New Evidence on Conditional Factor Models

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Abstract

We estimate conditional multifactor models over a large cross-section of stock returns matching 25 CAPM anomalies. Using conditioning information associated with different instruments improves the performance of the Hou, Xue, and Zhang (2015, HXZ) and Fama and French (2015, 2016, FF) models. The largest increase in performance holds for momentum, investment, and intangibles-based anomalies. Yet, there are significant differences in scaled models' performance: HXZ clearly dominates FF in explaining momentum and profitability anomalies, while the converse holds for value-growth anomalies. Thus, the asset pricing implications of alternative investment and profitability factors (in a conditional setting) differ in a non-trivial way.

Keywords: asset pricing models; conditional factor models; conditional CAPM; equity risk factors; investment and profitability risk factors; stock market anomalies; cross-section of stock returns; time-varying betas

JEL classification: G10; G12

I. Introduction

Explaining cross-sectional equity risk premia represents one of the major goals in asset pricing. Recently, this line of research has been particularly active with the emergence of new multifactor models having the objective of representing the new work horses in the empirical asset pricing literature. These include the four-factor model of Hou, Xue, and Zhang (2015) and the five-factor model of Fama and French (2015), which represent a response to the failure of the traditional multifactor models (e.g., three-factor model of Fama and French (1993) and four-factor model of Carhart (1997)) in explaining several market anomalies. The key risk factors in both models are related with the investment and profitability anomalies, yet, as shown in Maio and Santa-Clara (2017), Maio (2018), and Cooper and Maio (2018), among others, the performance of the two models varies widely when it comes to pricing a large cross-section of stock returns.

This paper contributes to the empirical asset pricing literature by testing conditional versions of the multifactor models mentioned above given the widespread evidence of predictable time-series variation in future stock returns.[1] In fact, a large body of the asset pricing literature has focused on estimating conditional factor models in an attempt to solve the failure of the baseline CAPM of Sharpe (1964) and Lintner (1965) when it comes to explaining several patterns in the cross-section of stock returns like the size, value, and momentum anomalies. A partial list includes Ferson, Kandel, and Stambaugh (1987), Harvey (1989), Cochrane (1996), He, Kan, Ng, and Zhang (1996), Jagannathan and Wang (1996), Ferson and Harvey (1999), Lettau and Ludvigson (2001), Wang (2003), Petkova and Zhang (2005), Avramov and Chordia (2006), Ferson, Sarkissian, and Simin (2008), and Maio (2013a). Yet, most of this literature focuses on the conditional CAPM and neglects the role of conditioning information for multifactor models (with He et al. (1996), Ferson and Harvey (1999), Wang (2003), and Maio (2013a) representing notable exceptions).[2]

We test conditional factor models over a large cross-section of stock returns associated with 25 different CAPM anomalies. These anomalies can be broadly classified as strategies related with

[1] Most of the time-series predictability literature focuses on the market return (see, e.g., Campbell and Thompson (2008), Welch and Goyal (2008), and Maio and Santa-Clara (2012) for a comprehensive empirical analysis). However, some studies have investigated the time-series predictability of value (see, e.g., Ferson and Harvey (1999), Stivers and Sun (2010), and Gulen, Xing, and Zhang (2011)) and momentum factors (see, e.g., Chordia and Shivakumar (2002), Cooper, Gutierrez Jr., and Hameed (2004), and Stivers and Sun (2010)). In related work, Maio (2014), (2016) and Maio and Santa-Clara (2015) look at the time-series predictability of the returns on portfolios sorted on size, book-to-market ratio, and momentum.

[2] In related work, Dumas and Solnik (1995) derive and test a conditional international asset pricing model.

value, momentum, investment, profitability, and intangibles. We test conditional versions of the CAPM, four-factor model of Hou et al. (2015), (2017) (HXZ), and the five-factor model of Fama and French (2015), (2016) (FF). We estimate a conditional HXZ model that contains the value spread, T-bill rate, investment-to-capital ratio, and return dispersion as instruments. In the estimation of the conditional FF model we use the value spread, relative T-bill rate, net equity expansion, and return dispersion as the conditioning variables. The choice of these variables stems from our evidence showing that they produce the largest forecasting power for the profitability and investment factors in each of these two models among a list of 21 predictors and is also consistent with previous evidence (see, e.g., Cohen, Polk, and Vuolteenaho (2003), Stivers and Sun (2010), and Maio (2016)). In line with the related literature, we employ the time-series regression approach to test and evaluate the different factor models.

The analysis of the alphas for the 25 "high-minus-low" spreads in returns suggests that using conditioning information has a positive impact on the performance of the two multifactor models mentioned above. The model that registers the greatest improvement relative to the unconditional test is the five-factor model. Yet, HXZ shows the best overall performance under both the unconditional and conditional tests. When we test the alternative models over the full cross-section of stock returns (for a total of 248 portfolios), our results also indicate that using conditioning information improves the performance of the two multifactor models for the broad cross-section of stock returns. The increased explanatory power is similar across both multifactor models: the explanatory ratios associated with the benchmark scaled HXZ and FF models are 52% and 27%, respectively, compared to 30% and 7% for the corresponding unconditional models, and these gains in fit are statistically significant. However, the conditional HXZ model clearly dominates when it comes to explaining the cross-sectional dispersion in risk premia as indicated by the substantially larger explanatory ratios. Our results also suggest that the investment-to-capital ratio is the most important instrument for the performance of the conditional HXZ model, while the value spread is the key instrument in terms of driving the fit of the augmented conditional FF model. Our findings are robust to several robustness checks: using alternative instruments in the construction of the scaled factors in the conditional models; employing an alternative sample that covers a cross-section of 29 market anomalies; and allowing the alphas to be time-varying.

We find that there is significant heterogeneity in the performance of the two multifactor models across groups of anomalies. On one hand, using conditioning information improves the performance of HXZ for the investment (like operating accruals, net operating assets, investment-to-assets, or inventory growth), intangibles (like organizational capital-to-assets and operating leverage), and momentum (like earnings momentum) anomalies. The performance of FF also improves substantially in terms of explaining the momentum (like industry momentum) and investment-based anomalies (like accruals-related anomalies). On the other hand, the scaled factors do not help HXZ and FF (or even have a negative impact) in terms of explaining the value-growth and profitability anomalies, respectively. With regards to relative performance, our results suggest that the conditional HXZ model outperforms the scaled FF model in terms of explaining the momentum and profitability anomalies, while the inverse holds when it comes to pricing the group of value-growth anomalies. This suggests, that even after accounting for the role of conditioning information, the asset pricing implications of the different versions of the investment and profitability factors are quite different for a large cross-section of stock returns.

In the last part of the paper, we estimate restricted versions of the conditional HXZ and FF models in which only the scaled factors associated with the investment and profitability factors are included. The objective is to better disentangle the effect of conditioning information associated with the investment and profitability factors in terms of driving the explanatory power of each model for the cross-section of stock returns. The results suggest that the scaled profitability and investment factors are the most relevant in terms of driving the performance of both the conditional HXZ and FF models. This implies that the remaining scaled factors in these models are of second-order importance at explaining cross-sectional risk premia. This pattern is especially notable in the case of the conditional HXZ models, while in the case of the scaled FF the missing factors have some contribution in terms of pricing several anomalies (e.g., momentum anomalies). This suggests that the conditional HXZ model not only achieves better overall pricing performance than the scaled FF model, but it also does so with fewer scaled factors.

We also compute a decomposition of risk premia for each scaled model across the high-minus-low return spreads associated with the 25 anomalies. Our results indicate that typically an instrument produces a higher explanatory power for cross-sectional risk premia when combined (into a scaled factor) with a raw factor for which it has greater forecasting power in the time-series.

The improved performance of the scaled models for momentum portfolios is consistent with the findings of time-variation in momentum profits (Chordia and Shivakumar (2002)). We hypothesize a real options explanation as follows. Winner firms are firms with valuable growth options, that is 'in-the-money' growth options, and are therefore riskier (see Sagi and Seasholes (2007) for a formal model relating the momentum effect in stock returns to real options). Winner stocks are likely high profitability stocks, whereas loser stocks likely experienced negative growth shocks and are less profitable. This conjecture is supported by our untabulated result that the momentum (UMD factor) and ROE factors are positively correlated (with a correlation coefficient of 0.5). Thus, allowing for time variation in the betas with the profitability factor helps explaining the time varying momentum profits. Conditioning is especially important for the profitability factor in the FF model (RMW), which is rebalanced annually, and less important for the quarterly-updated profitability factor (ROE) in the HXZ model in terms of explaining momentum profits. Hence, the scaled factors in the FF model can act as a (partial) substitute for the ROE factor when it comes to pricing momentum-based anomalies. Our hypothesized explanation certainly does not rule out other possible explanations.

The improvement of the models in pricing the investment anomalies is consistent with a time-varying cross-sectional dispersion in firms' real options. When the dispersion is large, investing firms are exercising particularly valuable growth options, leading to a sharp fall in their risk. Our evidence presented in the paper that the value spread (a measure of the cross-sectional dispersion in growth options) is a predictor of the investment factors of HXZ and FF lends support for the conjecture that the real options dispersion drives the improvement of the conditional factor models.

Furthermore, the predictability tests that we conduct indicate that in both HXZ and FF models the profitability and investment factor premiums exhibit countercyclical time variation. Thus, given the importance of these two factors in summarizing the cross section of stock returns, countercyclical risk aversion is potentially a driving force of time variation of several of the stock market anomalies.

