mean reversion in the conditional mean specification and both volatility clusters and asymmetries in the conditional variance specification).

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Table A2.5: ARMA-GARCH representation of each dynamic conditional RMW beta spread

Asset pricing puzzle	ARMA(1,1)-EGARCH(1,1,1)							ARMA(1,1)-GJR-GARCH(1,1,1)						
Stock portfolio sort	a	b	c	d	e	f	g	a	b	c	d	e	f	g
Size														
Coefficient	0.581	0.907	0.049	-0.027	0.071	0.989	0.017	0.579	0.892	0.052	0.001	0.041	0.977	-0.053
t-ratio	5.6	48.9	1.0	-9.8	5.5	2102663	16.0	5.8	45.2	1.1	11.3	7.9	121.6	-4.2
Momentum														
Coefficient	0.275	0.904	0.020	-0.023	-0.023	0.943	0.139	0.267	0.897	0.035	0.039	0.045	0.858	0.039
t-ratio	0.9	43.3	0.4	-1.0	-0.8	30.0	3.5	1.0	40.4	0.6	1.9	1.8	16.1	1.1
Book-to-market														
Coefficient	-1.161	0.889	0.067	-0.130	0.080	0.917	0.205	-1.184	0.898	0.044	0.010	0.189	0.838	-0.147
t-ratio	-6.5	48.3	2.2	-2.8	2.8	39	4.5	-8.1	41.4	0.8	3.2	3.5	28	-3.0
Cashflow-to-price														
Coefficient	-0.322	0.901	-0.014	-0.080	0.042	0.949	0.090	-0.331	0.904	-0.020	0.005	0.047	0.945	-0.045
t-ratio	-0.9	39.9	-0.3	-1.7	1.7	39.1	2.6	-2.0	44.7	-0.4	2.2	2.6	50.6	-2.3
Dividend-to-price														
Coefficient	-1.083	0.886	0.055	-0.019	0.018	0.962	0.225	-1.117	0.889	0.073	0.010	0.128	0.875	-0.052
t-ratio	-7.2	51.9	1.9	-0.8	0.8	58.0	4.8	-6.7	40.3	1.4	2.4	3.8	29.2	-1.5
Earnings-to-price														
Coefficient	-0.341	0.871	-0.049	-0.364	-0.006	0.757	0.360	-0.303	0.877	-0.019	0.001	0.014	0.988	-0.006
t-ratio	-3.7	38.3	-0.7	-3.0	-0.2	10.5	4.5	-2.1	34.5	-0.4	0.8	3.0	409.3	-0.7
Investment														
Coefficient	0.597	0.910	0.063	-0.224	-0.039	0.893	-0.008	0.622	0.899	0.086	0.001	0.000	1.000	-0.008
t-ratio	3.7	45.7	1.4	-10.6	-1.8	105	-0.4	4.2	45.6	2.9	4.1	0.0	49347	-10.8
Profitability														
Coefficient	1.460	0.891	0.105	-0.301	-0.003	0.858	0.151	1.505	0.900	0.093	0.001	0.005	1.000	-0.031
t-ratio	10.8	39.2	2.0	-2.1	-0.1	13.3	2.7	15.1	58.8	3.0	33.7	6.2	705608	-314.5
Short-term reversal														
Coefficient	0.217	0.897	0.035	-0.741	-0.102	0.117	0.390	0.127	0.894	0.030	0.331	0.173	0.000	0.211
t-ratio	0.8	44.5	0.7	-3.6	-1.7	0.5	4.5	0.5	45.8	0.6	12.7	1.9	0.0	1.4
Long-term reversal														
Coefficient	0.334	0.915	0.026	-0.162	-0.008	0.881	0.144	0.404	0.917	0.000	0.021	0.023	0.866	0.041
t-ratio	1.4	48.2	0.5	-1.9	-0.2	15.7	2.6	1.8	44.6	0.0	1.9	0.9	14.1	1.2

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Table A2.6: ARMA-GARCH representation of each dynamic conditional CMA beta spread

The econometrician demonstrates that each dynamic factor premium can be modeled as a typical financial time-series. The econometrician can use the canonical ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) models to fit each dynamic factor premiums that one extracts from the dynamic multifactor variant of the Fama-French (2015) asset pricing model. The conditional mean specification is ARMA(1,1) while the conditional variance specification can take the form of EGARCH(1,1,1) or GJR-GARCH(1,1,1). For simple and intuitive exposition, the econometrician describes the ARMA(1,1) conditional mean specification and EGARCH(1,1,1) and GJR-GARCH(1,1,1) conditional variance specifications below (Engle, 1982; Bollerslev, 1986; Nelson, 1991; Glosten, Jagannathan, and Runkle, 1993):

$$m_t = a + bm_{t-1} + cw_{t-1} + w_t \qquad w_t = \sqrt{h_t}\,\varepsilon_t$$

$$h_t = \exp\left\{ d + e\left(\frac{w_t}{\sqrt{h_{t-1}}}\right) + f\ln h_{t-1} + g\left(\left|\frac{w_t}{\sqrt{h_{t-1}}}\right| - \left|\frac{E(w_t)}{\sqrt{h_{t-1}}}\right|\right)\right\}$$

$$h_t = d + ew_{t-1}^2 + fh_{t-1} + gD_{t-1}w_{t-1}^2$$

where m_t is the dynamic alpha or beta spread; w_t is the residual error; h_t is the conditional variance process; ε_t is a Gaussian white noise; D_t is a binary variable with a numerical value of unity if w_t is negative or zero if w_t is positive; *a*, *b*, *c*, *d*, *e*, *f*, and *g* are the parameters for quasi-maximum likelihood estimation. While the ARMA model serves as the conditional mean specification to capture any serial correlation in the dynamic alpha or beta spread between the extreme deciles, the EGARCH or GJR-GARCH model fits the conditional variance specification to encapsulate any volatility clusters and asymmetries in the above time-series under study.

Table 14 shows the quantitative estimates of the key parameters for each dynamic CMA beta in the ARMA(1,1)-EGARCH(1,1,1) and ARMA(1,1)-GJR-GARCH(1,1,1) conditional mean-variance specifications. The main parameters *a*, *b*, *c*, *d*, *e*, *f*, and *g* correspond to the key coefficients in the above time-series representation. This table reports each coefficient estimate and its corresponding *t*-statistic across the pervasive asset pricing anomalies such as size, value, momentum, investment, profitability, short-term return reversal, and long-term return reversal. Each *t*-test statistic helps examine statistical significance. On this basis, the econometrician can assess the presence or absence of the common properties of a typical financial time-series (cf. autoregressive mean reversion in the conditional mean specification and both volatility clusters and asymmetries in the conditional variance specification).

