Macro Trends and Factor Timing*

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October 10, 2021

Abstract

We find that the value of well-known systematic (characteristics-based) risk factors, like SMB and HML, is anchored to macroeconomic trends related to inflation and real economic activity. Exploiting the cointegration logic, when the price of a factor is greater than the long-term value implied by the macro trends, expected returns should be lower over the next period. We provide strong supporting evidence for this intuition: deviations of factor prices from their value implied by macroeconomic conditions predict factor returns both in- and out-of-sample, translating into significant economic gains from the perspective of a mean-variance investor. Finally, our approach leads to an estimated SDF that displays sizable variation over time when benchmarked against standard long-run risk or habit models.

Keywords: Factor Models, Macro–Finance, Factor Timing, SDF, Risk Management.
JEL codes: C38, G11, G12, G17.

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*We thank seminar participants at Northwestern Kellogg for helpful comments. Alessandro Melone acknowledges financial support by the Austrian Science Fund (FWF).

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1 Introduction

In this paper, we document that the price of classical equity factors like value-minus-growth (HML) is anchored to the real economy in the long run. This long-run comovement translates in short-run equity factors (time-series) predictability, a.k.a. factor timing. Our result is summarized in Figure 1: Panel (a) shows that the price of HML (blue line) mean reverts toward a macroeconomic trend (green line). In Panel (b), we employ the deviations of the factor prices from the macro trend to time the factor: the fitted value (green line) explains about one-fourth of the variability in HML returns (blue line) at annual frequency.

Our result is important for two reasons. First, despite being a fundamental tenet of asset pricing, the link between asset returns and the real economy is still a matter of debate.[1] We propose that looking at macroeconomic trends, long-run comovement, and time-series predictability uncovers a novel link which is complementary to the one that looks at macroeconomic changes (innovations), short-run comovement (betas) and cross-sectional predictability. Second, the ability to time factors is informative about the properties of the stochastic discount factor (SDF) which drastically differ from the case when factor premiums are instead constant over time, the standard approach in previous work.

Our approach appeals to the intuitive notion that financial assets should not overtake the real economy. Accordingly, we propose a framework where the price level of a factor should comove with trends in economic fundamentals. Given than economic trends and factor prices are non-stationary variables, the validity of a given set of macroeconomic drivers to track asset prices is naturally investigated by assessing if there exists a stationary linear

[1] See, e.g., Chen, Roll, and Ross (1986) and Shanken and Weinstein (2006). See also Rapach and Zhou (2021) and Giglio, Xiu, and Zhang (2021) for methodological advances to detect possible sources of macroeconomic risk premia.

combination of them (i.e., if they are cointegrated). Importantly, the presence of a stationary combination of prices and macro drivers rules out the possibility of an omitted economic trend, since its omission would prevent cointegration in the first place.

We start by testing the presence of cointegration between macroeconomic trends related to real economic activity, inflation, and aggregate liquidity and the price of (characteristics-sorted) factors from leading asset pricing models such as those proposed by Fama and French (2015) and Hou, Xue, and Zhang (2015). We find the presence of co-integration to be borne out by the data. Importantly, the long-run relationship between factor prices and macroeconomic drivers has implications for short-run factor returns. Specifically, we show that factor returns should be predictable by the deviations of the portfolio value from its long-term economic value with a negative sign. The intuition is straightforward: when asset prices are higher (lower) than the long-run value implied by the macroeconomic drivers, expected returns are lower (higher) in the next period so that the long-run relationship is corrected.

We find that standard characteristics-based factors like High-Minus-Low (HML) are strongly predictable in- and out-of-sample, both at quarterly and annual frequencies. We then quantify the investment benefits to factor timing. Given the evidence of factor timing benefits, we use our approach to characterize the properties of the SDF. Quantitatively, the average variance of our estimated SDF increases from 0.80 (in the case of constant factor premiums) to 2.24 when taking into account the predictability of the factors induced by deviations of a portfolio value from its long-term economic value. Furthermore, changes in the means of the factors induces variation in the SDF, which is strongly heteroscedastic. The SDF fluctuations induced by factor timing are more pronounced than fluctuations in the SDF that accounts only for time variation in the market portfolio. These values are sizable and suggest that macro-finance theories developed to understand cyclical variation in the price of market risk (e.g., Bansal and Yaron, 2004; Campbell and Cochrane, 1999) are unlikely to capture the dynamic properties of the cross-section of returns. Indeed, these models generate SDFs that are much less volatile and heteroscedastic than our estimated SDF.

The rest of the paper is organized as follows. We discuss the related literature next. Section 2 lays out the model for factors returns and macro drivers. Section 3 describes our data (section 3.1), documents the existence of the Equilibrium Correction Term in the factor equity space (section 3.2), and illustrates the ability of our FECM model to time factors (section 3.3). We discuss the implications of our framework for risk management in Section 3.4. Section 4 concludes.

Related Literature.

It is important to immediately separate our paper from the large literature that has tried to establish a link between the macroeconomy and financial assets. Since the seminal contribution of Chen, Roll, and Ross (1986), and motivated by the theoretical work of Merton (1973), researches have explored the possibility that state variables like inflation and economic growth are a source of systematic investment risk and can explain the cross-sectional dispersion of stock returns.[2] The standard approach is to extract innovations and to estimate risk compensation using a Fama-MacBeth procedure (or its variants). We instead propose a cointegration framework that exploits long-run comovement between macroeconomic trends and factor prices, and use it to predict the time-series variation in a given equity factor. In this respect, our work contributes to the literature that exploits cointegration between divi-

[2]See, e.g., Ferson and Harvey (1991); Vassalou (2003); Boons, Duarte, De Roon, and Szymanowska (2020); Barroso, Boons, and Karehnke (2021); Rapach and Zhou (2021).

dends and prices (Campbell and Shiller, 1988), or between consumption and wealth (Lettau and Ludvigson, 2001), to predict the aggregate market factor. We show that factors beyond the aggregate market are predictable using macroeconomic variables and a similar cointegration logic. Bansal, Dittmar, and Kiku (2007) propose a measure of long-run consumption risk that exploits the cointegrating relationship between consumption and dividends of portfolios sorted on size and book-to-market. They show that such a measure describes well cross-sectional variation in expected equity returns. We complement their research by showing that cointegration between asset prices and real economy trends is informative about time-series predictability of classical sources of cross-sectional risk premia.

Another important literature (e.g., Fischer and Merton, 1984; Stock and Watson, 2003) documents that asset returns forecast inflation and output growth. We complement this literature by documenting that temporary deviations of factor prices from economic trends forecast asset returns instead.

Our paper is another step toward unifying cross-sectional and time-series predictability of returns. Despite the large literature documenting the variability of aggregate stock returns over time (e.g., Shiller, 1981; Fama and French, 1988), factor models (e.g., Fama and French, 1993) often abstract from the predictability of factors and mainly focus on their ability to generate cross-sectional dispersion in asset risk premiums. Haddad, Kozak, and Santosh (2020) constitute a notable exception. These authors propose a new statistical approach to predict "anomaly" portfolios, by predicting their principal components (PCs) using their own book-to-market ratios. Rather than predicting PCs we predict directly characteristics-based factor returns like those used in the Fama and French (2015) or Hou, Xue, and Zhang (2015) models. Furthermore, we rely on macroeconomic fundamentals rather than financial ratios. Another strand of the literature studies the predictability of returns at the firm-level and then aggregate the estimates into portfolios (Campbell, Polk, and Vuolteenaho, 2010 and Lochstoer and Tetlock, 2020) or anomaly by anomaly (e.g., Asness et al., 2000; Baba-Yara et al., 2020; Cohen, Polk, and Vuolteenaho, 2003; Favero, Melone, and Tamoni, 2020). Whereas these papers forecast a single return at a time, we instead study common sources of predictability across all anomalies by focusing on factors that are sources of risk premiums beyond the aggregate market.

2 A Macroeconomic-driven Model of Factors

Consider a tradeable set of k factors with log period return of $\mathbf{f}_t$. We define the price of the factors as the cumulative return:

$$\ln \mathbf{F}_t = \ln \mathbf{F}_{t-1} + \mathbf{f}_t \ . \tag{1}$$

Analogously, consider a set of p (stationary) macroeconomic factors $\mathbf{m}_{t+1}$ describing the state of the economy (e.g., inflation or productivity growth); we define the associated macro drivers, denoted by $\mathbf{M}_t$, as:

$$\ln \mathbf{M}_{t+1} = \ln \mathbf{M}_t + \mathbf{m}_{t+1} \ . \tag{2}$$

We assume (for now, and test it later) that any given characteristics-based factor price level $F_{j,t}$ is linked to the drivers capturing the (long run) state of the economy by:

$$\ln F_{j,t} = \alpha_{0,j} + \alpha_{1,j} t + \beta_j' \ln \mathbf{M}_t + w_{j,t} \ , \quad j = 1, \ldots, k \ .$$

This equation describes a long-run cointegrating relationship between financial markets and the real economy. The estimation of such regression delivers stationary residuals $w_{j,t}$ anytime the chosen set of macroeconomic drivers describes the long-run dynamics of (factor) prices. In this case, $w_{j,t}$ captures temporary deviations of prices from the long-run equilibrium value determined by the macroeconomic drivers.

Cointegration between macroeconomic drivers and the price-level of factors implies a natural predictive term for returns on factors. By taking first differences of the long-run cointegrating relationship, and representing $w_{j,t}$ as an AR(1) process for simplicity, we obtain:[3]

$$\ln F_{j,t+1} = \alpha_{0,j} + \alpha_{1,j} t + \beta_j' \ln \mathbf{M}_{t+1} + w_{j,t+1} \ , \qquad j = 1, \ldots, k \tag{3}$$

$$w_{j,t+1} = \rho_j w_{j,t} + v_{j,t+1}$$

$$f_{j,t+1} = \alpha_{1,j} + \beta_j' \mathbf{m}_{t+1} + \underbrace{(\rho_i - 1)}_{\delta_j} \underbrace{w_{j,t}}_{\equiv ECT^F_{j,t}} + v_{j,t+1}. \tag{4}$$

We refer to the residuals $w_{j,t}$ as the "Equilibrium Correction Term" (henceforth, ECT) associated with the factor j at time t.

$$ECT_{j,t} \equiv \ln F_{j,t} - \hat{\alpha}_{0,j} - \hat{\alpha}_{1,j} t - \hat{\beta}_j' \ln \mathbf{M}_t \ . \tag{5}$$

The system of equations (3) and (4) describing factor price and returns dynamics constitute our Macro Factor Error Correction Model (Macro-FECM).[4] The $ECT_{j,t}$ captures

[3]As discussed by Engle and Yoo (1987) and MacKinnon (2010), the inclusion of a trend in Eq. (3) is a simple way to avoid the dependence of the distribution of test statistics for residuals on α_1.

[4]The equilibrium correction representation (4) of cointegrated time-series (see equation (3)) is warranted by the Engle and Granger (1987) representation theorem.

deviations of factor j's prices from their equilibrium (implied by macro drivers), i.e., a given factor disequilibrium.[5]

Note that Equation (4) is a special case of

$$\mathbf{f}_{t+1} = E\left(\mathbf{f}_{t+1} \mid I_t\right) + \mathbf{v}_{t+1}.$$

In particular, should the macroeconomic series $\mathbf{m}_{t+1}$ be unpredictable and absent cointegration between factors $\mathbf{F}_t$ and macroeconomic drivers $\mathbf{M}_{t+1}$, i.e. when $\delta_j = 0$ for $j = 1, \ldots, k$, we obtain a constant expected return specification for factors, i.e. $\mathbf{f}_{t+1} = \gamma + \mathbf{v}_{t+1}$.