The paper proceeds as follows. Section II. shows the theoretical background and models, while Section III. describes the data and empirical methodology. In Section IV., we assess whether the lagged instruments forecast the equity factors, while the main empirical analysis is presented in Section V.. In Section VI., we provide a sensitivity analysis. Section VII. presents the estimation results for restricted conditional models, and Section VIII. concludes.

II. Conditional Factor Models

In this section, we present the theoretical background and the conditional factor models that are tested in the following sections.

A. Theoretical Background

Given a raw risk factor ($f_{j,t+1}, j = 1, ..., K$) and an instrument (z_t), the term $f_{j,t+1}z_t$ denotes a scaled factor. This is often interpreted as the return on a "managed portfolio" (see, e.g., Hansen and Richard (1987), Cochrane (1996), (2005), Bekaert and Liu (2004), and Brandt and Santa-Clara (2006)).

We consider the following factor model (in unconditional representation) in which the role of conditioning information is captured by the scaled factors,

$$\text{(1)} \qquad \mathrm{E}(R^e_{i,t+1}) = \sum_{j=1}^{K} \beta_{i,j}\lambda_j + \sum_{j=1}^{K} \beta_{i,j,z}\lambda_{j,z},$$

where $R^e_{i,t+1}$ denotes the excess return (relative to the risk-free rate) on an arbitrary risky asset i. The factor loadings are obtained from the following regressions:

$$\text{(2)} \qquad R^e_{i,t+1} = \alpha_i + \sum_{j=1}^{K} \beta_{i,j} f_{j,t+1} + \sum_{j=1}^{K} \beta_{i,j,z} f_{j,t+1} z_t + \varepsilon_{i,t+1}.$$

As shown in the online appendix, a K-factor conditional model with time-varying pricing kernel coefficients (that are affine in the lagged instrument) is equivalent to the $2K$-factor model presented above.[3] The regression above is equivalent to a conditional specification in which the loadings on the original factors are allowed to be time-varying and affine in the instrument:[4]

$$\text{(3)} \qquad R^e_{i,t+1} = \alpha_i + \sum_{j=1}^{K} (\beta_{i,j} + \beta_{i,j,z} z_t) f_{j,t+1} + \varepsilon_{i,t+1}.$$

[3]We follow most of the literature on the conditional CAPM by estimating the unconditional representation of the conditional factor models. Nagel and Singleton (2011) and Ang and Kristensen (2012) use alternative methods to estimate the conditional CAPM.

[4]The practice of specifying time-varying betas as a function of lagged instruments is popular in the literature (see, e.g., Shanken (1990), Ferson and Schadt (1996), Ferson and Harvey (1999), Lewellen (1999), Ferson et al. (2008), among others). In related work, Lewellen and Nagel (2006) and Boguth, Carlson, Fisher, and Simutin (2011) use realized betas estimated from daily returns.

As noted in Cochrane (2005), Lewellen, Nagel, and Shanken (2010), and Maio (2018), when the factors represent excess returns, the prices of risk must be equal to the corresponding factor means:

$$\mathrm{E}(f_{j,t+1}) = \lambda_j, \tag{4}$$

$$\mathrm{E}(f_{j,t+1} z_t) = \lambda_{j,z}, j = 1, ..., K. \tag{5}$$

These conditions are obtained by applying the beta equation above for each factor, and noting that each factor has a (multiple regression) beta of one on itself and a beta of zero on all the other factors.[5] By substituting the restrictions on the factor risk prices back into the beta equation, we obtain the following multifactor model:

$$\mathrm{E}(R^e_{i,t+1}) = \sum_{j=1}^{K} \beta_{i,j}\,\mathrm{E}(f_{j,t+1}) + \sum_{j=1}^{K} \beta_{i,j,z}\,\mathrm{E}(f_{j,t+1} z_t). \tag{6}$$

This specification represents the basis for the empirical work conducted in the following sections.

B. Models

Next, we present the empirical conditional factor models tested on the cross-section of stock returns. The first model analyzed is the conditional CAPM,

$$\mathrm{E}(R^e_{i,t+1}) = \mathrm{E}(\mathrm{RM}_{t+1})\beta_{i,M} + \mathrm{E}(\mathrm{RM}_{t+1} z_t)\beta_{i,M,z}, \tag{7}$$

where RM denotes the excess market return.

The second model is a conditional version of the four-factor model of Hou et al. (2015), (2017) (HXZ),

$$\begin{aligned} \mathrm{E}(R^e_{i,t+1}) &= \mathrm{E}(\mathrm{RM}_{t+1})\beta_{i,M} + \mathrm{E}(\mathrm{RM}_{t+1} z_t)\beta_{i,M,z} + \mathrm{E}(\mathrm{ME}_{t+1})\beta_{i,\mathrm{ME}} + \mathrm{E}(\mathrm{ME}_{t+1} z_t)\beta_{i,\mathrm{ME},z} \\ &+ \mathrm{E}(\mathrm{IA}_{t+1})\beta_{i,\mathrm{IA}} + \mathrm{E}(\mathrm{IA}_{t+1} z_t)\beta_{i,\mathrm{IA},z} + \mathrm{E}(\mathrm{ROE}_{t+1})\beta_{i,\mathrm{ROE}} + \mathrm{E}(\mathrm{ROE}_{t+1} z_t)\beta_{i,\mathrm{ROE},z}, \end{aligned} \tag{8}$$

where ME, IA, and ROE represent the size, investment (investment-to-assets), and profitability

[5] This restriction also applies to the scaled factors since they represent the returns on traded assets.

(return-on-equity) factors, respectively.

The third model represents a conditional version of the five-factor model of Fama and French (2015), (2016) (FF), which adds an investment (CMA) and a profitability (RMW) factor to the three-factor model of Fama and French (1993), (1996):

$$\begin{aligned}\mathrm{E}(R^e_{i,t+1}) &= \mathrm{E}(\mathrm{RM}_{t+1})\beta_{i,M} + \mathrm{E}(\mathrm{RM}_{t+1}z_t)\beta_{i,M,z} + \mathrm{E}(\mathrm{SMB}_{t+1})\beta_{i,\mathrm{SMB}} + \mathrm{E}(\mathrm{SMB}_{t+1}z_t)\beta_{i,\mathrm{SMB},z}\\ &+ \mathrm{E}(\mathrm{HML}_{t+1})\beta_{i,\mathrm{HML}} + \mathrm{E}(\mathrm{HML}_{t+1}z_t)\beta_{i,\mathrm{HML},z} + \mathrm{E}(\mathrm{RMW}_{t+1})\beta_{i,\mathrm{RMW}} + \mathrm{E}(\mathrm{RMW}_{t+1}z_t)\beta_{i,\mathrm{RMW},z}\\ &+ \mathrm{E}(\mathrm{CMA}_{t+1})\beta_{i,\mathrm{CMA}} + \mathrm{E}(\mathrm{CMA}_{t+1}z_t)\beta_{i,\mathrm{CMA},z}.\end{aligned} \tag{9}$$

Both RMW and CMA are constructed in a different way than the investment and profitability factors in Hou et al. (2015).

III. Data and Methodology

In this section, we describe the data and methodology employed in the empirical analysis conducted in the following sections.

A. Data

The data on the risk factors associated with the CAPM and FF models (RM, SMB, HML, RMW, and CMA) are retrieved from Kenneth French's data library. The data on the remaining factors (ME, IA, and ROE) are obtained from Lu Zhang. The sample is 1972:01 to 2013:12. The descriptive statistics for the factors are displayed in Table 1. The factors with the largest mean returns are ROE and RM, with estimates above 0.50% per month. On the other hand, the factor with the lowest mean is SMB (0.23% per month), followed by ME with an average return of 0.31%. This confirms previous evidence showing that the size premium has declined over time. The factor with the highest volatility is the equity premium, with a standard deviation above 4.5% per month. On the other hand, the investment factors (IA and CMA) are the least volatile, with standard deviations below 2% per month.

Panel B of Table 1 shows the pairwise correlations among the different factors. The two size (SMB and ME) and investment (IA and CMA) factors are strongly correlated as indicated by the correlation coefficients above or around 0.90. On the other hand, the two profitability factors (ROE and RMW) are not as strongly correlated (correlation of 0.67), thus indicating that they do not exhibit a very large degree of overlap. Both investment factors are positively correlated with HML (around 0.70). Further, both profitability factors show weak negative correlations with the size factors as indicated by the correlation coefficients between −0.31 and −0.39.

We use six conditioning variables in the construction of the scaled risk factors. The instruments are the T-bill rate (TB, Fama and Schwert (1977)); value spread (VS, Cohen et al. (2003), Campbell and Vuolteenaho (2004), Liu and Zhang (2008)); relative T-bill rate (RREL, Campbell (1991), Hodrick (1992)); stock return dispersion (RD, Stivers and Sun (2010), Maio (2016)); net equity expansion (NTIS, Boudoukh, Michaely, Richardson, and Roberts (2007), Welch and Goyal (2008)); and the investment-to-capital ratio (IK, Cochrane (1991)).