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Table A2.6: ARMA-GARCH representation of each dynamic conditional CMA beta spread

Asset pricing puzzle	ARMA(1,1)-EGARCH(1,1,1)							ARMA(1,1)-GJR-GARCH(1,1,1)						
Stock portfolio sort	a	b	c	d	e	f	g	a	b	c	d	e	f	g
Size														
Coefficient	0.044	0.898	0.114	-0.009	-0.053	0.992	0.057	0.078	0.890	0.097	0.001	0.006	0.960	0.051
t-ratio	0.4	46.0	2.2	-2.7	-4.1	28362	7.8	0.8	41.3	1.9	2.2	0.8	98.3	2.8
Momentum														
Coefficient	0.038	0.922	0.060	-0.010	-0.047	0.977	0.001	0.109	0.926	0.067	0.002	0.000	0.995	0.008
t-ratio	0.1	59.5	1.5	-3.5	-3.6	78097	0.3	0.3	53.4	1.5	1.4	0.0	1076.1	2.0
Book-to-market														
Coefficient	0.649	0.866	0.031	-0.697	0.096	0.641	0.192	0.644	0.870	0.026	0.065	0.169	0.434	-0.150
t-ratio	6.2	39.5	0.9	-2.3	2.3	4	2.5	5.5	36.9	0.5	3.1	2.5	3	-2.2
Cashflow-to-price														
Coefficient	-0.465	0.959	0.213	-0.074	-0.047	0.972	-0.140	0.034	0.953	0.144	0.003	0.000	1.000	-0.025
t-ratio	-1264	2157	1387	-2225	-1067	2563	-2295	2.3	68.4	3.7	25.0	0.0	20049	-25.9
Dividend-to-price														
Coefficient	1.901	0.944	0.135	-0.025	0.159	0.984	-0.090	0.804	0.934	0.090	0.001	0.024	1.000	-0.055
t-ratio	1737	3885	3314	-1576	98105	3586	-2159	9.0	4752.9	7.0	9.3	66.6	26788	-224.4
Earnings-to-price														
Coefficient	-0.293	0.884	0.068	-0.332	0.085	0.755	0.190	-0.218	0.927	0.054	0.003	0.000	1.000	-0.025
t-ratio	-3.2	47.9	4.8	-1.1	1.5	3.6	2.0	-1.6	64.0	1.5	24.1	0.7	48349	-35.9
Investment														
Coefficient	-1.341	0.880	0.147	-0.277	-0.028	0.872	0.128	-1.346	0.901	0.146	0.084	0.203	0.075	-0.184
t-ratio	-13.1	47.5	6.8	-2.0	-1.0	15	2.6	-9.4	41.0	2.9	4.5	2.3	0	-1.9
Profitability														
Coefficient	0.140	0.919	0.056	-0.083	0.000	0.973	-0.132	-0.093	0.925	0.069	0.001	0.000	1.000	-0.012
t-ratio	2287.7	2531.7	16.0	-3552	-3.2	3506	-1720	-0.4	50.7	1.6	3.4	0.0	25955	-3.4
Short-term reversal														
Coefficient	0.177	0.923	0.065	-0.976	-0.426	-0.105	0.016	0.166	0.893	0.079	0.001	0.005	1.000	-0.012
t-ratio	0.5	56.8	1.6	-7.3	-6.2	-0.8	0.2	0.6	46.5	1.8	1.6	9.3	3122	-7.4
Long-term reversal														
Coefficient	-1.119	0.927	0.023	-0.115	-0.034	0.905	0.092	-0.984	0.928	0.024	0.040	0.000	0.818	0.041
t-ratio	-12.8	47.0	0.5	-1.4	-0.9	15.1	2.4	-3.9	49.8	0.5	2.1	0.0	9.7	1.3

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Appendix 3: Macroeconomic variable definitions and their data sources

This appendix describes the main macroeconomic variable definitions and their public data sources in our vector autoregression analysis of Granger mutual causation between fundamental macro surprises and dynamic conditional factor premiums. To the extent that macroeconomic innovations manifest in the form of dynamic conditional factor premiums, this causation reveals the marginal investor's fundamental news and rational expectations about the cross-section of average returns.

We specify 15 major monthly time-series in a standard macroeconometric vector autoregressive system. There are 12 macroeconomic variables, 2 financial uncertainty time-series, and 2 investor sentiment proxies. For the Baker-Wurgler investor sentiment index, we use the original first principal component as a better empirical proxy. The resultant dataset spans the 285-month sample period from April 1990 to December 2013. These macroeconomic time-series include changes in the national economic activity index, Treasury bill rate, unemployment rate, term spread, default spread, prime bank loan rate, aggregate equity market dividend yield, and percent changes in U.S. industrial production, non-farm payroll, house price index, consumer price index, exchange rate, financial stress index, economic policy uncertainty, and investor sentiment.

Macroeconomic variable and name definition	Source
Chicago Fed's national economic activity index change from historical trend	Chicago Fed
St. Louis Fed Treasury 3-month secondary-market bill rate change	St. Louis Fed
St. Louis Fed unemployment rate change (total unemployment/labor force participation)	St. Louis Fed
Term spread between the 10-year Treasury and 3-month Treasury constant maturity rates	St. Louis Fed
Default spread between Moody's Baa-corporate-bond and 10-year Treasury bill rates	St. Louis Fed
Prime bank loan rate change for Top 25 U.S. commercial banks in terms of total assets	St. Louis Fed
S&P 500 dividend yield from Professor Robert Shiller's book on irrational exuberance	Shiller
St. Louis Fed national industrial production index change with the base year in 2007	St. Louis Fed
Bureau of Labor Statistics non-farm payroll (in thousands of persons) percent change	Bureau of Labor Statistics
Freddie Mac U.S. metropolitan-area residential house price index percent change	Freddie Mac
Bureau of Labor Statistics consumer price index (for urban consumers) percent change	Bureau of Labor Statistics
Federal Reserve U.S. trade-weighted average composite dollar index percent change	Federal Reserve Board
Baker-Bloom-Davis U.S. economic policy uncertainty index percent change	Baker, Bloom, and Davis (2012)
Kansas City Fed financial stress index change from 11 key financial market variables	Kansas City Fed
Baker-Wurgler investor sentiment percent change (from the first principal component)	Baker and Wurgler (2006)

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Appendix 4: Conceptual nexus between our study and several recent contributions

In this appendix, we discuss the conceptual similarities and differences between the current study and several recent contributions. This discussion clarifies the core themes of our study in comparison to several concurrent ideas in the recent asset pricing literature. For instance, Harvey, Liu, and Zhu (2015) introduce a multiple testing framework (e.g. Harvey and Liu (2014a, 2014b, 2014c, 2014d)) and provide a unique variety of historical significance cut-offs from the first empirical tests in the 1960s to the present. This recent strand of asset pricing literature suggests that financial economists should lift the test hurdle from a *t*-ratio of 2.0 to a *t*-ratio of 3.0 for most cross-sectional tests. Specifically, Harvey, Liu, and Zhu (2015) find that this higher hurdle reduces the number of cross-sectional anomalies from 316 to only 2 (value and momentum) (cf. Asness et al (2013); Fama and French (2016); Hou, Xue, and Zhang (2017)). In addition, Harvey, Liu, and Zhu (2015) contend that a theoretically-derived factor should have a lower hurdle than an empirically-discovered factor. In accordance with the central thesis of Harvey, Liu, and Zhu (2015), a factor can be important in some economic environments but unimportant in some other environments.

