Equity risk factors and the Intertemporal CAPM

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Abstract

We evaluate whether several equity factor models are consistent with the Merton's Intertemporal CAPM (Merton (1973), ICAPM) by using a large cross-section of portfolio returns. The state variables associated with (alternative) profitability factors help to forecast the equity premium in a way that is consistent with the ICAPM. Additionally, several state variables (particularly, those associated with investment factors) forecast a significant decline in stock volatility, being consistent with the corresponding factor risk prices. Moreover, there is strong evidence of predictability for future economic activity, especially from investment and profitability factors. Overall, the four-factor model of Hou, Xue, and Zhang (2014a) presents the best convergence with the ICAPM. The predictive ability of most equity state variables does not seem to be subsumed by traditional ICAPM state variables.

Keywords: Asset pricing models; Equity risk factors; Intertemporal CAPM; Predictability of stock returns; Cross-section of stock returns; stock market anomalies

JEL classification: G10, G11, G12

1 Introduction

Explaining the cross-sectional dispersion in average stock returns has been one of the major goals in the asset pricing literature. This task has been increasingly challengeable in recent years given the emergence of new market anomalies, which correspond to new patterns in cross-sectional risk premia unexplained by the baseline CAPM from Sharpe (1964) and Lintner (1965) (see, for example, Hou, Xue, and Zhang (2014a)). These include, for example, a number of investment-based and profitability-based anomalies. The investment anomaly can be broadly classified as a pattern in which stocks of firms that invest more exhibit lower average returns than the stocks of firms that invest less (Titman, Wei, and Xie (2004), Anderson and Garcia-Feijoo (2006), Cooper, Gulen, and Schill (2008), Fama and French (2008), Lyandres, Sun, and Zhang (2008), and Xing (2008)). The profitability-based cross-sectional pattern in stock returns indicates that more profitable firms earn higher average returns than less profitable firms (Ball and Brown (1968), Bernard and Thomas (1990), Haugen and Baker (1996), Fama and French (2006), Jegadeesh and Livnat (2006), Balakrishnan, Bartov, and Faurel (2010), and Novy-Marx (2013)).

The traditional workhorses in the empirical asset pricing literature (e.g., the three-factor model from Fama and French (1993, 1996)) have difficulties in explaining the new market anomalies (see, for example, Fama and French (2014a) and Hou, Xue, and Zhang (2014a, 2014b)). In response to this evidence, in recent years, we have seen the emergence of new multifactor models containing (different versions of) investment and profitability factors (e.g., Novy-Marx (2013), Fama and French (2014a), and Hou, Xue, and Zhang (2014a)) seeking to explain the new anomalies and the extended cross-section of stock returns. Yet, although these models perform relatively well in explaining the new patterns in cross-sectional risk premia, there is still some controversy about the theoretical background of such models. For example, Fama and French (2014a) motivate their five-factor model based on the present-value model from Miller and Modigliani (1961). Yet, Hou, Xue, and Zhang (2014b) raise several concerns about this link.

In this paper, we extend the work conducted in Maio and Santa-Clara (2012) by assessing whether equity factor models (in which all the factors are excess stock returns) are consistent with the Merton's Intertemporal CAPM framework (Merton (1973), ICAPM). We analyse six multifactor models, with special emphasis given to the recent four-factor models proposed by Novy-Marx (2013) and Hou, Xue, and Zhang (2014a) and the five-factor model from Fama and French (2014a). Maio and Santa-Clara (2012) identify general sign restrictions on the factor (other than the market) risk prices, which are estimated from the cross-section of stock returns, that a given multifactor model has to satisfy in order to be consistent with the ICAPM. Specifically, if a state variable forecasts a decline in future aggregate returns, the risk price associated with the corresponding risk factor in the asset pricing equation should also be negative. On the other hand, when future investment opportunities are measured by the second moment of aggregate returns, we have an opposite relation between the sign of the factor risk price and predictive slope in the time-series regressions. Hence, if a state variable forecasts a decline in future aggregate stock volatility, the risk price associated with the corresponding factor should be positive. Maio and Santa-Clara (2012) test these predictions and conclude that several of the multifactor models proposed in the empirical asset pricing literature are not consistent with the ICAPM.[1]

Our results for the cross-sectional tests confirm that the new models of Novy-Marx (2013), Fama and French (2014a), and Hou, Xue, and Zhang (2014a) have a good explanatory power for the large cross-section of portfolio returns, in line with the evidence presented in Fama and French (2014b) and Hou, Xue, and Zhang (2014a, 2014b). On the other hand, the factor models of Fama and French (1993) and Pástor and Stambaugh (2003) fail to explain cross-sectional risk premia. Most factor risk price estimates are positive and statistically significant. Among the most notable exceptions are the risk price for HML within the FF5 model and the liquidity risk price, with both estimates being significantly negative.

[1] Lutzenberger (2014) extends the analysis in Maio and Santa-Clara (2012) for the European stock market. In related work, Boons (2014) evaluates the consistency with the ICAPM, when investment opportunities are measured by broad economic activity.

Following Maio and Santa-Clara (2012), we construct state variables associated with each factor that correspond to the past 60-month cumulative sum on the factors. The results for forecasting regressions corresponding to the excess market return at multiple horizons indicate that the state variables associated with the profitability factors employed in Novy-Marx (2013), Fama and French (2014a), and Hou, Xue, and Zhang (2014a) help to forecast the equity premium. Moreover, the positive predictive slopes are consistent with the positive risk prices for the corresponding factors. When it comes to forecasting stock market volatility, several state variables forecast a significant decline in stock volatility, consistent with the corresponding factor risk price estimates. This includes the state variables associated with the value factor employed in Novy-Marx (2013), the size and investment factors from Hou, Xue, and Zhang (2014a), and the investment factor used in Fama and French (2014a). The slopes associated with the standard HML factor are also significantly negative, thus ensuring consistency with the positive risk price estimates within the factor models of Fama and French (1993), Carhart (1997), and Pástor and Stambaugh (2003). Yet, such consistency does not apply to the five-factor model from Fama and French (2014a) given the associated negative risk price estimate for HML. Overall, the four-factor model of Hou, Xue, and Zhang (2014a) presents the best convergence with the ICAPM, when investment opportunities are measure by both the expected aggregate return and market volatility.

We also evaluate if the equity state variables forecast future aggregate economic activity. The motivation for this exercise hinges on the Roll's critique (Roll (1977)), and the fact that the stock index is an imperfect proxy for aggregate wealth. Overall, the evidence of predictability for future economic activity is stronger than for the future market return, across most equity state variables. Specifically, the state variables associated with the liquidity factor, the momentum factor of Carhart (1997), and the investment and profitability factors of Hou, Xue, and Zhang (2014a) are valid forecasters of future economic activity. This forecasting behavior is consistent with the corresponding risk price estimates in the asset pricing equations. Surprisingly, the state variables corresponding with the profitability factors from

Novy-Marx (2013) and Fama and French (2014a) do not help to forecast business conditions, or do so in a way that is inconsistent with the ICAPM. These results suggest that despite the fact that the different versions of the investment and profitability factors employed in Novy-Marx (2013), Fama and French (2014a), and Hou, Xue, and Zhang (2014a) are highly correlated, they still differ significantly in terms of asset pricing implications, which is also consistent with the evidence found in Hou, Xue, and Zhang (2014b).

We also assess if the forecasting ability of the equity state variables for future investment opportunities is linked to other state variables that are typically used in the empirical ICAPM literature, like the term spread, default spread, dividend yield, or T-bill rate. The results from multiple forecasting regressions suggest that the predictive ability of most equity state variables, including the different investment and profitability variables, does not seem to be subsumed by the traditional ICAPM state variables. The exceptions are the state variables associated with the HML and liquidity factors, partially in line with the previous evidence found in Hahn and Lee (2006) and Petkova (2006).

The paper proceeds as follows. Section 2 contains the cross-sectional tests of the different multifactor models. Section 3 shows the results for the forecasting regressions associated with the equity premium and stock volatility, and evaluates the consistency of the factor models with the ICAPM. Section 4 presents the results for forecasting regressions for economic activity, and Section 5 evaluates whether the forecasting ability of the equity state variables is subsumed by traditional ICAPM variables. Finally, Section 6 concludes.

2 Cross-sectional tests and factor risk premia

In this section, we estimate the different multifactor models by using a large cross-section of equity portfolio returns.

2.1 Models

We evaluate the consistency of several multifactor models with the Merton's ICAPM (Merton (1973)). Common to these models is the fact that all the factors represent excess stock returns or the returns on tradable equity portfolios.

The first two models analyzed are the three-factor model from Fama and French (1993, 1996, FF3 henceforth),

$$\begin{aligned} \mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) + \gamma_{SMB} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, SMB_{t+1}) \\ +\gamma_{HML} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, HML_{t+1}), \end{aligned} \tag{1}$$

and the four-factor model from Carhart (1997) (C4),

$$\begin{aligned} \mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) + \gamma_{SMB} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, SMB_{t+1}) \\ +\gamma_{HML} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, HML_{t+1}) + \gamma_{UMD} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, UMD_{t+1}). \end{aligned} \tag{2}$$

For some time, these models have been the workhorses in the empirical asset pricing literature. In the above equations, RM, SMB, HML, and UMD represent the market, size, value, and momentum factors, respectively. R_i and R_f denote the return on an arbitrary risky asset i and the risk-free rate, respectively. Maio and Santa-Clara (2012) analyze the consistency of these two models with the ICAPM, yet, the cross-sectional tests conducted in that paper rely only on 25 portfolios sorted on both size and book-to-market and 25 size-momentum portfolios. In this paper, we estimate these two models and assess their consistency with the ICAPM by using a more comprehensive cross-section of equity portfolios, in line with the recent developments in the asset pricing literature (e.g., Fama and French (2014a) and Hou, Xue, and Zhang (2014a)).

The third model considered is the four-factor model employed by Pástor and Stambaugh

(2003) (PS4),

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) + \gamma_{SMB} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, SMB_{t+1}) + \gamma_{HML} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, HML_{t+1}) + \gamma_{LIQ} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, LIQ_{t+1}), \quad (3)$$

where LIQ denotes the stock liquidity factor. Maio and Santa-Clara (2012) also analyze a version of this model that includes the non-traded liquidity factor, yet, we use the tradable liquidity factor, in line with the focus of the current paper.

The next three models contain different versions of corporate investment and profitability factors. The fourth model is the four-factor model from Novy-Marx (2013) (NM4),

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) + \gamma_{HML^*} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, HML^*_{t+1}) + \gamma_{UMD^*} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, UMD^*_{t+1}) + \gamma_{PMU^*} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, PMU^*_{t+1}), \quad (4)$$

where HML^*, UMD^*, and PMU^* denote the industry-adjusted value, momentum, and profitability factors, respectively.

Hou, Xue, and Zhang (2014a, 2014b) propose the following four-factor model (HXZ4),

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) + \gamma_{ME} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, ME_{t+1}) + \gamma_{IA} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, IA_{t+1}) + \gamma_{ROE} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, ROE_{t+1}), \quad (5)$$

where ME, IA, and ROE represent their size, investment, and profitability factors, respectively.

Finally, we evaluate the five-factor model proposed by Fama and French (2014a, 2014b, FF5),

$$
\begin{aligned}
\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) + \gamma_{SMB} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, SMB_{t+1}) \\
+\gamma_{HML} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, HML_{t+1}) + \gamma_{RMW} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RMW_{t+1}) \\
+\gamma_{CMA} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, CMA_{t+1}),
\end{aligned} \tag{6}
$$

where RMW and CMA stand for their profitability and investment factors, respectively. As a reference point, we also estimate the baseline CAPM from Sharpe (1964) and Lintner (1965).

2.2 Data

The data on RM, SMB, HML, UMD, RMW, and CMA are obtained from Kenneth French's data library. LIQ is retrieved from Robert Stambaugh's webpage, while ME, IA, and ROE were provided by Lu Zhang. The data on the industry-adjusted factors (HML^*, UMD^*, and PMU^*) are obtained from Robert Novy-Marx's webpage. The sample used in this study is from 1972:01 to 2012:12, where the ending date is constrained by the availability of the Novy-Marx's industry-adjusted factors. The starting date is restricted by the availability of data on the portfolios sorted on investment-to-assets and return on equity.