The portfolio return data used in the cross-sectional asset pricing tests are associated with some of the most prominent market anomalies. We employ a total of 25 anomalies or portfolio sorts, which represents a subset of the anomalies considered in Hou et al. (2015). Table 2 contains the list and description of the anomalies included in our analysis. Following Hou et al. (2015), these anomalies can be broadly classified as strategies related with value-growth (BM, DUR, and CFP), momentum (MOM, SUE, ABR, IM, and ABR*), investment (IA, NSI, CEI, PIA, IG, IVC, IVG, NOA, OA, POA, and PTA), profitability (ROE, GPA, NEI, and RS), and intangibles (OCA and OL). All the portfolios are value-weighted and all the groups include decile portfolios, except IM and NEI with nine portfolios each. Compared to the portfolio groups employed in Hou et al. (2015), we do not use portfolios sorted on earnings-to-price ratio since these deciles are strongly correlated with the book-to-market (BM) deciles. Similarly, we do not consider the return on assets deciles because they are strongly correlated with the return on equity deciles (ROE). Moreover, we use only one measure of price momentum (MOM) and earnings surprise (SUE), since the other related anomalies used in Hou et al. (2015) are strongly correlated with either MOM or SUE. We also exclude all portfolio sorts used in Table 4 of Hou et al. (2015) that start after 1972:01. In contrast to Hou et al. (2015), we use the deciles associated with revenue surprise (RS) since the respective spread "high-minus-low" in average returns is statistically significant for the 1972:01–2003:12 sample (t-ratio of 1.97). All the portfolio return data are obtained from Lu Zhang. To construct portfolio excess returns, we use the one-month Treasury bill rate.

Table 3 presents the descriptive statistics for high-minus-low spreads in returns between the last and first deciles among each portfolio class. The anomaly with the largest spread in average returns is price momentum (MOM), with a premium above 1% per month. The spreads in returns associated with BM, ABR (abnormal one-month returns after earnings announcements), ROE, and net stock issues (NSI) are also strongly significant in economic terms with (absolute) means around 0.70% per month. The anomalies with lower average returns are ABR* (abnormal six-month returns after earnings announcements), RS, and operating leverage (OL), with average gaps in returns around or below 0.30% in magnitude. MOM is the anomaly with more return volatility (standard deviation above 7% per month) followed by IM and ROE (with standard deviations above 5%). The least volatile return spreads are ABR*, NEI, and IG, all with volatilities below 3%.

B. Methodology

We use time-series regressions to test the alternative factor models, as in Fama and French (1993), (1996), (2015) and Hou et al. (2015). This methodology is adequate when all the factors in the model represent excess stock returns as it is the case in this paper (see Cochrane (2005)). In this method, the implied risk price estimates are forced to be equal to the respective factor means.[6]

We estimate the conditional specifications associated with each of the multifactor models (HXZ and FF) by using different sets of four instruments in each case.[7] The conditional HXZ model includes VS, TB, IK, and RD as instruments, while the conditional FF model contains VS, RREL, NTIS, and RD as conditioning variables.[8] The choice of these variables stems from the analysis conducted in the next section showing that they produce the largest forecasting power for the profitability (ROE and RMW) and investment (IA and CMA) factors among a list of different 21 predictors.[9]

Therefore, the time-series regressions for the conditional CAPM associated with the first set of

[6]This avoids the critique of implausible risk price estimates (see Lewellen and Nagel (2006) and Lewellen et al. (2010)).

[7]The choice of four instruments in each scaled model is admittedly an ad hoc one. We follow previous studies that employ a similar number of instruments in conditional asset pricing tests (see, e.g., Ferson and Harvey (1999) and Petkova and Zhang (2005)).

[8]Other papers use lagged stock characteristics, like size and BM, as the instruments that drive factor loadings (e.g., Lewellen (1999) and Avramov and Chordia (2006)) in tests of the conditional CAPM.

[9]We thank the referee for suggesting this procedure in selecting the instruments.

instruments are given by

$$
\begin{aligned}
R^e_{i,t+1} &= \alpha_i + \beta_{i,M}\mathrm{RM}_{t+1} + \beta_{i,M,\mathrm{VS}}\mathrm{RM}_{t+1}\mathrm{VS}_t + \beta_{i,M,\mathrm{TB}}\mathrm{RM}_{t+1}\mathrm{TB}_t \\
&\quad + \beta_{i,M,\mathrm{IK}}\mathrm{RM}_{t+1}\mathrm{IK}_t + \beta_{i,M,\mathrm{RD}}\mathrm{RM}_{t+1}\mathrm{RD}_t + \varepsilon_{i,t+1},
\end{aligned} \tag{10}
$$

and similarly for the scaled HXZ model (containing $4 \times 4 = 16$ scaled factors).

By using the second set of instruments, the regressions for the scaled CAPM are as follows:

$$
\begin{aligned}
R^e_{i,t+1} &= \alpha_i + \beta_{i,M}\mathrm{RM}_{t+1} + \beta_{i,M,\mathrm{VS}}\mathrm{RM}_{t+1}\mathrm{VS}_t + \beta_{i,M,\mathrm{RREL}}\mathrm{RM}_{t+1}\mathrm{RREL}_t \\
&\quad + \beta_{i,M,\mathrm{NTIS}}\mathrm{RM}_{t+1}\mathrm{NTIS}_t + \beta_{i,M,\mathrm{RD}}\mathrm{RM}_{t+1}\mathrm{RD}_t + \varepsilon_{i,t+1},
\end{aligned} \tag{11}
$$

and similarly for the scaled FF (containing $4 \times 5 = 20$ scaled factors).

To control for possible overfitting and multicollinearity problems, in addition to the augmented conditional models (based on four instruments) we estimate single-instrument versions of the conditional HXZ and FF models. This also enables to assess which instruments are driving the performance of each conditional factor model and which instruments are less important. To evaluate the statistical significance of the factor loadings, we use t-ratios based on heteroskedasticity-adjusted standard errors.[10]

For the conditional models to be valid one needs to impose the condition that the intercepts are zero for every testing asset i ($\alpha_i = 0$), which arise by taking expectations on both sides of the regressions presented above. It is important to note that any conditional factor model does not necessarily outperform the corresponding unconditional specification. The reason is that adding factors to the time-series regressions does not imply lower intercept estimates (alphas).[11]

Assume that $\mathrm{E}(\mathbf{f})$ is the vector of factor means; T is the number of time-series observations; N is the number of testing assets; K is the number of factors (including the scaled factors); and $\widehat{\boldsymbol{\alpha}} \equiv (\widehat{\alpha}_1, ..., \widehat{\alpha}_N)$ denotes the vector of alphas. A formal statistical test for the null hypothesis that

[10] In the time-series tests, the lagged conditioning variables are demeaned, which is a common practice in the conditional CAPM literature (see, for example, Lettau and Ludvigson (2001) and Ferson, Sarkissian, and Simin (2003)).

[11] Ghysels (1998) provides evidence that the unconditional CAPM produces smaller pricing errors than the conditional CAPM.

the alphas are jointly equal to zero is the following Wald test,

$$T\left[1+\mathrm{E}(\mathbf{f})'\widehat{\boldsymbol{\Omega}}^{-1}\,\mathrm{E}(\mathbf{f})\right]^{-1}\widehat{\boldsymbol{\alpha}}'\widehat{\boldsymbol{\Sigma}}^{-1}\widehat{\boldsymbol{\alpha}}\sim\boldsymbol{\chi}^2(N), \tag{12}$$

which is based on the GMM distribution, and thus is only valid asymptotically (see Cochrane ((2005), chapter 12) for details). In the expression above, the covariance matrices of the factors ($\mathbf{f}_t \equiv (f_{1,t},...,f_{K,t})'$) and residuals from the time-series regressions ($\widehat{\boldsymbol{\varepsilon}}_t \equiv (\widehat{\varepsilon}_{1,t},...,\widehat{\varepsilon}_{N,t})'$) are given by

$$\widehat{\boldsymbol{\Omega}} = \frac{1}{T}\sum_{t=1}^{T}\left[\mathbf{f}_t-\mathrm{E}(\mathbf{f})\right]\left[\mathbf{f}_t-\mathrm{E}(\mathbf{f})\right]', \tag{13}$$

$$\widehat{\boldsymbol{\Sigma}} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\boldsymbol{\varepsilon}}_t\widehat{\boldsymbol{\varepsilon}}_t'. \tag{14}$$

This statistic generalizes the test provided by Gibbons, Ross, and Shanken (1989) (GRS) by relaxing the restrictive assumptions that the errors from the time-series regressions are jointly normally distributed and have a spherical variance (ie., the errors are homoskedastic and jointly orthogonal) and is valid for finite samples.[12]

Although the χ^2 statistic represents a formal test of the validity of a given model for explaining a given cross-section of average returns, it is in general not robust and may produce perverse results. The reason hinges on the problematic inversion of $\widehat{\boldsymbol{\Sigma}}$, especially when there is a large number of testing assets as in our case. Thus, one might reject a model (i.e., the value of both statistics is large) because of a large estimate of $\widehat{\boldsymbol{\Sigma}}^{-1}$ even with low magnitudes of the alphas.[13] This problem might be accentuated by the term involving $\widehat{\boldsymbol{\Omega}}^{-1}$, which might be poorly estimated with a large number of factors. This is especially relevant in this paper since the conditional models have significantly more factors than the corresponding unconditional models. Consequently, in the full estimation with the 25 anomalies, we report the number of anomalies (or portfolio groups) in which the model is not rejected (at the 5% level) rather than reporting the p-values for the null that the alphas for the 248 portfolios are jointly equal to zero. We also report the number of alphas that are individually statistically significant (at the 5% level) in each cross-sectional test.[14]

[12] The χ^2-test is slightly more conservative than the GRS-test, hence we do not report the results associated with the latter statistic.