We conclude with two remarks. First, when factor prices and macroeconomic drivers are cointegrated, the factor disequilibrium $ECT_{j,t}$ is stationary, and, it shows up in (4) with a coefficient δ_j capturing the speed with which the system eliminates disequilibria with respect to the long-run relationship. Indeed, δ_j is related to the persistence ρ_j of $ECT_{j,t}$. Second, when the macroeconomic drivers explain the buy-and-hold value of a given factor, the inclusion of the ECT ensures that the specification for returns is consistent with the long-run value implied by the real economy. The omission of the ECT leads instead to a misspecification of the factor dynamics, in the sense that the price level of the factor is left undetermined (and financial markets are disconnected from the real economy).

[5] Favero, Melone, and Tamoni (2020) study deviations of portfolio prices from the equilibrium dictacted by characteristics-based factors. Their *portfolio* disequilibrium $ECT^P_{i,t}$ is portfolio specific (or idiosyncratic), i.e., it depends on i. On the other hand, the *factor* disequilibrium $ECT^F_{j,t}$ is common across portfolios that load on factor j.

3 Empirical Results

3.1 Data

In our empirical analysis, we consider the factors featuring in two of the most prominent asset pricing models: the five-factor model of Fama and French (2015) (FF5 henceforth) and the q-factor model of Hou, Xue, and Zhang (2015).[6] To ease exposition we present and discuss the results for the Fama and French (2015) model and relegate the analysis for the q-factor model in Appendix C. Furthermore, in Appendix D we analyze the momentum factor.

As macro factors we use the WTI crude oil returns, the traded Pástor and Stambaugh (2003) liquidity factor, the potential output growth, and the Treasury term spread.[7] Our choice of the macro factors is inspired by the seminal contribution of Chen, Roll, and Ross (1986). The central idea is to find a set of economic state variables that influence investors and asset prices in a systematic way (through, e.g., their effect on nominal and real cash-flows). Following this logic, Ferson and Harvey (1991) propose inflation, the real short-term rate, and the slope of the Treasury yield curve to capture economic risks that influence financial assets. More recently, Ang (2014, Ch. 7, p. 215) points to inflation, economic

[6] The q-factor model has its theoretical foundation in the neoclassical q-theory of investment (Zhang, 2017), and consists of four factors: the market excess return (MKT), a size factor (ME), an investment factor (IA), and a profitability factor (ROE). The q-factors are available at `http://global-q.org/factors.html`. The FF5 factor model adds to the market and size factors, a value-growth factor (HML), a profitability factor (Robust-Minus-Weak, RMW), and an investment factor (Conservative-Minus-Aggressive, CMA).

[7] WTI crude oil (log) returns are calculated from (log) spot crude oil price downloaded at `https://fred.stlouisfed.org/series/WTISPLC`. Data on liquidity are from Robert Stambaugh's website (`http://finance.wharton.upenn.edu/~stambaug/`). The term spread is proxied by the difference between a 10-year bond and the short term rate. Potential output growth is the percentage annual log change in real potential output provided by the U.S. Congressional Budget Office and available at `https://fred.stlouisfed.org/series/GDPPOT`. Since the seminal work of Laubach and Williams (2003) it is standard to take that the growth of potential output as integrated of order 1.

growth, and volatility as the three most important macro factor categories. We employ the WTI crude oil returns as a tradable proxy for inflation. To measure aggregate economic condition we use potential output together with the term spread (Chen, Roll, and Ross, 1986; Harvey, 1988; Estrella and Hardouvelis, 1991; Hamilton and Kim, 2002). Finally, the liquidity factor of Pástor and Stambaugh (2003) is inversely related to aggregate volatility, and provides a longer history relative to the VIX. Importantly, with the sole exception of potential output growth, our benchmark macroeconomic factors are available in real time and not subject to revisions. Appendix B reports results for alternative choices of macro factors.

Our sample period is 1968–2019. Throughout we use quarterly observations and, accordingly, we focus on (non-overlapping) 3-months holding-period excess return, unless otherwise specified.

In Figure 2 we show the dynamics of the macroeconomic drivers (Panel A), the dynamics of (log) prices for the Fama-French factors (Panel B) and the dynamics of (log) prices associated with the four-factors of Hou, Xue, and Zhang (2015) (Panel C). We compute the price level of factors and the macroeconomic drivers as described in equations (1) and (2).

[Insert Figure 2 about here]

Next, we provide evidence of cointegration between the price of tradeable (FF5 and q-4) factors and macroeconomic drivers in Section 3.2. We then evaluate the usefulness of our Macro-FECM specification for factor timing and risk management.

3.2 The Long-Run Relation between Characteristic-Based Factors and Macro Drivers

We start by testing for cointegration among our set of macroeconomic drivers (inflation, potential output, term spread, and liquidity), and the price of the Fama and French (2015) factors. We consider the testing procedure suggested by Johansen (1991) that allows the researcher to estimate the number of cointegrating relationships. This procedure presumes a p-dimensional vector autoregressive (VAR) model with k lags, where p corresponds to the number of stochastic variables among which the investigator wishes to test for cointegration. For our application, $p = 5$ and we choose the number of lags in the VAR according to the AIC. The Johansen procedure provides two tests for cointegration: Under the null hypothesis, H_0, that there are exactly r cointegrating relations, the "Trace" statistic supplies a likelihood ratio test of H_0 against the alternative, H_1, that there are p cointegrating relations. A second approach uses the "L-max" statistic to test the null hypothesis of r cointegrating relations against the alternative of $r + 1$ cointegrating relations.

Table 1 presents the test results (along with the 95 percent critical values for these statistics). The Johansen L-max test results establish strong evidence of a single cointegrating relation among the macroeconomic drivers and each of the factor. Indeed, we may reject the null of no cointegration against the alternative of one cointegrating vector. In addition, we cannot reject the null hypothesis of one cointegrating relationship against the alternative of two or more for the size (SMB), value (HML), profitability (RMW), investment (CMW) factors and, to a lesser extent, for the market (MKT). We find similar evidence when we use the Trace statistic: we may reject the null of no cointegration, but we may not reject the null of one (or two) cointegrating relations.

We conclude by stressing that omitting a macroeconomic trend that is relevant to determine the price dynamics of a given factor would prevent cointegration between asset prices and any set of macro drivers that omits the relevant one. Thus, the existence of cointegration discards the possibility of an omitted macroeconomic driver.

3.3 The Short-Run Relation between Characteristic-Based Factors and Macro Risk-Drivers: Predictability

Given the evidence of cointegration, we proceed to estimate the short-run Macro Factor Error Correction Model (Macro-FECM) in (4) for each characteristics-based factor.[8] Our interest lies in understanding the ability of the Equilibrium Correction Term, derived from the estimation of the long-run cointegrating relationships, to predict characteristics-based factor returns. Table 2 displays the results.

[Insert Table 2 about here]

The ECT coefficient is economically and statistically significant, and negative: a positive deviation of (log) prices for the characteristics-based factor from their long-term relation with the macro drivers in this period implies a lower expected return for the next period, with an order of magnitude of about (minus) 0.1 per unit of deviation for the market, SMB, HML, RMW, and the CMA factors. Further supporting evidence about the importance of the ECT for understanding the time-series dynamics of (factor) returns is provided by the semi-partial R^2. The semi-partial R^2 is defined as the difference between the overall regression R^2 and the R^2 of the regression that includes all regressors except the ith-regressor for which

[8] Appendix Table A.1 reports the estimates for the long run regression (3).

the semi-partial R^2 is computed. We show the results for the semi-partial R2 associated to the ECT in the last row of Table 2. The ECT captures about 6% of the total variance of quarterly factor returns. Panel (b) of Figure 1 displays the realized and fitted value implied by our Macro-FECM for the case of HML returns.

Table 2 shows that the loadings on the growth rate of macroeconomic drivers are in general not significant: this is the classical result that short-term variation in macro factors is not associated with long-short characteristics-sorted returns. All the information about the state of the economy is instead conveyed by the ECT. Panel A in Table 3 indeed confirm that the loading on the ECT, its significance and explanatory power are hardly affect when we exclude the macro factors (i.e., when we zero the betas in (4)). The last row in Table 3 shows that the predictability is economically large: The regression implies that expected returns on the factors vary by more than their puzzling (unconditional) level.

Panel B in Table 3 provides out-of-sample evidence. Specifically, we use the out-of-sample R^2 statistic suggested by Campbell and Thompson (2008) to compare $\widehat{f}_{t+1}$ to the historical average forecast forecasts $\bar{f}_{t+1}$, where $\widehat{f}_{t+1}$ is the forecast based on the predictive regression model implied by Equation (4) (with zeroed betas).[9] When the out-of-sample $R^2 > 0$, the $\widehat{f}_{t+1}$ forecast outperforms the historical average forecast according to the mean square pricing error metric (MSPE). For out-of-sample R^2 statistics greater than zero, statistical significance is assessed with the Clark and West (2007) MSPE-adjusted statistic. Independently from the identity of the factor and the initial start of the out-of-sample period, the predictive regression model exploiting the ECT has a MSPE that is significantly lower than the historical average benchmark forecast.[10] Importantly, Appendix Table A.2 shows that results continue to hold

[9] The predictive regression is $f_{j,t+1} = \alpha_{1,j} + \delta_j ECT_{j,t} + v_{j,t+1}$.

[10] Identical conclusions are obtained when we forecast the returns from the $q4$ factor model. See Appendix Table C.1.

when we employ vintage data on potential output.[11]

[Insert Table 3 about here]

Consistently with our main empirical setting, so far we use non-overlapping quarterly holding period returns, i.e., we predict factors return in quarter $t+1$ using the ECT at time t. Appendix Table A.3 conducts the same analysis as in Table 3 but using quarterly observations of annual returns, i.e., we predict factors return realized between $t+1$ and $t+4$ using the ECT known at quarter t. Panel A continues to show ECT coefficients that are economically large and statistically significant: a positive deviation of (log) factor prices from their long-term relation with the macro drivers implies a lower return for next year, with an order of magnitude of about (minus) 0.5 per unit of deviation for the market, HML, RMW, and CMA. The R^2 is sizable, reaching about 30% for the MKT and HML. Panel B shows that, also in this case, the ECT contains information about the macroeconomy that is relevant for forecasting factor (annual) returns out-of-sample.[12]

Finally, the results discussed so far are based on a fixed cointegrating vector where the cointegrating parameters are set equal to their values estimated in the full sample. This case gives some idea of how the model would perform going forward if a practitioner used the existing estimates of these parameters and faced the same distribution of data. Next, we reestimate the cointegrating parameters every period, using only real-time (i.e., unrevised) data, and present the results in Table A.4. Even when the cointegrating parameters are

[11]Vintage data on potential output are available starting from 1991 in ALFRED (`https://alfred.stlouisfed.org/series?seid=GDPPOT`). We linearly interpolate semi-annual unrevised observations to get quarterly observations.

[12]Identical conclusions are obtained when we forecast annual returns from the $q4$ factor model. See Appendix Table C.2. Furthermore, in unreported results we find evidence of predictability for the Momentum factor with in-sample $\mathrm{R}^2 = 6.3\%$, and out-of-sample R^2 equals to 5.58 and significant at the 5% level (different out-of-sample periods deliver similar results).

re-estimated, we continue to find positive and significant, albeit smaller, out-of-sample R^2.