While our econometric innovation complements Harvey, Liu, and Zhu's (2015) multiple testing analysis, the current study serves as a time-series equivalent to their cross-sectional adjustment for empirical asset pricing tests. Back-of-the-envelope calculations suggest that the typical stock portfolio's Sharpe ratio has to increase by at least 3.1 to 8.2 times for the dynamic alphas to be jointly significant at the conventional confidence level. The critical values for the χ^2-test with 525 degrees of freedom are 603.31, 579.4, and 566.9 at the respective 99%, 95%, and 90% confidence levels. Table 3 suggests that the highest *C*-test or *Q*-test statistic is 59.29 while the lowest *C*-test or *Q*-test statistic is 8.97. Therefore, the smallest Sharpe ratio multiplier can be calculated as $(566.932/59.29)^{1/2}=3.092$ while the largest Sharpe ratio multiplier is $(603.31/8.97)^{1/2}=8.201$. As a consequence, the econometrician has to specify a higher test hurdle for each anomaly. Across the deciles, most dynamic conditional alphas need to be larger on average with much less variability for the resultant Sharpe ratio to increase by at least 3 to 8 times. The equivalent Sharpe ratio would be in the approximate range of 1.15 to 2.4 (cf. Kozak, Nagel, and Santosh (2017)). In other words, our dynamic analysis of conditional factor premiums proposes raising the bar for the econometric time-series asset pricing test. This recommendation echoes the cross-sectional counterpart of Harvey, Liu, and Zhu (2015).

McLean and Pontiff (2016) analyze the out-of-sample and post-publication stock return predictability of about 100 firm characteristics that prior academic papers demonstrate to explain the cross-sectional stock return heterogeneity. The long-short portfolio return for the average predictor declines by 26% out-of-sample. Moreover, the long-short stock portfolio return for the average predictor shrinks by 58% post-publication. While there is sufficient evidence to reject the null hypothesis that stock return predictability does not change post-publication, there is also sufficient evidence to reject the null hypothesis that stock return predictability completely vanishes. McLean and Pontiff (2016) interpret the results as sufficient evidence in support of the behavioral mispricing conjecture that investors learn from anomalous stock returns while the evidence accords with the comovement models of Lee, Shleifer, and Thaler (1991) and Barberis, Shleifer, and Wurgler (2005). As academic research draws public attention to many useful predictors, stock return predictability gradually dissipates over time.

Our evidence contradicts McLean and Pontiff's (2016) empirical study. Their study does not apply a dynamic variant of the Fama-French (2015) multifactor model. Neither do their regressions with several dummy variables incorporate state variables or factors that mimic intertemporal changes in the typical investor's hedging demand for investment opportunities. Our current study proposes the use of a recursive multivariate filter to extract key dynamic conditional factor premiums from the Fama-French (2015) multifactor model. The vast majority of dynamic conditional alphas turn out to be insignificant at the conventional confidence level. Moreover, most dynamic conditional alphas are not jointly different from zero and therefore would need to increase at least 3 to 8 times for the econometrician to reject the hypothesis that our chosen dynamic version of the Fama-French (2015) factor model is a correct specification. Our work shines skeptical light on McLean and Pontiff's (2016) behavioral mispricing interpretation of conditional factor premiums in the dynamic context. Should investors learn from a diverse set of asset pricing anomalies so that these anomalies decay over time, McLean and Pontiff (2016) cannot explain why the anomalous returns persist for a prolonged period of time in the first place. In contrast, our analysis suggests that the pervasive asset pricing puzzles can be readily reconciled within a dynamic conditional factor model. Regardless of whether investors can learn from unique and viable stock portfolio strategies, our dynamic analysis helps demystify at least some ubiquitous anomalies to the extent that mutual causation between macroeconomic innovations and dynamic conditional factor premiums reflects the rational investor's fundamental information about the mysterious cross-section of average returns..

Berk and Green (2004) derive a canonical model of how the financial market for mutual fund investment equilibrates in a way that accords with the empirical facts. In highly competitive financial markets, all mutual funds must have enough assets under management such that these funds face diminishing returns to scale. When new information arrives and convinces investors that a particular fund represents a positive net-present-value investment opportunity, investors react to this opportunity by injecting more capital into that mutual fund. This process continues until enough new capital gets invested to eliminate the opportunity. As a result, mutual fund flows reflect past fund performance. Investors chase past fund performance because this performance conveys rich information about whether the mutual fund manager has skill and expertise in stock selection. By competing to take advantage of this information, investors phase out the opportunity to predict future mutual fund performance.

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Berk and Van Binsbergen (2016) and Barber, Huang, and Odean (2016) independently report that mutual fund flows reveal investor preferences for their use of asset pricing models. Their evidence is consistent with the view that the single-beta CAPM is the clear "victor" in the empirical horserace against the multifactor Fama-French-Carhart and dynamic equilibrium models because the alpha or abnormal fund return seems most heavily discounted by the CAPM. This joint evidence has implications for the broader proposition that both the multifactor and dynamic equilibrium asset pricing models may not represent true progress toward a better model of the nexus between risk and return. Investor preferences appear to be more closely aligned with the CAPM despite the fact that the model has been found to perform poorly relative to the other models in explaining the cross-sectional variation in stock returns. This issue remains an important puzzle in the asset pricing literature. Kozak, Nagel, and Santosh's (2017, 2018) recent studies shed skeptical light on whether these empirical horseraces can reflect investor beliefs, behaviors, and preferences in a clear dichotomy between the rational risk paradigm and the behavioral mispricing counterpart.

Our current study provides a midle refutation of Berk and Van Binsbergen's (2016) and Barber, Huang, and Odean's (2016) joint inference that the CAPM outperforms the multifactor models in their separate tests on mutual fund flows data. There are several major differences between our work and these recent studies. First, Berk and Van Binsbergen (2016) and Barber, Huang, and Odean (2016) do not consider the Fama-French (2015) multifactor model. Just as the founders of a firm have incentives to employ proprietary technologies, state-of-the-art work mechanisms, or efficient means of production, financial economists should make proper use of innovative econometric methods and models that help resolve the pervasive anomalies. The exclusion of both asset investment growth and operating profitability variables *RMB* and *CMA* is likely to introduce a key omitted-variables bias. Second, Berk and Van Binsbergen (2016) and Barber, Huang, and Odean (2016) cannot account for the time variation in dynamic conditional factor premiums. Their independent studies rest upon the assumption that the multifactor premiums are invariant over time. The static analysis does not take into account the key impact of measurement noise that might be present in each factor premium. To the extent that conditional factor premiums tend to change over time, this measurement noise does not vanish but can persist even in a large long-term dataset. Given this rationale, the emergence of anomalous returns or significant alphas can arise from the fact that the conventional static multifactor model cannot properly control for time variation in dynamic conditional factor premiums. Finally, Berk and Van Binsbergen (2016) and Barber, Huang, and Odean (2016) both find that a large fraction of mutual fund flows remains unknown. Although the use of mutual fund flows or quantities is valid and innovative, this empirical work represents a major departure from most prior asset pricing literature that focuses on prices, returns, or factor premiums. In contrast to the unconventional use of stock quantities rather than stock prices, our current study helps reconcile many ubiquitous asset pricing anomalies with the dynamic conditional factor model. Consequently, our new approach poses a conceptual challenge to the behavioral mispricing interpretation of anomalous stock returns that the prior factor models cannot explain in practice.

