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Asset growth, profitability, and investment opportunities

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Abstract

We show that recent prominent equity factor models are to a large degree compatible with the Merton's (1973) Intertemporal CAPM (ICAPM) framework. Factors associated with alternative profitability measures forecast the equity premium in a way that is consistent with the ICAPM. Several factors based on firms' asset growth predict a significant decline in stock market volatility, thus being consistent with their positive prices of risk. The investment-based factors are also strong predictors of an improvement in future economic activity. The time-series predictive ability of most equity state variables is not subsumed by traditional ICAPM state variables. Importantly, factors that earn larger risk prices tend to be associated with state variables that are more correlated with future investment opportunities or economic activity. Moreover, these risk price estimates can be reconciled with plausible risk aversion parameter estimates. Therefore, the ICAPM can be used as a common theoretical background for recent multifactor models.

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 challenging 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 of Sharpe (1964) and Lintner (1965) (see, for example, Hou, Xue, and Zhang (2015) and Fama and French (2015, 2016)). 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 of Fama and French (1993, 1996)) have difficulties in explaining the new market anomalies (see, for example, Fama and French (2015) and Hou, Xue, and Zhang (2015, 2017)). In response to this evidence, recent years have witnessed the emergence of new multifactor models containing (different versions of) investment and profitability factors (e.g., Novy-Marx (2013), Fama and French (2015), and Hou, Xue, and Zhang (2015)) 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 are still some open questions about the theoretical background of such models. Specifically, the models proposed by Fama and French (2015, 2016) and Hou, Xue, and Zhang (2015, 2017) both contain profitability and investment (or asset growth) risk factors. However, while Fama and French (2015) motivate their five-factor model based on the present-value valuation model of Miller and Modigliani (1961), Hou, Xue, and Zhang (2015) rely on the q-theory of investment. Thus, it should be relevant to analyze whether there is a common theoretical background that legitimates these two (and other) factor models. In fact, an ongoing debate in the finance literature concerns the interpretation of the cross sectional patterns in stock returns and the equity-based factors models built to explain them. Researchers are still in disagreement over whether the association between firm characteristics and returns reflect risk or mispricing. That is, whether the characteristics themselves are the driving force of the cross sectional patterns, or whether these characteristics proxy for covariances with risk factors that investors require a premium for holding. The Intertemporal CAPM (ICAPM) of Merton (1973) is one of the pillars of rational asset pricing. Therefore, testing whether a factor model that summarizes well the cross section of stock returns is also consistent with the ICAPM predictions is important and contributes to the ongoing debate.[1]

In this paper, we assess whether equity factor models (in which all the factors are excess stock returns) are consistent with the Merton's ICAPM. We analyze four multifactor models: the four-factor models proposed by Novy-Marx (2013) (NM4) and Hou, Xue, and Zhang (2015) (HXZ4), the five-factor model of Fama and French (2015) (FF5), and a restricted version of FF5 that excludes the HML factor (FF4). These four models have in common the fact that they contain different versions of investment and profitability factors with the aim of explaining more CAPM anomalies in the cross-section of stock returns.

Following Merton (1973), 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 expected 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. The intuition is as follows: if asset i forecasts a decline in expected future investment opportunities (lower expected return or higher volatility) it pays well when future investment opportunities are worse. Hence, such an asset provides a hedge against adverse changes in future investment

[1] For example, Fama and French (2015, page 3) write in regard to their new five factor model: "The more ambitious interpretation proposes (5) as the regression equation for a version of Merton's (1973) model in which up to four unspecified state variables lead to risk premiums that are not captured by the market factor."

opportunities for a risk-averse investor, and thus it should earn a negative risk premium, which translates into a negative risk price for the "hedging" factor.[2]

We estimate the models indicated above by using a relatively large cross-section of equity portfolio returns. The testing portfolios are deciles sorted on size, book-to-market, momentum, return on equity, operating profitability, asset growth, accruals, and net share issues for a total of 80 portfolios. Employing a large cross-section enables us to obtain more stable risk price estimates and is consistent with the mission of the new factor models in terms of explaining more market anomalies than the traditional value and momentum anomalies. Our results for the cross-sectional tests confirm that the new models of Novy-Marx (2013), Fama and French (2015), and Hou, Xue, and Zhang (2015) have a large explanatory power for the large cross-section of portfolio returns, in line with the evidence presented in Fama and French (2015, 2016) and Hou, Xue, and Zhang (2015, 2017). Most factor risk price estimates are positive and statistically significant. The main exception is the SMB factor in which case the risk price estimates are not statistically significant.

Following Maio and Santa-Clara (2012), we construct state variables associated with each factor that correspond to the past 60-month rolling sum on the factors.[3] The results for forecasting regressions of 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 (2015), and Hou, Xue, and Zhang (2015) 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. In particular, the state variables associated with the investment factors of Hou, Xue, and Zhang (2015) and Fama and French (2015) predict a significant decline in stock volatility at multiple forecasting horizons, and hence, are consistent with the ICAPM framework.

Table 1 summarizes the results concerning the consistency between the risk price estimates and the corresponding slopes from the multiple predictive regressions for the equity premium and stock volatility. We define a given risk factor as being consistent with the ICAPM if the associated

[2] 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.

[3] In the ICAPM, the factors are the innovations in the state variables. Hence, we construct the state variables such that their innovations (or changes) correspond approximately to the original equity factor returns.

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. We can see that the different versions of the investment and profitability factors are all consistent with the ICAPM. The reason is that each of these variables forecast at least one dimension of future investment opportunities with the correct sign. Specifically, the three profitability state variables forecast an increase in the market return, while the two investment state variables predict a decline in future stock volatility. This entails consistency with the positive risk prices estimates for the corresponding profitability and investment factors. Thus, these two factor categories complement each other in terms of forecasting future investment opportunities within the HXZ4 and FF5 (FF4) models.

The two models that achieve the best global convergence with the ICAPM are NM4 and FF4 in the sense that each of the three factors predict either the equity premium or stock volatility with the correct sign. In the case of FF4, the insignificant slopes for the size state variable (in terms of forecasting either dimension of investment opportunities) are compatible with the corresponding insignificant risk price estimates for SMB. None of the other two models satisfy completely the sign restrictions in order to be fully consistent with the ICAPM. Specifically, the size factor within HXZ4 does not meet the consistency criteria, and the same happens to HML in the five-factor model. However, it is well known that these two factors play a relatively minor role in terms of explaining cross-sectional equity risk premia in these two models (see Hou, Xue, and Zhang (2015) and Fama and French (2015, 2016)).[4] This implies that the partial inconsistency of these two models with the ICAPM is not particularly relevant from an empirical perspective.

We also evaluate if the equity state variables forecast future aggregate economic activity, which is measured by the growth in industrial production and the Chicago FED index of 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. Overall, the evidence of predictability for future economic activity is stronger than for the future excess market return, across most equity state variables. In fact, while the investment state variables do not provide relevant information for the future

[4] Fama and French (2015, 2016) show that HML becomes redundant in the five-factor model.

stock market returns, they do help to forecast an increase in future economic activity. Moreover, the profitability factor from the Hou, Xue, and Zhang (2015) model also helps to predict positive business conditions, although this result is not as robust as for the investment factors. These results provide additional evidence that the investment and profitability factors associated with the models of Novy-Marx (2013), Fama and French (2015, 2016), and Hou, Xue, and Zhang (2015) proxy for different dimensions of future investment opportunities.

Further, we assess if the forecasting ability of the equity state variables for future investment opportunities is linked to traditional ICAPM state variables. The results from multiple forecasting regressions suggest that the predictive ability of most equity state variables, and specifically the different investment and profitability variables, does not seem to be subsumed by the alternative ICAPM state variables. In other words, the investment and profitability state variables proxy for components of the investment opportunity set not captured by the other state variables. Moreover, cross-sectional tests of augmented ICAPM specifications indicate that the investment and profitability factors remain priced in the presence of those traditional ICAPM factors.

In the last part of the paper, we discuss the magnitudes of the predictive slopes and risk price estimates. Our results suggest that factors that earn larger risk prices tend to be associated with state variables that are more correlated with future investment opportunities or economic activity, in line with the ICAPM prediction. In addition to the sign consistency documented in most of the paper, this represents another type of consistency with the ICAPM that takes into account the size of both the risk prices and predictive slopes. Furthermore, we consider the ICAPM frameworks of Campbell and Vuolteenaho (2004) and Campbell, Giglio, Polk, and Turley (2017), which take into account explicitly the relationship between the magnitudes of the predictive slopes and both the risk prices and structural parameters. The results show that these ICAPM specifications, when based on the equity state variables studied in the paper, produce reasonable estimates of the underlying risk aversion parameter in most cases (between 2 and 4).

This study is related to the work of Maio and Santa-Clara (2012). The key innovation relative to that study is that we analyze the consistency with the ICAPM of the recent multifactor models that represent the new workhorses in the asset pricing literature (e.g., the models of Fama and French (2015) and Hou, Xue, and Zhang (2015)). In related work, Lutzenberger (2015) extends the analysis in Maio and Santa-Clara (2012) for the European stock market. On the other hand, Boons

(2016) evaluates the consistency with the ICAPM, when investment opportunities are measured by broad economic activity, however, that study does not cover equity-based factors (which represent our focus).[5] This paper is also related to the recent studies that estimate and conduct horse-races among the alternative factor models in terms of explaining a broad cross-section of stock returns (e.g., Hou, Xue, and Zhang (2015, 2017), Fama and French (2016), Maio (2017), and Cooper and Maio (2016)). We deviate from these studies by focusing on the consistency of the (factor risk prices from) new factor models with the ICAPM rather than evaluating their explanatory power for cross-sectional equity risk premia.

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, while Section 5 looks at the relationship between the equity factors and traditional ICAPM variables. In Section 6, we discuss the role of magnitudes. Finally, Section 7 concludes.