The descriptive statistics for the equity factors are displayed in Table 1 (Panel A). UMD shows the highest mean (0.71% per month), followed by UMD^* and ROE, both with means around 0.60% per month. The factor with the lowest average is SMB (0.19% per month), followed by PMU^*, ME, and RMW, all with means around 0.30% per month. The factors that exhibit the highest volatility are the market equity premium and the standard momentum factor, with standard deviations around or above 4.5% per month. The least volatile factors are HML^* and PMU^*, followed by the investment factors (IA and CMA), all with standard deviations below 2.0% per month. Most factors exhibit low serial correlation, as shown by the first-order autoregressive coefficients below 20% in nearly all cases. The industry-adjusted value factor shows the highest autocorrelation (0.24), followed by PMU^* and RMW (each with an autocorrelation of 0.18).

The pairwise correlations of the equity factors are presented in Table 2 (Panel A). Several factors are by construction (almost) mechanically correlated. This includes SMB and ME, HML and HML^*, UMD and UMD^*, and IA and CMA, all pairs with correlations above 0.80. The three profitability factors (PMU^*, ROE, and RMW) are also positively correlated, although the correlations have smaller magnitudes than in the other cases (below 0.70).

Among the other relevant correlations, HML is positively correlated with both investment factors (correlations around 0.70), and the same pattern holds for HML^*, albeit with a slightly smaller magnitude. On the other hand, ROE is positively correlated with both UMD and UMD^* (correlations around 0.50). Yet, both PMU^* and RMW do not show a similar pattern, thus suggesting that there exists relevant differences among the three alternative profitability factors.

2.3 Factor risk premia

We estimate the models presented above by using a relatively large cross-section of equity portfolio returns. The testing portfolios are deciles sorted on size, book-to-market, momentum, investment-to-assets, return on equity, operating profitability, and asset growth, for a total of 70 portfolios. All the portfolio return data are obtained from Kenneth French's website, except the investment-to-assets and return on equity deciles, which were obtained from Lu Zhang. To compute excess portfolio returns, we use the one-month T-bill rate, available from French's webpage. This choice of testing portfolios is natural since they generate a large spread in average returns. Moreover, these portfolios are (almost) mechanically related with the factors associated with the different models outlined above. Thus, we expect ex ante that most models will perform well in pricing this large cross-section of stock returns.

Moreover, these portfolios are related with some of the major patterns in cross-sectional returns or anomalies that are not explained by the baseline CAPM (hence the designation of "market anomalies"). These include the value anomaly, which represents the evidence that value stocks (stocks with high book-to-market ratios, (BM)) outperform growth stocks (low BM) (e.g. Rosenberg, Reid, and Lanstein (1985) and Fama and French (1992)). Return momentum refers to the evidence showing that stocks with high prior short-term returns outperform stocks with low prior returns (Jegadeesh and Titman (1993) and Fama and French (1996)). The investment anomaly can be broadly classified as a pattern in which stocks of firms that invest more exhibit lower average returns than the stocks of firms that invest less (Titman, Wei, and Xie (2004), Cooper, Gulen, and Schill (2008), Fama and French (2008), and Lyandres, Sun, and Zhang (2008)). The profitability-based cross-sectional pattern in stock returns indicates that more profitable firms earn higher average returns than less profitable firms (Haugen and Baker (1996), Jegadeesh and Livnat (2006), Balakrishnan, Bartov, and Faurel (2010), and Novy-Marx (2013)).

We estimate the multifactor models above by first-stage GMM (Hansen (1982) and Cochrane (2005)). This method uses equally-weighted moments (identity matrix as the GMM weighting matrix), which is equivalent to an OLS cross-sectional regression of average excess returns on factor covariances. Under this procedure, we do not need to have previous estimates of the individual portfolio covariances since these are implied in the GMM moment conditions.

The GMM system has $70 + K$ moment conditions, where the first 70 sample moments correspond to the pricing errors associated with the 70 testing portfolio returns, and K is the number of factors in each model. To illustrate, in the case of the HXZ4 model the moment conditions are as follows:

$$g_T(\mathbf{b}) \equiv \frac{1}{T}\sum_{t=0}^{T-1}\left\{\begin{array}{c}(R_{i,t+1}-R_{f,t+1})-\gamma(R_{i,t+1}-R_{f,t+1})\,(RM_{t+1}-\mu_M)\\ -\gamma_{ME}(R_{i,t+1}-R_{f,t+1})\,(ME_{t+1}-\mu_{ME})\\ -\gamma_{IA}(R_{i,t+1}-R_{f,t+1})\,(IA_{t+1}-\mu_{IA})\\ -\gamma_{ROE}(R_{i,t+1}-R_{f,t+1})\,(ROE_{t+1}-\mu_{ROE})\\ RM_{t+1}-\mu_M\\ ME_{t+1}-\mu_{ME}\\ IA_{t+1}-\mu_{IA}\\ ROE_{t+1}-\mu_{ROE}\end{array}\right. = \mathbf{0}.$$

$$i = 1, ..., 70, \tag{7}$$

In the system presented above, the last four moment conditions enable us to estimate the factor means. Hence, the estimated risk prices correct for the estimation error in the factor means, as in Cochrane (2005) (Chapter 13), Maio and Santa-Clara (2012), and Lioui and Maio (2014). There are $N-K$ overidentifying conditions ($N+K$ moments and $2\times K$ parameters to estimate). Full details on the GMM estimation procedure are presented in Maio and Santa-Clara (2012).

We do not include an intercept in the pricing equations for the 70 assets, since we want to impose the economic restrictions associated with each factor model. If the model is correctly specified, the intercept in the cross-sectional regression should be equal to zero. This means that assets with zero betas with respect to all the factors should have a zero risk premium relative to the risk-free rate.[2]

By defining the first 70 residuals from the GMM system above as the pricing errors associated with the 70 test assets, $\widehat{\alpha}_i, i = 1, ..., 70$, a goodness-of-fit measure (to evaluate the explanatory power of a given model for cross-sectional risk premia) is the cross-sectional

[2]Another reason for not including the intercept in the cross-sectional regressions is that often the market betas for equity portfolios are very close to one, creating a multicollinearity problem (see, for example, Jagannathan and Wang (2007)).

OLS coefficient of determination,

$$R^2_{OLS} = 1 - \frac{\mathrm{Var}_N(\hat{\alpha}_i)}{\mathrm{Var}_N(\overline{R_i - R_f})},$$

where $\mathrm{Var}_N(\cdot)$ represents the cross-sectional variance. R^2_{OLS} measures the proportion of the cross-sectional variance of average excess returns explained by the factors associated with a specific model.

The results for the cross-sectional tests are presented in Table 3. We can see that most risk price estimates are positive and statistically significant. The most notable exception is the risk price for HML within the FF5 model, which is negative and significant at the 5% level. Moreover, γ_{LIQ} is also estimated negatively with large significance (1% level). On the other hand, the risk price estimates associated with SMB within the FF3, C4, and PS4 models are also negative, but there is no statistical significance. The estimates for the market risk price vary between 2.37 (CAPM) and 5.88 (NM4). Thus, these estimates represent plausible values for the risk aversion coefficient of the average investor.

In terms of explanatory power, we have the usual result that the baseline CAPM cannot explain the cross-section of portfolio returns, as indicated by the negative R^2 estimate (-41%). This means that the CAPM performs worse than a model that predicts constant expected returns in the cross-section of equity portfolios. Both FF3 and PS4 do not outperform significantly the CAPM as these models also produce negative explanatory ratios. This result is consistent with the evidence in Maio (2014) and Hou, Xue, and Zhang (2014a, 2014b) that these two models perform poorly when it comes to price momentum and profitability related portfolios. On the other hand, both C4 and FF5 have a good explanatory power for the cross-section of 70 equity portfolios, with R^2 estimates of 64% and 54%, respectively. Nevertheless, the best performing models are NM4 and HXZ4, both with explanatory ratios above 70%.

Following Maio and Santa-Clara (2012), for a given multifactor model to be consistent with the ICAPM, the factor (other than the market) risk prices should obey sign restrictions in relation to the slopes from predictive time-series regressions containing the corresponding state variables. Specifically, if a state variable forecasts a decline in future aggregate returns, the risk price associated with the corresponding risk factor in the asset pricing equation should also be negative. The intuition is as follows: if asset i forecasts a decline in expected market returns (because it is positively correlated with a state variable that is negatively correlated with the future aggregate return) it pays well when the future market return is lower in average. Hence, such an asset provides a hedge against adverse changes in future market returns for a risk-averse investor, and thus it should earn a negative risk premium. A negative risk premium implies a negative risk price for the "hedging" factor given the assumption of a positive covariance with the innovation in the state variable.[3] Given the results discussed above, for the multifactor models to be compatible with the ICAPM, most state variables associated with the equity factors should forecast an increase in future market returns. The exceptions are the state variables associated with the liquidity factor and HML (this last one, only in the context of the FF5 model). On the other hand, given that the SMB risk price is not significant within the FF3, C4, and PS4 models, the size factor should not be a significant predictor of the equity premium if we want to achieve consistency with the ICAPM.

When future investment opportunities are measured by the second moment of aggregate returns, we have an opposite relation between the sign of the factor risk price and predictive slope in the time-series regressions. Specifically, if a state variable forecasts a decline in future aggregate stock volatility, the risk price associated with the corresponding factor should be positive. The intuition is as follows. If asset i forecasts a decline in future stock volatility, it delivers high returns when the future aggregate volatility is also low. Since a multiperiod risk-averse investor dislikes volatility (because it represents higher uncertainty in his future

[3]This argument is also consistent with Campbell's version of the ICAPM (Campbell (1993, 1996)) for a risk-aversion parameter above one, since in this model the factor risk prices are functions of the VAR predictive slopes associated with the state variables (see also Maio (2013b)).

wealth), such an asset does not provide a hedge for changes in future investment opportunities. Therefore, this asset should earn a positive risk premium, which implies a positive risk price. In the context of the results above, it follows that most state variables should forecast a decline in stock volatility. Again, the exceptions hold for the state variables associated with LIQ and HML (this one within FF5). Moreover, the state variable associated with SMB should not help to forecast market volatility in order for FF3, C4, and PS4 models to be compatible with the ICAPM.

3 Equity risk factors and future investment opportunities

In this section, we analyze the forecasting ability of the state variables associated with the equity factors for future market returns and stock volatility. Moreover, we assess whether the predictive slopes are consistent with the factor risk price estimates presented in the previous section.

3.1 State variables

We start by defining the state variables associated with the equity factors. Following Maio and Santa-Clara (2012), the state variables correspond to the cumulative sums on the factors. For example, in the case of IA, the cumulative sum is obtained as

$$CIA_t = \sum_{s=t-59}^{t} IA_s,$$

and similarly for the remaining factors. As in Maio and Santa-Clara (2012), we use the cumulative sum over the last 60 months since the total cumulative sum is in several cases close to non-stationary (auto-regressive coefficients around one). The first-difference in the state variables correspond approximately to the original factors. Thus, this definition tries to resemble the empirical ICAPM literature in which the risk factors correspond to autoregressive (or VAR) innovations (or in alternative, the first-difference) in the associated state variables (see, for example, Hahn and Lee (2006), Petkova (2006), Campbell and Vuolteenaho (2004), and Maio (2013a)).

The descriptive statistics for the state variables are displayed in Table 1 (Panel B). We can see that all the state variables are quite persistent as shown by the autocorrelation coefficients close to one. This characteristic is shared by most predictors employed in the return predictability literature (e.g., dividend yield, term spread, or the default spread). The momentum state variable ($CUMD$) has the higher mean (above 40%), while $CSMB$ is the least pervasive state variable with a mean of 15%, consistent with the results for the original factors.

The pairwise correlations among the state variables are presented in Table 2 (Panel B). Similarly to the evidence for the original factors, both $CHML$ and $CHML^*$ are strongly positively correlated with the investment state variables (CIA and $CCMA$). On the other hand, $CROE$ also shows a large positive correlation with both momentum state variables ($CUMD$ and $CUMD^*$). Figure 1 displays the time-series for the different equity state variables. We can see that most state variables exhibit substantial variation across the business cycle. We also observe a significant declining trend since the early 2000's for all state variables, which is especially evident in the case of the value and momentum state variables.

3.2 Forecasting the equity premium

We employ long-horizon predictive regressions to evaluate the forecasting power of the state variables for future market returns (e.g., Keim and Stambaugh (1986), Campbell (1987), Fama and French (1988, 1989)),

$$r_{t+1,t+q} = a_q + b_q z_t + u_{t+1,t+q}, \tag{8}$$

where $r_{t+1,t+q} \equiv r_{t+1} + ... + r_{t+q}$ is the continuously compounded excess return over q periods into the future (from $t+1$ to $t+q$). We use the log on the CRSP value-weighted market return in excess of the log one-month T-bill rate as the proxy for r. The sign of the slope coefficient, b_q, indicates whether a given state variable (z) forecasts positive or negative changes in future expected aggregate stock returns. We use forecasting horizons of 1, 3, 12, 24, 36, 48, and 60 months ahead. The original sample is 1976:12 to 2012:12, where the starting date is constrained by the lags used in the construction of the state variables. To evaluate the statistical significance of the regression coefficients, we use Newey and West (1987) asymptotic t-ratios with q lags, which enables us to correct for the serial correlation in the residuals caused by the overlapping returns.