In summary, the results presented above indicate that the Macro-FECM displays superior forecasting performance relative to a model of constant expected excess returns. The ECT displays statistically significant out-of-sample predictive power for factor returns and establishes a novel link between financial factors and the real economy.

3.3.1 The Aggregate Market Predictability: Further Analysis

The literature on aggregate equity market return predictability is vast. It is then natural to ask to what extent the ECT uncovers new information relative to other aggregate stock returns predictors that have been proposed in the literature. To this end, we compare the forecasting power of ECT_{MKT} for the (equity) market factor to predictors that, similar to our Macro-FECM framework, exploit cointegration logic: the dividend-price ratio (Campbell and Shiller, 1988; Fama and French, 1988) and the consumption-wealth ratio (Lettau and Ludvigson, 2001).

Table 4 display the results for alternative horizons. Indeed, the theory behind the dividend-price ratio and the consumption-wealth ratio suggests that these variables should track longer-term tendencies in asset markets rather than provide accurate short-term forecasts. The dependent variable is the H-period log excess return, where $H = 1, 4, 20$ quarters in Panel A, B, and C, respectively. For each regression, the table reports the estimated coefficient and associated Hodrick (1992) standard errors on the included explanatory variables, and the adjusted R^2 statistic.

[Insert Table 4 about here]

In short, we see that the ECT has significant forecasting power for future market excess returns above and beyond standard predictors. For example, controlling for the consumption-wealth ratio (column 4), the dividend-price ratio (column 5) or both (column 6) produces results that are very similar to those using just the ECT (column 1). Furthermore, the predictive power of the equity market ECT is present at both short, intermediate, and long horizons.

Finally, Figure 3 shows that periods in which the market is overvalued relative to the long-term value implied by the real economy (ECT is large and positive) coincide with periods of high sentiment as proxied by the Baker and Wurgler (2006) index. The correlation between the two series is high at about 42%.

[**Insert Figure 3 about here**]

3.3.2 Optimal Factor Timing Portfolio and SDF properties

So far, we have provided strong evidence of predictability for *individual* factors. Next, we combine these forecasts to form an optimal factor timing portfolio, and study its benefits from an investor point of view.

With multiple assets, the optimal portfolio is given by (see, e.g., Haddad, Kozak, and Santosh, 2020)

$$R_{t+1}^{opt} \approx E_t\left[f_{t+1}\right]' \Sigma_{f,t}^{-1} f_{t+1} \tag{6}$$

where $\Sigma_{f,t}$ is the conditional covariance matrix of the factors f_{t+1}. We implement this portfolio as follows. In line with the evidence presented in Table 2, we use (4) with zeroed betas to predict means, $E_t\left[f_{t+1}\right]$. We then use these forecasts to construct forecast errors and compute an estimate of the conditional covariance matrix of the market and factor (HML, SMB, RMW, and CMW) returns, Σ_f, which we for now assume is homoscedastic in order to single out the role of forecasting means. We combine these estimates into portfolio weights $\omega_t^{opt} = \Sigma_{f,t}^{-1} E_t[f_{t+1}]$.

Table 5 quantifies the gains to factor timing in our setting. Following the lead of Haddad, Kozak, and Santosh (2020), we report performance for four variations of the optimal timing portfolio: (1) "Factor Timing" (FT) is the portfolio described above; (2) "Factor Investing" (FI) sets all return forecasts to their unconditional mean; (3) "Market Timing" (MT) does the same except for the market return; and (4) "Anomaly Timing" (AT) does the opposite: the market is forecasted by its unconditional mean, while anomalies receive dynamic forecasts.

[Insert Table 5 about here]

The first performance metric we consider is the unconditional Sharpe ratio. The factor investing, market timing, factor timing, and anomaly timing portfolio all produce meaningful performance, with Sharpe ratios around 0.9 in sample. More importantly, factor and anomaly timing improve out-of-sample performance relative to static factor investing: timing yields Sharpe ratios of about 1 relative to the 0.87 attained with static investing.[13]

Next, we investigate the economic value of factor timing to an investor. Specifically, we consider a mean-variance investor who faces the following objective function at the end of quarter t:

$$\arg\max_{w_{t+1|t}} E_t[R_{p,t+1}] - 0.5\gamma \mathrm{Var}(R_{p,t+1})$$

[13]It is important to remember that the factor timing portfolio is not designed to maximize the unconditional Sharpe ratio. Ferson and Siegel (2001) show that maximizing the unconditional Sharpe ratio requires portfolio weights that are nonlinear and nonmonotone in conditional expected returns.

where $R_{p,t+1} = w_{t+1|t} f_{t+1}$, $w_{t+1|t}$ is the allocation to the factors in period $t+1$ given the factors return forecast, and γ represents the coefficient of relative risk aversion. Given the optimal portfolio weights, the average utility realized by the investor is given by

$$\overline{U}_j = \overline{R}_{p,t+1} - 0.5\gamma \widehat{\text{Var}}\left(R_{p,t+1}\right) \text{ , for } j = 0, 1,$$

where a subscript of 0 or 1 indicates the mean and variance for the portfolio return when the investor uses the prevailing mean or the (competing) factors forecast for f_{t+1} provided by our Macro FECM model. Finally, we compute the average utility gain (or increase in certainty equivalent return) when the investor uses the competing forecast in lieu of the prevailing mean benchmark: $\Delta = \overline{U}_1 - \overline{U}_0$. The average utility gain (multiplied by four) can be interpreted as the annualized portfolio management fee (as a proportion of wealth) that the investor would be willing to pay to have access to the information in the competing forecast relative to that in the prevailing mean benchmark. The last row in Table 5 displays the utility gains of a mean-variance investor who exploits information conveyed by our macroeconomic drivers. The forecasts obtained from deviations of factor prices from the real economic value implied by our model all generate substantial utility gains. The smallest annualized gain is for the case of anomaly timing (1.07%). The annualized gain reaches 2.37% for the factor timing forecast, which is economically sizable. Both anomaly and market timing are equally important. Indeed, removing either market or anomaly timing from factor timing decreases expected utility by about half.

As discussed by Haddad, Kozak, and Santosh (2020), the optimal factor portfolio in (6) is informative of the combination of factors in the SDF:[14]

$$m_{t+1} \approx 1 - E_t\left[f_{t+1}\right]' \Sigma_{f,t}^{-1}\left(f_{t+1} - E_t\left[f_{t+1}\right]\right)$$

Given, the weights in the optimal portfolio $\omega_t^{opt} = \Sigma_{f,t}^{-1} E_t\left[f_{t+1}\right]$, the conditional variance of the SDF is therefore:

$$\mathrm{Var}_t\left(m_{t+1}\right) = \omega_t^{opt,\intercal} \Sigma_{f,t} \omega_t^{opt} \tag{7}$$

The utility calculations in Table 5 suggest large differences in SDF behavior relative to estimates that ignore the evidence of factor predictability. We quantify these differences in the first row of Table 6, where we report the average variance of the SDF. Column "Factor Timing (FT)" in Table 6 reports the estimate of the SDF variance which takes into account variation in the means of the factors. The Column "Factor Investing (FI)" imposes the assumption of no factor timing: conditional means are replaced by their unconditional counterpart. Finally, "Market Timing (MT)" only allows for variation in the mean of the market return. We find that timing factors with our Macro FECM approach yields estimates of SDF variance that are substantially larger than those obtained when timing the market alone or engaging in static factor investing. The magnitude of the SDF annualized variance, 2.24, is sizable if one recalls that, e.g., Bansal and Yaron (2004) report an annualized variance of the SDF of 0.85, whereas Campbell and Cochrane (1999) obtain a variance of about 1.2.

[Insert Table 6 about here]

Because the loadings of our estimated SDF change over time, the SDF is heteroscedastic.

[14]More precisely, this holds when factor timing is sufficient (in the sense that one need not time individual stocks), and in absence of near-arbitrage (Kozak, Nagel, and Santosh, 2018). See Proposition 1 in Haddad, Kozak, and Santosh (2020).

It is then natural to ask how much does the variance of the SDF change over time. To this end, the solid-blue line in Figure 4 represents the conditional variance at each point in time using Equation (7). The variance of our estimated SDF varies substantially over time: it fluctuates between low levels close to 0.2 and values as high as 12. The evidence of factor timing is the main driving force behind this result. As a comparison, we report estimates for an SDF estimated under the assumption of constant factor expected returns, but time variation in market risk premium. The corresponding SDF variance is much less volatile than our estimate, with a volatility of only 0.64 relative to 0.94 (c.f., last row of Table 6). Once again, the variations over time we find in SDF variance when timing factors is sizable: e.g., the variance of the SDF in Campbell and Cochrane (1999) has a standard deviation lower than 0.5.

[Insert Figure 4 about here]

Overall, we find that deviations of factor prices from the long-run economic value implied by our cointegrated framework are an important driver of the time variation in SDF variance.

3.4 The Short-Run Relation between Characteristic-Based Factors and Macro Drivers: Risk Measurement

Explicitly modeling the relationship between characteristics-based and macro drivers contributes to the description of the dynamics of returns. Indeed, the ECT is a predictive variable that is observed at time t and is related to the distribution of (factor) returns at time $t + 1$ (c.f. Section 3.3). Thus, our Macro-FECM model (see eqs. (3) and (4)) has important consequences for the predictive distribution of returns, which is helpful both for risk measurement and asset allocation.

To provide evidence about the relevance of the ECT specification for risk measurement, we use the Macro-FECM model to predict the distributions for one-year ahead Value (long leg of HML) returns for 2008 and 2009. Figure 5 shows the result.

[Insert Figure 5 about here]

Panel (a) on the left refers to a specification where factors are unpredictable and the unconditional distribution of factors is used for simulations:

$$\mathbf{f}_{t+1} = \mu_0 + \epsilon_{t+1} \ . \tag{8}$$

We refer to this model as to the constant expected return (CER). In Panel (b) we turn to the Macro-FECM specification that exploits the long-run relationship between characteristics-based and macro drivers. I.e.,

$$H_{HML,t+1} = \alpha + \delta_{H,MKT} ECT_t^{MKT} + \delta_{H,HML} ECT_t^{HML} + \ v_{t+1} \ , \tag{9}$$

where ECT_t^F are obtained as per equation (5) for $F = \{MKT, HML\}$. We augment the HML disequilibrium with the one from the market since we want to forecast the value (long only) leg.[15]

Each model is fitted on the sample up to 2007; then the out-of-sample predicted return distributions for 2008 are obtained by bootstrapping the correlated residuals ϵ_{t+1} and the

[15] We estimate (3) and (4) from 1968 to 2007 using annual observations. Then, we bootstrap residuals 10000 times to obtain the out-of-sample predicted distribution of returns for 2008. We follow the same procedure for predicting the distribution of returns in 2009. The ECT for MKT and HML are also computed out-of-sample as in equation (5); the macro factors are potential output growth, WTI crude oil returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the term spread 10-year minus 3-month Treasury bond yield.

idiosyncratic error v_{t+1}. We then include the 2008 information and follow the same procedure to produce forecasts for 2009 returns.[16]

Panel (a) in Figure 5 shows that the predictive distributions resulting from the CER model which does not include any (dis)equilibrium correction term: the figure highlights the immutability of the distribution of value returns despite the crash of 2008. In contrast, Panel (b) shows an evident shift to the right after the crisis when we employ the predictive distribution implied by the Macro-FECM specification with the factor-specific equilibrium correction terms. The shift to the right is easily explained: the crash of 2008 brought the price of H(ML) from above the long-run equilibrium to below the long-run equilibrium, causing a shift in the mean of the predictive distribution. Importantly, the one-year ahead 10% VaR from the Macro-FECM goes from -28.6 in 2008 to 3.1 in 2009, as a consequence of the crash, while the VaR from the standard model–reflecting the unconditional distribution of assets returns and factors–remains mostly unchanged and centered around the unconditional VaR -24.1. Appendix Figure D.1 provides a similar application for the Winner leg of the Momentum factor.