[13] It is well known that both the GRS and Wald tests have size distortions (tend to over-reject the null of zero pricing errors) when there is a large number of testing assets.

[14] We note that the number of significant t-ratios is not an exact measure of the joint statistical significance of the

Compared to the Wald statistic, a more robust (albeit less formal) goodness-of-fit measure to evaluate factor models is the mean absolute alpha,

$$\text{MAA} = \frac{1}{N}\sum_{i=1}^{N} |\widehat{\alpha}_i|. \tag{15}$$

The statistics mentioned above only refer to the magnitudes of the alphas (pricing errors), without relating them to the magnitudes of the raw portfolio risk premia that we seek to explain. To evaluate the capacity of the model in terms of explaining cross-sectional dispersion in risk premia, we compute the (constrained) cross-sectional R^2 proposed in Maio (2018),

$$R_C^2 = 1 - \frac{\text{Var}_N(\hat{\alpha}_i)}{\text{Var}_N(\overline{R_i^e})}, \tag{16}$$

where $\text{Var}_N(\cdot)$ stands for the cross-sectional variance and $\overline{R_i^e}$ is the sample mean of the excess return for asset i. R_C^2 represents a measure of the proportion of the cross-sectional variance of average excess returns on the testing assets explained by the factor loadings associated with a given model. Maio (2018) uses the above measure to evaluate the fit of multifactor models from a constrained cross-sectional regression of average excess returns on factor betas in which the factor risk price estimates correspond to the respective factor means. For example, in the case of the conditional CAPM the constrained regressions are given by

$$\overline{R_i^e} = \overline{\text{RM}}\beta_{i,M} + \overline{\text{RMVS}}\beta_{i,M,\text{VS}} + \overline{\text{RMTB}}\beta_{i,M,\text{TB}} + \overline{\text{RMIK}}\beta_{i,M,\text{IK}} + \overline{\text{RMRD}}\beta_{i,M,\text{RD}}, \tag{17}$$

$$\overline{R_i^e} = \overline{\text{RM}}\beta_{i,M} + \overline{\text{RMVS}}\beta_{i,M,\text{VS}} + \overline{\text{RMRREL}}\beta_{i,M,\text{RREL}} + \overline{\text{RMNTIS}}\beta_{i,M,\text{NTIS}} + \overline{\text{RMRD}}\beta_{i,M,\text{RD}}, \tag{18}$$

where $\overline{\text{RM}}$ denotes the sample mean of the market factor, and $\overline{RMz}$ represents the sample mean of each of the scaled factors where $z \equiv \text{VS}, \text{TB}, \text{IK}, \text{RD}, \text{RREL}, \text{NTIS}$. It is straightforward to show that the pricing errors from such cross-sectional equations are numerically equal to the alphas obtained from the time-series regressions. Thus, a cross-sectional regression where the factor risk prices are equal to the factor means is equivalent to the time-series regression approach.[15] This

alphas. The reason relies on a multiple testing problem, that is, the correlation of t-ratios (of alphas) among different testing portfolios.

[15] Fama and French (2015) employ a similar measure based on the alphas from the time-series regressions.

R^2 measure can assume negative values, which means that the multifactor model does worse than a simple cross-sectional regression containing just a constant. In other words, the factor betas underperform the cross-sectional average risk premium in terms of explaining cross-sectional variation in risk premia (the model performs worse than a model that predicts constant risk premia in the cross-section of average returns).

The focus of this paper is in evaluating the incremental performance of conditional multifactor models relative to the corresponding unconditional models. To assess the statistical significance of the gain in R^2_C between the scaled and unscaled models, $S = R^2_{C,C} - R^2_{C,U}$, we compute empirical p-values based on a bootstrap simulation (see, e.g., Kan and Zhang (1999), Jagannathan and Wang (2007), Maio and Santa-Clara (2017), and Maio (2018)). The empirical p-values represent the fractions of artificial samples in which the pseudo spread in R^2_C is higher than the corresponding sample estimate. In this bootstrap simulation, the joint data-generating process for portfolio returns and factors is simulated under the assumption that the factors are independent from the testing returns ("useless factors", as in Kan and Zhang (1999)). Nevertheless, this analysis of statistical significance of S should be interpreted with some caution given previous evidence showing that the cross-sectional R^2 (and its difference across two different models) often exhibits large sampling error in cross-sectional tests of multifactor models (see, e.g., Lewellen et al. (2010) and Kan, Robotti, and Shanken (2013)). The full details of the bootstrap simulation algorithm are available in the online appendix.

IV. Predicting Factors

In this section, we evaluate whether the factor risk prices are time-varying and predicted by conditioning variables. To achieve this goal, we regress the equity factors onto the lagged instruments.

A. Selecting Instruments

We start by selecting the instruments employed in the construction of the scaled factors. We use a set of popular variables from the equity premium predictability literature to forecast the equity factors. We use univariate predictive regressions to assess the forecasting power of each individual predictor in isolation. Our focus is on the profitability and investment factors since these are the most relevant factors in terms of driving the performance of the unconditional HXZ and FF models (see Fama and French (2015) and Hou et al. (2015)).

We use the following list of 21 predictors, many of them employed in the comprehensive analysis conducted in Welch and Goyal (2008): Term spread (TERM); Default spread (DEF); Dividend-to-price ratio (DP); T-bill rate (TB); Dividend-payout ratio (DE); Net equity expansion (NTIS); Cross-sectional portfolio return dispersion (RD); Default return spread (DFR); Value spread (VS); Realized stock market variance (SVAR); Inflation rate (INF); Change in the Fed funds rate (ΔFFR); Relative T-bill rate (RREL); Cross-sectional stock return dispersion (CSV); Industrial Production (IPG); Earnings-to-price ratio (EP); Stock-bond yield gap (YG); Price-earnings ratio (PE); Book-to-market ratio (BM); Consumption-to-wealth ratio (CAY); and the Investment-to-capital ratio (IK). A detailed description of these variables and their original references is included in the online appendix.

Table 4 displays the estimates, and respective heteroskedasticity-robust t-ratios, for the slopes in the single predictive regressions as well as the corresponding R^2 estimates.[16] We can see that both the relative T-bill rate and NTIS forecast a significant decline in RMW, while CAY is positively correlated with future RMW (t-ratio of 2.13). When it comes to predicting ROE, it turns out that the T-bill rate forecasts a rise in the profitability factor, with an explanatory ratio around 1%. IK is also positively correlated with future ROE, with the respective coefficient being marginally insignificant at the 5% level (t-ratio=1.92). Yet, the corresponding R^2 has a similar magnitude (1.12%) to the fit in the regression with TB.

Turning to the investment factors, we can see that the slopes associated with RD are marginally significant (10% level) when it comes to forecasting either IA or CMA, with the R^2 estimates being in the 1.32-1.91% range. This result is in line with the evidence in Stivers and Sun (2010) and Maio (2016) showing that RD forecasts an increase in the returns of the value-minus-growth portfolios. Since the investment factors are positively correlated with HML (see Table 1), it is natural that return dispersion also has some forecasting power for both IA and CMA. Furthermore, the value spread is a strong predictor (1% level) of a rise in both investment factors, with R^2 estimates around or above 2%. Most of the remaining predictors do not forecast significantly (at the 10% level) any

[16] In order to facilitate the interpretation of the size of the slope estimates, the predictors are standardized in this section.

of these four factors. The few exceptions are TERM and IPG (when it comes to predicting RMW).

In light of these results, we select VS, TB, IK, and RD as the conditioning variables employed in the conditional HXZ model. In the case of the conditional FF model, the instruments are VS, RREL, NTIS, and RD. The rationale subjacent to this choice is to employ the variables with greater forecasting power for the profitability and investment factors associated with the two multifactor models. Moreover, most of these slope estimates seem economically significant: the magnitudes vary between 0.20% and 0.30%, which indicates that a one-standard deviation increase in the predictor leads to a change in the predicted future monthly return of the factor of around 20-30 basis points. In Section VI., we estimate other specifications for these two models, which rely on alternative instruments.

Figure 1 presents plots of the time series of the profitability and investment factor premiums. These premiums represent the fitted values from the univariate regressions of each of the factors (on selected predictors) described above. Both the investment and profitability premia are countercyclical.[17] This result supports the notion that the factors' average returns represent compensations for risk required by investors with countercyclical risk aversion, as for example, in Campbell and Cochrane (1999). The prominence of the profitability and investment factors in summarizing the cross section of average returns (as shown in the following sections) suggests that several stock market anomalies might be time varying in a countercyclical fashion.

The predictive performance of the value spread for the investment factors can have the following economic interpretation, consistent with the predictions of real options models (see, e.g., Carlson, Fisher, and Giammarino (2006) and Cooper (2006)). A large value spread, that is book-to-market spread, indicates a large dispersion in firms' growth options, implying that some firms have very valuable growth options (while others have little growth options and are likely highly operationally leveraged). Under such circumstances, investing firms will be exercising valuable growth options and will experience a sharp fall in volatility and risk (as they no longer possess the risky growth options). Thus, the expected returns of high investment firms are substantially lower than those of low investment firms. Given the positive correlation between the investment factors and HML, the predictability associated with VS can also be explained by the present-value relation proposed in

[17] These results are confirmed by regressing each factor premium on the NBER business cycle dummy. Untabulated results show that the slopes of these regressions are significantly negative in all four cases.