The results for the univariate predictive regressions are presented in Table 4. We can see that $CPMU^*$ forecasts an increase in the future excess market return and this effect is statistically significant at intermediate horizons ($q = 12, 24$). A similar predictability pattern holds for $CRMW$, given that the respective slopes are positive and significant at the 12- and 24-month horizons. The univariate forecasting power associated with $CRMW$ is marginally higher in comparison to $CPMU^*$ as indicated by the adjusted R^2 estimates around 9% (compared to 6% for $CPMU^*$).

The other profitability state variable, $CROE$, is also positively correlated with the future market return, but this effect is more relevant at longer horizons as indicated by the significant coefficients at forecasting horizons beyond 24 months. The strongest forecasting power from $CROE$ occurs at the 60-month horizon with an R^2 of 18% and a slope that is significant at the 1% level. At the 24-month horizon, the coefficient for $CROE$ is marginally significant (10% level), but the explanatory ratio is higher than in the regression for $CRMW$ (11% versus 9%). Thus, the three profitability factors provide valuable information about future market returns. Moreover, the positive slopes for these state variables are consistent with the positive risk price estimates associated with PMU^*, ROE, and RMW, documented in the last section.

None of the remaining equity state variables are significant predictors of the equity premium at the 5% level. In the case of $CLIQ$, the slopes are negative and marginally significant (10% level) at long horizons, while the explanatory ratios are around 13%. These negative coefficients are, thus, consistent with the negative risk price estimate for the liquidity factor indicated above.

To assess the marginal forecasting power of each state variable within the respective multifactor model, we also conduct the following multivariate regressions:

$$r_{t+1,t+q} = a_q + b_q CSMB_t + c_q CHML_t + u_{t+1,t+q}, \tag{9}$$

$$r_{t+1,t+q} = a_q + b_q CSMB_t + c_q CHML_t + d_q CUMD_t + u_{t+1,t+q}, \tag{10}$$

$$r_{t+1,t+q} = a_q + b_q CSMB_t + c_q CHML_t + d_q CLIQ_t + u_{t+1,t+q}, \tag{11}$$

$$r_{t+1,t+q} = a_q + b_q CHML_t^* + c_q CUMD_t^* + d_q CPMU_t^* + u_{t+1,t+q}, \tag{12}$$

$$r_{t+1,t+q} = a_q + b_q CME_t + c_q CIA_t + d_q CROE_t + u_{t+1,t+q}, \tag{13}$$

$$r_{t+1,t+q} = a_q + b_q CSMB_t + c_q CHML_t + d_q CRMW_t + e_q CCMA_t + u_{t+1,t+q}. \tag{14}$$

The results for the multivariate regressions are presented in Table 5. To save space we only report results at the one-, 12-, and 60-month forecasting horizons. We can see that, conditional on both $CHML^*$ and $CPMU^*$, $CUMD^*$ predicts a decline in the equity premium at the one-month horizon. Thus, this estimate is inconsistent with the positive risk price associated with UMD^*. At the 12-month horizon, it turns out that $CPMU^*$ has significant marginal forecasting power for the market return, conditional on both $CHML^*$ and $CUMD^*$. A similar pattern holds for $CRMW$ conditional on $CSMB$, $CHML$, and $CCMA$. These results are thus consistent with the single regressions associated with $CPMU^*$ and $CRMW$ at the 12-month horizon. The forecasting power of the multiple regression associated with the FF5 model is marginally higher than that of the regression for NM4, as indicated by the R^2 of 10% (versus 8%).

At the 60-month horizon, the slope for $CROE$ is highly significant (1% level), confirming that the forecasting power of this profitability factor is robust to the presence of CME and CIA. This result is also in line with the univariate regression for $CROE$ at the 60-month horizon. At the longest horizon, the strongest amount of predictability is associated with the HZX4 model (R^2 of 18%) followed by the PS4 model (R^2 of 13%). Yet, the slope associated with $CLIQ$ is only marginally significant.

3.3 Forecasting stock market volatility

In this subsection, we assess whether the equity state variables forecast future stock market volatility. The proxy for the variance of the market return is the realized stock variance ($SVAR$), which is obtained from Amit Goyal's webpage. Following Maio and Santa-Clara (2012) and Paye (2012), we run predictive regressions of the type,

$$svar_{t+1,t+q} = a_q + b_q z_t + u_{t+1,t+q}, \tag{15}$$

where $svar_{t+1,t+q} \equiv svar_{t+1} + ... + svar_{t+q}$ and $svar_{t+1} \equiv \ln(SVAR_{t+1})$ is the log of the realized market volatility.

The results for the univariate predictive regressions associated with stock market volatility are presented in Table 6. There is stronger evidence of predictability for future stock volatility than for the market return across most state variables, as indicated by the number of significant slopes. $CSMB$ is negatively correlated with future stock volatility at short horizons (one and three months ahead). Thus, these estimates are consistent with the positive risk price for SMB within the FF5 model. A similar pattern holds for the other size state variable, CME, which is also compatible with the positive risk price associated with ME within the HXZ4 model. However, there is no consistency with the insignificant risk price estimates for SMB within the FF3, C4, and PS4 models.

The slopes associated with $CHML$ and $CHML^*$ are negative and statistically significant at horizons up to 12 months. The explanatory ratios are around 6%, thus indicating a larger forecasting power than the size factors. These estimates are thus inconsistent with the negative risk price estimate for HML within the FF5 model. However, we have consistency with the positive risk price estimates obtained in the FF3, C4, and PS4 models.

$CLIQ$ forecasts an increase in future market volatility and the respective slopes are significant at short horizons (one and three months ahead). Hence, these coefficients go in line with the negative risk price estimate for the liquidity factor. In contrast to the results for the predictive regressions associated with the equity premium, none of the three profitability factors is a significant predictor of stock volatility.

On the other hand, both investment factors are valid forecasters of market volatility. The slopes associated with both CIA and $CCMA$ are negative and statistically significant at most forecasting horizons. The exception is the longest horizon (60 months ahead) in which case none of the investment slopes is significant at the 5% level. We can also see that CIA outperforms $CCMA$ as the former factor produces higher R^2 estimates at all horizons. The largest forecasting power is achieved at the 24- and 36-month horizons with explanatory ratios around 22% for CIA, compared to estimates of 14% for $CCMA$. These negative slopes are compatible with the positive risk price estimates for IA and CMA within the HXZ4 and FF5 models, respectively.

Similarly to the market return, we conduct the following multiple regressions to assess the marginal forecasting ability for future market volatility:

$$svar_{t+1,t+q} = a_q + b_q CSMB_t + c_q CHML_t + u_{t+1,t+q}, \tag{16}$$

$$svar_{t+1,t+q} = a_q + b_q CSMB_t + c_q CHML_t + d_q CUMD_t + u_{t+1,t+q}, \tag{17}$$

$$svar_{t+1,t+q} = a_q + b_q CSMB_t + c_q CHML_t + d_q CLIQ_t + u_{t+1,t+q}, \tag{18}$$

$$svar_{t+1,t+q} = a_q + b_q CHML_t^* + c_q CUMD_t^* + d_q CPMU_t^* + u_{t+1,t+q}, \tag{19}$$

$$svar_{t+1,t+q} = a_q + b_q CME_t + c_q CIA_t + d_q CROE_t + u_{t+1,t+q}, \tag{20}$$

$$svar_{t+1,t+q} = a_q + b_q CSMB_t + c_q CHML_t + d_q CRMW_t + e_q CCMA_t + u_{t+1,t+q}. \tag{21}$$

The results for the multiple regressions are displayed in Table 7. The slopes associated with both $CHML$ and $CHML^*$ within the FF3, C4, PS4, and NM4 models are significantly negative at the one- and 12-month horizons, in line with the results from the corresponding univariate regressions. However, $CHML$ within the FF5 model is not significant at such forecasting horizons. At $q = 60$, $CHML$ helps to forecast an increase in stock market volatility, conditional on the other state variables of the FF5 model. Thus, this positive slope is consistent with the negative risk price for HML within the five-factor model.

The coefficient associated with $CSMB$ is significant at the one-month horizon in the regression associated with PS4, in line with the single regression. Yet, in the regressions associated with FF3, C4, and FF5 the slopes for the size state variable are not significant at any horizon (there is marginal significance in the regressions for FF3 and C4 at $q = 1$). $CLIQ$ is positively correlated with future stock volatility and the respective coefficients are significant at $q = 1$ and $q = 12$, in line with the single regressions for the liquidity state variable.

In contrast with the univariate regressions, $CUMD^*$ forecasts a significant decline in $SVAR$ at the 60-month horizon, which is compatible with the positive risk price estimate for UMD^*. As in the single regressions, CIA is negatively correlated with future stock volatility at the one- and 12-month horizons. On the other hand, the negative slopes for $CCMA$ are only significant at the longest horizon. Moreover, conditional on both CIA and $CROE$ the coefficients for CME are not significant at any forecasting horizon. Thus, the consistency criteria for the size factor within the HXZ4 model is not met in relation to the multiple regression.

Table 8 summarizes the results concerning the consistency between the risk price estimates and the corresponding slopes from the single predictive regressions. We define a given risk factor as being consistent with the ICAPM if the associated state variable forecasts one among the equity premium or stock volatility with the right sign (in relation to the respective risk price) and this estimate is statistically significant. If we restrict ourselves to the models that deliver a positive explanatory ratio for the large cross-section of stock returns, the HXZ4 model presents the best convergence with the ICAPM. The slopes associated with CME and CIA in the regressions for market volatility are consistent with the respective risk price estimates, while the coefficient for $CRMW$ in the regressions for the market return are in line with the corresponding risk price. In the case of C4, there is no consistency in the slopes associated with $CUMD$ for both r and $svar$, and the same happens with $CUMD^*$ within the NM4 model. Regarding the FF5 model, the consistency criteria is not met by $CHML$.

Both FF3 and PS4 are also compatible with the ICAPM. Yet, this comes as little aid as these models are useless to explain the extended cross-section of portfolio returns as shown in the last section. For most individual risk factors we observe consistency of the risk price estimates with the corresponding slopes for either the equity premium or market volatility. The exceptions are the two momentum factors and the value factor in the FF5 model, as referred before.

The summary of the consistency criteria based on the multiple forecasting regressions is presented in Table 9, which is identical to Table 8. The most salient fact is that the HXZ4 model does not meet anymore the consistency in sign across all three factors. The reason is that the size state variable CME is not a valid predictor of either the equity premium or $svar$ in the context of the multiple regressions. Nevertheless, as in the case of single regressions, the different versions of the investment and profitability factors are all consistent with the ICAPM. On the other hand, we do not consider the momentum factor associated with NM4 as satisfying the ICAPM criteria. The reason hinges on the fact that $CUMD^*$ predicts $svar$ with the correct sign, but is also correlated with future market returns with the wrong sign, and both slopes are statistically significant.

4 Equity risk factors and future economic activity

In this section, we investigate whether the equity state variables forecast future economic activity. The motivation for this exercise relies on the Roll's critique (Roll (1977)). Since the stock index is an imperfect proxy for aggregate wealth, changes in the future return on the unobservable wealth portfolio might be related with future economic activity. Specifically, several forms of non-financial wealth, like labor income, houses, or small businesses, are related with the business cycle, and hence, economic activity. Thus, analysing whether the state variables predict economic activity represents an alternative to the analysis of the predictability of the market return. This implies that, for a given state variable to be consistent with the ICAPM, the respective slope should have the same sign as the risk price for the associated factor. In related work, Boons (2014) evaluates the consistency of a typical ICAPM specification (including the term spread, default spread, and dividend yield) with the ICAPM, where investment opportunities are measured by economic activity.

As proxies for economic activity, we use the log growth in the industrial production index (IPG) and the Chicago FED National Activity Index ($CFED$). The data on both indexes are obtained from the St. Louis FED database (FRED). To assess the forecasting role of each state variable for economic activity, we run the following univariate regressions,

$$y_{t+1,t+q} = a_q + b_q z_t + u_{t+1,t+q}, \tag{22}$$

where $y \equiv IPG, CFED$ and $y_{t+1,t+q} \equiv y_{t+1} + ... + y_{t+q}$ denotes the forward cumulative sum in either IPG or $CFED$.