2 Cross-sectional tests and factor risk premia

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

[5] In a study subsequent to the first draft of our paper, Barbalau, Robotti, and Shanken (2015) also look at the consistency of equity factor models with the ICAPM by testing inequality constraints. There are several key distinctions between that study and ours. First, Barbalau, Robotti, and Shanken (2015) use only one dimension of investment opportunities (the market return), while we also consider other dimensions of the investment opportunity set like market volatility or economic activity. Previous studies have shown the importance of considering these other dimensions when testing the ICAPM (e.g., Maio and Santa-Clara (2012), Campbell, Giglio, Polk, and Turley (2017), Boons (2016)). Indeed, as stated above, our results show that the state variables associated with the investment factors forecast stock volatility in a way that is consistent with the ICAPM. Our results also indicate strong forecasting power for future economic activity. Second, among the new factor models Barbalau, Robotti, and Shanken (2015) only analyze the five-factor model of Fama and French (2015). In contrast, we also evaluate the factor models of Novy-Marx (2013) and Hou, Xue, and Zhang (2015), which also contain investment and profitability factors. In fact, as referred above, our results show that there are some relevant differences in the performance of the alternative investment and profitability state variables in terms of forecasting future investment opportunities, in particular economic activity. Third, we obtain the risk price estimates by forcing the factor models to price simultaneously a broad cross-section of stock returns, while Barbalau, Robotti, and Shanken (2015) rely on portfolios sorted on BM and momentum in isolation. In fact, the results provided in Maio and Santa-Clara (2012) show that the factor risk price estimates can change both in magnitude and sign between tests based on BM and momentum portfolios. This makes the consistency with the ICAPM quite dependent on the testing assets used in the asset price tests. We overcome this problem by forcing the models to price jointly several market anomalies. Finally, we asses the role of magnitudes of the non-market factor risk prices as another consistency criteria with the ICAPM.

2.1 Models

We evaluate the consistency of four multifactor models with the Merton's ICAPM (Merton (1973)), which contain different versions of asset growth and profitability factors. Common to these models is the fact that all the factors represent excess stock returns or the returns on tradable equity portfolios.

The first model is the four-factor model of Novy-Marx (2013) (NM4),

$$\begin{aligned} \mathrm{E}(R_{i,t+1} - R_{f,t+1}) &= \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) + \gamma_{HML^*} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, HML^*_{t+1}) \\ &+ \gamma_{UMD} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, UMD_{t+1}) + \gamma_{PMU} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, PMU_{t+1}), \end{aligned} \tag{1}$$

where RM is the market factor and HML^*, UMD, and PMU denote the (industry-adjusted) value, momentum, and profitability factors, respectively. R_i and R_f denote the return on an arbitrary risky asset i and the risk-free rate, respectively.

Hou, Xue, and Zhang (2015, 2017) propose the following four-factor model (HXZ4), which is based on the q-theory of investment,

$$\begin{aligned} \mathrm{E}(R_{i,t+1} - R_{f,t+1}) &= \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) + \gamma_{ME} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, ME_{t+1}) \\ &+ \gamma_{IA} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, IA_{t+1}) + \gamma_{ROE} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, ROE_{t+1}), \end{aligned} \tag{2}$$

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

Next, we evaluate the five-factor model proposed by Fama and French (2015, 2016, FF5),

$$\begin{aligned} \mathrm{E}(R_{i,t+1} - R_{f,t+1}) &= \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) + \gamma_{SMB} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, SMB_{t+1}) \\ &+ \gamma_{HML} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, HML_{t+1}) + \gamma_{RMW} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RMW_{t+1}) \\ &+ \gamma_{CMA} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, CMA_{t+1}), \end{aligned} \tag{3}$$

where SMB, HML, RMW, and CMA stand for their size, value, profitability, and investment factors, respectively.

Finally, we estimate a restricted version of FF5 (denoted by FF4) that excludes the value factor:

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) + \gamma_{SMB} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, SMB_{t+1}) \\ + \gamma_{RMW} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RMW_{t+1}) + \gamma_{CMA} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, CMA_{t+1}). \quad (4)$$

FF4 follows from the evidence in Fama and French (2015) showing that the value factor is redundant within the five-factor model. 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, RMW, and CMA are obtained from Kenneth French's data library. 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.[6]

The descriptive statistics for the equity factors are displayed in the online appendix. UMD and ROE have the highest average returns (around 0.60% per month), followed by the market and IA factors (with means around or above 0.45%). The factor with the lowest mean is SMB (0.23% per month), followed by PMU, ME, and RMW, all with means around 0.30% per month. The factor that exhibits the highest volatility is clearly the market equity premium with a standard deviation 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 (both with an autocorrelation of 0.18).

The pairwise correlations of the equity factors, also presented in the online appendix, show that several factors are by construction (almost) mechanically correlated. This includes SMB and ME,

[6] Hou, Xue, and Zhang (2015) explain that the starting date is restricted by the availability of quarterly earnings announcement dates as well as quarterly earnings and book equity data.

HML and HML^*, 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). Regarding the other relevant correlations among the factors, 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 the momentum factor (correlation of 0.52). Yet, both PMU and RMW do not show a similar pattern, thus suggesting the existence of 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. Estimating the models by using a common large cross-section rather than estimating separately on the different groups of portfolios (e.g., BM and momentum portfolios) avoids the issue of the consistency with the ICAPM being dependent on the choice of the testing assets (as documented in Maio and Santa-Clara (2012)). The testing portfolios are deciles sorted on size, book-to-market, momentum, return on equity, operating profitability, asset growth, accruals, and net share issues for a total of 80 portfolios. All the portfolio return data are obtained from Kenneth French's website, except the 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 Kenneth 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 to some of the factors associated with the different models outlined above. Thus, we expect ex ante that most of these 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)). Price 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 asset growth 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)). The accruals anomaly represents the evidence that stocks of firms with low accruals enjoy higher average returns than stocks of firms with high accruals (Sloan (1996) and Richardson, Sloan, Soliman, and Tuna (2005)). Finally, the net share issues anomaly refers to a pattern in which stocks with high net share issues earn lower returns than stocks with low net share issues (Daniel and Titman (2006) and Pontiff and Woodgate (2008)).

We estimate the factor models in beta representation by using the two-pass regression approach employed in Black, Jensen, and Scholes (1972), Jagannathan and Wang (1998), Cochrane (2005) (Chapter 12), Brennan, Wang, and Xia (2004), Maio and Santa-Clara (2017), among others.[7] Specifically, in the case of the HXZ4 model, the factor betas are estimated from the time-series regressions for each testing portfolio,

$$R_{i,t+1} - R_{f,t+1} = \delta_i + \beta_{i,M} RM_{t+1} + \beta_{i,ME} ME_{t+1} + \beta_{i,IA} IA_{t+1} + \beta_{i,ROE} ROE_{t+1} + \varepsilon_{i,t+1}, \quad (5)$$

and in the second step, the expected return-beta representation is estimated through an OLS cross-sectional regression,

$$\overline{R_i - R_f} = \lambda_M \beta_{i,M} + \lambda_{ME} \beta_{i,ME} + \lambda_{IA} \beta_{i,IA} + \lambda_{ROE} \beta_{i,ROE} + \alpha_i, \quad (6)$$

where $\overline{R_i - R_f}$ represents the average time-series excess return for asset i, and α_i denotes the respective pricing error. $\beta_{i,M}$, $\beta_{i,ME}$, $\beta_{i,IA}$, and $\beta_{i,ROE}$ represent the loadings for RM, ME, IA, and ROE, respectively, whereas λ_M, λ_{ME}, λ_{IA}, and λ_{ROE} denote the corresponding prices of risk.

The factors of each model are included as testing assets since all the factors presented above represent excess stock returns (see Lewellen, Nagel, and Shanken (2010)). The t-statistics associated

[7] See Cochrane (2005) (Chapter 6) for details on the equivalence between the covariance- and beta-representations of asset pricing models.

with the factor risk price estimates are based on Shanken's standard errors (Shanken (1992)). We do not include an intercept in the cross-sectional regression, since we want to impose the economic restrictions associated with each factor model. If a given 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.[8]

Although our focus is on the risk price estimates, we also assess the fit of each model by computing the cross-sectional OLS coefficient of determination,

$$R^2_{OLS} = 1 - \frac{\mathrm{Var}_N(\hat{\alpha}_i)}{\mathrm{Var}_N(\overline{R_i - R_f})}, \tag{7}$$

where $\mathrm{Var}_N(\cdot)$ stands for the cross-sectional variance. R^2_{OLS} represents the fraction of the cross-sectional variance of average excess returns on the testing assets that is explained by the factor loadings associated with the model.[9] Since an intercept is not included in the cross-sectional regression, this measure can assume negative values.[10]

The results for the OLS cross-sectional regressions are presented in Table 2 (Panel A). We can see that the majority of the risk price estimates are positive and statistically significant at the 5% or 1% levels. The exceptions are the risk price estimates associated with SMB, HML, and PMU, which are not significant at the 10% level. Moreover, the risk price estimate corresponding to ME is not significant at the 5% level (although there is significance at the 10% level).[11] 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 (-37%). This means that the CAPM performs worse than a model that predicts constant expected returns in the cross-section of equity portfolios. Both FF5 and FF4 have a reasonable explanatory power for the cross-section

[8] 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)). Results presented in the online appendix show that, when we include an intercept in the cross-sectional regression, the risk price estimates for the non-market factors are relatively similar to the benchmark case.

[9] Campbell and Vuolteenaho (2004), Kan, Robotti, and Shanken (2013), and Lioui and Maio (2014) use similar R^2 metrics.

[10] A negative estimate indicates that the regression including the betas does worse than a simple regression with just a constant, that is, the factor betas underperform the cross-sectional average risk premium in terms of explaining cross-sectional variation in average excess returns.

[11] By estimating the models separately on each group of deciles (e.g., BM portfolios) and excluding the factors from the testing returns, we obtain risk price estimates that are more unstable and further away from the theoretical correct estimates. Indeed, several of the risk price estimates are negative. This shows the advantages of using a large cross-section and including the factors as testing assets.

of 80 equity portfolios, with R^2 estimates of 44% and 30%, respectively. Nevertheless, the best performing models are NM4 and HXZ4, both with explanatory ratios around or above 60%.