Cohen, Polk, and Vuolteenaho (2003), which states that VS is positively correlated with future returns on the value-growth factor.

We propose the following real options explanation for the predictive role of the aggregate investment-to-capital ratio for ROE. The investment-to-capital ratio is highly persistent.[18] Thus, high IK in a given period indicates that many firms have exercised their investment options, whereas a large group of other firms are about the exercise their valuable growth options in near future.[19] Hence, high IK is associated with a large cross-sectional dispersion in growth options. A large cross-sectional dispersion in growth options implies that profitable firms are riskier because their expected investment is high as their growth options are in-the-money.[20]

B. Forecasting Factor Risk Premia

Next, we assess the joint forecasting power of the selected instruments for each of the factors within the HXZ and FF models.

Specifically, in the case of IA and CMA, we run the following multivariate regressions,

$$\text{IA}_{t+1} = \gamma_0 + \gamma_1 \text{VS}_t + \gamma_2 \text{TB}_t + \gamma_3 \text{IK}_t + \gamma_4 \text{RD}_t + \eta_{t+1}, \tag{19}$$

$$\text{CMA}_{t+1} = \gamma_0 + \gamma_1 \text{VS}_t + \gamma_2 \text{RREL}_t + \gamma_3 \text{NTIS}_t + \gamma_4 \text{RD}_t + \eta_{t+1}, \tag{20}$$

and similarly for the other factors in HXZ and FF. We test the null hypothesis of no joint significance of the four slopes in the regressions above ($\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4 = 0$) with a Wald test based on a $\chi^2(4)$ distribution.

From the regressions above it follows that the conditional mean of each factor, which corresponds to the conditional risk price, is time-varying and affine on the lagged instruments. Since the stochastic discount factor (SDF) coefficients are a linear transformation of the conditional risk prices

[18] Quarterly IK has an autocorrelation of 0.97 during the sample period.

[19] Gourio and Kashyap (2007) find that changes in the number of establishments undergoing investment spikes (and thus exercising their growth options) account for the bulk of variation in aggregate investment.

[20] Hou, Mo, Xue, and Zhang (2018) find that an expected investment growth factor, defined as the excess returns of high expected investment growth firms over low investment growth firms, earns on average 0.56% per month (t-ratio = 6.66). An extensive literature documents that cash flows are significant predictors of future investment (Fazzari, Hubbard, and Petersen (1988)). Profitable firms are likely high cash-flow firms. Hou et al. (2015) define ROE as the ratio of income before extraordinary items to lagged book equity. The common definition of cash flows in the literature is the ratio of the income before extraordinary items and depreciation and amortization to lagged total assets. Because total assets and book equity are slow moving variables, much of the variation of ROE and cash flows comes emanates from income before extraordinary items.

(see Cochrane (2005)), the presence of time-variation in the conditional factor means legitimates an SDF with time-varying coefficients (as suggested in Section II.).

The results for the multiple forecasting regressions for the equity factors are presented in Table 5. Starting with the HXZ factors (Panel A), we can see that there is a significant amount of predictability in the regression for IA as the null of joint no-predictability from the four predictors is strongly rejected (p-value of 1%) and the explanatory ratio is 3%. We do not reject the null of joint no-predictability in the case of the other factors, including ROE, as the p-values are always above 10%. In terms of individual significance, only the slopes associated with VS and TB in the regression corresponding with future IA are significant at the 5% level. This arises from the multicollinearity induced by the correlation among the predictors, which is especially relevant when it comes to forecast ROE as none of the coefficients (including the slopes associated with TB and IK) is significant at the 10% level.

The predictability results associated with the FF factors indicate stronger forecasting power. Specifically, there are three factors (HML, RMW, and CMA) in which the null of no joint predictability from the four instruments is rejected at the 5% or 1% levels. In terms of individual marginal significance, VS helps to predict CMA, while the slopes associated with RREL are significant in the regressions for all five factors. On the other hand, in contrast with the evidence for the single regressions, there is no significance at the 5% level for both NTIS and RD, which again should be a consequence of multicollinearity (the positive slope of RD is marginally significant in the regression for HML).[21]

Overall, the results in this subsection indicate that there is a relevant share of multivariate predictability from the lagged macro variables for the equity factors. This predictability is stronger for the profitability (especially RMW), investment, and value factors.

V. Main results

In this section, we test the two conditional multifactor models presented above by using a broad cross-section of stock returns. Our focus is more on assessing the impact of conditioning information

[21] The positive correlation between RD and future HML is consistent with the empirical and theoretical evidence that both variables are countercyclical (see, e.g., Gomes, Kogan, and Zhang (2003), Petkova and Zhang (2005), Zhang (2005), and Stivers and Sun (2010)).

in the performance of each model rather than conducting a formal comparison of conditional models.

A. Return Spreads

As a preliminary exercise, we assess whether the loadings associated with the original equity factors are time-varying. This justifies testing the conditional models in the first place. Hence, we conduct Wald tests to assess if the loadings on the four scaled factors associated with a given factor (e.g., the four scaled factors corresponding to IA) are jointly statistically significant. The testing assets employed are the spreads high-minus-low for each of the 25 market anomalies. The results presented and discussed in the online appendix suggest that the betas associated with the scaled factors within both HXZ and FF are statistically significant in most cases. Hence, it makes sense to conduct conditional asset pricing tests in order to evaluate these two multifactor models.

We estimate time-series regressions for each factor model applied to the spreads high-minus-low in returns. The alphas for the return spreads associated with both the unconditional and conditional multifactor models are presented in Table 6. Results presented in the online appendix show that all the 25 alphas associated with the baseline CAPM are statistically significant, thus confirming that the single-factor model in its unconditional form cannot explain any of these 25 patterns in stock returns.[22] The conditional CAPM based on VS, TB, IK, and RD does not significantly improve the corresponding baseline model as only in one case (GPA spread) is the respective alpha not significant at the 5% level (still, there is significance at the 10% level). These results are in line with previous evidence showing that the conditional CAPM is not a valid answer for explaining cross-sectional equity risk premia (see Lewellen and Nagel (2006)).

The benchmark conditional HXZ model (with four instruments) improves marginally the baseline four-factor model of Hou et al. (2015), (2017), with a mean absolute alpha (across the 25 spreads) of 0.19% (versus 0.20%). Among the major changes relative to the unconditional model, the alphas associated with both the BM and DUR return spreads become significant at the 5% level. In opposite direction, the ABR* and NOA return spreads produce insignificant alphas under the conditional model. Interestingly, the alpha estimate associated with the BM return spread becomes insignificant in the conditional HXZ specification based on a single instrument (IK), while the corresponding mean absolute alpha is the same as in the augmented model (0.19%). The scaled

[22] This is why these patterns in cross-sectional returns are often denominated as CAPM or market anomalies.

HXZ based on TB produces a similar average pricing error, yet with more significant alphas (six in total). This provides preliminary evidence that adding more instruments does not necessarily improve the performance of the conditional HXZ model. On the other hand, the scaled model based on RD does not seem to improve the unconditional model in terms of pricing the 25 return spreads, with an average alpha of 0.21%.

The results for the scaled FF models (based on VS, RREL, NTIS, and RD) show that the benchmark conditional model (with four instruments) registers an improvement against the respective unconditional model of Fama and French (2015), (2016), with 12 significant alphas and a mean absolute alpha of 0.29% (compared to 14 and 0.33%, respectively, for the unscaled model). The main changes occur for the IM and NSI spreads, whose alphas become insignificant under the conditional tests. The single-instrument conditional FF models based on VS and NTIS perform slightly worse than the corresponding augmented model with mean alphas of 0.31%, with the return spreads corresponding to NSI (both scaled models) and IM (version based on NTIS) being now significant at the 5% level. The conditional model corresponding to RREL seems to be the worst performer among the scaled FF models with a mean absolute alpha of 0.34% and 14 return spreads with significant alphas, thus indicating that it does not improve the baseline model. We can also see that the alphas associated with the ABR and OA return spreads are statistically significant across both the benchmark and single-instrument conditional specifications associated with both HXZ and FF.

Overall, the evidence from Table 6 suggests that using conditioning information has a small positive impact on the performance of the two multifactor models. The model that registers the greatest improvement relative to the corresponding unconditional tests is the five-factor model. Yet, HXZ shows the best overall performance under both the unconditional and conditional tests.

B. Full Cross-Section of Stock Returns

Analyzing the spreads high-minus-low in average returns is important because a large portion of the cross-sectional variation in average returns is associated with the extreme first and last deciles within each portfolio group. Nevertheless, this represents a rather incomplete picture of the cross-section of average returns since it ignores all the remaining deciles within each anomaly. For this reason, we assess the explanatory power of the different factor models for all the deciles associated with each anomaly, which represents a total of 248 portfolios.

The results are presented in Table 7. First, both versions of the conditional CAPM cannot really outperform the baseline CAPM as indicated by the negative R_C^2 estimates, which shows that the scaled CAPM does worse than a trivial model that predicts constant equity risk-premia in the cross-section. The benchmark conditional HXZ model improves considerably the performance of the corresponding unconditional model as indicated by the MAA and R_C^2 estimates of 0.09% and 52%, respectively (which compare to 0.11% and 30%, respectively, for the baseline four-factor model). This represents an economically significant gain in fit for the large cross-section of 248 portfolios that arises by incorporating conditioning information. Moreover, the gain in R_C^2 is also statistically significant (at the 10% level). There are 28 individual portfolios with significant alphas in the conditional model compared to 39 in the unconditional case. Moreover, there are 13 anomalies or portfolio groups in which the conditional model passes the specification test, compared to only seven anomalies for the baseline four-factor model.