The results for the single predictive regressions associated with industrial production growth are presented in Table 10. We can see that both momentum state variables forecast a significant rise in industrial production growth at long horizons (48 and 60 months). However, $CUMD^*$ is negatively correlated with IPG at the one-month horizon (t-ratio around -2). Hence, while the slopes for $CUMD$ are consistent with the positive risk price for UMD, in the case of the other momentum factor we have an ambiguous relation since the predictive slopes have opposite signs at short and long horizons. The liquidity state variable forecasts a decline in output at long horizons, which is compatible with the negative risk price associated with LIQ. On the other hand, the significant negative slope for $CHML^*$ at the 60-month horizon is at odds with the positive risk price estimate for the Novy-Marx's value factor.

Consistent with the results for the market return regressions, $CROE$ predicts a significant increase in IPG for horizons beyond 12 months. Yet, unlike the case of the equity premium prediction, the other two profitability factors ($CPMU^*$ and $CRMW$) do not contain forecasting ability for industrial production growth as the associated coefficients are insignificant at all forecasting horizons. In contrast to the results for the market return, CIA is positively correlated with future output at short horizons, which goes in line with the positive risk price for IA. This result is in line with the evidence in Cooper and Priestley (2011) showing that alternative investment factors help to forecast industrial production at short horizons. It turns out that the investment and profitability state variables associated with the HXZ4 model complement each other: while CIA helps to forecast output at short horizons, $CROE$ has significant forecasting power at intermediate and long horizons. In comparison, we cannot find a similar pattern for the other investment state variable, $CCMA$. Actually, this variable forecasts a decline in IPG (significant at the 5% level) at the 60-month horizon, which goes gainst the positive risk price for CMA.

When we compare with the forecasting regressions associated with the equity premium, there is stronger evidence of predictability for future output from the equity state variables across most state variables. This can be confirmed by the greater number of significant coefficients and also by the higher R^2 estimates across most state variables and forecasting horizons. The greatest degree of predictability is associated with $CROE$ at long horizons, as indicated by the R^2 estimates around 40%, which represent more than twice the fit of the corresponding predictive regression for r at the 60-month horizon.

The results for the forecasting regressions associated with $CFED$ are presented in Table

11. Among the most salient differences relative to the regressions for IPG, we can see that $CHML$ is a significant predictor of the economic index at short and middle horizons ($q < 36$). Hence, the positive slopes are consistent with the positive estimates for γ_{HML} within FF3, C4, and PS4, but incompatible with the negative estimated risk price in the FF5 model. The coefficients associated with $CHML^*$ are also significantly positive for horizons up to 24 months. However, this state variable also forecasts a significant decline in $CFED$ at the 60-month horizon, making ambiguous the overall assessment of its predictive role.

Both $CUMD$ and $CUMD^*$ are significantly positively correlated with future economic activity, and thus, there is consistency with the corresponding positive risk price estimates. On the other hand, the predictive power from CIA is stronger than in the case of industrial production as the positive slopes are significant at all horizons less than 48 months. The largest forecasting power is achieved at the 12- an 24-month horizons with R^2 around 27%. Similarly, there is strong evidence of predictability associated with $CCMA$, in contrast with the evidence for IPG, as indicated by the significant positive slopes until $q = 24$. However, at the 60-month horizon the relation between $CCMA$ and future economic activity turns significantly negative, making the overall assessment ambiguous.

The summary of the consistency criteria based on the forecasting regressions for economic activity is presented in Table 12. We can see that several factors (UMD, LIQ, IA, and ROE) meet the consistency in sign with the respective slopes in the predictive regressions for both economic indicators. On the other hand, it turns out that several factors (HML within FF5, HML^*, PMU^*, CME, RMW, and CMA) do not satisfy the sign restriction (or this assessment is ambiguous) for neither economic activity indicator. In particular, when we compare with the results obtained for the equity premium regressions, it follows that both PMU^* and RMW cease to be consistent with the ICAPM if investment opportunities are measured by future business conditions. On the other hand, UMD, UMD^*, LIQ, and CIA are compatible with the ICAPM, in contrast to the findings based on the predictive slopes associated with the market return. When we combine the results for the forecasting regressions for economic activity and stock volatility (the two dimensions of investment opportunities), it follows that four models (FF3, C4, PS4, and HXZ4) satisfy the sign restriction for at least one among economic activity proxy and $svar$. However, both FF3 and PS4 have no explanatory power for the cross-section of stock returns as already referred. When we take all dimensions of the investment opportunity set together (market return, stock volatility, and economic activity) our results suggest that the HXZ4 model offers the best overall consistency with the ICAPM.

5 Relation with ICAPM state variables

In this section, we investigate if the forecasting ability of the equity state variables for future investment opportunities is linked to other state variables that are typically used in the empirical ICAPM literature. The motivation for this exercise comes from previous evidence that the SMB and HML factors are linked to traditional ICAPM state variables like the term or default spreads (e.g., Hahn and Lee (2006) and Petkova (2006)). Thus, we want to assess if the equity state variables remain significant predictors of either the equity premium or market volatility after controlling for these other predictors.

The control variables employed are the term spread ($TERM$), default spread (DEF), log market dividend yield (dp), one-month T-bill rate (TB), and value spread (vs). Several ICAPM applications have used innovations in these state variables as risk factors to price cross-sectional risk premia (e.g., Campbell and Vuolteenaho (2004), Hahn and Lee (2006), Petkova (2006), Maio (2013b), among others). $TERM$ represents the yield spread between the ten-year and the one-year Treasury bonds, and DEF is the yield spread between BAA and AAA corporate bonds from Moody's. The bond yield data are available from the St. Louis Fed Web page. TB stands for the one-month T-bill rate, available from Kenneth French's website. dp is computed as the log ratio of annual dividends to the level of the S&P 500 index. pe denotes the log price-earnings ratio associated with the same index, where the earnings measure is based on a 10-year moving average of annual earnings. The data on the price, dividends, and earnings are retrieved from Robert Shiller's website. Following Campbell and Vuolteenaho (2004), vs represents the difference in the log book-to-market ratios of small-value and small-growth portfolios, where the book-to-market data are from French's data library.

To accomplish our goal, we run the following multiple forecasting regressions for both the equity premium,

$$r_{t+1,t+q} = a_q + b_q z_t + c_q TERM_t + d_q DEF_t + e_q dp_t + f_q TB_t + g_q vs_t + h_q pe_t + u_{t+1,t+q}, \quad (23)$$

and market volatility:

$$svar_{t+1,t+q} = a_q + b_q z_t + c_q TERM_t + d_q DEF_t + e_q dp_t + f_q TB_t + g_q vs_t + h_q pe_t + u_{t+1,t+q}. \quad (24)$$

The results for the forecasting regressions associated with the market return and stock volatility are displayed in Tables 13 and 14, respectively. In the case of the equity premium prediction, we can see that the forecasting ability of all three profitability state variables is robust to the presence of the alternative predictors. Actually, this forecasting power increases for both $CPMU^*$ and $CRMW$ as the respective coefficients are statistically significant at more horizons. Moreover, both momentum state variables are now significantly positively correlated with future market returns at long horizons, in contrast to the evidence based on the corresponding single regressions. Therefore, the inclusion of the control variables clarifies the forecasting role of the momentum variables for the equity premium.

In the case of the stock volatility regressions we have a somewhat different picture than the equity premium prediction. The forecasting power from $CSMB$, CME, CIA, and $CCMA$ is maintained, or even reinforced, when we control by the alternative state variables. On the other hand, in the case of both momentum state variables, we observe a significant negative correlation with future $svar$ at intermediate and long horizons, in contrast with the results for the corresponding univariate regressions. A similar pattern holds for both $CPMU^*$ and $CRMW$, both of which forecast a significant decline in future stock volatility at several horizons (all horizons in the case of $CPMU^*$), in contrast with the evidence based on the single regressions. On the other hand, the slopes for $CROE$ are not significant at any forecasting horizon, as in the univariate case.

Regarding both value state variables and $CLIQ$, the respective slopes are also not significant at any horizon, which is at odds with the results from the single regressions. Therefore, these results suggest that the forecasting ability of the value and liquidity factors for market volatility is subsumed by the alternative predictors. In contrast, the predictive ability of the other state variables, including the different investment and profitability variables, does not seem to be subsumed by the traditional ICAPM state variables.

6 Conclusion

We evaluate whether equity factor models (in which all the factors are excess stock returns) are consistent with the Merton's Intertemporal CAPM framework (Merton (1973), ICAPM). We analyse six multifactor models, with especial emphasis given to the recent four-factor models proposed by Novy-Marx (2013) and Hou, Xue, and Zhang (2014a) and the five-factor model of Fama and French (2014a). Our results for the cross-sectional tests confirm that the new models of Novy-Marx (2013), Fama and French (2014a), and Hou, Xue, and Zhang (2014a) have a good explanatory power for the large cross-section of portfolio returns, whereas the factor models of Fama and French (1993) and Pástor and Stambaugh (2003) fail to explain cross-sectional risk premia. Most factor risk price estimates are positive and statistically significant, the exceptions being the risk price estimate for HML within the FF5 model and the liquidity risk price.

Following Maio and Santa-Clara (2012), we construct state variables associated with each factor that correspond to the past 60-month cumulative sum on the factors. The results for forecasting regressions corresponding to the excess market return at multiple horizons indicate that the state variables associated with the profitability factors employed in Novy-Marx (2013), Fama and French (2014a), and Hou, Xue, and Zhang (2014a) help to forecast the equity premium. Moreover, the positive predictive slopes are consistent with the positive risk prices for the corresponding factors. When it comes to forecast stock market volatility, several state variables forecast a significant decline in stock volatility, and thus, are consistent with the corresponding factor risk price estimates. This includes the state variables associated with the value factor employed in Novy-Marx (2013), the size and investment factors of Hou, Xue, and Zhang (2014a), and the investment factor used in Fama and French (2014a). Overall, the four-factor model of Hou, Xue, and Zhang (2014a) presents the best convergence with the ICAPM, when investment opportunities are measure by both the expected aggregate return and market volatility.

Furthermore, we evaluate if the equity state variables forecast future aggregate economic activity. Overall, the evidence of predictability for future economic activity is stronger than for the future market return, across most equity state variables. Specifically, the state variables associated with the liquidity factor, the momentum factor of Carhart (1997), and the investment and profitability factors of Hou, Xue, and Zhang (2014a) are valid forecasters of future economic activity. Moreover, this forecasting behavior is consistent with the corresponding risk price estimates in the asset pricing equations. Surprisingly, the state variables corresponding with the profitability factors of Novy-Marx (2013) and Fama and French (2014a) do not help to forecast business conditions, or do so in a way that is inconsistent with the ICAPM. These results suggest that despite the fact that the different versions of the investment and profitability factors employed in Novy-Marx (2013), Fama and French (2014a), and Hou, Xue, and Zhang (2014a) are highly correlated, they still differ significantly in terms of asset pricing implications.

We also assess if the forecasting ability of the equity state variables for future investment opportunities is linked to other state variables that are typically used in the empirical ICAPM literature. The results suggest that the predictive ability of most equity state variables, including the different investment and profitability variables, does not seem to be subsumed by the traditional ICAPM state variables. The exceptions are the state variables associated with the HML and liquidity factors.

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Table 1: Descriptive statistics for equity factors

This table reports descriptive statistics for the equity factors from alternative factor models. RM, SMB, HML, UMD, and LIQ denote the market, size, value, momentum, and liquidity factors, respectively. HML^*, UMD^*, and PMU^* represent the value, momentum, and profitability factors from Novy-Marx. ME, IA, and ROE denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. RMW and CMA denote the Fama-French profitability and investment factors, respectively. Panel B shows the descriptive statistics for the state variables associated with the equity factors. The sample is 1972:01–2012:12. ϕ designates the first-order autocorrelation coefficient.