Having documented the ability of our model to generate shifts in the mean of the predictive distribution that align well with realized returns around crises, it is natural to ask whether this evidence is systematic throughout our sample. Figure 6 reports the realized returns to the Value portfolio and the predictive distributions implied by our model in (3)-(4). The dots represents the mean forecasts. The dotted (dashed) lines represent 90% (95%) confidence intervals. The ability of our model to track the distribution of assets returns is apparent.

[16] A remarkable stability of the parameters emerges for the FECM specification estimated on the full sample and estimated only up to 2007.

[**Insert Figure 6 about here**]

In Figure 6 the ECT has been computed over the full sample. Appendix Figure A.1 reports the analysis for a fully out-of-sample exercise where not only the parameters α, β, δ are estimated recursively (as in Figure 6) but also the ECT is estimated using only information up to time t.[17] We continue to see substantial shift in the predictive distribution which align very well with the realized returns.

Overall, our analysis points to an important quantitative role played by the ECT, in particular the one capturing disequilibrium between characteristics-sorted and macro drivers, for risk management purposes.

3.5 Robustness

In this section we provide robustness against the choice of the macroeconomic trends. To this end, we reproduce the evidence in Table 3 for alternative choices of macroeconomic drivers.

We start by excluding liquidity from the set of macroeconomic drivers. Table B.1 shows the results. With the sole exception of RMW, the deviations of MKT, SMB, HML, and CMA from the long-run value implied by the macro drivers continue to forecast these factor returns both in- and out-of-sample.

[17] We consider as a burn-in sample the first 22-year period from 1968 to 1989. Using only information until the end of this period, we construct the ECTs following the methodology described in Section 2. Next, we regress the portfolio excess return on the lagged ECT to determine the loading δ_P. Due to the predictive nature of the regression, the last observation in the right-hand-side variables is that of 1989. We use the resultant coefficients and the value of the ECT on 1990 to produce out-of-sample forecasts of one-year ahead excess returns. We then include the 1991 information and follow the same procedure to produce forecasts of the 1992 returns, and so on until the end of the sample (i.e., 2019).

Next, we consider our benchmark set of macroeconomic drivers, but replace the potential output with the return to capital. The return on capital is computed from the investment first-order condition of a neoclassical business cycle model and is driven by fluctuations in the marginal product of capital and relative prices of investment goods. We view the return on capital as a measure of how the market reacts to news about the future value of capital.[18]. Table B.2 shows the results. We provide robustness against alternative measures of inflation trends in Table B.3. Specifically, we replace the WTI crude oil return with gold.[19]. Finally, in Table B.4 we replace the term spread with the corporate spread, proxied by the difference between Aaa and Baa corporate bonds yields.[20]

In all these case, we continue to confirm that: (1) factors are predictable in- and out-of-sample by their disequilibrium with the real economy (as proxied by the ECT); and (2) the loading of future factor returns on the current ECT is negative, suggesting that when factor prices are higher (lower) than the long-run equilibrium implied by the real economy, expected returns are lower (higher) next period so that the "disequilibrium" is corrected;

We also recall here that replacing our potential output with real time output growth (c.f. Table A.2), delivers positive and significant out-of-sample R^2 for all our factors, providing further support to the results presented in Table 3.

Finally, in Table B.5 we take an agnostic view and, following Ludvigson and Ng (2009), we treat the principal components (PCs) extracted from a panel of 130 macroeconomic indicators (such as measures of output, income, consumption, orders, surveys, labor market variables, house prices, consumer and producer prices, money, credit and asset prices) as

[18]The code to replicate the return to capital can be found at Paul Gomme's website (`https://paulgomme.github.io/`).

[19]Gold price is in USD from Macrobond Financial (series name: wocaes0091)

[20]Corporate bonds have experienced less of a secular decline in their yield than Treasuries.

statistical macroeconomic factors.[21,22] Since Ludvigson and Ng (2009) document that the first PC loads heavily on measures of employment and production, and the third and fourth PCs load most heavily on measures of inflation but display little relation to employment and output, we employ these factors as proxies of real activity and inflation. We find that adding the eight PC (which Ludvigson and Ng (2009) find to be related to the stock market) grants cointegration. Table B.5 largely confirms once again the conclusion drawn from Table 3.

Our purpose here was to show that the prices of prominent cross-sectional factors are anchored to macroeconomic trends. Whereas we measure the trend in the real economy with standard and simple proxies for economic activity, inflation, and liquidity, we believe the analysis on the identity of the trends and the most suitable statistical approach to extract them warrant future research.

4 Conclusions

We have shown that macroeconomic trends related to economic activity, inflation and aggregate liquidity track the prices of factors featuring in leading asset pricing models like the Fama and French (2015) and Hou, Xue, and Zhang (2015). In other words, factor prices share a common stochastic trend with key drivers of the macroeconomy.

This finding is at first surprising given the mixed evidence on workhorse macro-finance models like the Consumption-CAPM. However, our channel linking financial markets with the real economy operates through *prices* rather than *returns*. Accordingly, we propose to

[21] Stock and Watson (2002a,b) show that taking principal components is an effective way of summarizing information in a broad panel of macroeconomic variables.

[22] This database is maintained by the Research Division of the Federal Reserve Bank of St. Louis (McCracken and Ng, 2016).

model this new empirical fact through cointegration. Importantly, the *long run* comovement between factor prices and macro drivers has implications for the *short run* predictability of factor returns: when the price of a factor is greater than the long-term value implied by the macro trends, expected returns should be lower over the next period. We test this implication and find support for it in- and out-of-sample. Moreover the documented predictability is economically large as confirmed by (1) variation in expected factors' returns that is large relative to their unconditional level; and (2) significant economic gains from the perspective of a mean-variance investor. Finally, an SDF that incorporates the predictable deviations of factor prices from the value implied by economic trends, displays a large time-varying variance.

Overall our evidence shows that by looking at asset prices together with returns may prove a fruitful way to link financial markets to the real economy.

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Tables and Figures

Table 1: Johansen Cointegration Test for FF5

This table reports results for the Johansen (1991) procedure to test for cointegration of several I(1) series. We study the five factors proposed by Fama and French (2015). The macro-factors are potential output growth, WTI crude oil returns, the Treasury term spread computed as the 10-year minus 3-month Treasury bond yield, and the traded liquidity factor from Pástor and Stambaugh (2003). The I(1) series used for the cointegration test are the price level of factors and the macroeconomic drivers computed as in equations (1) and (2). The null hypothesis is that there are at most r cointegrating relationships. Panel A reports results for the "L-Max" statistics. Panel B reports results for the "Trace" statistics. The number of lags for the Johansen test is chosen according to the Akaike information criterion (AIC); we include a linear trend. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.

Panel A: L-Max

	MKT	SMB	HML	RMW	CMA	95% CV
r <= 4 |	8.740	6.038	7.094	9.080	8.766	12.250
r <= 3 |	12.727	10.716	11.097	10.064	11.426	18.960
r <= 2 |	14.033	19.094	11.770	16.483	13.735	25.540
r <= 1 |	33.939	31.093	17.484	28.653	20.293	31.460
r = 0 |	48.740	48.754	41.575	41.710	42.900	37.520

Panel B: Trace

	MKT	SMB	HML	RMW	CMA	95% CV
r <= 4 |	8.740	6.038	7.094	9.080	8.766	12.250
r <= 3 |	21.467	16.754	18.191	19.143	20.192	25.320
r <= 2 |	35.500	35.848	29.961	35.627	33.927	42.440
r <= 1 |	69.439	66.941	47.446	64.280	54.220	62.990
r = 0 |	118.179	115.694	89.021	105.990	97.120	87.310

Table 2: FECM for FF5

This table reports results from regressing tradeable factors on macro-factors plus their lagged ECTs. We employ the Fama and French (2015) factor model; thus, ECT_{factor} refers to $factor = \{MKT, SMB, HML, RMW, CMA\}$. The macro-factors are potential output growth, WTI crude oil returns, the Treasury term spread computed as the 10-year minus 3-month Treasury bond yield, and the traded liquidity factor from Pástor and Stambaugh (2003). Sp R^2_{ECT} is the semi-partial R^2 associated to a specific factor-ECT. Values in parenthesis are heteroskedasticity and autocorrelation consistent (HAC) standard errors using Newey and West (1987) with automatic bandwidth selection procedure as described in Newey and West (1994). ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.

	Factors				
	MKT	SMB	HML	RMW	CMA
potential output	2.542	0.849	4.808	−2.210	2.149
	(3.061)	(2.259)	(3.591)	(1.855)	(1.685)
oil	−0.014	0.007	0.030	−0.044**	0.027
	(0.056)	(0.026)	(0.024)	(0.021)	(0.022)
term spread	0.754*	0.588**	0.290	0.018	0.112
	(0.426)	(0.238)	(0.288)	(0.170)	(0.246)
liquidity	0.106	0.083	−0.034	0.056	−0.042
	(0.113)	(0.078)	(0.078)	(0.048)	(0.052)
ECT_{factor} (-1)	−0.143***	−0.075***	−0.131***	−0.126***	−0.127**
	(0.037)	(0.018)	(0.048)	(0.048)	(0.053)
Constant	−1.334	−0.946	−2.860	2.290*	−0.753
	(2.299)	(1.581)	(2.516)	(1.274)	(1.273)
Observations	207	207	207	207	207
R^2	0.115	0.087	0.093	0.084	0.090
Sp R^2_{ECT}	0.063	0.049	0.068	0.063	0.060

Table 3: Factor Return Predictability: FF5

This table reports results from predictive regressions for factors using their ECTs. We employ the Fama and French (2015) factor model; thus, ECT_{factor} refers to $factor = \{MKT, SMB, HML, RMW, CMA\}$. The macro-factors are potential output growth, WTI crude oil returns, the term spread computed as the 10-year minus 3-month Treasury bond yield, and the traded liquidity factor from Pástor and Stambaugh (2003). Panel A reports the in-sample results. $\sigma\left[E_t(factor)\right]$ stands for $\sigma\left[E_t\left(\widehat{\delta} \times ECT_{factor}\right)\right]$. Panel B reports the out-of-sample R^2 (R^2_{OOS}) for different periods. The R^2_{OOS} is computed as in Campbell and Thompson (2008); p-values for R^2_{OOS} are computed as in Clark and West (2007). We use an expanding window for estimating the predictive regressions; the in-sample period starts in Jan 1968 and ends in Dec 1979, Dec 1989, and Dec 1999. Values in parenthesis are heteroskedasticity and autocorrelation consistent (HAC) standard errors using Newey and West (1987) with automatic bandwidth selection procedure as described in Newey and West (1994). ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.