Turning to the single-instrument conditional HXZ models, the specification that performs better is the one using IK as instrument, with an average alpha of 0.10% and a R_C^2 of 48%, which nearly matches the fit of the augmented HXZ. This suggests there is a good deal of overlapping among the alternative instruments and scaled factors in terms of explaining cross-sectional risk premia and it is consistent with the results obtained for the return spreads discussed above. Moreover, that single-instrument model is not formally rejected in 12 of the 25 anomalies. This performance signals an economically significant improvement relative to the unconditional HXZ. Yet, the conditional models based on either VS or RD also register a sizable gain in terms of explaining risk premia relative to the baseline model: a substantial fraction (around 40%) of the cross-sectional variation in equity risk premia is explained by the factor loadings associated with those scaled models. The single-instrument model that produces the smaller improvement relative to the four-factor model is the one based on TB, with an explanatory ratio of 33% and seven anomalies in which the model is not formally rejected (same as in the baseline case).[23]

The results presented in Panel B of Table 7 indicate that using conditioning information also

[23] As discussed in Section II., the scaled factors can originate from time-varying risk prices or time-varying conditional factor loadings in which both are affine in the lagged instrument. Hence, the fact that a given instrument (e.g., TB) forecasts factor risk premia does not necessarily imply that the corresponding scaled factor explains cross-sectional risk premia.

produces a considerable improvement in the performance of the FF model: the average alpha and R_C^2 estimates associated with the augmented conditional FF model are 0.10% and 27%, respectively, which compare to 0.11% and 7%, respectively, for the baseline five-factor model. This rise in fit is statistically significant (10% level) and of similar magnitude to that observed for the conditional HXZ model (around 20 percentage points), representing also a substantial improvement relative to both the baseline and scaled CAPM. Turning to the single-instrument scaled FF models, we can see the specification based on VS dominates the other versions as suggested by the explanatory ratio of 19% and 46 significant alphas. The versions associated with NTIS and RD have a weaker performance, but the R_C^2 estimates around 10% suggests that these two instruments contribute in a non-negligible way for the fit of the augmented scaled FF model. On the other end of the spectrum, the conditional FF based on RREL does not seem to improve the baseline five-factor model, with a R_C^2 around zero (4%) and as many as 56 significant alphas, which is consistent with the performance for the return spreads discussed above. This suggests that the choice of instruments can have a relevant impact in the performance of conditional factor models. Indeed, instruments with high forecasting power for factor risk premia (e.g., RREL) do not necessarily translate into scaled factors with high predictive power for cross-sectional risk premia. On the other hand, instruments like the value spread do have consistent predictive power in both the time-series and cross-sectional dimensions.

When it comes to comparing the two conditional multifactor models, the augmented conditional HXZ appears to clearly dominate the augmented conditional FF in terms of explaining cross-sectional dispersion in risk premia, as indicated by the difference in R_C^2 estimates (a gap around 25 percentage points), and this difference is statistically significant at the 10% level (p-values reported in the online appendix). Moreover, the conditional HXZ also produces a smaller number of portfolios with significant alphas (28 versus 43) and a larger number of anomalies in which the specification test is passed (13 versus 9). Comparing the two scaled models when the sole conditioning variable is either VS or RD allows for a sharper comparison since the instrument is common in both models. Results presented in the online appendix show that the scaled HXZ model outperforms the scaled FF in both specifications, with the differences in R_C^2 being significant at the 10% and 5% levels when the instruments are VS and RD, respectively.

Overall, the results of this subsection indicate that using conditioning information improves in a relevant way the performance of the two multifactor models for the broad cross-section of stock returns. The increased explanatory power is similar across both multifactor models. However, the conditional HXZ model clearly dominates when it comes to explaining the cross-sectional dispersion in risk premia as indicated by the substantially larger explanatory ratios. Our results suggest that IK is the most important instrument for the performance of the conditional HXZ model, while VS seems to be the most relevant instrument in terms of driving the fit of the augmented conditional FF model.[24] Furthermore, our results also show a substantial larger improvement in model's performance (by adding conditioning information) in comparison to the tests for return spreads documented in the last subsection. This confirms the importance of looking at the full cross-section of portfolios (rather than focusing only at the very extreme deciles within each portfolio group) and shows that cross-sectional dispersion in risk premia is not exclusively concentrated in these extreme deciles.

C. Categories

Next, we estimate the conditional factor models by categories of anomalies, whose results appear in Table 8.

We conclude that using conditioning information tends to deteriorate the performance of the HXZ model in terms of pricing the three value-growth anomalies (BM, DUR, and CFP): the average alpha increases from 0.10% to values in the 0.12-0.13% range (depending on the instruments used), while the cross-sectional R^2 declines from 36% to values in the 9-30% range. The exception is the scaled model based on TB, which produces a marginally better fit (explanatory ratio of 41%) than the baseline model. In comparison, the fit of both the augmented conditional FF model and the single-instrument versions based on VS and RD is slightly higher than the corresponding baseline model, as indicated by the decline in average alpha (from 0.08% to 0.06-0.07%) and the increase in the explanatory ratio from 66% to 72-79%. Hence, the conditional FF models seem to dominate the conditional HXZ models when it comes to explaining the value-growth anomalies and the difference in R_C^2 estimates across the two models is significant when we use the augmented specifications as well as the single-instrument models based on VS (results provided in the online appendix).

[24] We estimate a conditional version of the four-factor model of Carhart (1997). Unreported results show that using conditioning information has a negligible effect in the models's performance in terms of explaining the 25 anomalies.

Moreover, all five versions of the conditional FF model pass the specification test for the three value-growth anomalies (in contrast to the conditional HXZ models).

Using instruments improves substantially the performance of the five-factor model for the five momentum anomalies (MOM, SUE, ABR, IM, and ABR*), particularly when we consider the augmented version containing four instruments: the average alpha declines from 0.16% to 0.13%, while the cross-sectional R^2 rises from negative (-33%) to marginally positive values (7%), with such improvement being statistically significant (5% level). Yet, as with the unscaled model, the benchmark conditional FF model is rejected by the χ^2-test in the estimation with each of the five momentum groups. Further, all the four single-instrument specifications produce negative R_C^2 estimates (although significantly less negative than the baseline FF model when the conditioning variable is VS with the gain in fit being statistically significant). This means that those conditional models perform worse than a trivial model that predicts constant cross-sectional momentum risk premia. Apart from the model scaled by TB, the improvement in the performance of HXZ (resulting from adding the scaled factors) for the momentum anomalies seems economically significant: the explanatory ratios vary between 53% (conditional model based on RD) and 66% (augmented specification), compared to 42% for the unconditional model. Yet, none of these gains is statistically significant at the 10% level, which suggests high statistical uncertainty when it comes to pricing momentum risk premia. Still, the benchmark conditional HXZ is not formally rejected when tested on three (out of the five) momentum anomalies, and there are only three individual portfolios with significant alphas (compared to 12 in the augmented conditional FF model). These results suggest a sharp dominance of HXZ relative to FF when it comes to pricing the five momentum anomalies even after incorporating conditioning information (despite the significant gain in performance of the second model by incorporating the scaled factors). Indeed, the results reported in the appendix indicate that the spread in explanatory ratios between the two models is strongly significant (5% level) when we use VS or RD as scaling variables as well as when comparing both augmented scaled models.

In comparison to the momentum anomalies, the scaled factors have a smaller impact in the performance of HXZ for the four profitability-based anomalies (ROE, GPA, NEI, and RS): the average alphas associated with both the augmented conditional model and the specification based on IK (0.08-0.09%) are very close to the corresponding estimate for the unconditional model, while the explanatory ratios increase marginally from 48% to values in the 56-58% range. These two conditional specifications are not rejected by the χ^2-test in the estimation with three of the four profitability groups. On the other hand, the conditional HXZ models based on TB, RD, and VS do not improve the performance of the baseline four-factor model (R_C^2 in the 45-49% range). Using conditioning information has nearly no impact in the performance of the five-factor model for the profitability anomalies as the R_C^2 estimates are negative in the augmented conditional model as well as in the single-instrument models based on RREL, NTIS, and VS, similarly to the baseline model. In the case of the model based on NTIS, the mean alpha is around 0.11%, while the explanatory ratio is around zero (2%). Therefore, these results also suggest that the conditional HXZ models clearly outperform the conditional FF models in terms of explaining the four profitability anomalies, with the gap in fit assuming similar magnitudes to the case of the momentum anomalies (around 60 percentage points). In fact, the positive gaps in R_C^2 estimates between the two models are statistically significant at the 5% level when comparing the augmented models as well as the versions based on VS and RD.