	Mean (%)	Stdev. (%)	Min. (%)	Max. (%)	ϕ
			Panel A		
RM	0.48	4.64	−23.24	16.10	0.08
SMB	0.19	3.16	−16.39	22.02	0.01
HML	0.40	3.04	−12.68	13.83	0.15
UMD	0.71	4.51	−34.72	18.39	0.07
LIQ	0.47	3.59	−10.14	21.01	0.09
HML^*	0.43	1.49	−5.02	6.56	0.24
UMD^*	0.62	2.89	−23.38	12.18	0.10
PMU^*	0.27	1.18	−4.62	6.79	0.18
ME	0.30	3.17	−14.45	22.41	0.03
IA	0.45	1.89	−7.13	9.41	0.07
ROE	0.58	2.64	−13.85	10.39	0.10
RMW	0.30	2.27	−17.60	12.24	0.18
CMA	0.38	1.98	−6.76	8.93	0.13
			Panel B		
$CSMB$	15.01	29.23	−44.08	78.84	0.99
$CHML$	23.30	23.69	−42.12	93.44	0.98
$CUMD$	44.57	29.98	−31.29	108.31	0.99
$CLIQ$	30.50	28.65	−21.07	87.64	0.99
$CHML^*$	26.32	14.32	−11.84	59.07	0.99
$CUMD^*$	38.83	19.49	−18.51	82.65	0.99
$CPMU^*$	18.67	11.78	−13.69	46.01	0.98
CME	20.48	31.20	−41.86	89.21	0.99
CIA	25.62	15.45	−13.40	61.01	0.98
$CROE$	38.07	16.60	−6.79	62.95	0.98
$CRMW$	19.99	16.67	−24.07	78.32	0.98
$CCMA$	21.60	18.11	−11.35	77.39	0.99

Table 2: Correlations of equity factors

This table reports the pairwise correlations of the equity factors from alternative factor models. RM, SMB, HML, UMD, and LIQ denote the market, size, value, momentum, and liquidity factors, respectively. HML^*, UMD^*, and PMU^* represent the value, momentum, and profitability factors from Novy-Marx. ME, IA, and ROE denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. RMW and CMA denote the Fama-French profitability and investment factors, respectively. Panel B shows the correlations for the state variables associated with the equity factors. The sample is 1976:12–2012:12.

Panel A

	RM	SMB	HML	UMD	LIQ	HML^*	UMD^*	PMU^*	ME	IA	ROE	RMW	CMA
RM	1.00	0.28	−0.32	−0.14	−0.03	−0.19	−0.19	−0.29	0.25	−0.37	−0.18	−0.23	−0.40
SMB		1.00	−0.23	−0.01	−0.02	−0.03	−0.08	−0.28	0.95	−0.23	−0.39	−0.44	−0.12
HML			1.00	−0.15	0.04	0.81	−0.19	−0.08	−0.07	0.69	−0.09	0.15	0.70
UMD				1.00	−0.04	−0.13	0.95	0.25	0.00	0.04	0.50	0.09	0.02
LIQ					1.00	0.07	−0.04	0.00	−0.04	0.03	−0.08	0.02	0.04
HML^*						1.00	−0.18	−0.22	0.09	0.55	−0.22	−0.01	0.61
UMD^*							1.00	0.28	−0.07	0.02	0.52	0.12	−0.01
PMU^*								1.00	−0.26	0.03	0.59	0.68	−0.03
ME									1.00	−0.12	−0.31	−0.38	−0.01
IA										1.00	0.06	0.10	0.90
ROE											1.00	0.67	−0.09
RMW												1.00	−0.03
CMA													1.00

Panel B

	$CSMB$	$CHML$	$CUMD$	$CLIQ$	$CHML^*$	$CUMD^*$	$CPMU^*$	CME	CIA	$CROE$	$CRMW$	$CCMA$
$CSMB$	1.00	0.28	0.12	0.28	0.15	−0.08	−0.29	0.97	0.15	−0.28	−0.28	0.23
$CHML$		1.00	0.03	0.40	0.89	0.06	−0.11	0.38	0.68	−0.05	−0.02	0.70
$CUMD$			1.00	−0.22	0.18	0.94	0.06	0.16	0.34	0.63	−0.12	0.19
$CLIQ$				1.00	0.40	−0.16	0.24	0.28	0.19	−0.34	0.25	0.39
$CHML^*$					1.00	0.29	0.19	0.24	0.79	0.09	0.18	0.82
$CUMD^*$						1.00	0.25	−0.04	0.41	0.70	0.08	0.26
$CPMU^*$							1.00	−0.28	0.14	0.26	0.87	0.22
CME								1.00	0.22	−0.34	−0.31	0.34
CIA									1.00	0.25	0.17	0.91
$CROE$										1.00	0.33	−0.07
$CRMW$											1.00	0.20
$CCMA$												1.00

Table 3: Factor risk premiums for equity risk factors

This table reports estimates of factor risk premiums associated with alternative multifactor models. The estimation procedure is first-stage GMM with equally weighted errors. The testing assets are decile portfolios sorted on size, book-to-market, momentum, investment-to-assets, return on equity, operating profitability, and asset growth, for a total of 70 portfolios. γ represents the risk price for the market factor. γ_{SMB}, γ_{HML}, γ_{UMD}, and γ_{LIQ} represent the risk prices associated with the size, value, momentum, and liquidity factors, respectively. γ_{HML^*}, γ_{UMD^*}, and γ_{PMU^*} denote the value, momentum, and profitability factor risk prices from Novy-Marx. γ_{ME}, γ_{IA}, and γ_{ROE} stand for the risk prices associated with the Hou-Xue-Zhang size, investment, and profitability factors, respectively. γ_{RMW} and γ_{CMA} denote the Fama-French profitability and investment factor risk prices, respectively. The first line associated with each model presents the covariance risk price estimates, while the second line reports the robust t-statistics (in parentheses). The column R^2 denotes the OLS cross-sectional coefficient of determination. The sample is 1972:01–2012:12. Underlined and bold numbers denote statistical significance at the 5% and 1% levels, respectively.

Model	γ	γ_{SMB}	γ_{HML}	γ_{UMD}	γ_{LIQ}	γ_{HML^*}	γ_{UMD^*}	γ_{PMU^*}	γ_{ME}	γ_{IA}	γ_{ROE}	γ_{RMW}	γ_{CMA}	R^2
CAPM	2.37													−0.41
	(2.29)													
FF3	3.36	−1.07	4.03											−0.20
	(**2.96**)	(−0.62)	(2.25)											
C4	4.85	−0.28	7.93	5.22										0.64
	(**3.65**)	(−0.17)	(**4.15**)	(**3.51**)										
PS4	3.24	−1.25	4.33		−9.32									−0.15
	(**2.59**)	(−0.68)	(2.07)		(−**2.77**)									
NM4	5.88					23.27	6.82	16.97						0.77
	(**3.99**)					(**4.70**)	(**2.67**)	(2.07)						
HXZ4	4.43								5.37	13.25	10.56			0.74
	(**3.39**)								(2.57)	(**3.71**)	(**3.60**)			
FF5	5.33	5.46	−7.38									16.57	23.27	0.54
	(**3.96**)	(**2.75**)	(−2.08)									(**5.18**)	(**4.06**)	

Table 4: Single predictive regressions: equity premium

This table reports the results associated with single long-horizon predictive regressions for the excess stock market return, at horizons of 1, 3, 12, 24, 36, 48, and 60 months ahead. The forecasting variables are state variables associated with alternative equity factors. $CSMB$, $CHML$, $CRMW$, and $CCMA$ denote the Fama-French size, value, profitability, and investment factors, respectively. $CUMD$ and $CLIQ$ refer to the momentum and liquidity factors. $CHML^*$, $CUMD^*$, and $CPMU^*$ represent respectively the value, momentum, and profitability factors from Novy-Marx. CME, CIA, and $CROE$ denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. The original sample is 1976:12–2012:12, and q observations are lost in each of the respective q-horizon regressions. For each regression, in line 1 are reported the slope estimates whereas line 2 presents Newey-West t-ratios (in parentheses) computed with q lags. T-ratios marked with * and ** denote statistical significance at the 5% and 1% levels, respectively. R^2 denotes the adjusted coefficient of determination.

	$q=1$	$q=3$	$q=12$	$q=24$	$q=36$	$q=48$	$q=60$
$CSMB$	−0.00	−0.01	−0.10	0.02	0.01	0.01	−0.04
	(−0.15)	(−0.39)	(−0.16)	(0.25)	(0.06)	(0.07)	(−0.17)
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$CHML$	0.00	0.01	0.08	0.12	0.12	−0.09	−0.19
	(0.07)	(0.28)	(1.03)	(0.70)	(0.41)	(−0.25)	(−0.54)
R^2	0.00	0.00	0.01	0.02	0.01	0.01	0.02
$CUMD$	−0.01	−0.03	−0.04	0.01	0.16	0.31	0.25
	(−1.37)	(−1.33)	(−0.47)	(0.06)	(0.76)	(1.38)	(1.21)
R^2	0.00	0.01	0.01	0.00	0.02	0.06	0.03
$CLIQ$	−0.00	−0.01	−0.03	−0.07	−0.20	−0.33	−0.36
	(−0.59)	(−0.60)	(−0.38)	(−0.58)	(−1.29)	(−1.90)	(−1.90)
R^2	0.00	0.00	0.00	0.01	0.05	0.12	0.13
$CHML^*$	0.01	0.02	0.12	0.21	0.18	−0.16	−0.47
	(0.37)	(0.50)	(0.86)	(0.74)	(0.39)	(−0.25)	(−0.73)
R^2	0.00	0.00	0.01	0.01	0.01	0.00	0.04
$CUMD^*$	−0.02	−0.05	−0.08	−0.01	0.17	0.50	0.51
	(−1.55)	(−1.55)	(−0.58)	(−0.04)	(0.45)	(1.21)	(1.35)
R^2	0.01	0.01	0.01	0.00	0.01	0.05	0.04
$CPMU^*$	0.03	0.08	0.33	0.43	0.31	0.07	−0.01
	(1.44)	(1.89)	(2.11*)	(2.19*)	(1.23)	(0.19)	(−0.03)
R^2	0.00	0.01	0.06	0.06	0.02	0.00	0.00
CME	−0.00	−0.01	−0.02	0.01	0.00	−0.03	−0.11
	(−0.42)	(−0.72)	(−0.36)	(0.17)	(0.01)	(−0.17)	(−0.48)
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.01
CIA	0.01	0.05	0.21	0.31	0.30	0.16	−0.08
	(0.81)	(1.00)	(1.23)	(1.16)	(0.93)	(0.38)	(−0.14)
R^2	0.00	0.01	0.04	0.04	0.03	0.01	0.00
$CROE$	0.00	0.02	0.21	0.47	0.64	0.67	0.88
	(0.22)	(0.61)	(1.47)	(1.91)	(2.45*)	(2.39*)	(2.96**)
R^2	0.00	0.00	0.04	0.11	0.13	0.12	0.18
$CRMW$	0.01	0.05	0.28	0.38	0.23	0.01	0.05
	(1.09)	(1.81)	(2.18*)	(2.06*)	(1.31)	(0.03)	(0.25)
R^2	0.00	0.01	0.08	0.09	0.02	0.00	0.00
$CCMA$	0.01	0.02	0.08	0.14	0.12	−0.10	−0.34
	(0.40)	(0.53)	(0.71)	(0.85)	(0.49)	(−0.26)	(−0.79)
R^2	0.00	0.00	0.01	0.01	0.01	0.00	0.04

Table 5: Multiple predictive regressions: equity premium

This table reports the results associated with multiple long-horizon predictive regressions for the excess stock market return, at horizons of 1, 12, and 60 months ahead. The forecasting variables are state variables associated with alternative equity factors. $CSMB$, $CHML$, $CRMW$, and $CCMA$ denote the Fama-French size, value, profitability, and investment factors, respectively. $CUMD$ and $CLIQ$ refer to the momentum and liquidity factors. $CHML^*$, $CUMD^*$, and $CPMU^*$ represent respectively the value, momentum, and profitability factors from Novy-Marx. CME, CIA, and $CROE$ denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. The original sample is 1976:12–2012:12, and q observations are lost in each of the respective q-horizon regressions. For each regression, in line 1 are reported the slope estimates whereas line 2 presents Newey-West t-ratios (in parentheses) computed with q lags. T-ratios marked with * and ** denote statistical significance at the 5% and 1% levels, respectively. R^2 denotes the adjusted coefficient of determination.