Panel A: In-Sample

	Factors				
	MKT	SMB	HML	RMW	CMA
ECT_{factor} (-1)	-0.155^{***}	-0.071^{***}	-0.126^{***}	-0.103^{**}	-0.126^{***}
	(0.034)	(0.018)	(0.045)	(0.052)	(0.047)
Constant	1.306^{**}	0.353	0.794^{*}	0.765^{**}	0.856^{***}
	(0.581)	(0.373)	(0.475)	(0.314)	(0.298)
Observations	207	207	207	207	207
R^2	0.089	0.045	0.064	0.045	0.069
$\sigma[E_t(factor)]/E(factor)$	2.042	3.322	1.818	1.196	1.170

Panel B: Out-Of-Sample R^2

	MKT	SMB	HML	RMW	CMA
From 1980	8.79^{***}	5.25^{***}	4.85^{***}	2.25^{**}	4.28^{***}
From 1990	9.6^{***}	4.56^{**}	5.22^{**}	0.78	5.76^{**}
From 2000	14.69^{***}	4.72^{**}	10.96^{***}	3.58^{*}	10.97^{***}

Table 4: Aggregate Market Predictability: Horserace

We regress log market excess return on several aggregate market predictors. ECT_{MKT} is the ECT of the market computed using potential output growth, WTI crude oil returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the term spread 10-year minus 3-month Treasury bond yield as macro-factors; cay is the consumption-based predictor proposed by Lettau and Ludvigson (2001); dp is the log of 12-month moving sums of dividends paid on the S&P 500 index minus the log of the S&P 500 index. Panel A reports results for quarterly returns (non-overlapping). Panel B reports results for annual returns. Panel C reports results for three-year returns In Panel A, standard errors are computed as in Newey and West (1987) with automatic bandwidth selection procedure as described in Newey and West (1994); in Panel B and C, standard errors are computed as in Hodrick (1992). ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. All regressions include a constant term, whose coefficient is omitted. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.

Panel A: Quarter

	(1)	(2)	(3)	(4)	(5)	(6)
ECT_{MKT}	-0.155^{***}			-0.153^{***}	-0.160^{***}	-0.158^{***}
	(0.032)			(0.032)	(0.033)	(0.034)
cay		0.307		0.221		0.208
		(0.298)		(0.321)		(0.306)
dp			0.014		-0.007	-0.005
			(0.015)		(0.016)	(0.016)
Observations	207	207	207	207	207	207
Adjusted R^2	0.085	0.0004	-0.0002	0.083	0.081	0.079

Panel B: 1-Year

	(1)	(2)	(3)	(4)	(5)	(6)
ECT_{MKT}	-0.573^{***}			-0.565^{***}	-0.587^{***}	-0.572^{***}
	(0.142)			(0.119)	(0.096)	(0.110)
cay		1.514		1.263		1.237
		(1.486)		(1.722)		(1.671)
dp			0.058		-0.018	-0.009
			(0.073)		(0.074)	(0.073)
Observations	204	204	204	204	204	204
Adjusted R^2	0.303	0.025	0.014	0.321	0.302	0.318

Panel C: 5-Year

	(1)	(2)	(3)	(4)	(5)	(6)
ECT_{MKT}	-1.222^{***}			-1.190^{***}	-1.202^{***}	-1.117^{***}
	(0.385)			(0.234)	(0.351)	(0.335)
cay		5.358^{*}		4.729^{**}		5.155^{*}
		(3.164)		(2.286)		(2.674)
dp			0.186		0.024	0.085
			(0.202)		(0.251)	(0.254)
Observations	188	188	188	188	188	188
Adjusted R^2	0.377	0.089	0.048	0.447	0.374	0.453

Table 5: Performance of Different Portfolio Strategies

This table reports Sharpe Ratios generated by different portfolio strategies. FI is factor investing which imposes the assumption of no factor timing; MT is market timing which only allows for variation in the mean of the market return; FT is factor timing which takes into account variation in the means of the factors; AT stands for anomaly timing which takes into account variation in the means of all factors but the market. For our empirical analysis of certainty equivalent return, we assume that $\gamma = 5$. Out-of-sample (OOS) values are based on split-sample analysis with parameters estimated using half of the sample. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.

	FI	MT	FT	AT
IS Sharpe Ratio	0.873	0.894	0.906	0.827
OOS Sharpe Ratio	0.873	0.804	0.999	0.965
Fee in %	—	1.20	2.37	1.07

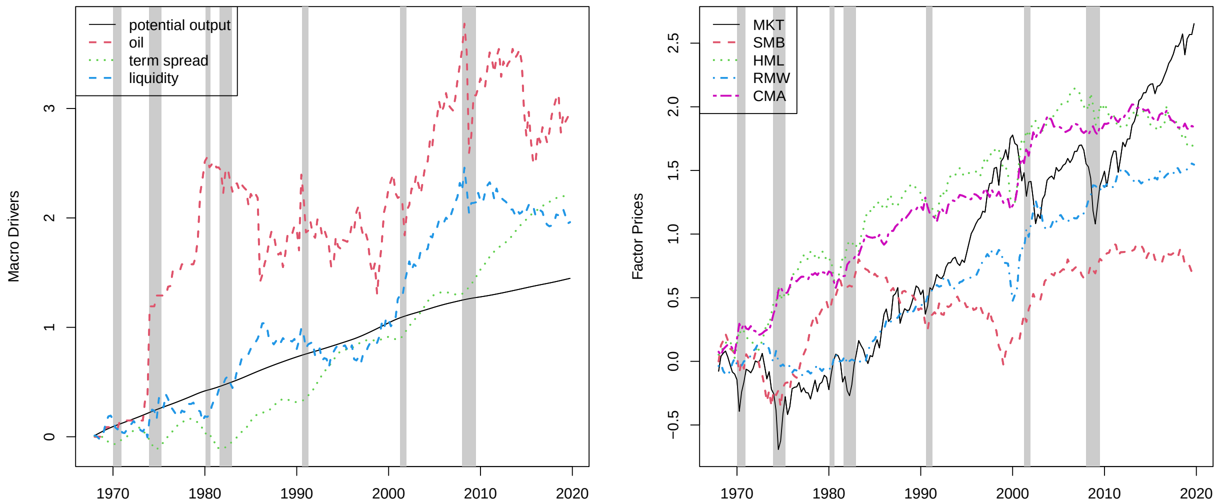
Table 6: Unconditional Moments of Conditional Variance of the SDF

This table reports first and second moment of the conditional annualized variance of SDFs implied by different portfolio strategies. FI is factor investing; MT is market timing; FT is factor timing. These three names coincide with the portfolios of Table 5, because portfolio weights and SDF exposures are equal. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.

	FI	MT	FT
$E[var_t(m_{t+1})]$	0.80	1.40	2.24
$std[var_t(m_{t+1})]$	0	0.64	0.94

(a) Prices. **(b)** Returns.

Figure 1: HML and its Macro-Trend. This figure shows actual and fitted dynamics for the value factor (HML) in the Fama and French (2015) factor model. The macro-factors are potential output growth, WTI crude oil returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the term spread 10-year minus 3-month Treasury bond yield. Shaded areas are NBER recessions. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.



(a) Macro-Factors.

(b) FF5.

Figure 2: Factor- and Macro-Risk Drivers. This figure shows the dynamics of the macroeconomic drivers (Panel A), and the dynamics of (log) prices for the Fama and French (2015) factors (FF5, Panel B). We start with factors and macro/factors and compute the price level of factors and the macroeconomic drivers as described in equations (1) and (2), respectively. The macro-factors are potential output growth, WTI crude oil returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the term spread 10-year minus 3-month Treasury bond yield. Shaded areas are NBER recessions. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.

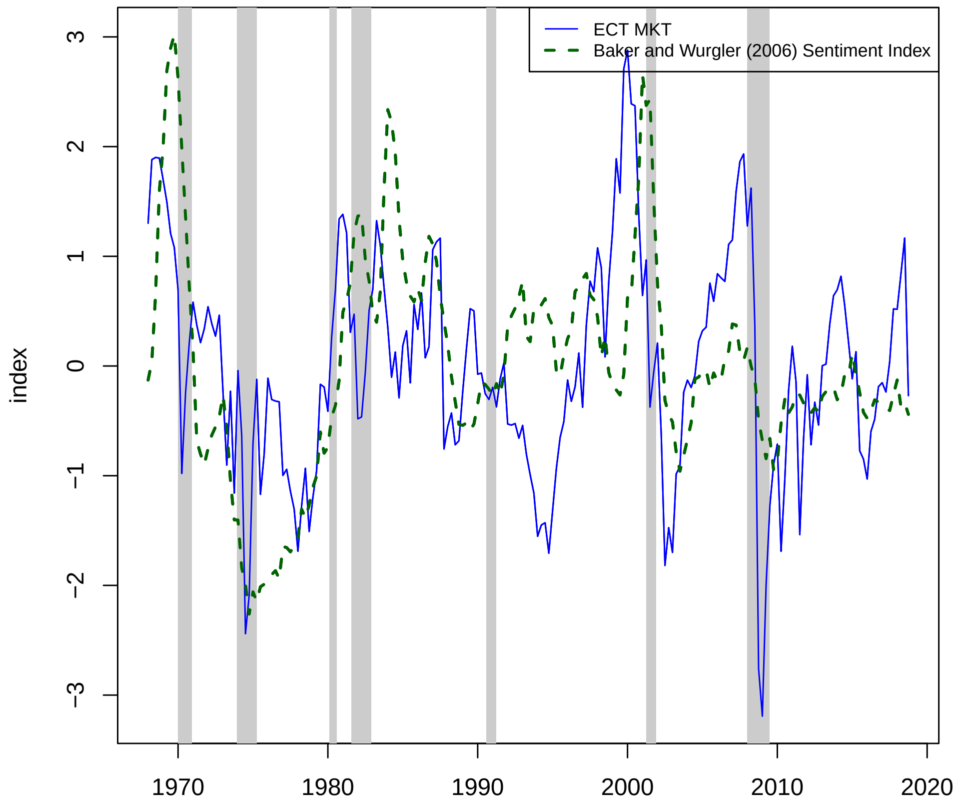


Figure 3: Market ECT and Investor Sentiment. This figure shows the ECT of the market and the sentiment index of Baker and Wurgler (2006). Both series are normalized to have mean zero and unit standard deviation. Shaded areas are NBER recessions. Quarterly observations. The sample period is 1968 to 2018.