One important limitation of the OLS cross-sectional regression approach when testing models in which all the factors represent excess returns is that the risk price estimates can be significantly different than the theoretical correct estimates (the corresponding sample factor means), even if the factors are added as testing assets. To overcome this problem, and following Cochrane (2005) (Chapter 12), Lewellen, Nagel, and Shanken (2010), and Maio (2017), we also estimate the risk prices by conducting a GLS cross-sectional regression. When the factors of each model are included in the menu of testing assets, it follows that the GLS risk price estimates are numerically equal to the factor means (reported in the online appendix). Moreover, this method enables us to obtain standard errors for the risk price estimates and assess their statistical significance.

The GLS cross-sectional regression can be represented in matrix form as

$$\boldsymbol{\Sigma}^{-\frac{1}{2}}\overline{\mathbf{r}} = \left(\boldsymbol{\Sigma}^{-\frac{1}{2}}\boldsymbol{\beta}\right)\boldsymbol{\lambda} + \boldsymbol{\alpha}, \tag{8}$$

where $\overline{\mathbf{r}}(N\times1)$ is a vector of average excess returns; $\boldsymbol{\beta}(N\times K)$ is a matrix of K factor loadings for the N test assets; $\boldsymbol{\lambda}(K\times 1)$ is a vector of risk prices; and $\boldsymbol{\Sigma}\equiv \mathrm{E}(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t')$ denotes the variance-covariance matrix associated with the residuals from the time-series regressions (see Cochrane (2005), Shanken and Zhou (2007), Lewellen, Nagel, and Shanken (2010), among others). Under this approach, the testing assets with a lower variance of the residuals (from the time-series regressions) receive more weight in the cross-sectional regression.

The cross-sectional GLS coefficient of determination is given by

$$R^2_{GLS} = 1 - \frac{\hat{\boldsymbol{\alpha}}'\boldsymbol{\Sigma}^{-1}\hat{\boldsymbol{\alpha}}}{\overline{\mathbf{r}^*}'\boldsymbol{\Sigma}^{-1}\overline{\mathbf{r}^*}}, \tag{9}$$

where $\overline{\mathbf{r}^*}$ denotes the $N\times 1$ vector of (cross-sectionally) demeaned average excess returns. This measure gives us the fraction of the cross-sectional variation in risk premia among the "transformed" portfolios explained by the factors associated with a given model. Since the factors are included in the testing assets, the values for this metric will tend to be fairly large in most cases. Thus, a given factor model may have a very large value of R^2_{GLS} even if it fails completely in pricing the original testing assets (portfolios) of economic interest (see Cochrane (2005)). Hence, R^2_{GLS} is not valid to evaluate the global explanatory power of a given model for a set of original portfolios (e.g., book-to-market portfolios).

The results for the GLS cross-sectional regressions are presented in Table 2 (Panel B). The results are qualitatively similar to the OLS risk price estimates, as nearly all estimates are positive and statistically significant. In comparison to the OLS case, the risk prices for HML, PMU, and ME are now estimated significantly positive. Hence, only the risk price estimates corresponding to SMB are not significant at the 5% level.[12] As expected, the GLS R^2 estimates associated with the HXZ4, FF5, and FF4 models are very close to one since the factors in those models are in the set of testing returns. As discussed above, the GLS risk price estimates are more reliable than the OLS counterparts, thus, we conclude from these results that all factors earn significant positive risk premiums, with the exception of SMB.

2.4 Implications for the ICAPM

Following Merton (1973) and 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 (for future investment opportunities) containing the corresponding state variables. Specifically, if a state variable forecasts a decline in future expected 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.

When future investment opportunities are measured by the second moment of aggregate returns,

[12]The OLS risk price estimates associated with HML, HML^*, UMD, and PMU are more than 10 basis points away from the corresponding (correct) GLS estimates. In the cases of the other factors, these differences tend to be substantially smaller. On the other hand, the OLS estimates of λ_{SMB}, λ_{RMW}, and λ_{CMA} within the FF5 model tend to be closer to the respective GLS estimates than the corresponding OLS estimates within the FF4 model.

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 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.

To be more precise, consider the following stylized version of the Merton's ICAPM in discrete time,

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \gamma\,\mathrm{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) + \gamma_z\,\mathrm{Cov}(R_{i,t+1} - R_{f,t+1}, \widetilde{z}_{t+1}), \tag{10}$$

where γ is the coefficient of relative risk aversion, $\widetilde{z}$ denotes the innovation in the state variable z, and γ_z denotes the corresponding risk price, which is given by

$$\gamma_z \equiv -\frac{J_{Wz}(W,z,t)}{J_W(W,z,t)}, \tag{11}$$

where $J_W(\cdot)$ denotes the marginal value of wealth and $J_{Wz}(\cdot)$ represents the change in the marginal value of wealth with respect to the state variable. γ_z may be interpreted as a measure of aversion to intertemporal risk.[13] Since $J_W(\cdot)$ is always positive, it follows that the sign of $J_{Wz}(\cdot)$ determines the sign of the "hedging" risk price. If the state variable z forecasts an improvement in future investment opportunities (either an increase in the expected future return on wealth and/or a decrease in the volatility of the aggregate equity portfolio) it turns out that the marginally value of wealth declines ($J_{Wz}(\cdot) < 0$). The reason is that an improvement in future investment opportunities (higher level of wealth) represents "good times" for the average multiperiod investor, and thus, a lower marginal utility of wealth. Therefore, the risk price γ_z associated with that state variable is positive. Conversely, if the state variable forecasts adverse changes in the future investment opportunity set (either a decrease in the expected future return on wealth and/or an increase in

[13] For a textbook treatment of the ICAPM see Cochrane (2005), Pennacchi (2008), or Back (2010).

the volatility of the aggregate equity portfolio), the respective risk price should be negative. This argument is also consistent with the more parametric Campbell's version of the ICAPM (Campbell (1993, 1996)), since in this model the factor risk prices are functions of the VAR predictive slopes associated with the state variables (see also Maio (2013b)). However, this reasoning is only valid for a risk-aversion parameter above one (which tends to be the relevant case from an empirical viewpoint).

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 the future market return and/or a decline in stock volatility. The sole exception is the state variable associated with SMB: since the respective risk price is not consistently significant within FF5 and FF4, the size state variable should not be a significant predictor of the equity premium and/or stock volatility if we want to achieve consistency of those two models with the ICAPM. However, the size factor in HXZ4 should forecast improving investment opportunities (higher market return and/or lower stock volatility).

We also estimate the covariance representation of each factor model by using first-stage GMM (e.g., Hansen (1982) and Cochrane (2005)). The covariance representation is equivalent to a specification with single-regression betas and can lead to different signs in the risk price estimates (compared to the risk prices based on multiple-regression betas) as a result of non-zero correlations among the factors in a model. The results presented in the online appendix show that most covariance risk price estimates are positive and statistically significant. The sole exception is the risk price for HML within the FF5 model, which is negative and significant at the 1% level. On the other hand, the estimates for the market risk price vary between 2.27 (CAPM) and 5.92 (NM4). Thus, these estimates represent plausible values for the risk aversion coefficient of the average investor, which represents another constraint arising from the ICAPM.

3 Forecasting 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 rolling sums on the factors. For example, in the case of IA, the rolling 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 rolling sum over the last 60 months because the total sum (from the beginning of the sample) is in several cases close to non-stationary (auto-regressive coefficients around one). The first-difference in the state variables corresponds approximately to the original factors. Thus, this definition tries to resemble the empirical ICAPM literature in which the risk factors correspond to auto-regressive (or VAR) innovations (or in alternative, the first-difference) in the original state variables (see, for example, Hahn and Lee (2006), Petkova (2006), Campbell and Vuolteenaho (2004), and Maio (2013a)).[14]

The descriptive statistics for the state variables reported in the appendix indicate that all the state variables are quite persistent as shown by the autocorrelation coefficients being close to one. This characteristic is shared by most predictors employed in the stock return predictability literature (e.g., dividend yield, term spread, or the default spread). $CUMD$ and $CROE$ have the higher mean returns (close to 40% per month), while $CSMB$ is the least pervasive state variable with a mean around 17%, consistent with the results for the original factors.

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 the momentum state variable. 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 variables.

[14]Since the state variables are typically very persistent it turns out that the simple change in the state variable is approximately equal to the innovation obtained from an AR(1) process.

3.2 Forecasting the equity premium

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

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

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

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

$$r_{t+1,t+q} = a_q + b_q CSMB_t + c_q CRMW_t + d_q CCMA_t + u_{t+1,t+q}, \tag{15}$$

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 each slope coefficient indicates whether a given equity state variable forecasts positive or negative changes in future expected aggregate stock returns. We use forecasting horizons of 1, 3, 12, 24, 36, and 48 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 $q-1$ lags, which enables us to correct for the serial correlation in the residuals caused by the overlapping returns.[15]

To complement the Newey-West t-ratios, we compute empirical p-values obtained from a bootstrap experiment. This bootstrap simulation produces an empirical distribution for the estimated predictive slopes that may represent a better approximation for the finite sample distribution of those estimates. In this simulation, the excess market return and the forecasting variables are simulated (10,000 times) under the null of no predictability of the market return and also assuming that each of the predictors (z_t) follows an AR(1) process:

$$r_{t+1,t+q} = a_q + u_{t+1,t+q}, \tag{16}$$

$$z_{t+1} = \psi + \phi z_t + \varepsilon_{t+1}. \tag{17}$$

[15]We obtain qualitatively similar results (in terms of achieving or not statistical significance) by using the Hansen and Hodrick (1980) t-ratios.

This bootstrap procedure accounts for the high persistence of the forecasting variables and the cross-correlation between the residuals associated with the excess market return and the state variables, thus correcting for the Stambaugh (1999) bias. The empirical p-values represent the fraction of artificial samples in which the slope estimate is higher (lower) than the original estimate from the observed sample if this last estimate is positive (negative).[16] The full description of the bootstrap algorithm is provided in the online appendix.

The results for the predictive regressions are presented in Table 3. We can see that at horizons of 12 and 24 months $CPMU$ has significant positive marginal forecasting power for the market return, controlling for both $CHML^*$ and $CUMD$. A similar pattern holds for $CRMW$, conditional on $CSMB$, $CHML$, and $CCMA$, at the 12- and 24-month horizons. On the other hand, the slope for $CRMW$ is significantly positive, conditional on $CSMB$ and $CCMA$, at the 12-month horizon (at $q = 24$ there is significance only based on the empirical p-value). The forecasting power of the multiple regressions associated with the FF5 model at $q = 12, 24$ is slightly higher than the regressions for NM4 and FF4, as indicated by the R^2 estimates around 10-11% compared to 6-8% for NM4 and 8-10% for FF4.