Row	$CSMB$	$CHML$	$CUMD$	$CLIQ$	$CHML^*$	$CUMD^*$	$CPMU^*$	CME	CIA	$CROE$	$CRMW$	$CCMA$	R^2
							Panel A ($q = 1$)						
1	−0.00	0.00											−0.00
	(−0.17)	(0.12)											
2	−0.00	0.00	−0.01										−0.00
	(−0.02)	(0.12)	(−1.37)										
3	−0.00	0.00		−0.00									−0.00
	(−0.06)	(0.32)		(−0.57)									
4					0.01	−0.02	0.03						0.01
					(0.62)	(−2.09*)	(1.81)						
5								−0.01	0.02	−0.01			−0.00
								(−0.72)	(0.94)	(−0.39)			
6	0.00	−0.00									0.01	0.00	−0.00
	(0.10)	(−0.10)									(0.98)	(0.17)	
							Panel B ($q = 12$)						
1	−0.03	0.09											0.01
	(−0.47)	(1.07)											
2	−0.03	0.09	−0.03										0.01
	(−0.39)	(1.10)	(−0.38)										
3	−0.02	0.12		−0.06									0.02
	(−0.28)	(1.19)		(−0.68)									
4					0.08	−0.15	0.37						0.08
					(0.65)	(−1.20)	(2.50*)						
5								−0.01	0.18	0.16			0.06
								(−0.12)	(1.05)	(1.08)			
6	0.03	0.13									0.32	−0.11	0.10
	(0.38)	(1.02)									(2.52*)	(−0.62)	
							Panel C ($q = 60$)						
1	0.00	−0.19											0.02
	(0.01)	(−0.65)											
2	−0.05	−0.09	0.22										0.04
	(−0.23)	(−0.34)	(1.29)										
3	0.06	0.04		−0.40									0.13
	(0.42)	(0.14)		(−1.90)									
4					−0.32	0.44	−0.08						0.06
					(−0.49)	(1.70)	(−0.19)						
5								0.09	−0.04	0.97			0.18
								(0.55)	(−0.09)	(4.79**)			
6	0.03	0.00									0.16	−0.39	0.04
	(0.18)	(0.00)									(0.85)	(−1.34)	

Table 6: Single predictive regressions: stock market volatility

This table reports the results associated with single long-horizon predictive regressions for the stock market variance, at horizons of 1, 3, 12, 24, 36, 48, and 60 months ahead. The forecasting variables are state variables associated with alternative equity factors. $CSMB$, $CHML$, $CRMW$, and $CCMA$ denote the Fama-French size, value, profitability, and investment factors, respectively. $CUMD$ and $CLIQ$ refer to the momentum and liquidity factors. $CHML^*$, $CUMD^*$, and $CPMU^*$ represent respectively the value, momentum, and profitability factors from Novy-Marx. CME, CIA, and $CROE$ denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. The original sample is 1976:12–2012:12, and q observations are lost in each of the respective q-horizon regressions. For each regression, in line 1 are reported the slope estimates whereas line 2 presents Newey-West t-ratios (in parentheses) computed with q lags. T-ratios marked with * and ** denote statistical significance at the 5% and 1% levels, respectively. R^2 denotes the adjusted coefficient of determination.

	$q=1$	$q=3$	$q=12$	$q=24$	$q=36$	$q=48$	$q=60$
$CSMB$	−0.43	−1.17	−4.02	−5.48	−3.37	1.94	11.50
	(−3.10**)	(−2.37*)	(−1.37)	(−0.70)	(−0.25)	(0.10)	(0.49)
R^2	0.02	0.02	0.02	0.01	0.00	0.00	0.02
$CHML$	−0.88	−2.55	−8.33	−10.35	−4.76	8.18	16.04
	(−5.19**)	(−4.36**)	(−2.41*)	(−0.97)	(−0.25)	(0.31)	(0.58)
R^2	0.06	0.07	0.06	0.03	0.00	0.01	0.02
$CUMD$	0.09	0.18	−1.68	−7.33	−15.19	−21.85	−15.29
	(0.50)	(0.27)	(−0.46)	(−0.78)	(−1.03)	(−1.10)	(−0.63)
R^2	0.00	0.00	0.00	0.02	0.04	0.05	0.02
$CLIQ$	0.61	1.83	7.37	14.20	21.32	27.51	28.98
	(3.26**)	(2.47*)	(1.60)	(1.37)	(1.42)	(1.47)	(1.46)
R^2	0.04	0.05	0.08	0.09	0.12	0.14	0.13
$CHML^*$	−1.33	−3.97	−15.38	−24.78	−22.28	−4.44	15.88
	(−3.76**)	(−3.14**)	(−2.42*)	(−1.41)	(−0.74)	(−0.11)	(0.36)
R^2	0.05	0.06	0.07	0.05	0.02	0.00	0.01
$CUMD^*$	0.22	0.51	−2.53	−13.57	−32.68	−58.05	−57.68
	(0.77)	(0.48)	(−0.44)	(−0.86)	(−1.23)	(−1.70)	(−1.86)
R^2	0.00	0.00	0.00	0.03	0.06	0.11	0.09
$CPMU^*$	0.44	0.76	−4.64	−15.41	−18.62	−11.30	7.31
	(1.06)	(0.47)	(−0.47)	(−0.74)	(−0.71)	(−0.40)	(0.27)
R^2	0.00	0.00	0.01	0.02	0.02	0.00	0.00
CME	−0.41	−1.14	−3.89	−5.58	−4.04	1.48	10.96
	(−3.23**)	(−2.49*)	(−1.42)	(−0.76)	(−0.32)	(0.08)	(0.51)
R^2	0.02	0.02	0.03	0.02	0.01	0.00	0.02
CIA	−1.67	−5.18	−21.23	−42.02	−56.01	−58.21	−40.13
	(−4.41**)	(−3.71**)	(−3.23**)	(−3.52**)	(−3.54**)	(−2.43*)	(−1.30)
R^2	0.09	0.12	0.18	0.22	0.21	0.13	0.04
$CROE$	0.14	0.10	−4.23	−14.43	−25.79	−31.62	−32.28
	(0.44)	(0.09)	(−0.60)	(−0.78)	(−0.90)	(−0.93)	(−0.88)
R^2	0.00	0.00	0.01	0.03	0.04	0.04	0.04
$CRMW$	0.45	0.89	−2.90	−12.17	−16.76	−14.43	−10.09
	(1.46)	(0.77)	(−0.42)	(−0.79)	(−0.92)	(−0.76)	(−0.49)
R^2	0.01	0.00	0.00	0.02	0.02	0.01	0.01
$CCMA$	−0.97	−3.07	−13.28	−27.53	−37.05	−34.94	−20.07
	(−3.12**)	(−2.63**)	(−2.25*)	(−2.56*)	(−2.56*)	(−1.66)	(−0.77)
R^2	0.04	0.06	0.10	0.14	0.14	0.08	0.02

Table 7: Multiple predictive regressions: stock market volatility

This table reports the results associated with multiple long-horizon predictive regressions for the stock market variance, at horizons of 1, 12, and 60 months ahead. The forecasting variables are state variables associated with alternative equity factors. $CSMB$, $CHML$, $CRMW$, and $CCMA$ denote the Fama-French size, value, profitability, and investment factors, respectively. $CUMD$ and $CLIQ$ refer to the momentum and liquidity factors. $CHML^*$, $CUMD^*$, and $CPMU^*$ represent respectively the value, momentum, and profitability factors from Novy-Marx. CME, CIA, and $CROE$ denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. The original sample is 1976:12–2012:12, and q observations are lost in each of the respective q-horizon regressions. For each regression, in line 1 are reported the slope estimates whereas line 2 presents Newey-West t-ratios (in parentheses) computed with q lags. T-ratios marked with * and ** denote statistical significance at the 5% and 1% levels, respectively. R^2 denotes the adjusted coefficient of determination.

Row	$CSMB$	$CHML$	$CUMD$	$CLIQ$	$CHML^*$	$CUMD^*$	$CPMU^*$	CME	CIA	$CROE$	$CRMW$	$CCMA$	R^2
							Panel A ($q = 1$)						
1	−0.24	−0.80											0.06
	(−1.80)	(−4.42**)											
2	−0.26	−0.79	0.14										0.06
	(−1.86)	(−4.43**)	(0.77)										
3	−0.45	−1.29		1.17									0.18
	(−2.97**)	(−7.15**)		(5.93**)									
4					−1.60	0.46	0.63						0.06
					(−4.52**)	(1.62)	(1.81)						
5								−0.14	−1.73	0.45			0.10
								(−1.06)	(−4.22**)	(1.44)			
6	−0.16	−0.56									0.46	−0.48	0.07
	(−1.20)	(−1.62)									(1.64)	(−0.88)	
							Panel B ($q = 12$)						
1	−2.31	−7.45											0.07
	(−0.95)	(−2.33*)											
2	−2.03	−7.70	−1.80										0.07
	(−0.77)	(−2.39*)	(−0.51)										
3	−4.57	−13.09		12.88									0.26
	(−1.52)	(−4.73**)		(2.91**)									
4					−15.06	−0.64	−1.06						0.07
					(−2.20*)	(−0.12)	(−0.14)						
5								−2.01	−19.99	−1.44			0.18
								(−1.01)	(−3.02**)	(−0.25)			
6	−2.40	−1.46									−1.61	−10.76	0.10
	(−0.98)	(−0.23)									(−0.32)	(−1.09)	
							Panel C ($q = 60$)						
1	8.68	12.41											0.03
	(0.44)	(0.59)											
2	12.18	5.13	−16.06										0.05
	(0.64)	(0.20)	(−0.61)										
3	4.03	−4.96		29.65									0.13
	(0.25)	(−0.34)		(1.89)									
4					−12.54	−71.70	32.07						0.11
					(−0.23)	(−1.96*)	(0.75)						
5								10.45	−48.91	−24.73			0.10
								(0.50)	(−1.54)	(−0.85)			
6	11.57	52.50									12.48	−77.29	0.17
	(0.59)	(2.16*)									(0.78)	(−2.66**)	

Table 8: Consistency of factors with the ICAPM: single regressions

This table reports the consistency of the factor risk prices from multifactor models with the ICAPM. The criteria represents the consistency in sign of the risk prices of the hedging factors with the corresponding predictive slopes in predictive single regressions of the state variables over the excess market return (Panel A) and the market variance (Panel B). $CSMB$, $CHML$, $CRMW$, and $CCMA$ denote the Fama-French size, value, profitability, and investment factors, respectively. $CUMD$ and $CLIQ$ refer to the momentum and liquidity factors. $CHML^*$, $CUMD^*$, and $CPMU^*$ represent respectively the value, momentum, and profitability factors from Novy-Marx. CME, CIA, and $CROE$ denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. A "✓" indicates that there is consistency in sign and both the risk price and slope are statistically significant. "×" means that either the slope or risk price estimates are not significant, while "××" indicates a situation in which both estimates are significant but have conflicting signs. "?" corresponds to an ambiguous comparison.

Model	$CSMB$	$CHML$	$CUMD$	$CLIQ$	$CHML^*$	$CUMD^*$	$CPMU^*$	CME	CIA	$CROE$	$CRMW$	$CCMA$
Panel A (r)												
FF3	✓	×										
C4	✓	×	×									
PS4	✓	×		×								
NM4					×	×	✓					
HXZ4								×	×	✓		
FF5	×	×									✓	×
Panel B ($svar$)												
FF3	×	✓										
C4	×	✓	×									
PS4	×	✓		✓								
NM4					✓	×	×					
HXZ4								✓	✓	×		
FF5	✓	×									×	✓

Table 9: Consistency of factors with the ICAPM: multiple regressions

This table reports the consistency of the factor risk prices from multifactor models with the ICAPM. The criteria represents the consistency in sign of the risk prices of the hedging factors with the corresponding predictive slopes in predictive multiple regressions of the state variables over the excess market return (Panel A) and the market variance (Panel B). $CSMB$, $CHML$, $CRMW$, and $CCMA$ denote the Fama-French size, value, profitability, and investment factors, respectively. $CUMD$ and $CLIQ$ refer to the momentum and liquidity factors. $CHML^*$, $CUMD^*$, and $CPMU^*$ represent respectively the value, momentum, and profitability factors from Novy-Marx. CME, CIA, and $CROE$ denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. A "✓" indicates that there is consistency in sign and both the risk price and slope are statistically significant. "×" means that either the slope or risk price estimates are not significant, while "××" indicates a situation in which both estimates are significant but have conflicting signs. "?" corresponds to an ambiguous comparison.

Model	$CSMB$	$CHML$	$CUMD$	$CLIQ$	$CHML^*$	$CUMD^*$	$CPMU^*$	CME	CIA	$CROE$	$CRMW$	$CCMA$
Panel A (r)												
FF3	✓	×										
C4	✓	×	×									
PS4	✓	×		×								
NM4					×	××	✓					
HXZ4								×	×	✓		
FF5	×	×									✓	×
Panel B ($svar$)												
FF3	✓	✓										
C4	✓	✓	×									
PS4	×	✓		✓								
NM4					✓	✓	×					
HXZ4								×	✓	×		
FF5	×	✓									×	✓

Table 10: Single predictive regressions: industrial production growth

This table reports the results associated with single long-horizon predictive regressions for the growth in industrial production, at horizons of 1, 3, 12, 24, 36, 48, and 60 months ahead. The forecasting variables are state variables associated with alternative equity factors. $CSMB$, $CHML$, $CRMW$, and $CCMA$ denote the Fama-French size, value, profitability, and investment factors, respectively. $CUMD$ and $CLIQ$ refer to the momentum and liquidity factors. $CHML^*$, $CUMD^*$, and $CPMU^*$ represent respectively the value, momentum, and profitability factors from Novy-Marx. CME, CIA, and $CROE$ denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. The original sample is 1976:12–2012:12, and q observations are lost in each of the respective q-horizon regressions. For each regression, in line 1 are reported the slope estimates whereas line 2 presents Newey-West t-ratios (in parentheses) computed with q lags. T-ratios marked with * and ** denote statistical significance at the 5% and 1% levels, respectively. R^2 denotes the adjusted coefficient of determination.