Using conditioning information has a significant positive effect in the performance of both multifactor models for the larger group of 11 investment-based anomalies. This is especially true for HXZ, with average alphas varying between 0.09% (augmented model) and 0.10% (versions based on VS and IK), compared to 0.11% for the baseline model. The range for the R_C^2 estimates is between 33% (version based on VS) and 48% (four-instrument model), which represents an economically significant gain relative to the fit of the unscaled HXZ model (10%). This gain in performance is statistically significant (at the 10% or 5% level) in the cases of the augmented HXZ as well as the version scaled by IK, while being borderline insignificant in the version based on VS (p-value marginally above 10%). The number of individually significant alphas is in the 11-14 range for these three scaled models compared to 20 in the baseline case. In comparison, the models scaled by either TB or RD do not improve significantly the baseline model. The augmented conditional FF model outperforms the corresponding baseline model in a relevant way, as indicated by the R_C^2 of 31% (compared to 18% in the baseline case). The scaled FF based on VS also improves the performance of the baseline model as suggested by the R_C^2 estimate of 26%, while the remaining three single-instrument versions do not add explanatory power (explanatory ratios in the 16-20% interval). By comparing the performance of the two augmented conditional models, we can see that

HXZ dominates FF, although by a significantly smaller margin than in the cases of the momentum and profitability anomalies (which can also be seen by the fact that both models are not formally rejected in four of the 11 investment-based anomalies). Indeed, the spreads in R_C^2 between the two models are not significant at the 10% level (as shown in the online appendix).

Finally, we assess the models' performance for the two anomalies related to intangibles (OCA and OL). We can see that both the augmented conditional HXZ and the version based on IK improve the baseline model by a considerable margin: the explanatory ratios are in the 54-65% range (compared to 11% in the baseline case), while the mean alpha is 0.09% (compared to 0.12%). Moreover, these gains in R_C^2 are statistically significant (10% or 5% level). The scaled HXZ based on VS also outperforms considerably the baseline model ($MAA = 0.11\%$ and $R_C^2 = 42\%$), and this gain is insignificant by a small margin (p-value of 11%). Using conditioning information improves the performance of the FF model for the 20 portfolios as indicated by the MAA of 0.08% (compared to 0.10% in the baseline case) and the explanatory ratio of 35% (versus 18%), when we use the four instruments. Yet, this level of fit is substantially smaller than that associated with the augmented scaled HXZ and the difference in R_C^2 (relative to the baseline FF model) is not statistically significant. The single-instrument FF specifications based on RREL, RD, and NTIS offer a marginal incremental explanatory power relative to the baseline model (explanatory ratio in the 21-24% range), but the same does not occur with the specification associated with VS ($R_C^2 = 15\%$). In terms of comparing the scaled HXZ and FF models, the former model deliver higher R_C^2 estimates but the differences are not significant at the 10% level.

By comparing the single-instrument HXZ models, we can see that the version based on IK dominates the other specifications across the profitability, intangibles, and investment (by a smaller margin in the latter case) anomalies. When it comes to explaining the momentum anomalies, the models scaled by VS and IK deliver a similar performance, while in the case of the value-growth anomalies the model based on TB achieves the best fit. In the case of the conditional FF models, the specification based on VS tends to outperform the other versions when it comes to pricing the momentum and investment anomalies, while the model scaled by NTIS seems to dominate in terms of explaining the profitability and intangibles anomalies.

The improved pricing of momentum-based anomalies for the scaled FF model stems largely from the fact that RMW is updated only annually. Conditioning enables a monthly version of

RMW, improving its ability to capture the time-varying momentum premium. Profitability is important in capturing momentum because winner stocks are likely profitable stocks with good growth opportunities, whereas loser stocks likely lack such options. Growth opportunities resemble in nature to financial call options, and hence their moneyness (capture by their loadings with respect to either ROE or RMW) is positively related to their risk.

Relatedly, Liu and Zhang (2014) find that winners have higher expected investment growth and higher expected marginal productivity of capital (see also Maio and Philip (2018) for further related evidence). Intuitively, high expected future value of capital (which means higher expected investment) next period (relative to investment this period) implies higher riskiness. Similarly, high expected capital productivity relative to current investment also signals higher risk. It is plausible that high profitability firms have both features. That is, high current profitability implies high expected profitability (see Hou et al. (2015)). Moreover, high profitability is also associated with higher expected investment (see Hou et al. (2018). Therefore an updated RMW might have a substantial advantage over the unscaled RMW in pricing momentum-related anomalies. An alternative explanation is related to Johnson (2002). According to Johnson (2002), stock prices are convex in growth rates, and given that winners are likely to have experienced positive growth rate shocks, they are riskier. This explanation is also consistent with the substantial improvement of the scaled FF model in terms of pricing the momentum-related anomalies.

We conjecture that the improvement of the conditional HXZ in describing the investment anomaly is partially due to conditioning on the value spread. The value spread is the spread in book-to-market ratios and hence is a proxy for the dispersion in growth options. Therefore, at times of high value spread, investing firms are exercising valuable growth options, entailing a sharp fall in their risk. On the other hand, low investment firms are likely particularly highly operationally (or financially) levered during times of large value spreads, implying they are particularly risky in such times.

Overall, the results of this subsection indicate that there is significant heterogeneity in the performance of the two multifactor models across groups of anomalies. On one hand, using conditioning information improves the performance of HXZ for the investment, intangibles, and momentum anomalies, while the performance of FF improves substantially in terms of explaining the momentum and investment anomalies. On the other hand, the scaled factors do not help HXZ and FF (or even have a negative impact) in terms of explaining the value-growth and profitability anomalies, respectively.[25] With regards to relative performance, our results suggest that the conditional HXZ model outperforms the scaled FF model in terms of explaining the momentum and profitability anomalies, while the inverse holds when it comes to pricing the group of value-growth anomalies. The scaled HXZ also produces higher explanatory ratios than the scaled FF in the estimation with the investment and intangibles anomaly groups, yet the gaps in fit are not statistically significant in those cases.

D. Selected Anomalies

Next, we assess the performance of the two multifactor models for a selected number of relevant market anomalies. We select nine anomalies with magnitudes of average spreads high-minus-low above 0.50% per month (see Table 3). These include the spreads associated with BM, DUR, MOM, ABR, IM, ROE, NSI, CEI, and OCA. Thus, these nine portfolio groups represent each of the five categories described in Section III.. In principle, these anomalies are more difficult to explain than the remaining anomalies given the largest spreads in average returns among the extreme deciles. We also include ABR*, NOA, and OA given the evidence above showing that the return spreads associated with these three anomalies are not explained by both unconditional multifactor models.

The results for the two multifactor models tested on each of the 12 anomalies referred above are presented in Table 9. To keep the table readable, we only present results for selected single-instrument conditional specifications associated with both HXZ and FF. Incorporating conditioning information improves significantly the performance of HXZ in terms of pricing the ABR, ABR*, NOA, OA, and OCA deciles as the the R^2_C estimates increase by around or more than 20 percentage points relative to the fit in the baseline four-factor model and these differences in R^2_C are statistically significant at the 5% in most cases (in the case of ABR*, there is significance at the 10% level). This rise in fit is especially notable in the case of the OA deciles as the R^2_C rises from a very negative estimate (-1.05%) to a positive (albeit quite modest) fit when one uses the four instruments (5%). Moreover, the augmented conditional HXZ passes the specification test (at the 5% level) in the

[25]The improved performance in terms of pricing the momentum anomalies of both models in their conditional forms is consistent with evidence of time-variation in momentum profits (e.g., Chordia and Shivakumar (2002)). The improved performance of the conditional models in pricing the investment-related anomalies is consistent with time variation in the cross-sectional dispersion of growth options.

estimations with the DUR, IM, ABR*, CEI, and OCA deciles.

The scaled FF model outperforms the respective unconditional model by a big margin when it comes to pricing the MOM and IM deciles as indicated by the positive explanatory ratios (21% and 53%, respectively), although only in the latter case the gain in R^2_C is statistically significant (5% level). There is also a substantial rise in fit in the estimation with the ABR, ABR*, and OA deciles. Yet, such improvement is not enough to warrant a positive performance of the conditional FF since the explanatory ratios are still negative in all three cases. Moreover, the gain in R^2_C is only statistically significant in the estimation with the OA deciles. The augmented conditional FF is not rejected by the χ^2-test when the testing assets are BM and DUR, thus confirming the good performance for the value-growth anomalies.

At the other end of the spectrum, adding the scaled factors seems to hurt the performance of HXZ when it comes to explaining the BM, DUR, ROE, and NSI deciles as indicated by the lower R^2_C estimates (relative to the baseline model), although these differences are not statistically different from zero. On the other hand, the augmented scaled FF model produces lower explanatory ratios than the corresponding unconditional model when it comes to pricing the ROE and NSI deciles, but again these gaps in R^2_C are not statistically significant.

Turning to the single-instrument HXZ specifications, we can see that the version based on IK seems to dominate the model based on VS when it comes to pricing the DUR, OA, and OCA deciles: the positive spreads in cross-sectional R^2 are above or around 20 percentage points, which is consistent with the evidence above for the full cross-section. The model scaled by IK dominates statistically the baseline model in terms of pricing the NOA, OA, and OCA deciles, while in the case of the model scaled by VS, such dominance only occurs in the estimation with the OA deciles. In what relates the single-instrument FF models, the results suggest that the version based on VS outperforms the specification associated with NTIS when it comes to pricing the MOM, IM, and NOA deciles, while an inverse pattern holds in the estimation with the OA deciles. However, these two conditional models do not outperform in statistical terms the baseline FF model for any of these 12 anomalies (marginally so for the version based on VS in the estimation with the IM portfolios).