More recent studies contribute to the ongoing debate on whether the Fama-French (2015) multi-factor asset pricing model wins the horse race against most alternative static counterparts. For instance, Fama and French (2016) apply their factor model to dissect many asset pricing anomalies such as market beta, net share issuance, idiosyncratic volatility, accrual, and momentum. Each of these variables sorts stocks into deciles that result in abnormal returns or pricing errors. Fama and French (2016) report that the list of anomalies shrinks when the econometrician applies their static factor model. Positive exposures to the state variables for investment and profitability RMW_t and CMA_t capture the high average returns on profitable firms that invest conservatively with low market beta, share buyback, and low volatility. Conversely, negative exposures to RMW_t and CMA_t help explain the low average stock returns on unprofitable firms that invest aggressively with high market beta, high share buyback, and high volatility. Thus, each stock's fundamental factors such as size, value, investment, and profitability help better explain the cross-section of average stock returns.

In addition to Fama and French's (2016) recent attempt to dissect many anomalies with their factor model, Hou, Xue, and Zhang (2016) apply an alternative *q*-theoretic factor model to examine an extensive database with 430 anomalies. In comparison to the Fama-French five-factor model, the *q*-theoretic factor model yields smaller average static alphas. Yet, at least 161 to 216 anomalies persist with significant alphas. Although these separate empirical contributions of Fama and French (2016) and Hou, Xue, and Zhang (2016) seem to tell the same economic intuition that fundamental characteristics such as asset investment and operating profitability explain much of the cross-sectional variation in average returns, it is difficult to draw a clear distinction between both rational risk and behavioral mispricing models because numerous anomalies remain statistically significant in the general form of non-trivial static alphas (Kozak, Nagel, and Santosh, 2017, 2018).

Contrary to Fama and French's (2016) and Hou, Xue, and Zhang's (2016) fixation on the explanatory power of their static multifactor models, our current study designs a rigorous conditional specification test to differentiate the new and useful dynamic conditional model from the static baseline model. Not only does our dynamic conditional model outperform the static counterpart in driving the long-term average pricing errors to zero, but the dynamic conditional factor model also passes the conditional specification test that rejects the static counterpart across 104 of 110 deciles for the major portfolio tilts. In direct response to Cochrane's critique (2005: 168), the test evidence corroborates the central economic story that most static asset pricing anomalies evaporate after the econometrician properly accounts for time variation in conditional factor premiums. Our analysis helps demystify the inexorable puzzle that significant asset-pricing errors persist in the static cross-section of average returns.

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Appendix 5: Fama-French beta coefficients and t-statistics on multiple factors

Table A5.1 shows the average dynamic conditional MRP betas across the deciles for each anomaly. While there is no monotonic relation between average MRP beta and decile rank, the vast majority of these average MRP betas hover around unity. Also, the average MRP betas are all significantly greater than nil (p-values>0.001). This key evidence affirms the close empirical nexus between the excess returns on both the market portfolio and each portfolio tilt.

Also, the average conditional MRP beta spread between the extreme deciles is significant for all the portfolio strategies except the momentum and investment tilts. One has to interpret this result with caution because the lack of a monotonic trend in the average conditional MRP betas does not necessarily suggest the absence of a positive relation between risk and average return. It would be important to consider the complete set of results within the broader context of dynamic portfolio efficiency. Along with most other dynamic conditional factor betas, the conditional MRP beta varies sufficiently to reflect time variation in the sensitivity of each given portfolio to changes in the market risk premium. This time variation may arise due to shifts in the marginal investor's information set or changes in the macroeconomic environment. In light of this logic, we defer the assessment of a risk-reward nexus to an in-depth subsequent analysis.

Table A5.2 presents the average conditional SMB betas across the deciles for each anomaly. SMB helps capture the predictable variation in excess returns on the size deciles. The average conditional SMB beta monotonically declines from 1.096 for the smallest size decile to –0.28 for the largest size decile (p-values<0.08). Ceteris paribus small stocks carry higher conditional SMB factor premiums than large stocks with an average conditional SMB beta spread of –1.376 (p-value<0.01). Moreover, the average conditional SMB beta spread is significant for the value, profitability, and long-term reversal tilts (p-values<0.06). Yet, the average SMB beta spread is insignificant for the momentum, asset growth, and short-run reversal tilts (p-values>0.18). This evidence suggests that SMB helps explain the variation in excess returns on some but not all of the portfolio tilts. The average SMB betas are lower than the MRP counterparts by an order of magnitude. Thus, the conditional SMB beta exhibits non-negligible heterogeneity over time as a complement to the conditional MRP beta and other factor betas.

Table A5.3 encapsulates the average conditional HML betas on the deciles for each anomaly. The long-term average conditional HML betas are predominantly significant across the deciles for the size, value, investment, profitability, and long-run return reversal tilts. In particular, the average conditional HML beta monotonically decreases from the top decile to the bottom decile for all of the value tilts. For example, the average conditional HML beta declines monotonically from 1.118 for the top book-to-market decile to –0.899 for the bottom decile. For the cashflow-to-price, dividend-to-price, and earnings-to-price value tilts, the mean HML beta monotonically shrinks from 1.001, 0.983, and 1.028 respectively for the top decile to –0.68, –0.46, and –0.698 for the bottom decile. This evidence contradicts the recent studies of Fama and French (2015) and Hou, Xue, and Zhang (2014) who empirically show that HML becomes a redundant factor in U.S. data after the econometrician includes the investment and profitability return spreads in the factor model. Whether HML serves as an empirical proxy for financial distress risk remains open to controversy (Fama and French, 1995, 1996; Griffin and Lemmon, 2002; Vassalou and Xing, 2004; Petkova, 2006; Campbell, Hilscher, and Szilagyi, 2008; Fama and French, 2016). Notwithstanding this controversy, the current study shines new light on the explanatory role of HML in a dynamic conditional context. This rare resurrection suggests that one might want to revisit the economic content of HML and even SMB in the Fama-French (2015) factor model.