	$q=1$	$q=3$	$q=12$	$q=24$	$q=36$	$q=48$	$q=60$
$CSMB$	−0.00	−0.00	−0.02	−0.03	−0.04	−0.06	−0.08
	(−0.33)	(−0.48)	(−0.88)	(−0.99)	(−0.95)	(−1.12)	(−1.17)
R^2	0.00	0.00	0.01	0.02	0.03	0.05	0.08
$CHML$	0.00	0.00	0.01	0.02	−0.05	−0.13	−0.18
	(0.70)	(0.72)	(0.75)	(0.44)	(−0.81)	(−1.43)	(−1.94)
R^2	0.00	0.00	0.01	0.00	0.02	0.11	0.21
$CUMD$	−0.00	−0.00	0.01	0.05	0.11	0.18	0.16
	(−1.24)	(−1.10)	(0.30)	(0.82)	(1.67)	(2.50*)	(2.25*)
R^2	0.00	0.00	0.00	0.04	0.11	0.22	0.14
$CLIQ$	−0.00	−0.01	−0.02	−0.05	−0.09	−0.15	−0.18
	(−1.50)	(−1.50)	(−1.21)	(−1.06)	(−1.49)	(−2.33*)	(−2.74**)
R^2	0.01	0.01	0.03	0.04	0.11	0.27	0.33
$CHML^*$	0.00	0.01	0.03	0.05	−0.05	−0.19	−0.35
	(1.39)	(1.36)	(1.04)	(0.81)	(−0.56)	(−1.36)	(−2.03*)
R^2	0.00	0.01	0.01	0.01	0.01	0.07	0.21
$CUMD^*$	−0.00	−0.01	−0.00	0.06	0.17	0.34	0.31
	(−2.02*)	(−1.93)	(−0.02)	(0.66)	(1.42)	(2.26*)	(2.11*)
R^2	0.01	0.01	0.00	0.02	0.10	0.23	0.16
$CPMU^*$	0.00	0.00	0.07	0.15	0.17	0.12	0.08
	(0.14)	(0.37)	(1.33)	(1.76)	(1.87)	(0.82)	(0.42)
R^2	0.00	0.00	0.04	0.08	0.07	0.03	0.01
CME	−0.00	−0.00	−0.02	−0.03	−0.05	−0.07	−0.10
	(−0.46)	(−0.60)	(−0.98)	(−1.04)	(−1.12)	(−1.44)	(−1.59)
R^2	0.00	0.00	0.01	0.02	0.04	0.08	0.13
CIA	0.01	0.02	0.08	0.11	0.07	0.00	−0.17
	(2.16*)	(1.96*)	(1.59)	(1.50)	(1.14)	(0.01)	(−1.17)
R^2	0.02	0.05	0.08	0.07	0.02	0.00	0.05
$CROE$	−0.00	−0.00	0.05	0.18	0.31	0.37	0.42
	(−0.36)	(−0.08)	(1.20)	(2.04*)	(3.73**)	(4.83**)	(5.11**)
R^2	0.00	0.00	0.04	0.19	0.35	0.38	0.42
$CRMW$	−0.00	−0.00	0.04	0.11	0.11	0.05	0.04
	(−0.46)	(−0.19)	(1.08)	(1.55)	(1.82)	(0.49)	(0.31)
R^2	0.00	0.00	0.03	0.08	0.06	0.01	0.00
$CCMA$	0.00	0.01	0.04	0.04	−0.01	−0.10	−0.24
	(1.59)	(1.47)	(1.17)	(0.81)	(−0.25)	(−1.22)	(−2.30*)
R^2	0.01	0.02	0.03	0.01	0.00	0.04	0.20

Table 11: Single predictive regressions: Chicago FED Index

This table reports the results associated with single long-horizon predictive regressions for the Chicago FED National Activity Index, at horizons of 1, 3, 12, 24, 36, 48, and 60 months ahead. The forecasting variables are state variables associated with alternative equity factors. $CSMB$, $CHML$, $CRMW$, and $CCMA$ denote the Fama-French size, value, profitability, and investment factors, respectively. $CUMD$ and $CLIQ$ refer to the momentum and liquidity factors. $CHML^*$, $CUMD^*$, and $CPMU^*$ represent respectively the value, momentum, and profitability factors from Novy-Marx. CME, CIA, and $CROE$ denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. The original sample is 1976:12–2012:12, and q observations are lost in each of the respective q-horizon regressions. For each regression, in line 1 are reported the slope estimates whereas line 2 presents Newey-West t-ratios (in parentheses) computed with q lags. T-ratios marked with * and ** denote statistical significance at the 5% and 1% levels, respectively. R^2 denotes the adjusted coefficient of determination.

	$q=1$	$q=3$	$q=12$	$q=24$	$q=36$	$q=48$	$q=60$
$CSMB$	0.08	0.11	−0.70	−1.50	−1.59	−3.74	−6.47
	(0.36)	(0.13)	(−0.17)	(−0.20)	(−0.16)	(−0.30)	(−0.41)
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.01
$CHML$	0.83	2.48	9.35	12.85	1.92	−16.87	−33.12
	(4.64**)	(3.98**)	(2.81**)	(2.06*)	(0.18)	(−0.99)	(−1.79)
R^2	0.04	0.06	0.07	0.05	0.00	0.04	0.16
$CUMD$	0.02	0.10	3.37	13.80	31.72	51.13	50.34
	(0.12)	(0.19)	(0.88)	(1.30)	(2.35*)	(3.10**)	(3.03**)
R^2	0.00	0.00	0.01	0.08	0.21	0.37	0.33
$CLIQ$	−0.21	−0.67	−2.91	−5.52	−12.71	−24.56	−31.90
	(−1.12)	(−0.97)	(−0.71)	(−0.58)	(−0.92)	(−1.53)	(−2.05*)
R^2	0.00	0.01	0.01	0.01	0.05	0.15	0.23
$CHML^*$	1.59	4.81	18.54	28.69	12.92	−23.12	−67.91
	(4.53**)	(3.67**)	(2.75**)	(2.39*)	(0.70)	(−0.85)	(−2.11*)
R^2	0.06	0.08	0.09	0.07	0.01	0.02	0.19
$CUMD^*$	−0.09	−0.23	3.15	18.58	48.85	86.35	83.47
	(−0.49)	(−0.36)	(0.60)	(1.14)	(2.01*)	(2.64**)	(2.66**)
R^2	0.00	0.00	0.00	0.05	0.17	0.32	0.28
$CPMU^*$	−0.44	−0.86	5.75	19.10	22.99	9.98	−8.85
	(−0.83)	(−0.43)	(0.49)	(0.91)	(1.15)	(0.42)	(−0.27)
R^2	0.00	0.00	0.01	0.03	0.03	0.00	0.00
CME	0.08	0.14	−0.43	−1.08	−2.16	−6.02	−10.48
	(0.43)	(0.20)	(−0.12)	(−0.16)	(−0.25)	(−0.57)	(−0.75)
R^2	0.00	0.00	0.00	0.00	0.00	0.01	0.03
CIA	2.24	6.92	27.59	45.80	46.72	31.84	−13.33
	(5.29**)	(4.25**)	(3.30**)	(3.34**)	(3.49**)	(1.32)	(−0.50)
R^2	0.13	0.19	0.26	0.27	0.17	0.05	0.01
$CROE$	0.10	0.54	9.55	35.21	65.72	80.59	90.10
	(0.37)	(0.54)	(1.26)	(1.93)	(3.05**)	(3.65**)	(4.23**)
R^2	0.00	0.00	0.03	0.16	0.34	0.38	0.45
$CRMW$	−0.41	−0.92	3.89	15.96	17.91	4.87	−6.38
	(−1.18)	(−0.70)	(0.46)	(0.95)	(1.15)	(0.30)	(−0.31)
R^2	0.01	0.00	0.01	0.04	0.03	0.00	0.00
$CCMA$	1.40	4.29	16.43	24.29	18.82	−0.95	−36.33
	(4.31**)	(3.45**)	(2.56*)	(2.45*)	(1.67)	(−0.06)	(−2.02*)
R^2	0.07	0.10	0.13	0.11	0.04	0.00	0.11

Table 12: Consistency of factors with the ICAPM: economic activity

This table reports the consistency of the factor risk prices from multifactor models with the ICAPM. The criteria represents the consistency in sign of the risk prices of the hedging factors with the corresponding predictive slopes in predictive single regressions of the state variables for the growth in industrial production (Panel A) and the Chicago FED National Activity Index (Panel B). $CSMB$, $CHML$, $CRMW$, and $CCMA$ denote the Fama-French size, value, profitability, and investment factors, respectively. $CUMD$ and $CLIQ$ refer to the momentum and liquidity factors. $CHML^*$, $CUMD^*$, and $CPMU^*$ represent respectively the value, momentum, and profitability factors from Novy-Marx. CME, CIA, and $CROE$ denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. A "✓" indicates that there is consistency in sign and both the risk price and slope are statistically significant. "×" means that either the slope or risk price estimates are not significant, while "××" indicates a situation in which both estimates are significant but have conflicting signs. "?" corresponds to an ambiguous comparison.

Model	$CSMB$	$CHML$	$CUMD$	$CLIQ$	$CHML^*$	$CUMD^*$	$CPMU^*$	CME	CIA	$CROE$	$CRMW$	$CCMA$
Panel A (IPG)												
FF3	✓	×										
C4	✓	×	✓									
PS4	✓	×		✓								
NM4					××	?	×					
HXZ4								×	✓	✓		
FF5	×	×									×	××
Panel B ($CFED$)												
FF3	✓	✓										
C4	✓	✓	✓									
PS4	✓	✓		✓								
NM4					?	✓	×					
HXZ4								×	✓	✓		
FF5	×	×									×	?

Table 13: Predictive regressions for equity premium: controls

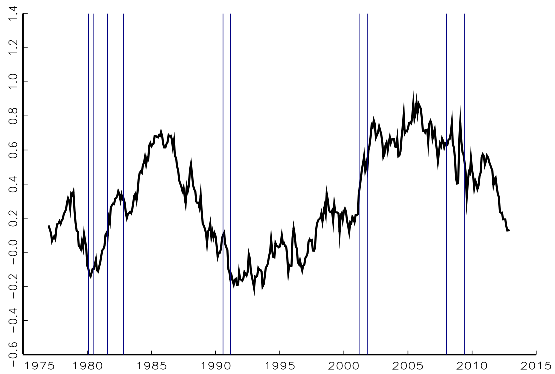
This table reports the results associated with long-horizon predictive regressions for the excess stock market return, at horizons of 1, 3, 12, 24, 36, 48, and 60 months ahead. The forecasting variables are state variables associated with alternative equity factors. $CSMB$, $CHML$, $CRMW$, and $CCMA$ denote the Fama-French size, value, profitability, and investment factors, respectively. $CUMD$ and $CLIQ$ refer to the momentum and liquidity factors. $CHML^*$, $CUMD^*$, and $CPMU^*$ represent respectively the value, momentum, and profitability factors from Novy-Marx. CME, CIA, and $CROE$ denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. Each regression contains the following predictors as controls: term spread ($TERM$), default spread (DEF), log dividend yield (dp), one-month T-bill rate (TB), value spread (vs), and smoothed log price-to-earnings ratio (pe). The original sample is 1976:12–2012:12, and q observations are lost in each of the respective q-horizon regressions. For each regression, in line 1 are reported the slope estimates whereas line 2 presents Newey-West t-ratios (in parentheses) computed with q lags. T-ratios marked with * and ** denote statistical significance at the 5% and 1% levels, respectively. R^2 denotes the adjusted coefficient of determination.