At horizons greater than 12 months, the slopes for $CROE$ are highly significant (5% or 1% level), thus showing that the forecasting power of this profitability factor is robust to the presence of CME and CIA. For horizons beyond 12 months, the strongest amount of predictability is associated with the HXZ4 model (R^2 estimates between 13% and 17%), which significantly outperforms the alternative models (especially at the two longest horizons). However, at the 12-month horizon, the FF5 model outperforms the alternative models.

Therefore, these results indicate that the three profitability factors provide valuable information about future excess market returns. Moreover, the positive slopes for these state variables are consistent with the significant positive risk price estimates associated with PMU, ROE, and RMW, as documented in the last section. The remaining equity state variables are insignificant predictors of the equity premium for any horizon (at the 5% level), when we consider both the empirical p-values and the Newey-West t-ratios. The sole exception is the case of $CUMD$, which predicts a significant decline in the equity premium at the three-month horizon. Hence, this estimate is

[16] Similar bootstrap simulations are conducted in Goyal and Santa-Clara (2003), Goyal and Welch (2008), Maio and Santa-Clara (2012), and Maio (2013c, 2016).

inconsistent with the positive risk price associated with UMD.

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), Paye (2012), Sizova (2013), among others, we run predictive regressions of the type,

$$svar_{t+1,t+q} = a_q + b_q CHML_t^* + c_q CUMD_t + d_q CPMU_t + u_{t+1,t+q}, \tag{18}$$

$$svar_{t+1,t+q} = a_q + b_q CME_t + c_q CIA_t + d_q CROE_t + u_{t+1,t+q}, \tag{19}$$

$$svar_{t+1,t+q} = a_q + b_q CSMB_t + c_q CHML_t + d_q CRMW_t + e_q CCMA_t + u_{t+1,t+q}, \tag{20}$$

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

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 forecasting regressions are displayed in Table 4. There is stronger evidence of predictability for future stock volatility than for the excess market return across the majority of the state variables, as indicated by the greater number of significant slopes. The slopes associated with $CHML^*$ are significantly negative for horizons between one and 12 months. On the other hand, at the longest horizon ($q = 48$), $CHML$ helps to forecast a significant increase in stock market volatility, conditional on the other state variables of the FF5 model. Hence, this estimate is inconsistent with the corresponding positive risk price estimated in the last section. Moreover, the negative coefficients associated with $CSMB$ (within FF5 and FF4) and $CHML$ are not significant at short horizons. Further, 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 satisfied in the case of the regressions for stock volatility. $CUMD$ forecasts a significant decline in $svar$ at $q = 48$, which is compatible with the corresponding positive risk price estimate.

More importantly, CIA is negatively correlated with future stock volatility at all forecasting horizons, and the slopes are strongly significant (1% level) in all cases. On the other hand, the negative slopes associated with $CCMA$ within FF5 are significant for horizons beyond 12 months. Thus, conditional on the other state variables of the FF5 model, $CCMA$ does not predict a significant decline in stock volatility at short horizons. In the case of FF4, the slopes for the investment factor are significantly negative at all horizons, except $q = 48$. 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 aggregate stock volatility at the 5% level based on both types of p-values (the slopes associated with $CROE$ are negative at long horizons, but there is significance only based on the bootstrap inference).

Therefore, the results of this subsection indicate that the state variables associated with the investment factors predict a significant decline in stock volatility at multiple forecasting horizons, and hence, are consistent with the ICAPM framework. We conclude that the different versions of the investment and profitability factors are consistent with the ICAPM. The reason is that each of these variables forecasts at least one dimension of future investment opportunities with the correct sign. Thus, these two factor categories complement each other in terms of forecasting future investment opportunities within the multifactor models of Fama and French (2015) and Hou, Xue, and Zhang (2015).

3.4 Sensitivity analysis

We present several robustness checks to the analysis conducted above. The results are presented and discussed in the online appendix. First, we estimate univariate predictive regressions. Second, we conduct forecasting regressions for the market return, as opposed to the equity premium. Third, we include the current excess market return as a new predictor in the predictive regressions for the equity premium. Fourth, we include the current stock volatility as an additional predictor in the regressions for $svar$. Fifth, we employ alternative measures of stock return variance in the respective forecasting regressions. Specifically, we use the level (rather than the log) of realized stock volatility and also employ the stock variance measures proposed by Bansal, Khatchatrian, and Yaron (2005) and Beeler and Campbell (2012). Sixth, we use expanded samples in the estimation of the multiple predictive regressions associated with the HXZ4, FF5, and FF4 models. Finally, we conduct an alternative bootstrap simulation to assess the statistical significance of the slopes corresponding to the investment and profitability state variables in the multivariate regressions.[17]

Overall, the new results are qualitatively similar to the benchmark results of this section in most cases. Specifically, the profitability variables help to forecast an increase in the market return or equity premium, whereas the investment state variables predict a decline in stock market volatility.

3.5 Other dimensions of the investment opportunity set

In this subsection, we evaluate if the ICAPM state variables forecast other dimensions of the investment opportunity set. The results and full discussion are presented in the online appendix.

First, following Maio and Santa-Clara (2012), we measure the impact of each state variable in an aggregate conditional Sharpe ratio (see Whitelaw (1994)), which proxies for the net change in the investment opportunity set for an investor with mean-variance or quadratic utility. A rise in this ratio signals an improvement in future investment opportunities (better mean and/or lower variance). Following the discussion in the previous section, if a given state variable is positively (negatively) correlated with the conditional Sharpe ratio, the corresponding factor risk price should be positive (negative). Thus, the signs of the slopes are interpreted in the same way as the coefficients in the regressions for the equity premium. The results indicate that all investment and profitability state variables are positively correlated with the future aggregate Sharpe ratio, and thus, positively correlated with future positive investment opportunities, in line with the respective positive risk prices.

Second, we investigate the forecasting ability for future stock market realized skewness (see Neuberger (2012) and Amaya, Christoffersen, Jacobs, and Vasquez (2015)).[18] The original Merton's ICAPM allows for state-dependence of the first two moments of stock returns, which a multi-period risk-averse investor (with quadratic or mean-variance utility) wants to hedge. However, changes in higher moments of the stock return distribution might also be of concern for investors with different utility functions. In particular, changes in the skewness of future stock returns may be of hedging concerns: A higher skewness represents a higher probability of positive returns, and hence, a risk averse investor will demand a higher risk premium to hold an asset that covaries positively with a state variable that forecasts an increase in future stock return skewness. The reasoning is similar

[17]We thank two anonymous referees for suggesting some of these robustness checks.
[18]We thank an anonymous referee for suggesting this analysis.

to that provided for the first moment of stock returns (equity premium). The results show that the equity state variables have lower forecasting power for realized skewness in comparison to the first two-moments of stock market returns (only $CROE$ and $CCMA$ have some forecasting ability for realized skewness). This finding is not totally surprising as the third moment of the stock return distribution should have less hedging concerns for a risk-averse investor than the first two moments.

Third, we assess if the equity state variables are able to forecast the bond premium. Since the market portfolio contains all types of financial wealth, it follows that bond returns represent one dimension of the investment opportunity set in the same vein as stock returns. Hence, we investigate if the investment and profitability state variables forecast an increase in the bond premium to achieve consistency with the positive risk prices, similarly to the case of the equity premium. The results indicate that both $CPMU$, and especially $CRMW$, forecast an increase in the bond premium at several forecasting horizons, in line with the results obtained for the equity premium.

4 Equity risk factors and future economic activity

4.1 Main results

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 given. Indeed, several forms of non-financial wealth, like labor income, houses, or small businesses, are related with the business cycle, and hence, economic activity. Hence, economic activity is likely to be positively correlated with the non-observable return on aggregate wealth.[19] Thus, an increase in economic activity might represent an increase in the return on aggregate wealth and assessing whether the state variables predict economic activity complements 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 corresponding factor. In related work, Boons (2016)

[19] For example, labour income represents the return to human capital, which is a component of aggregate wealth (see Campbell (1996), Jagannathan and Wang (1996), and Lettau and Ludvigson (2001), among others. One can also specify an ICAPM in which human capital is included explicitly in total wealth (see Back (2010)). In this setup, the state variables should forecast changes in future labor income.

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. In this paper, we focus on the predictive ability (for future economic activity) of state variables constructed from equity factors.[20]

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). We lag the economic variables by one month when matching with the state variables. This is to ensure that the macro data is publicly available in real time given the usual time lag in the release of such data.

To assess the forecasting role of the state variables within each model for economic activity, we run the following multivariate regressions,

$$y_{t+1,t+q} = a_q + b_q CHML_t^* + c_q CUMD_t + d_q CPMU_t + u_{t+1,t+q}, \tag{22}$$

$$y_{t+1,t+q} = a_q + b_q CME_t + c_q CIA_t + d_q CROE_t + u_{t+1,t+q}, \tag{23}$$

$$y_{t+1,t+q} = a_q + b_q CSMB_t + c_q CHML_t + d_q CRMW_t + e_q CCMA_t + u_{t+1,t+q}, \tag{24}$$

$$y_{t+1,t+q} = a_q + b_q CSMB_t + c_q CRMW_t + d_q CCMA_t + u_{t+1,t+q}. \tag{25}$$

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

The results for the predictive regressions associated with industrial production growth are presented in Table 5. We can see that the momentum state variable forecasts a significant decline in industrial production growth at $q = 3$. Hence, this slope estimate is inconsistent with the positive risk price associated with UMD. At long horizons, the momentum slopes are positive, but there is significance only based on the empirical p-values. In line with the results for the equity premium regressions, $CROE$ predicts a significant increase in IPG for horizons beyond 24 months. Yet, unlike the case of the equity premium prediction, the other two profitability factors ($CPMU$ and $CRMW$) have poor forecasting ability for industrial production growth as the corresponding

[20]Some studies argue that the ability of return spreads to forecast macroeconomic variables constitutes evidence that these spreads provide exposure to macroeconomic risk that investors would like to hedge against. Specifically, Vassalou (2003) shows that the HML and SMB factors can predict future GDP growth. Cooper and Priestley (2011) show that the asset growth return spread can forecast macroeconomic activity.

coefficients are not consistently significant (at the 5% level) at any forecasting horizon (there is significance for horizons of 24 and 36 months only based on the empirical p-values).