Yet, HML cannot readily contain the time variation in the excess returns on the short-term reversal and momentum portfolio tilts. Analogous to SMB, HML helps explain the variation in the excess returns on some but not all of the portfolio tilts. Thus, SMB and HML only serve as imperfect states variables that enter the marginal investor's intertemporal information set. The joint economic content of HML and SMB pertains to whether these factors serve as proxies for financial distress risk (Griffin and Lemmon, 2002; Vassalou and Xing, 2004), macroeconomic innovations in the term and default spreads (Liew and Vassalou, 2000; Vassalou, 2003; Petkova, 2006; Hahn and Lee, 2006), or some behavioral mispricing considerations (Campbell, Hilscher, and Szilagyi, 2008).

Table A5.4 presents the average dynamic conditional RMW betas across the deciles for each portfolio tilt. RMW explains the variation in the excess returns for the size, momentum, book-to-market, dividend-to-price, investment growth, operating profitability, and long-term return reversal tilts (p-values<0.006). However, the average conditional RMW betas are insignificant for the cash-flow-to-price, earnings-to-price, and short-run return reversal tilts. In stark contrast to the separate cases of SMB and HML, the average RMW beta does not monotonically increase from the bottom decile to the top decile for the profitability tilt. It is thus difficult to rationalize whether this result represents a statistical aberration or a rotten apple in the barrel of the hefty profitability premium.

Similar to the informative cases of SMB and HML, the absolute values of dynamic RMW betas turn out to be smaller by a full order of magnitude than the dynamic MRP beta near unity. On this basis, it is fair to infer that each of the state variables (SMB, HML, and RMW) provides at best a partial view of time variation in the excess returns for multiple tilts that are known to produce anomalous returns in static regression analysis. Subsequent analysis should shed some fresh light on the economic content of each of these factors in a dynamic conditional context.

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Table A5.5 summarizes the average conditional CMA betas across the deciles for each anomaly. CMA explains the variation in excess returns on the top-and-bottom deciles for the size, value, momentum, and long-run return reversal tilts and most of the investment deciles. For the former intermediate deciles, however, CMA lacks explanatory power. This evidence shows that CMA complements the other state variables only marginally in the dynamic conditional factor model. Unlike SMB and HML, CMA does not carry average conditional factor betas that demonstrate a monotonic trend across the asset growth deciles. Nevertheless, the average conditional CMA betas are significantly positive for the bottom asset growth deciles and become negative for the top asset growth deciles. This evidence accords with q-theoretic economic intuition: stocks with high asset growth experience lower subsequent average returns. For the extreme asset growth deciles, the conditional CMA factor beta spread of –1.432 is significant at any confidence level. CMA complements the other Fama-French (2015) factors in capturing time variation in excess returns for a variety of portfolio tilts.

It is important to further explain the q-theoretic prediction of a negative empirical relation between corporate investment and average return performance. Recent literature focuses on the q-theory that connects a given firm's sequential investment decisions to its market risk exposure and subsequent average return (Berk, Green, and Naik, 1999; Gomes, Kogan, and Zhang, 2003; Carlson et al, 2004, 2006; Zhang, 2005; Cooper, 2006; Anderson and Garcia-Feijoo, 2006; Liu, Whited, and Zhang, 2009; Li, Livdan, and Zhang, 2009). When the firm invests in M&A and capital stock, this investment transforms risky real options into less risky assets that yield steady streams of future cash flows. This transformation continues until the firm exhausts its positive net-present-value investment projects. As a result, the firm reduces its exposure to systematic risk during this investment transformation while most rational investors require a lower average stock return. So the q-theory predicts a negative empirical nexus between corporate investment and subsequent average stock return performance. Anderson and Garcia-Feijoo (2006) confirm this negative nexus.

Overall, the Fama-French factors serve as useful state variables for the typical investor who cares about his or her intertemporal payoffs (Merton, 1973; Campbell, 1993; Fama, 1996; Fama and French, 2004). Each of these state variables carries significant long-run average conditional betas across the deciles for a variety of portfolio tilts that are known to generate abnormal return spreads in a static regression analysis. In fact, the collective wisdom of the Fama-French factors suggests that the dynamic conditional recursion exhausts nearly all time variation in the excess returns on most deciles. As a consequence, the vast majority of average conditional alphas turn out to be insignificant at the conventional confidence level. More formal hypothesis tests further affirm that these alphas exhibit substantial variability around nil. Therefore, there is insufficient evidence for the econometrician to infer that dynamic conditional alphas jointly differ from nil. Thus, the evidence suggests an affirmative case for the dynamic conditional factor model. The resultant tangency portfolio is multifactor mean-variance efficient in a dynamic sense that this portfolio achieves the highest excess returns for a unique set of return variances and covariances. As one swallow does not make a summer, the transient emergence of mispricing opportunities does not necessarily indicate an econometrically persistent trend. Dynamic conditional alphas thus converge toward zero, and transitory price misalignment vanishes on the conditional mean-variance efficient frontier.

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Table A5.1: Average dynamic MRP betas, MRP beta spreads, and Newey-West *t*-tests

Over the 50-year period from January 1964 to December 2013, the econometrician applies the recursive multivariate Filter to extract dynamic factor premiums from the Fama-French (2015) five-factor asset pricing model. At each time increment, the econometrician takes into account the Fama-French (2015) factors such as the excess return on the market portfolio (MRP), the return spread between the top 30% small and bottom 30% big stocks (SMB), the return spread between the top 30% high book-to-market and bottom 30% low book-to-market stocks (HML), the return spread between the top 30% robust and bottom 30% weak stocks in terms of their relative profitability (RMW), and the return spread between the top 30% conservative investment and bottom 30% aggressive investment stocks (CMA) to explain the variation in the excess return on each stock decile for size, momentum, value (cf. book-to-market, cashflow-to-price, dividend-to-price, and earnings-to-price), investment, profitability, short-term return reversal, and long-term return reversal. The econometrician presents the mathematical time-series representation below:

$$R_{kt} - R_{ft} = \alpha_t + \beta_{mt}\left(R_{mt} - R_{ft}\right) + \beta_{st} SMB_t + \beta_{ht} HML_t + \beta_{rt} RMW_t + \beta_{ct} CMA_t + \varepsilon_t$$

Table A5.1 sums up the long-run mean MRP beta for each stock decile sorted on size, value, momentum, investment, profitability, short-run return reversal, and long-run return reversal. The first 10 columns summarize each long-term average MRP beta and its corresponding *p*-value for the null hypothesis of zero dynamic MRP beta. The next column encapsulates the long-term average MRP beta spread for the long-short trading strategy that entails both a long position in the top decile and a short position in the bottom decile in the 50-year period from January 1964 to December 2013. For each hypothesis test, the econometrician uses the Newey-West (1987) method with quadratic spectral kernel estimation to correct the standard errors to safeguard against any serial correlation and heteroskedasticity.