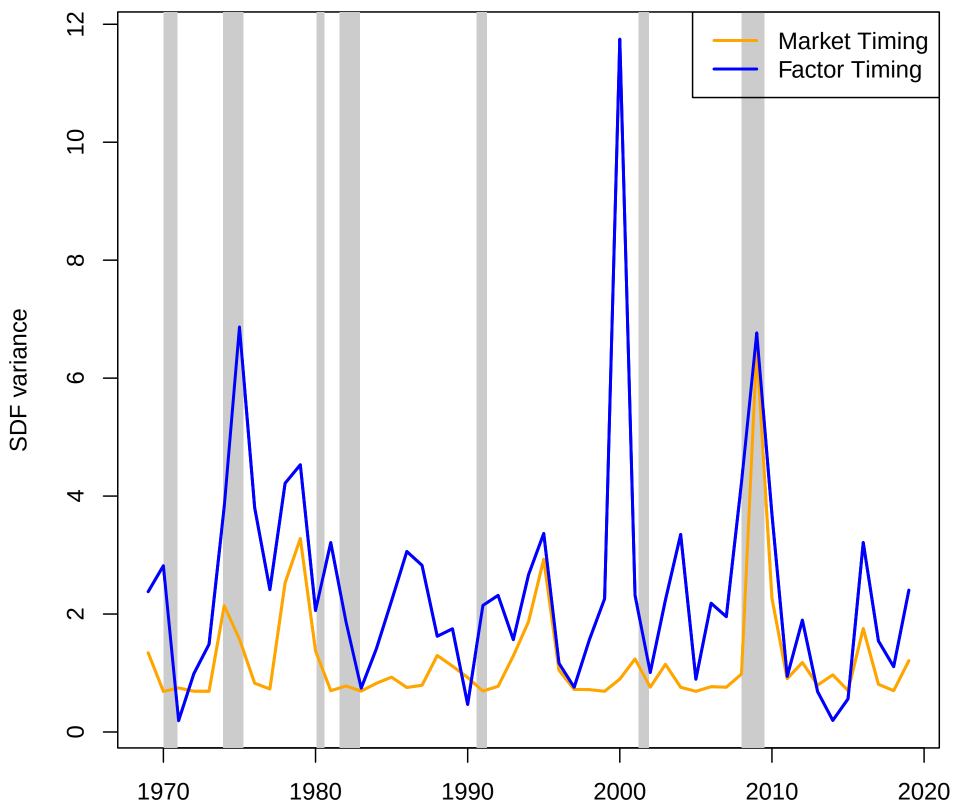
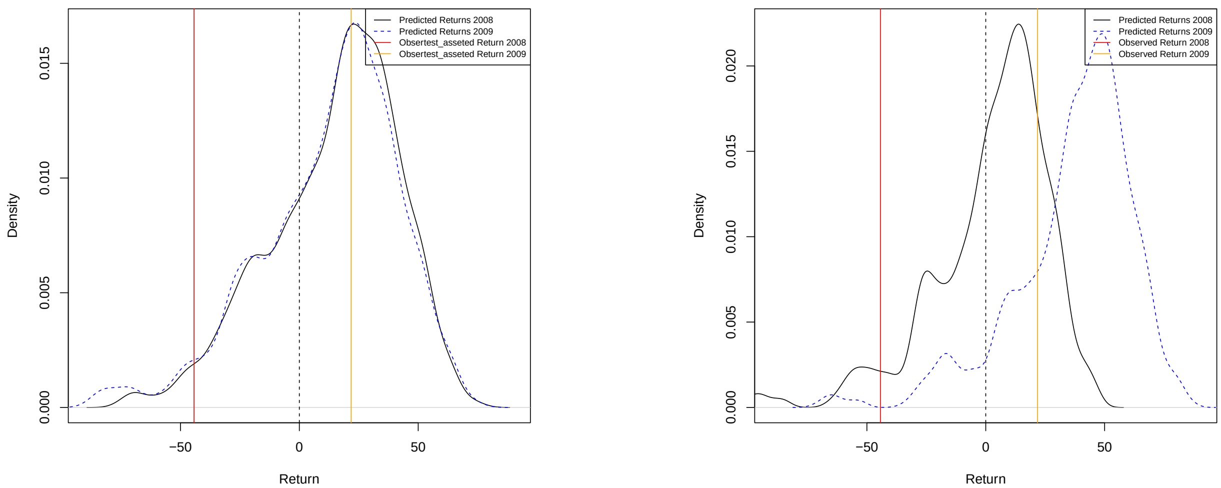


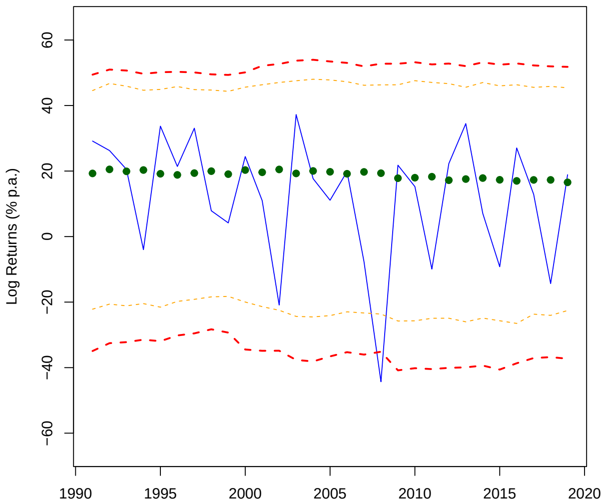
Figure 4: Conditional variance of SDFs. This figure shows the conditional variance of SDFs implied by two portfolio strategies. The solid blue line represents the SDF associated with "factor timing", i.e., when we allow for variation in the means of the factors. The orange line represents the SDF associated with "market timing", i.e., when we only use forecasts of the market return and ignore predictability of the other anomaly factors. Shaded areas are NBER recessions. Annual observations. The sample period is 1968 to 2019.



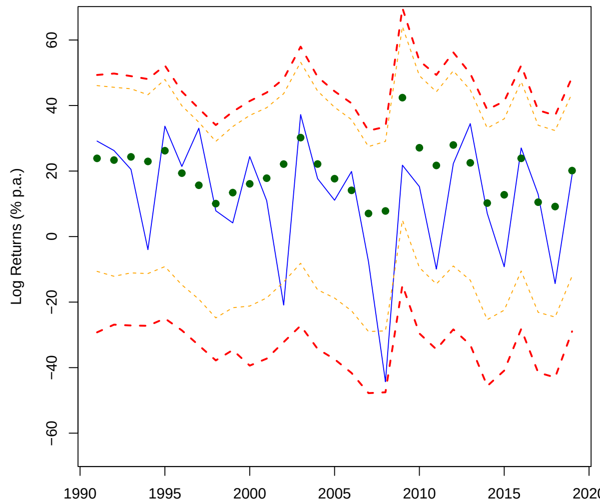
(a) CER.

(b) Macro-Factor Timing.

Figure 5: Risk Management: High (Value) Portfolio. This figure shows observed and out-of-sample predicted return distributions for the High Portfolio (the average return on the two value portfolios constructed using the 6 value-weight portfolios formed on size and book-to-market) during the crash 2008–2009 using the traditional and the Macro-FECM specifications. We employ the Fama and French (2015) factor model. The macro-factors are potential output growth, WTI crude oil returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the term spread computed as the 10-year minus 3-month Treasury bond yield. We estimate the model in the sample period 1968 to 2007 and we predict the distribution of returns in years 2008 and 2009 by bootstrapping residuals (number of iterations = 10000). The one-year ahead 10% VaR for the CER goes from −24.1 for 2008 to −25.8 for 2009, for our specification the VaR goes from −28.6 for 2008 to 3.1 for 2009; the unconditional VaR is −20.5. Annual observations. The sample period is 1968 to 2019



(a) CER.



(b) Macro-FECM.

Figure 6: Risk Management High Portfolio. This figure shows observed and out-of-sample predicted return distributions' confidence intervals for the High Portfolio (the average return on the two value portfolios constructed using the 6 value-weight portfolios formed on size and book-to-market) using the traditional and the Macro-FECM specification. Dashed red lines are 95% bands, dashed orange lines are 90% bands. Dark green solid circles represent the medians of the predicted distribution. We employ the Fama and French (2015) factor model. The macro-factors are potential output growth, WTI crude oil returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the term spread 10-year minus 3-month Treasury bond yield. We estimate the model in the sample period 1968 to 1990 and we predict the distribution of returns in years 1991 to 2019 by bootstrapping residuals (number of iterations = 10000). Annual observations. The sample period is 1968 to 2019.

Appendix

A Additional Results for FF5 Factor Model

Table A.1: Long-Run Regression for FF5

This table reports results from regressing factor prices on their macro drivers. We employ the Fama and French (2015) factor model. The macro factors are potential output growth, WTI crude oil returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the Treasury term spread computed as the 10-year minus 3-month Treasury bond yield. Values in parenthesis are heteroskedasticity and autocorrelation consistent (HAC) standard errors using Newey and West (1987) with automatic bandwidth selection procedure as described in Newey and West (1994). ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.

	MKT	SMB	HML	RMW	CMA
potential output	1.387	−2.730	3.835*	0.903	2.363**
	(1.887)	(12.105)	(2.089)	(0.964)	(1.037)
oil	−0.209***	0.135	0.058	−0.130***	0.055
	(0.073)	(0.249)	(0.074)	(0.048)	(0.037)
term spread	0.601*	−0.554	−0.087	0.323	0.045
	(0.352)	(1.698)	(0.326)	(0.220)	(0.170)
liquidity	−0.259	0.276	0.081	0.249*	0.133
	(0.244)	(0.181)	(0.247)	(0.139)	(0.108)
Constant	−31.450**	−7.974	0.245	−9.566*	7.231
	(12.533)	(40.335)	(10.881)	(5.456)	(5.352)
trend	1.143	9.989	−7.474	−0.906	−4.071
	(6.444)	(43.829)	(6.778)	(3.418)	(3.414)
Observations	208	208	208	208	208
R^2	0.963	0.756	0.962	0.978	0.980

Table A.2: Factor Return Predictability with Real-Time Output

This table reports results from regressing factors on macro factors plus their ECTs. We employ the Fama and French (2015) factor model; thus, ECT$_{factor}$ refers to $factor = \{MKT, SMB, HML, RMW, CMA\}$. The macro factors are real-time output growth, WTI crude oil returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the term spread computed as the 10-year minus 3-month Treasury bond yield. Panel A reports the in-sample results. Panel B reports the out-of-sample R^2 (R^2_{OOS}) for the period 2010–2019. The R^2_{OOS} is computed as in Campbell and Thompson (2008); p-values for R^2_{OOS} are computed as in Clark and West (2007). We use an expanding window for estimating the predictive regressions; the in-sample period starts in Jan 1968 and ends in Dec 1979, Dec 1989, and Dec 1999. Standard errors are computed as in Hodrick (1992). ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.

Panel A: In-Sample

	MKT	SMB	HML	RMW	CMA
ECT$_{factor}$ (-1)	-0.162^{***}	-0.074^{***}	-0.099^{**}	-0.097^{**}	-0.101^{***}
	(0.032)	(0.017)	(0.041)	(0.045)	(0.036)
Constant	1.307^{**}	0.349	0.797^{*}	0.767^{***}	0.859^{***}
	(0.580)	(0.366)	(0.473)	(0.286)	(0.293)
Observations	207	207	207	207	207
R^2	0.096	0.055	0.047	0.042	0.054

Panel B: Out-Of-Sample R^2

	MKT	SMB	HML	RMW	CMA
From 1980	9.14^{***}	6.60^{***}	2.52^{**}	2.18^{**}	2.58^{**}
From 1990	9.96^{***}	6.04^{***}	2.66^{*}	0.89	2.55^{**}
From 2000	15.94^{***}	8.78^{***}	6.30^{**}	3.21^{*}	4.70^{**}

Table A.3: Factor Return Predictability: FF5 (Annual Returns)

This table reports results from regressing factors on their ECTs. We employ the Fama and French (2015) factor model; thus, ECT_{factor} refers to $factor = \{MKT, SMB, HML, RMW, CMA\}$. The macro factors are potential output growth, WTI crude oil returns, the term spread computed as the 10-year minus 3-month Treasury bond yield, and the traded liquidity factor from Pástor and Stambaugh (2003). Panel A reports the in-sample results. Panel B reports the out-of-sample R^2 (R^2_{OOS}) for different periods. The R^2_{OOS} is computed as in Campbell and Thompson (2008); p-values for R^2_{OOS} are computed as in Clark and West (2007). We use an expanding window for estimating the predictive regressions; the in-sample period starts in Jan 1968 and ends in Dec 1979, Dec 1989, and Dec 1999. Values in parenthesis are heteroskedasticity and autocorrelation consistent (HAC) standard errors using Newey and West (1987) with automatic bandwidth selection procedure as described in Newey and West (1994). ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. Quarterly observations of annual returns. The sample period is 1968:Q1 to 2019:Q4.