Also in contrast to the results for the excess market return, CIA is positively correlated with future output at short horizons ($q = 1, 3$), which goes in line with the positive risk price associated with the investment factor. Hence, it turns out that the investment and profitability state variables associated with the HXZ4 model complement each other in terms of forecasting aggregate output: while CIA helps to forecast output at short horizons, $CROE$ has significant forecasting power at intermediate and long horizons.[21] In comparison, the positive slopes associated with $CCMA$ (within FF4) are significant only at the three-month horizon (at other short horizons there is significance only based on one type of inference).

The results for the forecasting regressions associated with $CFED$ are presented in Table 6. When we compare with the forecasting regressions associated with the equity premium, there is stronger evidence of predictability for future output across most equity state variables. This can be confirmed by the greater number of significant coefficients and also by the higher R^2 estimates across most models and forecasting horizons.

Among the most salient differences relative to the regressions for IPG, we can see that $CHML^*$ is a significant positive predictor of the economic index at short and middle horizons ($q < 36$). Hence, these positive slopes are consistent with the positive estimates for λ_{HML^*} within the NM4 model. On the other hand, $CUMD$ is significantly positively correlated with future economic activity at the longest horizon, and thus, there is consistency with the corresponding positive risk price estimate.

The predictive power of CIA is stronger than in the case of industrial production as the positive slopes are statistically significant at all forecasting horizons. Similarly, there is strong evidence of predictability associated with $CCMA$ within the FF4 model, in contrast with the evidence for IPG, as indicated by the significant positive slopes at short and intermediate horizons ($q < 36$). In comparison, $CCMA$ within FF5 helps to predict upward business conditions ($CFED$) only at short horizons ($q = 1, 3$). As in the regressions for industrial production, $CROE$ helps to forecast improving business conditions at long horizons ($q > 24$). Conditional on the other state variables

[21] This result is also consistent with the evidence in Cooper and Priestley (2011) showing that alternative investment factors help to forecast industrial production at short horizons.

of the FF5 and FF4 models, we can see that $CRMW$ is negatively correlated with the economic index at short horizons, indicating an inconsistency with the respective risk price estimate. In terms of explanatory power, the HXZ4 model achieves the largest fit among all forecasting models at long horizons, as indicated by the explanatory ratios close to 40% (50%) in the regressions corresponding to IPG ($CFED$). This represents more than twice the fit of the corresponding predictive regressions for the excess market return at those horizons.

Overall, the results of this section to a large extent complement the results in the previous section concerning the aggregate equity premium prediction. In fact, while the investment state variables do not provide relevant information for the future excess stock return, they help to forecast an increase in future economic activity. Moreover, the profitability factor from the HXZ4 model also helps to predict positive aggregate business conditions. This provides additional evidence that, to some degree, the investment and profitability factors associated with the HXZ4 and FF5 models proxy for different dimensions of the broad investment opportunity set.

However, the forecasting results for economic activity should be interpreted with some caution. The reason is that the economic indicators have considerably higher measurement error than asset returns and volatilities. Moreover, the economic variables are only moderately correlated with investment opportunities.

4.2 Sensitivity analysis

We conduct two robustness checks to the results described above. The full discussion is presented in the online appendix.

First, we conduct single forecasting regressions for the two measures of economic activity. Second, we use an extended sample in the predictive regressions. Third, we conduct an alternative bootstrap simulation to assess the statistical significance of the predictive slopes (associated with the investment and profitability state variables) for future economic activity. Overall, the results are qualitatively similar to the corresponding results in the benchmark case and indicate a robust predictive power of future economic activity.

In another robustness check, we assess whether the profitability and investment state variables forecast alternative dimensions of economic activity. Specifically, we include the log growth in monthly GDP, log growth in retail sales, log growth in total nonfarm payrolls, and log growth in total compensation. The results suggest that the predictive performance associated with the alternative economic indicators is more or less consistent with the benchmark results associated with $CIPG$ and $CFED$. However, there are some discrepancies concerning the relative forecasting power of the investment variables on one hand and the profitability state variables on the other hand: the investment variables do a better job in terms of forecasting labor market activity while the profitability variables outperform when it comes to forecast retail sales.

4.3 Forecasting economic volatility

We evaluate the forecasting ability of the state variables for future economic volatility.[22] Specifically, we compute the variances of both IPG and $CFED$ by using the method employed in Beeler and Campbell (2012). Following the Roll's critique (Roll (1977)), in the some vein that the expected growth in economic activity can be used as a proxy for the expected market return, the economic volatility can proxy for the stock market volatility.

The results presented in the online appendix show that both investment state variables forecast a decline in both measures of economic volatility at nearly all forecasting horizons. Interestingly, we also observe that all three profitability state variables (in particular, $CPMU$ and $CRMW$) predict lower economic volatility. Therefore, these results indicate that the investment and profitability state variables have similar or greater forecasting power for future economic activity in comparison to stock return volatility.

5 Relation with ICAPM state variables

In this section, we investigate the relationship of the equity factors analyzed above with other risk factors that are typically used in the empirical ICAPM literature.

5.1 Forecasting investment opportunities

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

[22]We thank an anonymous referee for suggesting this analysis.

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 and Santa-Clara (2012), Maio (2013a), 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. The data on the index price and dividends 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,

$$r_{t+1,t+q} = a_q + b_q z_t + c_q TERM_t + d_q DEF_t + e_q dp_t + f_q TB_t + g_q vs_t + u_{t+1,t+q}, \qquad (26)$$

and stock market volatility:

$$svar_{t+1,t+q} = a_q + b_q z_t + c_q TERM_t + d_q DEF_t + e_q dp_t + f_q TB_t + g_q vs_t + u_{t+1,t+q}, \qquad (27)$$

where z stands for one of the equity state variables.

Results displayed in the online appendix indicate that the forecasting ability of all three profitability state variables (for the equity premium) is robust to the presence of the alternative state variables. Actually, this forecasting power increases for these variables, and especially for $CPMU$, as the respective coefficients are now statistically significant at more forecasting horizons. Therefore, the inclusion of the control variables clarifies the forecasting role of the profitability state variables for the equity premium.

In the case of the forecasting regressions for stock volatility it turns out that both investment state variables are no longer significant predictors of $svar$ at short horizons. However, at intermediate and long horizons such predictability remains statistically significant. This suggests that the predictive power of the investment variables at short horizons is captured by the traditional ICAPM state variables. In the case of the profitability state variables ($CPMU$ and $CRMW$), we observe a significant negative correlation with future $svar$ at intermediate and long horizons, in contrast to the results for the corresponding univariate regressions. Hence, these negative slope estimates are consistent with the respective positive risk price estimates, and show that the presence of the alternative state variables clarifies the predictive role of the profitability state variables for $svar$.

Overall, the results of this subsection indicate that the predictive ability of the different investment and profitability state variables for future investment opportunities does not seem to be subsumed by the more traditional ICAPM state variables. In other words, the investment and profitability state variables proxy for alternative components of the aggregate investment opportunity set.

5.2 Asset pricing tests

Next, we assess if the equity factors are still priced in the cross-section of stock returns when we include ICAPM factors frequently used in the literature.

Following the empirical ICAPM literature (e.g., Campbell (1996), Campbell and Vuolteenaho (2004), Petkova (2006), Botshekan, Kraeussl, and Lucas (2012), and Maio (2013a, 2013b)), the factors represent the innovations in each state variable, which are obtained from an AR(1) process:

$$\widetilde{x}_{t+1} = x_{t+1} - \psi - \phi x_t, \tag{28}$$

where $x \equiv TERM, DEF, dp, TB, vs$.

Similar to the analysis conducted in Petkova (2006), to check whether the equity factors have incremental explanatory power for cross-sectional risk premia, beyond and above that of the traditional ICAPM factors, we estimate augmented models by including the new five risk factors. For example, the augmented HXZ4 model (denoted by HXZ4*) is given by

$$\begin{aligned}\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_{TERM} \beta_{i,TERM} + \lambda_{DEF} \beta_{i,DEF} \\ + \lambda_{dp} \beta_{i,dp} + \lambda_{TB} \beta_{i,TB} + \lambda_{vs} \beta_{i,vs} \\ + \lambda_{ME} \beta_{i,ME} + \lambda_{IA} \beta_{i,IA} + \lambda_{ROE} \beta_{i,ROE},\end{aligned} \tag{29}$$

where λ_{TERM}, λ_{DEF}, λ_{dp}, λ_{TB}, and λ_{vs} denote the risk prices for the new factors. The augmented versions of the NM4, FF5, and FF4 models (denoted, respectively, by NM4*, FF5*, and FF4*) are constructed in a similar way.

The estimation (by OLS) results presented in the online appendix show that, as in the benchmark models (which exclude the traditional ICAPM factors), most risk price estimates are significantly positive. The exceptions are the size risk prices and λ_{HML}, which are not significant at the 10% level, in line with the results for the benchmark models. The cross-sectional OLS R^2 estimates associated with the four augmented models range between 57% (FF5* and FF4* models) and 72% (NM4*). This shows that including the traditional ICAPM factors does not lead to a substantial increase in the fit of the models. The most notable exception is the FF4* model, in which case the explanatory ratio increases by more than 20 percentage points (from 30% to 57%). On the other hand, in the case of HXZ4 the increase in fit is rather marginal (from 58% to 61%), which suggests that most of the explanatory power associated with the ICAPM factors is already contained in the factors included in HXZ4. Overall, the results from this subsection show that the investment and profitability factors remain priced in the presence of some of the most popular ICAPM factors used in the literature.

6 The role of magnitudes

This section provides a discussion of the magnitudes of the predictive slopes and risk price estimates. The full discussion and results are provided in the online appendix.[23]

[23] We thank two anonymous referees, the editor, and the associated editor for suggesting the analysis conducted in this section.