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Table A5.1: Average dynamic MRP betas, MRP beta spreads, and Newey-West *t*-tests

Portfolio	Low	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	High	Spread
Size											
Beta (test statistic)	0.892	1.057	1.073	1.065	1.051	1.044	1.077	1.082	1.030	0.957	0.065
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.038
Momentum											
Beta (test statistic)	1.225	1.128	0.997	0.977	0.921	0.983	0.996	0.993	1.009	1.124	-0.101
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.268
Book-to-market											
Beta (test statistic)	0.891	0.991	1.035	1.077	1.029	1.025	1.017	1.015	1.073	1.124	0.234
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cashflow-to-price											
Beta (test statistic)	0.966	0.926	0.949	1.029	0.996	1.014	1.007	1.077	1.069	1.091	0.125
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.009
Dividend-to-price											
Beta (test statistic)	1.022	0.959	0.992	0.996	1.014	1.019	1.032	1.000	0.925	0.806	-0.215
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Earnings-to-price											
Beta (test statistic)	0.954	0.971	0.949	0.935	0.990	1.020	0.970	1.016	1.087	1.130	0.176
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Investment											
Beta (test statistic)	1.122	1.040	1.054	0.954	0.987	0.952	0.962	0.967	0.989	1.103	-0.019
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.595
Profitability											
Beta (test statistic)	1.193	1.008	1.033	0.972	0.990	1.029	1.046	1.018	0.989	0.891	-0.302
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Short-term reversal											
Beta (test statistic)	1.199	1.101	1.054	1.057	1.010	0.971	0.936	0.963	0.983	0.985	-0.214
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.005
Long-term reversal											
Beta (test statistic)	1.250	1.091	1.061	1.029	1.015	0.946	0.965	0.907	0.983	1.065	-0.185
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002

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Table A5.2: Average dynamic SMB betas, SMB beta spreads, and Newey-West *t*-tests

Over the 50-year period from January 1964 to December 2013, the econometrician applies the recursive multivariate Filter to extract dynamic factor premiums from the Fama-French (2015) five-factor asset pricing model. At each time increment, the econometrician takes into account the Fama-French (2015) factors such as the excess return on the market portfolio (MRP), the return spread between the top 30% small and bottom 30% big stocks (SMB), the return spread between the top 30% high book-to-market and bottom 30% low book-to-market stocks (HML), the return spread between the top 30% robust and bottom 30% weak stocks in terms of their relative profitability (RMW), and the return spread between the top 30% conservative investment and bottom 30% aggressive investment stocks (CMA) to explain the variation in the excess return on each stock decile for size, momentum, value (cf. book-to-market, cashflow-to-price, dividend-to-price, and earnings-to-price), investment, profitability, short-term return reversal, and long-term return reversal. The econometrician presents the mathematical time-series representation below:

$$R_{kt} - R_{ft} = \alpha_t + \beta_{mt}\left(R_{mt} - R_{ft}\right) + \beta_{st}SMB_t + \beta_{ht}HML_t + \beta_{rt}RMW_t + \beta_{ct}CMA_t + \varepsilon_t$$

Table A5.2 sums up the long-run mean SMB beta for each stock decile sorted on size, value, momentum, investment, profitability, short-run return reversal, and long-run return reversal. The first 10 columns summarize each long-term average SMB beta and its corresponding *p*-value for the null hypothesis of zero dynamic SMB beta. The next column encapsulates the long-term average SMB beta spread for the long-short trading strategy that entails both a long position in the top decile and a short position in the bottom decile in the 50-year period from January 1964 to December 2013. For each hypothesis test, the econometrician uses the Newey-West (1987) method with quadratic spectral kernel estimation to correct the standard errors to safeguard against any serial correlation and heteroskedasticity.

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Table A5.3: Average dynamic SMB betas, SMB beta spreads, and Newey-West *t*-tests

Portfolio	Low	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	High	Spread
Size											
Beta (test statistic)	1.096	1.044	0.919	0.856	0.703	0.513	0.350	0.184	0.046	-0.280	-1.376
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.079	0.000	0.000
Momentum											
Beta (test statistic)	0.380	0.079	-0.022	0.017	0.016	-0.070	-0.108	0.046	0.053	0.411	0.031
p-value	0.000	0.231	0.655	0.681	0.659	0.046	0.006	0.249	0.395	0.000	0.843
Book-to-market											
Beta (test statistic)	-0.031	-0.061	-0.001	-0.036	-0.073	0.041	0.004	0.100	0.141	0.362	0.393
p-value	0.343	0.088	0.964	0.322	0.051	0.257	0.902	0.002	0.001	0.000	0.000
Cashflow-to-price											
Beta (test statistic)	0.113	-0.033	-0.124	-0.095	-0.071	-0.053	0.001	-0.058	0.068	0.206	0.093
p-value	0.025	0.342	0.001	0.021	0.075	0.111	0.978	0.229	0.064	0.000	0.223
Dividend-to-price											
Beta (test statistic)	0.140	0.011	-0.058	-0.047	-0.042	-0.154	-0.201	-0.131	-0.210	-0.139	-0.279
p-value	0.004	0.771	0.122	0.284	0.342	0.000	0.000	0.004	0.000	0.010	0.000
Earnings-to-price											
Beta (test statistic)	0.118	-0.030	-0.056	-0.185	-0.064	-0.072	-0.052	0.058	0.035	0.268	0.150
p-value	0.012	0.389	0.079	0.000	0.058	0.062	0.101	0.166	0.382	0.000	0.059
Investment											
Beta (test statistic)	0.333	0.213	-0.027	-0.054	-0.056	-0.114	-0.109	-0.083	0.033	0.247	-0.085
p-value	0.000	0.000	0.411	0.055	0.081	0.000	0.007	0.010	0.281	0.000	0.283
Profitability											
Beta (test statistic)	0.455	0.084	0.042	0.049	-0.088	-0.045	-0.074	-0.042	-0.082	0.003	-0.451
p-value	0.000	0.002	0.336	0.264	0.018	0.252	0.030	0.201	0.005	0.920	0.000
Short-term reversal											
Beta (test statistic)	0.434	0.159	0.046	-0.034	-0.099	-0.041	-0.094	-0.087	-0.015	0.279	-0.155
p-value	0.000	0.003	0.320	0.332	0.006	0.224	0.020	0.014	0.737	0.000	0.188
Long-term reversal											
Beta (test statistic)	0.697	0.225	0.090	0.038	-0.010	-0.110	-0.068	-0.187	-0.065	0.128	-0.570
p-value	0.000	0.000	0.064	0.416	0.783	0.001	0.051	0.000	0.109	0.011	0.000

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Table A5.3: Average dynamic HML betas, HML beta spreads, and Newey-West *t*-tests

Over the 50-year period from January 1964 to December 2013, the econometrician applies the recursive multivariate Filter to extract dynamic factor premiums from the Fama-French (2015) five-factor asset pricing model. At each time increment, the econometrician takes into account the Fama-French (2015) factors such as the excess return on the market portfolio (MRP), the return spread between the top 30% small and bottom 30% big stocks (SMB), the return spread between the top 30% high book-to-market and bottom 30% low book-to-market stocks (HML), the return spread between the top 30% robust and bottom 30% weak stocks in terms of their relative profitability (RMW), and the return spread between the top 30% conservative investment and bottom 30% aggressive investment stocks (CMA) to explain the variation in the excess return on each stock decile for size, momentum, value (cf. book-to-market, cashflow-to-price, dividend-to-price, and earnings-to-price), investment, profitability, short-term return reversal, and long-term return reversal. The econometrician presents the mathematical time-series representation below:

$$R_{kt} - R_{ft} = \alpha_t + \beta_{mt}\left(R_{mt} - R_{ft}\right) + \beta_{st}SMB_t + \beta_{ht}HML_t + \beta_{rt}RMW_t + \beta_{ct}CMA_t + \varepsilon_t$$