	$q=1$	$q=3$	$q=12$	$q=24$	$q=36$	$q=48$	$q=60$
$CSMB$	0.00	−0.01	0.03	0.16	0.18	0.22	0.12
	(0.16)	(−0.30)	(0.36)	(1.46)	(1.20)	(1.24)	(0.60)
R^2	−0.00	0.02	0.15	0.30	0.44	0.51	0.56
$CHML$	−0.01	−0.03	−0.04	0.06	0.17	−0.12	−0.10
	(−0.62)	(−0.78)	(−0.48)	(0.39)	(0.82)	(−0.43)	(−0.70)
R^2	−0.00	0.02	0.15	0.28	0.42	0.49	0.55
$CUMD$	−0.01	−0.01	0.02	0.10	0.31	0.39	0.25
	(−0.74)	(−0.59)	(0.23)	(0.75)	(2.21*)	(2.39*)	(1.55)
R^2	−0.00	0.02	0.15	0.29	0.47	0.54	0.57
$CLIQ$	−0.00	−0.01	−0.04	0.02	−0.20	−0.09	0.29
	(−0.11)	(−0.21)	(−0.32)	(0.11)	(−1.18)	(−0.79)	(1.56)
R^2	−0.00	0.02	0.15	0.28	0.43	0.49	0.57
$CHML^*$	0.01	0.02	0.04	0.25	0.50	0.23	0.05
	(0.38)	(0.36)	(0.26)	(0.86)	(1.39)	(0.52)	(0.16)
R^2	−0.00	0.02	0.15	0.29	0.44	0.49	0.55
$CUMD^*$	−0.01	−0.03	−0.01	0.09	0.32	0.60	0.68
	(−0.98)	(−0.89)	(−0.07)	(0.43)	(1.57)	(2.68**)	(2.25*)
R^2	0.00	0.02	0.15	0.28	0.44	0.52	0.59
$CPMU^*$	0.07	0.23	0.84	1.18	1.06	0.84	1.15
	(2.83**)	(3.70**)	(3.15**)	(5.74**)	(3.54**)	(2.01*)	(3.26**)
R^2	0.01	0.07	0.31	0.47	0.53	0.55	0.64
CME	−0.00	−0.02	0.01	0.16	0.21	0.18	0.06
	(−0.33)	(−0.79)	(0.18)	(1.58)	(1.46)	(1.07)	(0.39)
R^2	−0.00	0.00	0.15	0.30	0.45	0.50	0.55
CIA	0.02	0.08	0.23	0.27	0.23	−0.06	−0.29
	(1.10)	(1.39)	(1.00)	(1.07)	(1.27)	(−0.36)	(−0.96)
R^2	0.00	0.03	0.17	0.30	0.43	0.49	0.56
$CROE$	0.01	0.06	0.35	0.63	0.61	0.27	0.44
	(0.62)	(1.32)	(1.76)	(2.61**)	(2.80**)	(0.99)	(1.42)
R^2	−0.00	0.03	0.20	0.38	0.49	0.50	0.58
$CRMW$	0.02	0.09	0.40	0.56	0.35	0.15	0.36
	(1.63)	(2.67**)	(2.47*)	(3.24**)	(2.21*)	(0.68)	(1.86)
R^2	0.00	0.04	0.26	0.40	0.46	0.49	0.58
$CCMA$	0.01	0.03	0.07	0.14	0.22	−0.05	−0.21
	(0.48)	(0.62)	(0.44)	(0.74)	(1.24)	(−0.22)	(−0.74)
R^2	−0.00	0.02	0.15	0.28	0.43	0.49	0.56

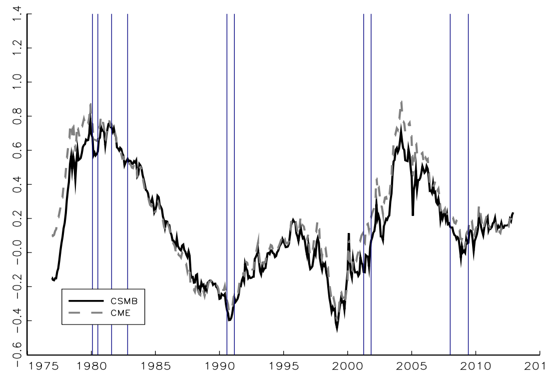
Table 14: Predictive regressions for stock market volatility: controls

This table reports the results associated with long-horizon predictive regressions for the stock market variance, at horizons of 1, 3, 12, 24, 36, 48, and 60 months ahead. The forecasting variables are state variables associated with alternative equity factors. $CSMB$, $CHML$, $CRMW$, and $CCMA$ denote the Fama-French size, value, profitability, and investment factors, respectively. $CUMD$ and $CLIQ$ refer to the momentum and liquidity factors. $CHML^*$, $CUMD^*$, and $CPMU^*$ represent respectively the value, momentum, and profitability factors from Novy-Marx. CME, CIA, and $CROE$ denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. Each regression contains the following predictors as controls: term spread ($TERM$), default spread (DEF), log dividend yield (dp), one-month T-bill rate (TB), value spread (vs), and smoothed log price-to-earnings ratio (pe). The original sample is 1976:12–2012:12, and q observations are lost in each of the respective q-horizon regressions. For each regression, in line 1 are reported the slope estimates whereas line 2 presents Newey-West t-ratios (in parentheses) computed with q lags. T-ratios marked with * and ** denote statistical significance at the 5% and 1% levels, respectively. R^2 denotes the adjusted coefficient of determination.

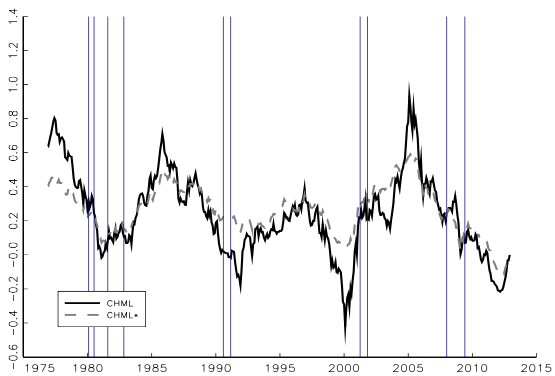
	$q=1$	$q=3$	$q=12$	$q=24$	$q=36$	$q=48$	$q=60$
$CSMB$	−1.13	−3.07	−11.83	−20.55	−17.56	−3.81	19.26
	(−5.85**)	(−4.85**)	(−3.61**)	(−3.00**)	(−1.80)	(−0.33)	(1.56)
R^2	0.35	0.41	0.49	0.58	0.61	0.63	0.62
$CHML$	−0.20	−0.47	−3.02	−4.30	7.67	22.16	17.72
	(−0.66)	(−0.42)	(−0.66)	(−0.31)	(0.42)	(1.46)	(1.15)
R^2	0.28	0.35	0.40	0.49	0.57	0.64	0.60
$CUMD$	0.07	−0.11	−4.56	−13.27	−18.69	−7.82	11.39
	(0.36)	(−0.17)	(−1.98*)	(−3.17**)	(−3.08**)	(−0.69)	(0.75)
R^2	0.28	0.35	0.42	0.54	0.61	0.63	0.60
$CLIQ$	0.10	0.33	2.25	6.89	18.22	15.91	1.18
	(0.36)	(0.34)	(0.46)	(0.74)	(1.61)	(1.14)	(0.08)
R^2	0.28	0.35	0.40	0.50	0.59	0.64	0.59
$CHML^*$	−0.09	−0.55	−8.58	−26.03	−35.21	−38.90	−45.34
	(−0.19)	(−0.34)	(−1.19)	(−1.13)	(−1.05)	(−1.33)	(−1.54)
R^2	0.28	0.35	0.41	0.51	0.59	0.64	0.61
$CUMD^*$	0.31	0.34	−6.93	−23.45	−41.04	−50.23	−38.19
	(1.06)	(0.33)	(−1.76)	(−3.01**)	(−6.89**)	(−3.95**)	(−2.30*)
R^2	0.29	0.35	0.41	0.55	0.64	0.66	0.61
$CPMU^*$	−1.08	−4.86	−32.91	−66.57	−80.92	−77.57	−56.04
	(−2.08*)	(−2.62**)	(−2.95**)	(−3.02**)	(−3.62**)	(−3.69**)	(−2.15*)
R^2	0.29	0.38	0.52	0.65	0.70	0.71	0.63
CME	−0.94	−2.53	−10.64	−20.52	−20.32	−7.39	13.92
	(−5.19**)	(−4.22**)	(−3.74**)	(−3.22**)	(−2.12*)	(−0.66)	(1.21)
R^2	0.33	0.40	0.48	0.59	0.62	0.63	0.61
CIA	−0.38	−1.89	−13.75	−37.69	−59.53	−67.68	−69.84
	(−0.91)	(−1.25)	(−1.70)	(−2.55*)	(−4.05**)	(−4.45**)	(−2.63**)
R^2	0.29	0.36	0.44	0.59	0.68	0.71	0.64
$CROE$	0.91	1.65	−1.98	−9.22	−9.25	6.71	20.11
	(2.37*)	(1.26)	(−0.26)	(−0.61)	(−0.52)	(0.39)	(0.97)
R^2	0.30	0.35	0.40	0.50	0.57	0.63	0.60
$CRMW$	−0.19	−1.28	−11.78	−26.69	−34.44	−35.99	−36.52
	(−0.66)	(−1.33)	(−1.94)	(−2.06*)	(−2.92**)	(−4.62**)	(−3.11**)
R^2	0.28	0.35	0.44	0.57	0.64	0.68	0.64
$CCMA$	−0.22	−1.17	−10.71	−32.44	−58.63	−78.02	−88.05
	(−0.66)	(−0.99)	(−1.76)	(−2.73**)	(−4.70**)	(−7.67**)	(−5.11**)
R^2	0.28	0.35	0.43	0.59	0.72	0.77	0.73



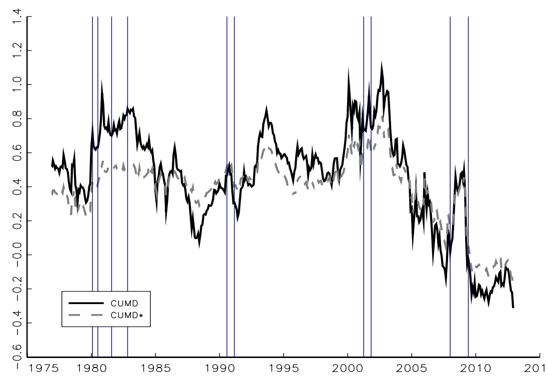
Panel A ($CLIQ$)



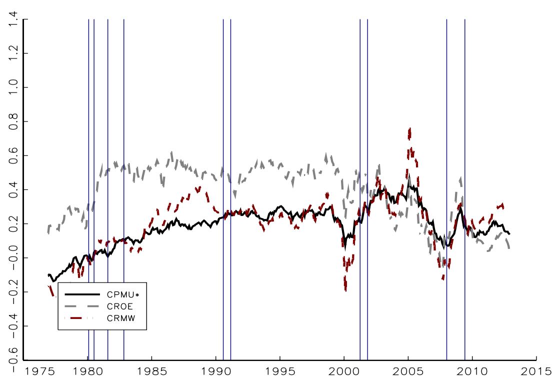
Panel B ($CSMB$, CME)



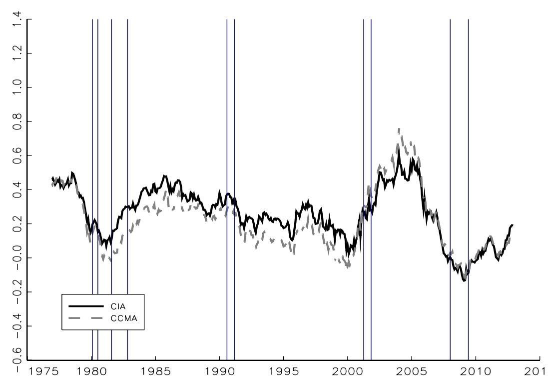
Panel C ($CHML$, $CHML^*$)



Panel D ($CUMD$, $CUMD^*$)



Panel E ($CPMU^*$, $CROE$, $CRMW$)



Panel F (CIA, $CCMA$)

Figure 1: Equity state variables

This figure plots the time-series for the state variables associated with alternative equity factors. $CSMB$, $CHML$, $CRMW$, and $CCMA$ denote the Fama-French size, value, profitability, and investment factors, respectively. $CUMD$ and $CLIQ$ refer to the momentum and liquidity factors. $CHML^*$, $CUMD^*$, and $CPMU^*$ represent respectively the value, momentum, and profitability factors from Novy-Marx. CME, CIA, and $CROE$ denote the Hou-Xue-Zhang size, investment, and profitability factors, respectively. The sample is 1976:12–2012:12. The vertical lines indicate the NBER recession periods.