6.1 Comparing magnitudes of slopes and risk prices

In the previous sections, the consistency of multifactor models with the ICAPM is made exclusively by comparing the signs of the predictive slopes of the state variables with the corresponding risk prices and no reference is made to the magnitudes of these estimates. The main reason for this is that in general one can not solve analytically for the value function $J(W, z, t)$ in the ICAPM framework, and thus, we can not obtain specific expressions for the risk prices associated with the hedging factors $\gamma_z \equiv -J_{Wz}(W, z, t)/J_W(W, z, t)$ (see Cochrane (2007) for a discussion).

However, while we can not say too much about what should be the right magnitudes of these risk price estimates (as a function of fundamental parameters of the value function), we can say something about the relationship between these magnitudes and the size of the corresponding predictive slopes. Specifically, a state variable that covaries more with future investment opportunities (either r or $svar$) will be subjective to stronger hedging concerns (i.e., a higher magnitude of J_{Wz}), leading to a bigger size of the respective risk price (in comparison to a state variable that is less correlated with future investment opportunities).

To test this proposition, we conduct the following simple cross-sectional regression of the factor GLS risk price estimates ($\widehat{\lambda}_j$) on the size of the predictive slopes associated with the corresponding state variables,

$$\widehat{\lambda}_j = \theta_0 + \theta_1 \widehat{b}_{j,r} + \varsigma_j, \tag{30}$$

$$\widehat{\lambda}_j = \theta_0 + \theta_1 |\widehat{b}_{j,svar}| + \varsigma_j, \tag{31}$$

where j denotes each of the 10 non-market equity factors. $\widehat{b}_{j,r} = max\{\widehat{b}_{j,r,q}\}$ denotes the maximum slope (across the six forecasting horizons) associated with state variable j in the regressions for the equity premium. Similarly, $\widehat{b}_{j,svar} = min\{\widehat{b}_{j,svar,q}\}$ represents the minimum (more negative) slope estimate corresponding to state variable j in the regressions for $svar$.

We also conduct the cross-sectional regressions when the slopes are retrieved from the forecasting regressions for future economic activity,

$$\widehat{\lambda}_j = \theta_0 + \theta_1 \widehat{b}_{j,ipg} + \varsigma_j, \tag{32}$$

$$\widehat{\lambda}_j = \theta_0 + \theta_1 \widehat{b}_{j,cfed} + \varsigma_j, \tag{33}$$

where $\widehat{b}_{j,y} = max\{\widehat{b}_{j,y,q}\}, y \equiv IPG, CFED$. Given the discussion above, we expect a positive slope estimate (θ_1) in these four regressions, that is, more positive risk prices are associated with larger magnitudes of the corresponding predictive slopes.

The OLS estimation results of the above regressions indicate that the slope estimates are significantly positive. Therefore, this shows that factors that earn larger risk prices tend to be associated with state variables that are more correlated with future investment opportunities or economic activity, in line with the ICAPM prediction. In addition to the sign consistency documented in the previous sections, this represents another type of consistency with the ICAPM that takes into account the magnitudes of both the risk prices and predictive slopes.

6.2 Relation to alternative ICAPM frameworks

In this subsection, we consider alternative ICAPM frameworks that take into account explicitly the relationship between the magnitudes of the predictive slopes and both the risk prices and structural parameters. Specifically, we assess if these magnitudes can be reconciled with plausible risk aversion coefficient estimates.

For that purpose, we estimate by first-stage GMM the two-factor model of Campbell and Vuolteenaho (2004) (CV2) and the three-factor model of Campbell, Giglio, Polk, and Turley (2017) (CGPT3). The factors in these models are news or shocks to future aggregate cash flows (N_{CF}), discount-rates (N_{DR}), and stock variance (N_V). In both models, there is only one structural parameter (γ, the coefficient of relative risk aversion), which affects the magnitudes of the factor risk prices.

Following Campbell and Vuolteenaho (2004) and Campbell, Giglio, Polk, and Turley (2017), the factors represent linear functions of innovations in state variables that are obtained from a first-order VAR. In order to make a bridge with the equity multifactor models studied in the rest of the paper, we use the equity state variables (associated with each multifactor model) to forecast future investment opportunities within the VAR. Specifically, taking the example of HXZ4, the VAR state vector contains CME, CIA, and $CROE$ (in addition to the excess market return and realized stock variance). Hence, we estimate four versions of both CV2 and CGPT3 (one for each of the multifactor models studied in the previous sections).

Overall, the results discussed in the online appendix suggest that the ICAPM frameworks of

Campbell and Vuolteenaho (2004) and Campbell, Giglio, Polk, and Turley (2017), when based on the equity state variables studied in the previous sections, produce reasonable estimates of the underlying risk aversion parameter in most cases (between 2 and 4).

Nevertheless, these results should be interpreted with some caution. First, each our versions of both CV2 and CGPT3 models is misspecified since the only state variables that drive future investment opportunities are the equity state variables corresponding to each multifactor model. As shown in the last section, and in the ICAPM literature in general, there are other important state variables that forecast either the equity premium or stock variance. Second, the first-order VAR is a central assumption in both CV2 and CGPT3. However, the results in Section 3 show that the bulk of predictability associated with the equity state variables for both the equity premium and stock variance is at horizons longer than one month ahead. Yet, the first-order VAR misses the forecasting power at those horizons.[24]

7 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 analyze four multifactor models: the four-factor models proposed by Novy-Marx (2013) (NM4) and Hou, Xue, and Zhang (2015) (HXZ4), the five-factor model of Fama and French (2015) (FF5), and a restricted version of FF5 that excludes the HML factor (FF4). Our results for the cross-sectional tests confirm that the new models have a large explanatory power for the large cross-section of portfolio returns, in line with the evidence presented in Fama and French (2015, 2016) and Hou, Xue, and Zhang (2015, 2017). Most factor risk price estimates are positive and statistically significant.

Following Maio and Santa-Clara (2012), we construct state variables associated with each factor that correspond to the past 60-month rolling sum on the factors. The results for forecasting regressions of the excess market return at multiple horizons indicate that the state variables associated with the profitability factors employed in NM4, HXZ4, and FF5 (FF4) 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 vari-

[24]The results presented in the online appendix show that both CV2 and CGPT3 are formally rejected by the χ^2 specification test, in line with the evidence provided in Campbell, Giglio, Polk, and Turley (2017).

ables forecast a significant decline in stock volatility, consistent with the corresponding factor risk price estimates. In particular, the state variables associated with the investment factors of Hou, Xue, and Zhang (2015) and Fama and French (2015) predict a significant decline in stock volatility at multiple forecasting horizons, and hence, are consistent with the ICAPM framework. We conclude that the different versions of the investment and profitability factors are consistent with the ICAPM. The reason is that each of these variables forecasts one dimension of future investment opportunities with the correct sign. Thus, these two factor categories complement each other in terms of forecasting future investment opportunities within the HXZ4 and FF5 (FF4) models.

We also evaluate if the equity state variables forecast future aggregate economic activity, which is measured by the growth in industrial production and the Chicago FED index of economic activity. Overall, the evidence of predictability for future economic activity is stronger than for the future excess market return, across most equity state variables. In fact, while the investment state variables do not provide relevant information for the future stock market returns, they help to forecast an increase in future economic activity. This result provides additional evidence that the investment and profitability factors associated with the models of Novy-Marx (2013), Fama and French (2015, 2016), and Hou, Xue, and Zhang (2015) proxy for different dimensions of future investment opportunities.

Further, we assess if the forecasting ability of the equity state variables for future investment opportunities is linked to traditional ICAPM state variables. The results from multiple forecasting regressions suggest that the predictive ability of most equity state variables, and specifically the different investment and profitability variables, does not seem to be subsumed by the alternative ICAPM state variables.

In the last part of the paper, we show that factors that earn larger risk prices tend to be associated with state variables that are more correlated with future investment opportunities or economic activity, in line with the ICAPM prediction. On the other hand, by estimating the ICAPM specifications of Campbell and Vuolteenaho (2004) and Campbell, Giglio, Polk, and Turley (2017), based on the equity state variables studied in the paper, we obtain reasonable estimates of the underlying risk aversion parameter.

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Table 1: Consistency of factors with the ICAPM

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. $CHML^{*}$, $CUMD$, 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 "$\checkmark$" indicates that there is consistency in sign and both the risk price and slope are statistically significant. "$\times$" means that either the slope or risk price estimates are not significant, or a situation in which both estimates are significant but have conflicting signs.

Model	$CSMB$	$CHML$	$CHML^{*}$	$CUMD$	$CPMU$	CME	CIA	$CROE$	$CRMW$	$CCMA$
Panel A (r)										
NM4			$\times$	$\times$	$\checkmark$					
HXZ4						$\times$	$\times$	$\checkmark$		
FF5	$\checkmark$	$\times$							$\checkmark$	$\times$
FF4	$\checkmark$								$\checkmark$	$\times$
Panel B ($svar$)										
NM4			$\checkmark$	$\checkmark$	$\times$					
HXZ4						$\times$	$\checkmark$	$\times$		
FF5	$\checkmark$	$\times$							$\times$	$\checkmark$
FF4	$\checkmark$								$\times$	$\checkmark$

Table 2: Factor risk premia estimates

This table reports the factor risk price estimates for alternative multifactor models based on the OLS (Panel A) and GLS (Panel B) cross-sectional regression approaches. The testing assets are decile portfolios sorted on size, book-to-market, momentum, return on equity, operating profitability, asset growth, accruals, and net share issues for a total of 80 portfolios. The factors of each model are included as testing assets. λ_M, λ_{SMB}, and λ_{HML} denote the risk price estimates (in %) for the market, size, and value factors, respectively. λ_{HML^*}, λ_{UMD}, and λ_{PMU} denote the value, momentum, and profitability factor risk prices from Novy-Marx. λ_{ME}, λ_{IA}, and λ_{ROE} represent the risk prices associated with the Hou–Xue–Zhang size, investment, and profitability factors, respectively. λ_{RMW} and λ_{CMA} denote the risk price estimates for the Fama–French profitability and investment factors. Below the risk price estimates are displayed t-statistics based on Shanken's standard errors (in parentheses). The column labeled R^2_{OLS}/R^2_{GLS} denotes the cross-sectional OLS/GLS R^2. The sample is 1972:01–2012:12. Underlined and bold t-ratios denote statistical significance at the 5% and 1% levels, respectively.