Panel A: In-Sample

	MKT	SMB	HML	RMW	CMA
ECT_{factor} (-4)	-0.573^{***}	-0.296^{***}	-0.573^{***}	-0.488^{***}	-0.526^{***}
	(0.090)	(0.057)	(0.101)	(0.152)	(0.107)
Constant	4.875^{**}	1.278	3.268^{**}	3.154^{***}	3.503^{***}
	(2.085)	(1.745)	(1.511)	(1.173)	(1.162)
Observations	204	204	204	204	204
R^2	0.307	0.195	0.282	0.199	0.266

Panel B: Out-Of-Sample R^2

	MKT	SMB	HML	RMW	CMA
From 1980	34.77^{***}	17.73^{***}	28.57^{***}	18.7^{***}	22.95^{***}
From 1990	40.25^{***}	18.02^{***}	29.95^{***}	17.68^{***}	26.21^{***}
From 2000	47.86^{***}	24.36^{***}	34.03^{***}	21.70^{***}	30.54^{***}

One possible concern about the forecasting results presented in the main text is the potential for "look-ahead" bias due to the fact that the coefficients in ECT are estimated using the full sample. This concern may be addressed by performing out-of-sample forecasts where the parameters in ECT are reestimated every period, using only data available at the time of the forecast. The difficulty with this technique is that consistent estimation of the parameters in ECT requires a large number of observations, and an out-of-sample procedure is likely to induce significant sampling error in the coefficient estimates during the early estimation recursions. This would make it more difficult for the ECT to display forecasting power if the theory is true. With this caveat in mind, we report the results for this challenging case in Table A.4.

Table A.4: Factor Predictability in Real-Time

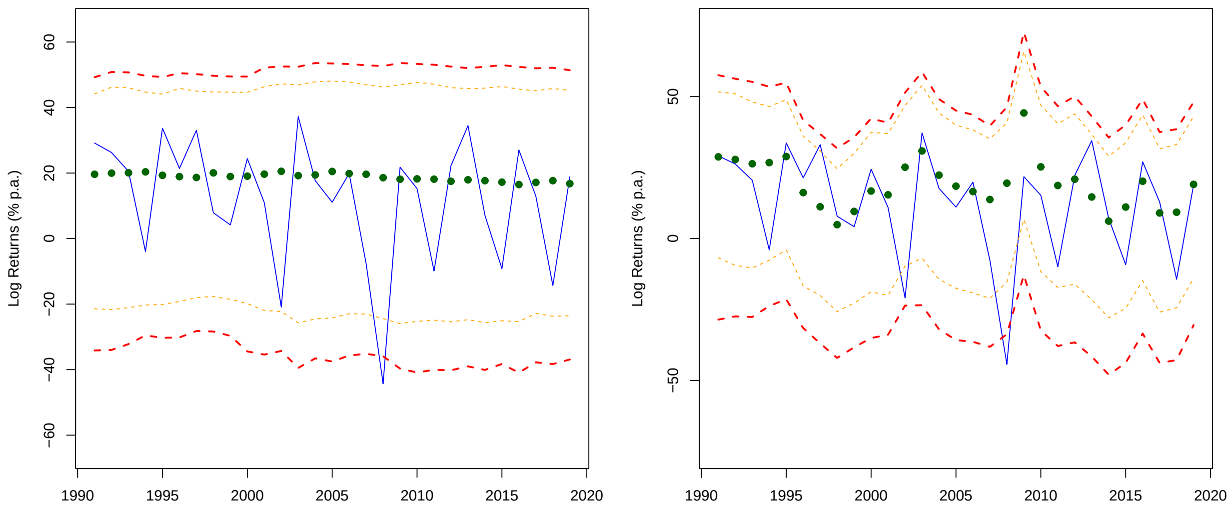
This table reports the out-of-sample R^2 (R^2_{OOS}) from regressing factors on their ECTs. The ECTs are computed OOS on an expanding window from Jan 2000 until Dec 2019. We employ the Fama and French (2015) factor model. The macro factors are real-time output growth, WTI crude oil returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the term spread 10-year minus 3-month Treasury bond yield. The R^2_{OOS} is computed as in Campbell and Thompson (2008); p-values for R^2_{OOS} are computed as in Clark and West (2007). We use a rolling window for estimating the predictive regressions; the training sample starts in Jan 1968 and ends in Dec 1999. ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.

Panel A: Quarter

MKT	SMB	HML	RMW	CMA
7.40***	3.36**	3.90***	-2.31	0.88

Panel B: Annual

MKT	SMB	HML	RMW	CMA
29.37***	19.28***	14.49***	2.98*	3.49*



(a) CER. **(b)** Macro-FECM.

Figure A.1: Risk Management High Portfolio with OOS ECT. This figure shows observed and out-of-sample predicted return distributions' confidence intervals for the High Portfolio (the average return on the two value portfolios constructed using the 6 value-weight portfolios formed on size and book-to-market) using the traditional and the Macro-FECM specification. The ECTs are computed OOS on an expanding window from 1990 until 2019. Dashed red lines are 95% bands, dashed orange lines are 90% bands. Dark green solid circles represent the medians of the predicted distribution. We employ the Fama and French (2015) factor model. The macro factors are potential output growth, WTI crude oil returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the term spread 10-year minus 3-month Treasury bond yield. We estimate the model in the sample period 1968 to 1990 and we predict the distribution of returns in years 1991 to 2019 by bootstrapping residuals (number of iterations = 10000). Annual observations. The sample period is 1968 to 2019.

B Robustness to Macro Drivers

B.1 Alternative Choices of Macro Drivers

Table B.1: Factor Predictability without Liquidity

This table reports results from predictive regressions for factors using their ECTs. We employ the Fama and French (2015) factor model; thus, ECT_{factor} refers to $factor = \{MKT, SMB, HML, RMW, CMA\}$. The macro factors are potential output growth, WTI crude oil returns, and the term spread 10-year minus 3-month Treasury bond yield. Panel A reports the in-sample results. Panel B reports the out-of-sample R^2 (R^2_{OOS}) for the period 2010–2019. The R^2_{OOS} is computed as in Campbell and Thompson (2008); *p*-values for R^2_{OOS} are computed as in Clark and West (2007). We use an expanding window for estimating the predictive regressions; the in-sample period starts in Jan 1968 and ends in Dec 1979, Dec 1989, and Dec 1999. ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.

Panel A: In-Sample

	MKT	SMB	HML	RMW	CMA
ECT_{factor} (-1)	-0.130^{***}	-0.071^{***}	-0.124^{***}	-0.070	-0.106^{**}
	(0.034)	(0.018)	(0.046)	(0.052)	(0.050)
Constant	1.307^{**}	0.354	0.795^{*}	0.765^{**}	0.856^{***}
	(0.586)	(0.368)	(0.474)	(0.341)	(0.299)
Observations	207	207	207	207	207
R^2	0.069	0.050	0.063	0.029	0.054

Panel B: Out-Of-Sample R^2

	MKT	SMB	HML	RMW	CMA
From 1980	4.97^{***}	4.56^{***}	4.30^{**}	0.14	2.20^{*}
From 1990	4.15^{**}	2.28^{*}	5.59^{**}	-1	5.21^{**}
From 2000	11.38^{***}	3.47^{*}	11.29^{***}	0.53	10.12^{***}

Table B.2: Factor Predictability: Return to Capital

This table reports results from predictive regressions for factors using their ECTs. We employ the Fama and French (2015) factor model; thus, ECT_{factor} refers to $factor = \{MKT, SMB, HML, RMW, CMA\}$. The macro factors are return to capital constructed as in Gomme, Ravikumar, and Rupert (2011), WTI crude oil returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the term spread 10-year minus 3-month Treasury bond yield. Panel A reports the in-sample results. Panel B reports the out-of-sample R^2 (R^2_{OOS}) for the period 2010–2019. The R^2_{OOS} is computed as in Campbell and Thompson (2008); *p*-values for R^2_{OOS} are computed as in Clark and West (2007). We use an expanding window for estimating the predictive regressions; the in-sample period starts in Jan 1968 and ends in Dec 1979, Dec 1989, and Dec 1999. ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. Monthly observations of annual returns. The sample period is 1968 to 2019.

Panel A: In-Sample

	MKT	SMB	HML	RMW	CMA
ECT_{factor} (-1)	-0.163^{***}	-0.075^{***}	-0.081^{**}	-0.146^{**}	-0.098^{***}
	(0.035)	(0.018)	(0.035)	(0.069)	(0.033)
Constant	1.305^{**}	0.349	0.797^{*}	0.762^{**}	0.860^{***}
	(0.596)	(0.365)	(0.459)	(0.326)	(0.292)
Observations	207	207	207	207	207
R^2	0.095	0.057	0.039	0.069	0.056

Panel B: Out-Of-Sample R^2

	MKT	SMB	HML	RMW	CMA
From 1980	8.96^{***}	6.17^{***}	3.10^{**}	3.95^{**}	3.20^{***}
From 1990	9.23^{***}	5.94^{***}	1.58^{*}	1.56	3.12^{**}
From 2000	15.13^{***}	8.37^{***}	3.95^{**}	4.73	5.19^{**}

Table B.3: Factor Predictability: Gold

This table reports results from predictive regressions for factors using their ECTs. We employ the Fama and French (2015) factor model; thus, ECT_{factor} refers to $factor = \{MKT, SMB, HML, RMW, CMA\}$. The macro factors are potential output growth, gold returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the term spread 10-year minus 3-month Treasury bond yield. Panel A reports the in-sample results. Panel B reports the out-of-sample R^2 (R^2_{OOS}) for the period 2010–2019. The R^2_{OOS} is computed as in Campbell and Thompson (2008); p-values for R^2_{OOS} are computed as in Clark and West (2007). We use an expanding window for estimating the predictive regressions; the in-sample period starts in Jan 1968 and ends in Dec 1979, Dec 1989, and Dec 1999. ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. Monthly observations of annual returns. The sample period is 1968 to 2019.