Table A5.3 sums up the long-run mean HML beta for each stock decile sorted on size, value, momentum, investment, profitability, short-run return reversal, and long-run return reversal. The first 10 columns summarize each long-term average HML beta and its corresponding *p*-value for the null hypothesis of zero dynamic HML beta. The next column encapsulates the long-run average HML beta spread for the long-short trading strategy that entails both a long position in the top decile and a short position in the bottom decile in the 50-year period from January 1964 to December 2013. For each hypothesis test, the econometrician uses the Newey-West (1987) method with quadratic spectral kernel estimation to correct the standard errors to safeguard against any serial correlation and heteroskedasticity.

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Table A5.3: Average dynamic HML betas, HML beta spreads, and Newey-West *t*-tests

Portfolio	Low	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	High	Spread
Size											
Beta (test statistic)	0.476	0.288	0.181	0.206	0.119	0.186	0.156	0.204	0.232	-0.147	-0.624
p-value	0.000	0.000	0.000	0.000	0.002	0.000	0.004	0.000	0.000	0.000	0.000
Momentum											
Beta (test statistic)	0.216	0.075	0.256	0.175	0.136	0.153	0.195	0.109	-0.010	-0.199	-0.415
p-value	0.234	0.519	0.006	0.016	0.059	0.007	0.002	0.084	0.903	0.068	0.109
Book-to-market											
Beta (test statistic)	-0.899	-0.475	-0.092	0.174	0.374	0.610	0.833	0.896	0.870	1.118	2.016
p-value	0.000	0.000	0.150	0.015	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Cashflow-to-price											
Beta (test statistic)	-0.686	-0.586	-0.229	0.014	0.089	0.250	0.303	0.411	0.743	1.001	1.687
p-value	0.000	0.000	0.007	0.793	0.269	0.000	0.001	0.000	0.000	0.000	0.000
Dividend-to-price											
Beta (test statistic)	-0.462	-0.394	-0.309	-0.081	-0.110	0.172	0.382	0.515	0.631	0.983	1.445
p-value	0.000	0.000	0.000	0.284	0.129	0.019	0.000	0.000	0.000	0.000	0.000
Earnings-to-price											
Beta (test statistic)	-0.698	-0.506	-0.365	-0.176	-0.036	0.306	0.444	0.536	0.818	1.028	1.726
p-value	0.000	0.000	0.000	0.014	0.687	0.000	0.000	0.000	0.000	0.000	0.000
Investment											
Beta (test statistic)	0.249	0.221	0.267	0.018	0.272	0.126	0.074	-0.127	-0.373	-0.412	-0.661
p-value	0.001	0.000	0.000	0.764	0.000	0.030	0.131	0.031	0.000	0.000	0.000
Profitability											
Beta (test statistic)	0.314	0.452	0.514	0.366	0.227	0.035	0.079	-0.156	-0.213	-0.533	-0.847
p-value	0.000	0.000	0.000	0.000	0.000	0.508	0.092	0.016	0.000	0.000	0.000
Short-term reversal											
Beta (test statistic)	-0.001	-0.037	0.027	0.185	0.077	0.002	0.095	-0.013	0.000	-0.116	-0.116
p-value	0.994	0.535	0.696	0.005	0.092	0.964	0.130	0.818	0.994	0.150	0.419
Long-term reversal											
Beta (test statistic)	0.399	0.418	0.145	0.359	0.313	0.209	0.191	-0.006	-0.176	-0.601	-1.000
p-value	0.007	0.000	0.141	0.000	0.000	0.000	0.004	0.913	0.004	0.000	0.000

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Table A5.4: Average dynamic RMW betas, RMW beta spreads, and Newey-West *t*-tests

Over the 50-year period from January 1964 to December 2013, the econometrician applies the recursive multivariate Filter to extract dynamic factor premiums from the Fama-French (2015) five-factor asset pricing model. At each time increment, the econometrician takes into account the Fama-French (2015) factors such as the excess return on the market portfolio (MRP), the return spread between the top 30% small and bottom 30% big stocks (SMB), the return spread between the top 30% high book-to-market and bottom 30% low book-to-market stocks (HML), the return spread between the top 30% robust and bottom 30% weak stocks in terms of their relative profitability (RMW), and the return spread between the top 30% conservative investment and bottom 30% aggressive investment stocks (CMA) to explain the variation in the excess return on each stock decile for size, momentum, value (cf. book-to-market, cashflow-to-price, dividend-to-price, and earnings-to-price), investment, profitability, short-term return reversal, and long-term return reversal. The econometrician presents the mathematical time-series representation below:

$$R_{kt} - R_{ft} = \alpha_t + \beta_{mt}\left(R_{mt} - R_{ft}\right) + \beta_{st}SMB_t + \beta_{ht}HML_t + \beta_{rt}RMW_t + \beta_{ct}CMA_t + \varepsilon_t$$

Table A5.4 shows the long-run mean RMW beta for each stock decile sorted on size, value, momentum, investment, profitability, short-run return reversal, and long-run return reversal. The first 10 columns summarize each long-term average RMW beta and its corresponding *p*-value for the null hypothesis of zero dynamic RMW beta. The next column presents the long-run average RMW beta spread for the long-short trading strategy that entails both a long position in the top decile and a short position in the bottom decile in the 50-year period from January 1964 to December 2013. For each hypothesis test, the econometrician uses the Newey-West (1987) method with quadratic spectral kernel estimation to correct the standard errors to safeguard against any serial correlation and heteroskedasticity.