	λ_M	λ_{SMB}	λ_{HML}	λ_{HML^*}	λ_{UMD}	λ_{PMU}	λ_{ME}	λ_{IA}	λ_{ROE}	λ_{RMW}	λ_{CMA}	R^2_{OLS}/R^2_{GLS}
Panel A: OLS												
CAPM	0.49											−0.37
	($\underline{2.32}$)											
NM4	0.51			0.32	0.45	0.12						0.65
	($\underline{2.45}$)			(**3.61**)	(**3.22**)	(1.30)						
HXZ4	0.48						0.28	0.35	0.51			0.58
	($\underline{2.29}$)						(1.85)	(**3.34**)	(**3.76**)			
FF5	0.47	0.20	0.13							0.32	0.43	0.44
	($\underline{2.22}$)	(1.41)	(0.83)							(**2.82**)	(**4.22**)	
FF4	0.46	0.18								0.38	0.21	0.30
	($\underline{2.18}$)	(1.28)								(**3.26**)	($\underline{2.05}$)	
Panel B: GLS												
CAPM	0.48											0.48
	($\underline{2.28}$)											
NM4	0.48			0.43	0.62	0.27						0.17
	($\underline{2.28}$)			(**6.38**)	(**4.73**)	(**5.11**)						
HXZ4	0.48						0.30	0.45	0.58			1.00
	($\underline{2.28}$)						($\underline{2.13}$)	(**5.27**)	(**4.89**)			
FF5	0.48	0.23	0.40							0.30	0.38	0.98
	($\underline{2.28}$)	(1.63)	(**2.96**)							(**2.90**)	(**4.25**)	
FF4	0.48	0.23								0.30	0.38	0.99
	($\underline{2.28}$)	(1.63)								(**2.90**)	(**4.25**)	

Table 3: Predictive regressions for equity premium

This table reports the results associated with multiple long-horizon predictive regressions for the excess stock market return, at horizons of 1, 3, 12, 24, 36, and 48 months ahead. The predictors are state variables associated with alternative equity factors. $CSMB$, $CHML$, $CRMW$, and $CCMA$ denote the Fama–French size, value, profitability, and investment factors, respectively (FF4, FF5). $CHML^*$, $CUMD$, and $CPMU$ represent respectively the value, momentum, and profitability factors from Novy-Marx (NM4). CME, CIA, and $CROE$ denote the Hou–Xue–Zhang size, investment, and profitability factors, respectively (HXZ4). 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 $q-1$ lags. t-ratios marked with * and ** denote statistical significance at the 5% and 1% levels, respectively. Slope estimates marked with * and ** denote statistical significance at the 5% and 1% levels, respectively, based on the empirical p-values from a bootstrap simulation. R^2 denotes the adjusted coefficient of determination.

Model	$CSMB$	$CHML$	$CHML^*$	$CUMD$	$CPMU$	CME	CIA	$CROE$	$CRMW$	$CCMA$	R^2
Panel A ($q=1$)											
NM4			0.01	−0.02	0.03						0.01
			(0.62)	(−2.07*)	(1.85)						
HXZ4						−0.01	0.02	−0.01			−0.00
						(−0.75)	(1.03)	(−0.40)			
FF5	−0.00	−0.00							0.01	0.00	−0.00
	(−0.07)	(−0.09)							(0.92)	(0.21)	
FF4	−0.00								0.01	0.00	−0.00
	(−0.08)								(0.98)	(0.23)	
Panel B ($q=3$)											
NM4			0.03	−0.07*	0.10						0.03
			(0.74)	(−2.30*)	(2.42*)						
HXZ4						−0.03	0.06	−0.01			0.01
						(−1.05)	(1.21)	(−0.24)			
FF5	−0.00	0.00							0.05	0.01	0.00
	(−0.21)	(0.09)							(1.55)	(0.14)	
FF4	−0.00								0.05	0.01	0.01
	(−0.19)								(1.63)	(0.31)	
Panel C ($q=12$)											
NM4			0.08	−0.15*	0.37*						0.08
			(0.65)	(−1.22)	(2.54*)						
HXZ4						−0.01	0.18*	0.16*			0.06
						(−0.12)	(1.06)	(1.10)			
FF5	0.02	0.13							0.32**	−0.11	0.10
	(0.34)	(1.01)							(2.55*)	(−0.61)	
FF4	0.04								0.30**	0.00	0.08
	(0.50)								(2.32*)	(0.00)	

Table 3: (continued)

Model	$CSMB$	$CHML$	$CHML^*$	$CUMD$	$CPMU$	CME	CIA	$CROE$	$CRMW$	$CCMA$	R^2
Panel D ($q = 24$)											
NM4			0.12	−0.10	0.45*						0.06
			(0.41)	(−0.37)	(2.03*)						
HXZ4						0.09	0.18	0.51**			0.14
						(1.04)	(0.69)	(2.04*)			
FF5	0.08	0.14							0.46**	−0.12	0.11
	(0.86)	(0.62)							(2.01*)	(−0.50)	
FF4	0.09								0.44**	−0.01	0.10
	(0.86)								(1.90)	(−0.04)	
Panel E ($q = 36$)											
NM4			0.16	0.13	0.23						0.02
			(0.34)	(0.34)	(0.71)						
HXZ4						0.12	0.19	0.74**			0.17
						(0.93)	(0.54)	(2.82**)			
FF5	0.03	0.13							0.26	−0.06	0.03
	(0.19)	(0.40)							(0.95)	(−0.20)	
FF4	0.04								0.25	0.05	0.02
	(0.24)								(0.97)	(0.24)	
Panel F ($q = 48$)											
NM4			0.01	0.53**	−0.11						0.04
			(0.02)	(1.58)	(−0.27)						
HXZ4						0.11	0.10	0.77**			0.13
						(0.73)	(0.26)	(3.42**)			
FF5	0.04	−0.09							0.04	−0.05	−0.00
	(0.21)	(−0.26)							(0.14)	(−0.19)	
FF4	0.03								0.05	−0.12	−0.00
	(0.13)								(0.20)	(−0.47)	

Table 4: Predictive regressions for stock market volatility

This table reports the results associated with multiple long-horizon predictive regressions for the stock market variance. In everything else it is identical to Table 3.

Model	$CSMB$	$CHML$	$CHML^*$	$CUMD$	$CPMU$	CME	CIA	$CROE$	$CRMW$	$CCMA$	R^2
Panel A ($q = 1$)											
NM4			-1.60^{**}	0.46	0.63						0.06
			(-5.82^{**})	(2.06^{*})	(2.29^{*})						
HXZ4						-0.14	-1.73^{**}	0.45			0.10
						(-1.28)	(-5.59^{**})	(1.81)			
FF5	-0.15	-0.54							0.45	-0.47	0.07
	(-1.46)	(-2.05^{*})							(2.01^{*})	(-1.14)	
FF4	-0.20								0.55	-0.97^{*}	0.06
	(-1.82)								(2.44^{*})	(-3.82^{**})	
Panel B ($q = 3$)											
NM4			-4.60^{**}	1.21	1.32						0.07
			(-4.04^{**})	(1.30)	(1.16)						
HXZ4						-0.35	-5.31^{**}	1.11			0.13
						(-0.87)	(-3.94^{**})	(1.09)			
FF5	-0.43	-1.36							1.00	-1.78	0.08
	(-1.12)	(-1.15)							(1.11)	(-0.93)	
FF4	-0.56								1.24	-3.01^{**}	0.07
	(-1.33)								(1.35)	(-2.74^{**})	
Panel C ($q = 12$)											
NM4			-15.06^{**}	-0.64	-1.06						0.07
			(-2.27^{*})	(-0.12)	(-0.15)						
HXZ4						-2.01	-19.99^{**}	-1.44			0.18
						(-1.02)	(-3.09^{**})	(-0.26)			
FF5	-2.64	-1.05							-1.93	-10.56	0.10
	(-1.22)	(-0.17)							(-0.39)	(-1.08)	
FF4	-2.75								-1.78	-11.47^{**}	0.11
	(-1.21)								(-0.34)	(-1.97^{*})	
Panel D ($q = 24$)											
NM4			-5.02^{*}	-3.13^{*}	-1.24						0.08
			(-1.26)	(-0.82)	(-0.32)						
HXZ4						-3.80	-38.42^{**}	-11.57^{*}			0.23
						(-0.78)	(-3.58^{**})	(-0.81)			
FF5	-5.04	11.17							-7.33	-32.89^{**}	0.16
	(-0.95)	(0.83)							(-0.61)	(-1.98^{*})	
FF4	-3.81								-8.60	-23.67^{**}	0.14
	(-0.68)								(-0.80)	(-2.21^{*})	
Panel E ($q = 36$)											
NM4			-27.99^{*}	-36.09^{**}	-0.79						0.09
			(-0.90)	(-1.45)	(-0.03)						
HXZ4						-3.50	-52.48^{**}	-25.20^{**}			0.24
						(-0.36)	(-3.56^{**})	(-1.24)			
FF5	-3.90	31.50^{**}							-5.14	-60.66^{**}	0.21
	(-0.42)	(1.48)							(-0.33)	(-2.92^{**})	
FF4	-0.34								-8.53	-35.03^{**}	0.14
	(-0.03)								(-0.78)	(-2.50^{*})	
Panel F ($q = 48$)											
NM4			-28.17^{*}	-71.60^{**}	18.29						0.13
			(-0.60)	(-2.09^{*})	(0.50)						
HXZ4						1.00	-58.62^{**}	-30.42^{**}			0.17
						(0.06)	(-2.67^{**})	(-1.27)			
FF5	0.64	51.81^{**}							4.98	-81.87^{**}	0.23
	(0.05)	(2.11^{*})							(0.28)	(-3.71^{**})	
FF4	6.25								-1.29	-38.25^{**}	0.09
	(0.37)								(-0.09)	(-1.80)	

Table 5: Predictive regressions for industrial production growth

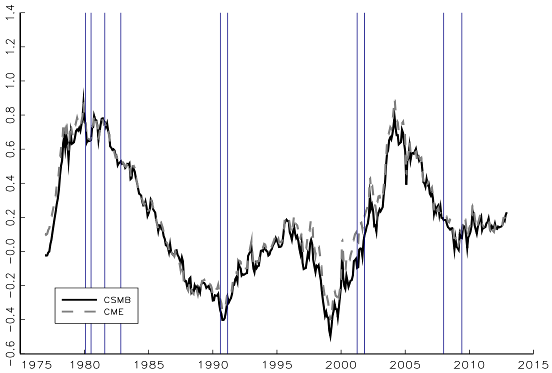
This table reports the results associated with multiple long-horizon predictive regressions for the growth in industrial production. In everything else it is identical to Table 3.