Panel A: In-Sample

	MKT	SMB	HML	RMW	CMA
ECT_{factor} (-1)	-0.168^{***}	-0.063^{***}	-0.124^{***}	-0.099^{*}	-0.124^{***}
	(0.038)	(0.019)	(0.046)	(0.051)	(0.044)
Constant	1.311^{**}	0.352	0.792^{*}	0.765^{**}	0.855^{***}
	(0.581)	(0.379)	(0.476)	(0.328)	(0.295)
Observations	207	207	207	207	207
R^2	0.087	0.034	0.059	0.050	0.065

Panel B: Out-Of-Sample R^2

	MKT	SMB	HML	RMW	CMA
From 1980	6.79^{***}	3.94^{***}	4.04^{**}	2.90^{**}	4.46^{***}
From 1990	9.35^{***}	3.70^{**}	5.46^{**}	1.86	5.78^{***}
From 2000	11.55^{***}	4.40^{**}	10.22^{***}	4.12^{*}	9.96^{***}

Table B.4: Factor Predictability: Corporate Spread

This table reports results from predictive regressions for factors using their ECTs. We employ the Fama and French (2015) factor model; thus, ECT_{factor} refers to $factor = \{MKT, SMB, HML, RMW, CMA\}$. The macro factors are potential output growth, WTI crude oil returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the corporate spread BAA minus AAA Moody's Seasoned Corporate Bond Yield. Panel A reports the in-sample results. Panel B reports the out-of-sample R^2 (R^2_{OOS}) for the period 2010–2019. The R^2_{OOS} is computed as in Campbell and Thompson (2008); *p*-values for R^2_{OOS} are computed as in Clark and West (2007). We use an expanding window for estimating the predictive regressions; the in-sample period starts in Jan 1968 and ends in Dec 1979, Dec 1989, and Dec 1999. ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. Monthly observations of annual returns. The sample period is 1968 to 2019.

Panel A: In-Sample

	MKT	SMB	HML	RMW	CMA
ECT_{factor} (-1)	-0.135^{***}	-0.075^{***}	-0.139^{***}	-0.100^{**}	-0.132^{***}
	(0.039)	(0.020)	(0.049)	(0.050)	(0.045)
Constant	1.314^{**}	0.350	0.793^{*}	0.767^{**}	0.856^{***}
	(0.606)	(0.378)	(0.476)	(0.319)	(0.297)
Observations	207	207	207	207	207
R^2	0.067	0.039	0.070	0.045	0.071

Panel B: Out-Of-Sample R^2

	MKT	SMB	HML	RMW	CMA
From 1980	6.03^{***}	2.90^{**}	5.73^{***}	2.29^{**}	5.1^{***}
From 1990	6.75^{***}	3.83^{**}	5.35^{**}	1.09^{*}	5.6^{***}
From 2000	10.06^{***}	2.04^{*}	11.9^{***}	4.16^{**}	10.59^{***}

B.2 Macro Factors Extracted from a Large Cross-Section

Table B.5: Factor Return Predictability: FF5

This table reports results from regressing factors on macro factors plus their ECTs. We employ the Fama and French (2015) factor model; thus, ECT_{factor} refers to $factor = \{MKT, SMB, HML, RMW, CMA\}$. The macro factors are PC1, PC3, PC4, and PC8 in the 8 PCs estimated in Ludvigson and Ng (2009). Panel A reports the in-sample results. Panel B reports the out-of-sample R^2 (R^2_{OOS}) for different periods. The R^2_{OOS} is computed as in Campbell and Thompson (2008); p-values for R^2_{OOS} are computed as in Clark and West (2007). We use an expanding window for estimating the predictive regressions; the in-sample period starts in Jan 1968 and ends in Dec 1979, Dec 1989, and Dec 1999. Standard errors are computed as in Hodrick (1992). Constant estimates are not tabulated. ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.

Panel A: In-Sample

	MKT	SMB	HML	RMW	CMA
ECT_{factor} (-1)	-0.145^{***}	-0.060^{***}	-0.110^{**}	-0.113^{**}	-0.090^{***}
	(0.041)	(0.018)	(0.047)	(0.057)	(0.033)
Constant	1.313^{**}	0.351	0.797^{*}	0.764^{**}	0.857^{***}
	(0.633)	(0.376)	(0.472)	(0.317)	(0.286)
Observations	207	207	207	207	207
R^2	0.062	0.035	0.045	0.047	0.040

Panel B: Out-Of-Sample R^2

	MKT	SMB	HML	RMW	CMA
From 1980	6.73^{***}	3.63^{**}	2.54^{**}	2.56^{*}	2.32^{**}
From 1990	7.12^{***}	1.96	2.45^{*}	2.35	1.37^{*}
From 2000	10.19^{***}	3.92^{**}	6.64^{**}	3.75	5.05^{**}

C Macro Drivers and the q4-Factor Model

Table C.1: Factor Return Predictability: q4

This table reports results from regressing factors on their ECTs. We employ the Hou, Xue, and Zhang (2015) q-factor model; thus, ECT_{factor} refers to $factor = \{MKT, ME, IA, ROE\}$. The macro factors are potential output growth, WTI crude oil returns, the term spread computed as the 10-year minus 3-month Treasury bond yield, and the traded liquidity factor from Pástor and Stambaugh (2003). Panel A reports the in-sample results. Panel B reports the out-of-sample R^2 (R^2_{OOS}) for different periods. The R^2_{OOS} is computed as in Campbell and Thompson (2008); p-values for R^2_{OOS} are computed as in Clark and West (2007). We use an expanding window for estimating the predictive regressions; the in-sample period starts in Jan 1968 and ends in Dec 1979, Dec 1989, and Dec 1999. Values in parenthesis are heteroskedasticity and autocorrelation consistent (HAC) standard errors using Newey and West (1987) with automatic bandwidth selection procedure as described in Newey and West (1994). ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. Quarterly observations. The sample period is 1968:Q1 to 2019:Q4.

Panel A: In-Sample

	MKT	ME	ROE	IA
ECT_{factor} (-1)	-0.162^{***}	-0.084^{***}	-0.075^{*}	-0.106^{**}
	(0.034)	(0.018)	(0.040)	(0.042)
Constant	1.245^{**}	0.562	1.499^{***}	1.077^{***}
	(0.578)	(0.370)	(0.322)	(0.259)
Observations	207	207	207	207
R^2	0.094	0.053	0.021	0.061

Panel B: Out-Of-Sample R^2

	MKT	ME	ROE	IA
From 1980	9.31^{***}	5.9^{***}	1.30^{*}	2.41^{**}
From 1990	9.81^{***}	5.18^{**}	1.48^{*}	3.67^{**}
From 2000	14.97^{***}	5.30^{**}	2.40^{*}	6.23^{**}

Table C.2: Factor Return Predictability: q4 (Annual Returns)

This table reports results from regressing factors on their ECTs. We employ the Hou, Xue, and Zhang (2015) q-factor model; thus, ECT_{factor} refers to $factor = \{MKT, ME, IA, ROE\}$. The macro factors are potential output growth, WTI crude oil returns, the term spread computed as the 10-year minus 3-month Treasury bond yield, and the traded liquidity factor from Pástor and Stambaugh (2003). Panel A reports the in-sample results. Panel B reports the out-of-sample R^2 (R^2_{OOS}) for different periods. The R^2_{OOS} is computed as in Campbell and Thompson (2008); *p*-values for R^2_{OOS} are computed as in Clark and West (2007). We use an expanding window for estimating the predictive regressions; the in-sample period starts in Jan 1968 and ends in Dec 1979, Dec 1989, and Dec 1999. Values in parenthesis are heteroskedasticity and autocorrelation consistent (HAC) standard errors using Newey and West (1987) with automatic bandwidth selection procedure as described in Newey and West (1994). ***, **, and * indicates respectively 1%, 5%, and 10% level of significance. Quarterly observations of annual returns. The sample period is 1968:Q1 to 2019:Q4.

Panel A: In-Sample

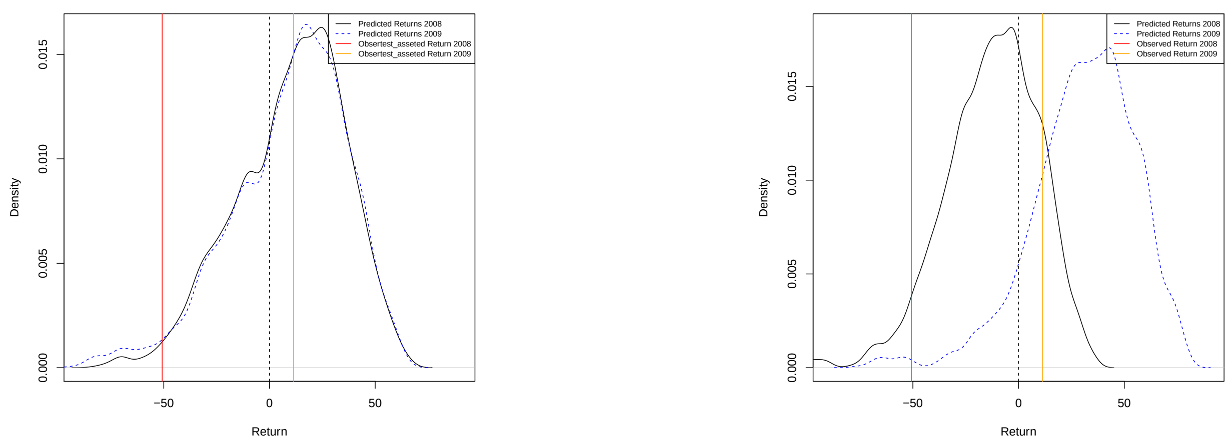
	MKT	ME	ROE	IA
ECT_{factor} (-4)	-0.599^{***}	-0.328^{***}	-0.280^{**}	-0.440^{***}
	(0.093)	(0.069)	(0.129)	(0.110)
Constant	4.647^{**}	2.151	6.056^{***}	4.428^{***}
	(2.044)	(1.613)	(1.166)	(1.109)
Observations	204	204	204	204
R^2	0.323	0.206	0.083	0.228

Panel B: Out-Of-Sample R^2

	MKT	ME	ROE	IA
From 1980	36.40^{***}	19.03^{***}	7.65^{***}	17.78^{***}
From 1990	41.02^{***}	17.70^{***}	8.77^{***}	20.00^{***}
From 2000	49.10^{***}	24.64^{***}	10.44^{***}	19.46^{***}

D Macro Risk Drivers and the Momentum Factor

We consider risk management for momentum. Daniel and Moskowitz (2016) show that momentum strategies can experience infrequent and persistent strings of negative returns. E.g., 2009/04 and 2009/08 rank fourth and tenth among the worst monthly momentum returns in the long sample 1927–2013. Figure D.1 shows that the Macro-FECM specification is successful in predicting the shift to the left of the one-year ahead winner returns distributions from 2008 to 2009; such a shift is instead missed entirely by the classical CER model, see Panel (a) in Figure D.1. Once again, we find that the improvement is obtained when one accounts for the long-run relationship between the price level of the factor and the macro drivers. In the case of the Winner portfolio, the one-year ahead 10% VaR from the Macro-FECM specification in Panel (b) goes from −41.6 for 2008 to 0.9 for 2009.



(a) CER.

(b) Macro-Factor Timing.

Figure D.1: Risk Management Winner Portfolio. This figure shows observed and out-of-sample predicted return distributions for the Winner Portfolio (Decile 10 in the 10 Portfolios sorted on Momentum) during the crash 2008–2009 using the traditional and the Macro-FECM specifications. We employ the Fama and French (2015) factor model. The macro factors are potential output growth, WTI crude oil returns, the traded liquidity factor from Pástor and Stambaugh (2003), and the term spread computed as the 10-year minus 3-month Treasury bond yield. We estimate the model in the sample period 1968 to 2007 and we predict the distribution of returns in years 2008 and 2009 by bootstrapping residuals (number of iterations = 10000). The one-year ahead 10% VaR for the CER goes from −26.1 for 2008 to −28.3 for 2009, for our specification the VaR goes from −41.6 for 2008 to 0.9 for 2009; the unconditional VaR is −17. Annual observations. The sample period is 1968 to 2019.