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Table A5.4: Average dynamic RMW betas, RMW beta spreads, and Newey-West *t*-tests

Portfolio	Low	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	High	Spread
Size											
Beta (test statistic)	-0.461	-0.289	-0.323	-0.149	-0.104	-0.270	-0.169	-0.307	-0.281	0.203	0.664
p-value	0.000	0.000	0.000	0.044	0.011	0.000	0.007	0.000	0.000	0.000	0.000
Momentum											
Beta (test statistic)	-0.479	-0.218	-0.291	0.036	-0.066	-0.100	0.000	-0.002	0.082	0.093	0.572
p-value	0.003	0.027	0.000	0.589	0.384	0.163	0.996	0.982	0.216	0.336	0.006
Book-to-market											
Beta (test statistic)	0.498	0.166	0.242	-0.142	-0.282	-0.230	-0.305	-0.532	-0.568	-0.590	-1.088
p-value	0.000	0.009	0.000	0.102	0.003	0.001	0.000	0.000	0.000	0.000	0.000
Cashflow-to-price											
Beta (test statistic)	0.152	0.195	0.117	-0.053	-0.122	-0.198	-0.198	0.246	0.194	-0.030	-0.183
p-value	0.066	0.003	0.093	0.467	0.105	0.006	0.007	0.009	0.016	0.734	0.153
Dividend-to-price											
Beta (test statistic)	0.373	0.197	0.046	0.125	0.174	0.030	-0.168	-0.013	-0.186	-0.737	-1.111
p-value	0.000	0.006	0.528	0.264	0.032	0.652	0.090	0.885	0.088	0.000	0.000
Earnings-to-price											
Beta (test statistic)	0.017	0.230	0.150	-0.022	-0.083	-0.110	-0.071	0.044	0.048	-0.103	-0.119
p-value	0.850	0.002	0.046	0.713	0.296	0.199	0.417	0.596	0.540	0.363	0.414
Investment											
Beta (test statistic)	-0.442	-0.029	-0.103	-0.092	-0.013	-0.036	0.062	0.167	0.166	0.184	0.626
p-value	0.000	0.687	0.142	0.137	0.863	0.524	0.373	0.003	0.015	0.016	0.000
Profitability											
Beta (test statistic)	-1.006	-1.016	-0.776	-0.587	-0.378	0.299	0.101	0.395	0.464	0.562	1.567
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.197	0.000	0.000	0.000	0.000
Short-term reversal											
Beta (test statistic)	-0.394	-0.138	-0.142	-0.031	-0.005	0.028	-0.021	0.045	0.142	-0.047	0.347
p-value	0.000	0.229	0.145	0.594	0.948	0.708	0.792	0.538	0.047	0.620	0.051
Long-term reversal											
Beta (test statistic)	-0.345	-0.584	-0.186	-0.283	-0.116	0.013	0.108	0.118	0.136	0.299	0.644
p-value	0.022	0.000	0.059	0.001	0.167	0.853	0.171	0.235	0.039	0.000	0.000

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Table A5.5: Average dynamic CMA betas, CMA beta spreads, and Newey-West *t*-tests

Over the 50-year period from January 1964 to December 2013, the econometrician applies the recursive multivariate Filter to extract dynamic factor premiums from the Fama-French (2015) five-factor asset pricing model. At each time increment, the econometrician takes into account the Fama-French (2015) factors such as the excess return on the market portfolio (MRP), the return spread between the top 30% small and bottom 30% big stocks (SMB), the return spread between the top 30% high book-to-market and bottom 30% low book-to-market stocks (HML), the return spread between the top 30% robust and bottom 30% weak stocks in terms of their relative profitability (RMW), and the return spread between the top 30% conservative investment and bottom 30% aggressive investment stocks (CMA) to explain the variation in the excess return on each stock decile for size, momentum, value (cf. book-to-market, cashflow-to-price, dividend-to-price, and earnings-to-price), investment, profitability, short-term return reversal, and long-term return reversal. The econometrician presents the mathematical time-series representation below:

$$R_{kt} - R_{ft} = \alpha_t + \beta_{mt}\left(R_{mt} - R_{ft}\right) + \beta_{st} SMB_t + \beta_{ht} HML_t + \beta_{rt} RMW_t + \beta_{ct} CMA_t + \varepsilon_t$$

Table A5.5 shows the long-run mean CMA beta for each stock decile sorted on size, value, momentum, investment, profitability, short-run return reversal, and long-run return reversal. The first 10 columns summarize each long-term average CMA beta and its corresponding *p*-value for the null hypothesis of zero dynamic CMA beta. The next column presents the long-run average CMA beta spread for the long-short trading strategy that entails both a long position in the top decile and a short position in the bottom decile in the 50-year period from January 1964 to December 2013. For each hypothesis test, the econometrician uses the Newey-West (1987) method with quadratic spectral kernel estimation to correct the standard errors to safeguard against any serial correlation and heteroskedasticity.

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Table A5.5: Average dynamic CMA betas, CMA beta spreads, and Newey-West *t*-tests

Portfolio	Low	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	High	Spread
Size											
Beta (test statistic)	0.039	0.047	-0.046	-0.146	-0.173	-0.203	-0.099	-0.140	-0.168	0.107	0.069
p-value	0.689	0.332	0.377	0.004	0.011	0.035	0.277	0.061	0.013	0.005	0.444
Momentum											
Beta (test statistic)	-0.608	-0.188	-0.044	-0.039	-0.130	0.118	0.076	0.002	0.190	-0.249	0.359
p-value	0.004	0.222	0.769	0.710	0.140	0.112	0.386	0.980	0.014	0.108	0.255
Book-to-market											
Beta (test statistic)	-0.318	0.061	0.116	0.038	0.220	0.072	0.168	-0.027	0.145	0.333	0.651
p-value	0.000	0.278	0.108	0.667	0.003	0.297	0.018	0.753	0.015	0.002	0.000
Cashflow-to-price											
Beta (test statistic)	-0.362	-0.134	0.011	-0.035	0.188	0.240	0.266	0.408	0.024	-0.415	-0.052
p-value	0.000	0.056	0.875	0.671	0.034	0.011	0.009	0.000	0.846	0.017	0.763
Dividend-to-price											
Beta (test statistic)	-0.444	-0.167	-0.083	-0.029	0.142	0.088	0.217	0.409	0.335	0.274	0.718
p-value	0.000	0.125	0.210	0.758	0.075	0.359	0.004	0.000	0.010	0.112	0.001
Earnings-to-price											
Beta (test statistic)	-0.384	-0.094	0.041	0.213	0.119	0.208	0.260	0.077	-0.033	-0.650	-0.266
p-value	0.000	0.064	0.521	0.004	0.123	0.007	0.002	0.451	0.620	0.000	0.109
Investment											
Beta (test statistic)	0.622	0.639	0.669	0.671	0.297	-0.094	-0.202	-0.230	-0.594	-0.809	-1.432
p-value	0.000	0.000	0.000	0.000	0.000	0.203	0.013	0.001	0.000	0.000	0.000
Profitability											
Beta (test statistic)	0.136	-0.014	-0.029	0.010	0.038	-0.004	0.055	0.042	0.018	-0.071	-0.207
p-value	0.109	0.830	0.747	0.895	0.574	0.955	0.429	0.447	0.753	0.337	0.116
Short-term reversal											
Beta (test statistic)	-0.262	-0.188	0.032	-0.005	-0.007	-0.026	-0.091	0.130	-0.152	-0.282	-0.021
p-value	0.136	0.080	0.765	0.956	0.911	0.662	0.234	0.221	0.078	0.016	0.933
Long-term reversal											
Beta (test statistic)	0.477	0.295	0.467	0.138	0.077	0.185	-0.002	-0.212	-0.224	-0.480	-0.957
p-value	0.001	0.020	0.000	0.181	0.401	0.030	0.980	0.028	0.016	0.001	0.000

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