Model	$CSMB$	$CHML$	$CHML^*$	$CUMD$	$CPMU$	CME	CIA	$CROE$	$CRMW$	$CCMA$	R^2
					Panel A ($q = 1$)						
NM4			0.00	−0.00	−0.00						0.01
			(2.03*)	(−2.16*)	(−0.07)						
HXZ4						−0.00	0.01*	−0.00			0.03
						(−1.66)	(2.94**)	(−1.84)			
FF5	−0.00	−0.00							−0.00	0.01	0.01
	(−1.53)	(−0.72)							(−1.80)	(1.91)	
FF4	−0.00								−0.00	0.01	0.02
	(−1.64)								(−1.75)	(2.30*)	
					Panel B ($q = 3$)						
NM4			0.01	−0.01*	0.00						0.02
			(1.84)	(−2.28*)	(0.20)						
HXZ4						−0.01	0.03**	−0.01*			0.06
						(−1.50)	(2.50*)	(−1.76)			
FF5	−0.01	−0.01							−0.01	0.02*	0.03
	(−1.34)	(−0.71)							(−1.61)	(1.60)	
FF4	−0.01								−0.01	0.02*	0.03
	(−1.43)								(−1.57)	(1.97*)	
					Panel C ($q = 12$)						
NM4			0.03	−0.02	0.06						0.04
			(0.85)	(−0.63)	(1.24)						
HXZ4						−0.02*	0.09**	0.01			0.12
						(−1.16)	(1.87)	(0.18)			
FF5	−0.02	−0.01							0.01	0.06	0.05
	(−1.11)	(−0.17)							(0.32)	(0.91)	
FF4	−0.02								0.01	0.05*	0.05
	(−1.17)								(0.36)	(1.39)	
					Panel D ($q = 24$)						
NM4			0.03	0.02	0.13*						0.08
			(0.45)	(0.28)	(1.41)						
HXZ4						−0.01	0.11**	0.14**			0.22
						(−0.39)	(1.49)	(1.51)			
FF5	−0.03	0.02							0.08*	0.03	0.09
	(−0.82)	(0.29)							(1.27)	(0.37)	
FF4	−0.03								0.08*	0.04	0.09
	(−0.80)								(1.16)	(0.77)	
					Panel E ($q = 36$)						
NM4			−0.04	0.12**	0.14*						0.12
			(−0.38)	(0.98)	(1.32)						
HXZ4						0.01	0.07	0.31**			0.36
						(0.20)	(0.98)	(3.78**)			
FF5	−0.02	−0.04							0.09*	0.02	0.08
	(−0.55)	(−0.47)							(1.53)	(0.27)	
FF4	−0.03								0.10*	−0.01	0.07
	(−0.63)								(1.71)	(−0.13)	
					Panel F ($q = 48$)						
NM4			−0.10	0.29**	0.05						0.24
			(−0.79)	(1.85)	(0.36)						
HXZ4						−0.00	0.02	0.36**			0.38
						(−0.08)	(0.32)	(5.18**)			
FF5	−0.04	−0.11*							0.03	0.02	0.12
	(−0.85)	(−1.01)							(0.32)	(0.19)	
FF4	−0.05								0.04	−0.07	0.08
	(−0.97)								(0.52)	(−0.89)	

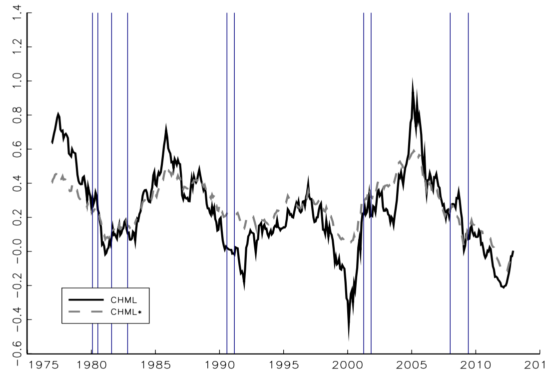
Table 6: Predictive regressions for Chicago FED Index

This table reports the results associated with multiple long-horizon predictive regressions for the Chicago FED National Activity Index. In everything else it is identical to Table 3.

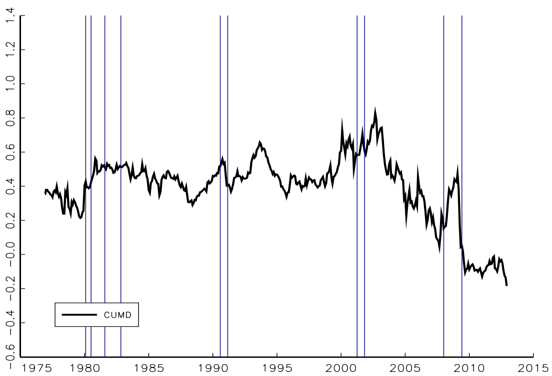
Model	$CSMB$	$CHML$	$CHML^*$	$CUMD$	$CPMU$	CME	CIA	$CROE$	$CRMW$	$CCMA$	R^2
Panel A ($q = 1$)											
NM4			1.91**	−0.31	−0.89						0.08
			(5.94**)	(−1.56)	(−2.12*)						
HXZ4						−0.30	2.57**	−0.68			0.14
						(−1.61)	(6.56**)	(−2.34*)			
FF5	−0.40	0.19							−1.05*	1.62*	0.10
	(−2.47*)	(0.71)							(−3.76**)	(3.50**)	
FF4	−0.38								−1.08*	1.80**	0.10
	(−2.31*)								(−4.09**)	(5.85**)	
Panel B ($q = 3$)											
NM4			5.66**	−0.98	−2.22						0.09
			(4.24**)	(−1.20)	(−1.36)						
HXZ4						−1.01	7.85**	−2.10*			0.20
						(−1.27)	(4.58**)	(−1.81)			
FF5	−1.22	0.38							−3.01*	5.10**	0.13
	(−1.82)	(0.32)							(−2.98**)	(2.35*)	
FF4	−1.19								−3.07*	5.44**	0.13
	(−1.69)								(−3.38**)	(4.18**)	
Panel C ($q = 12$)											
NM4			19.26**	0.35	−0.40						0.09
			(2.66**)	(0.06)	(−0.04)						
HXZ4						−3.47	29.54**	−0.35			0.28
						(−0.85)	(3.42**)	(−0.05)			
FF5	−4.59	1.79							−4.37	18.43**	0.15
	(−1.28)	(0.23)							(−0.86)	(1.53)	
FF4	−4.41								−4.62	19.98**	0.15
	(−1.19)								(−0.89)	(2.91**)	
Panel D ($q = 24$)											
NM4			30.16**	16.12**	4.89						0.13
			(2.23*)	(0.90)	(0.27)						
HXZ4						−0.51	43.75**	26.10**			0.38
						(−0.07)	(3.18**)	(1.48)			
FF5	−5.54	3.20							5.69	24.71**	0.14
	(−0.75)	(0.24)							(0.46)	(1.40)	
FF4	−5.19								5.33	27.36**	0.14
	(−0.72)								(0.40)	(2.29*)	
Panel E ($q = 36$)											
NM4			25.56*	50.11**	0.66						0.19
			(1.56)	(1.84)	(0.03)						
HXZ4						6.70	42.21**	67.35**			0.49
						(0.80)	(3.30**)	(3.73**)			
FF5	−3.09	−11.53							8.98	30.98*	0.08
	(−0.30)	(−0.61)							(0.64)	(1.45)	
FF4	−4.40								10.22	21.61*	0.07
	(−0.43)								(0.78)	(1.52)	
Panel F ($q = 48$)											
NM4			13.76	96.00**	−23.55						0.32
			(0.63)	(2.61**)	(−0.91)						
HXZ4						8.59	31.57**	88.36**			0.46
						(1.00)	(2.30*)	(4.77**)			
FF5	−3.38	−28.63**							−2.89	30.08*	0.06
	(−0.29)	(−1.19)							(−0.17)	(1.11)	
FF4	−6.48								0.57	5.97	0.01
	(−0.50)								(0.04)	(0.32)	



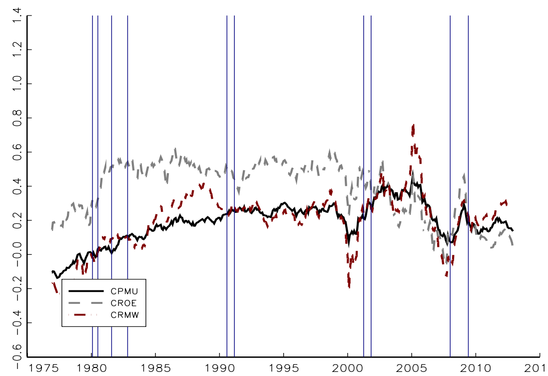
Panel A ($CSMB$, CME)



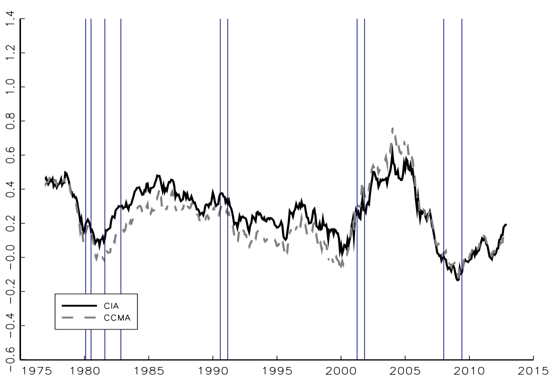
Panel B ($CHML$, $CHML^*$)



Panel C ($CUMD$)



Panel D ($CPMU$, $CROE$, $CRMW$)



Panel E (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. $CHML^*$, $CUMD$, 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.