The good performance of the scaled models also holds for some of the other anomalies studies in this paper. Results presented in the online appendix show that the augmented scaled HXZ generates statistically significant gains in R^2_C (relative to the baseline model) in terms of pricing the GPA, OL, IA, PIA, and IVG deciles. A similar pattern holds for the single-instrument model based on IK when it comes to pricing the first four of these anomalies in addition to the RS deciles. On the other hand, the model scaled by VS generates statistically significant gains when it comes to price the GPA, PIA, and IVG deciles. Turning to the five-factor model, the gain in performance of the augmented scaled FF model (relative to the five-factor model) is statistically significant in the estimation with the GPA, POA, PTA, and RS deciles. Yet, in the case of the single-instrument FF model based on VS the difference in cross-sectional R^2 is statistically significant only in the estimation with the GPA deciles, while in the version based on $NTIS$ there are no significant gains in R_C^2 for any of these 13 anomalies. This suggests that excluding some of the scaled factors affects more the performance of the conditional FF model in comparison to the scaled HXZ model. Moreover, these results also suggest that the critical instruments for the performance of the augmented scaled HXZ are VS and IK, while in the case of the augmented scaled FF model the other two instruments (RREL and RD) also seem to play a relevant role for its pricing performance.

Overall, the results of this subsection are in line with the evidence above showing that the role of conditioning information is especially important in driving the performance of both models for the momentum and investment-based anomalies and the intangibles anomalies (in the case of HXZ). However, this role is less relevant in terms of improving the performance (and is actually negative in some cases) of HXZ and FF for the value-growth and profitability anomalies, respectively.

VI. Sensitivity Analysis

In this section, we present some robustness checks to the results presented in the last section.

A. Alternative Conditional Specifications

We estimate the conditional HXZ and FF models by using alternative instruments. First, we replace IK by the log earnings yield (EP) in the augmented conditional HXZ, while NTIS is substituted by CAY in the conditional FF model. The rationale for using these instruments is that EP is borderline insignificant (at the 10% level) when it comes to predicting ROE (t-ratio=1.61), while CAY helps to predict a significant rise in RMW, as shown in Table 4.

The results reported in the online appendix are similar to the corresponding results for the benchmark conditional models. Specifically, we obtain MAA and R^2_C estimates of 0.10% and 49%, respectively for the augmented conditional HXZ (based on VS, TB, EP, and RD), while the corresponding estimates for the four-instrument conditional FF (based on VS, RREL, CAY, and RD) are 0.10% and 28%, respectively. It turns out that the pricing performance of the single-instrument conditional HXZ model based on EP is quite similar to the version based on IK ($MAA = 0.10\%, R^2_C = 46\%$). On the other hand, the single-instrument FF version based on CAY outperforms marginally the version based on NTIS when it comes to explaining cross-sectional dispersion in risk premia, as indicated by the explanatory ratio of 19% (versus 12%). Hence, the single-instrument FF models based on CAY and VS have an identical global explanatory power. In terms of the spreads high-minus-low the results are also quite similar to those in the benchmark scaled models: the main differences are that the return spread associated with CEI becomes significant in the new augmented HXZ model, while the same occurs for the new augmented FF model in terms of pricing the NSI return spread.

In the second alternative conditional tests, the lagged instruments associated with both the scaled HXZ and FF models are TERM, DEF, DP, and TB. These conditioning variables have been widely used in previous cross-sectional tests of conditional factor models (see, e.g., Harvey (1989), Jagannathan and Wang (1996), Ferson and Harvey (1999), Petkova and Zhang (2005), and Maio (2013a)), and represent traditional predictors of the aggregate equity premium.

The results tabulated in the online appendix indicate that the performance of the new augmented HXZ (based on TERM, DEF, DP, and TB) is similar to the benchmark conditional model as indicated by the average alpha and explanatory ratio of 0.10% and 53%, respectively. Among the single-variable specifications, the version based on DP clearly dominates the versions based on TERM, DEF, and TB, as indicated by the cross-sectional R^2 of 53%, which coincides with the fit obtained for the corresponding augmented model.[26] This implies that the scaled HXZ models based on TERM and DEF (as well as the case of TB already reported in the last section) improve marginally (or do not improve) the baseline model.

Using the traditional equity premium predictors as instruments also leads to a significant rise in the performance of the five-factor model: the mean alpha and R^2_C estimates are 0.09% and 34%,

[26]These results are consistent with the evidence in Maio (2013a) showing that a scaled factor based on the lagged dividend yield helps explaining cross-sectional equity risk premia.

respectively, which indicates a slightly better fit than the benchmark augmented conditional FF model. The gain in performance relative to the unconditional FF is in the same order of magnitude as that registered for the conditional HXZ and is economically significant. The instruments that drive the performance of the new scaled FF are DP and TERM as indicated by the explanatory ratios above 20% in the corresponding single-instrument specifications.[27]

This conditional specification allows a more appropriate comparison between the two conditional multifactor models, as the set of instruments is fixed across the two models. The results suggest that the conditional HXZ clearly dominates the conditional FF when it comes to explaining cross-sectional dispersion in risk premia, as indicated by the higher R_C^2 estimates. Turning to the anomaly return spreads, the results displayed in the appendix confirm the positive performance of the scaled HXZ based on DP: only three anomalies (ABR, NSI, and OA) have significant alphas. In comparison, the single-instrument scaled FF based on DP originates 10 significant alphas (compared to 14 in the baseline model), which is another sign of the dominance of the HXZ model in terms of explaining the extreme deciles.

B. Alternative Sample

We estimate the conditional factor models by using a restricted sample, 1976:07 to 2013:12. This enables to include deciles associated with four additional anomalies in the set of testing returns: Net payout yield (NPY, Boudoukh et al. (2007)); revisions in analysts' earnings forecasts with one-month holding period (RE, Chan, Jegadeesh, and Lakonishok (1996)); advertisement expense-to-market (ADM, Chan, Lakonishok, and Sougiannis (2001)); and R&D-to-market (RDM, Chan et al. (2001)). Following Hou et al. (2015), NPY and RE belong to the larger groups of value-growth and momentum anomalies, respectively, while ADM and RDM are included in the group of intangibles. In total, we have 29 anomalies corresponding to 288 testing portfolios.

The results reported in the online appendix are qualitatively similar to the findings obtained for the full sample (with 25 anomalies). Specifically, the augmented conditional HXZ produces an explanatory ratio of 44%, which is more than twice the fit obtained for the unconditional four-factor

[27] These results also suggest that instruments with relatively weak time-series predictive power (e.g., DP, as shown in Table 4) can originate scaled factors with large explanatory power for the cross-section of average returns. Hence, DP can be motivated as a driving force of the (unobserved) conditional factor loading rather than a source of time-varying factor risk premia.

model (18%). As in the benchmark tests, the best performing single-instrument HXZ model is the version associated with IK, with a R^2_C of 36%, while the versions based on vs and RD, with explanatory ratios around 30%, also outperform the baseline model.

In the restricted sample, using conditioning information has a smaller contribution to the performance of the FF model, as indicated by the R^2_C of 20%, which represents an increase of about 10 percentage points relative to the fit of the baseline five-factor model (9%). As in the benchmark tests, the key instrument for the performance of the scaled FF is VS: the explanatory ratio of the single-instrument version based on this variable is about the same magnitude as that of the augmented model (20%), while the other single-instrument specifications improve rather marginally (versions based on NTIS and RD) or do not improve at all (RREL) the baseline model in terms of explaining cross-sectional risk premia.

Regarding the new anomalies, it turns out that the alpha for the high-minus-low spread corresponding to NPY is priced by the conditional FF models (unlike the respective baseline model), as suggested by the insignificant alphas. A similar pattern holds for the augmented conditional HXZ in terms of driving the RDM spread. On the other hand, both the unconditional and conditional HXZ models price the RE and ADM spreads and the same occurs for the FF model in terms of explaining the ADM and RDM return gaps. Hence, incorporating conditioning information is especially important for the FF and HXZ models in terms of explaining the NPY and RDM anomalies, respectively.

C. Time-Varying Alphas

In this subsection, we allow alphas to be time-varying following Christopherson, Ferson, and Glassman (1998), Ferson and Harvey (1999), Ferson et al. (2008), among others,

$$\alpha_{i,t} = \alpha_{i,0} + \alpha_{i,\mathrm{VS}}\mathrm{VS}_t + \alpha_{i,\mathrm{TB}}\mathrm{TB}_t + \alpha_{i,\mathrm{IK}}\mathrm{IK}_t + \alpha_{i,\mathrm{RD}}\mathrm{RD}_t, \quad (21)$$

which implies that the time-series regression for the conditional CAPM (based on VS, TB, IK, and RD) is now as follows,

$$R^e_{i,t+1} = \alpha_{i,0} + \alpha_{i,\mathrm{VS}}\mathrm{VS}_t + \alpha_{i,\mathrm{TB}}\mathrm{TB}_t + \alpha_{i,\mathrm{IK}}\mathrm{IK}_t + \alpha_{i,\mathrm{RD}}\mathrm{RD}_t$$
$$+\beta_{i,M}\mathrm{RM}_{t+1} + \beta_{i,M,\mathrm{VS}}\mathrm{RM}_{t+1}\mathrm{VS}_t + \beta_{i,M,\mathrm{TB}}\mathrm{RM}_{t+1}\mathrm{TB}_t$$
$$+\beta_{i,M,\mathrm{IK}}\mathrm{RM}_{t+1}\mathrm{IK}_t + \beta_{i,M,\mathrm{RD}}\mathrm{RM}_{t+1}\mathrm{RD}_t + \varepsilon_{i,t+1}, \tag{22}$$

and similarly for the other factor models (and alternative conditional specification).

Since the instruments are demeaned, by taking unconditional expectations of the previous regressions, we obtain:

$$\mathrm{E}(R^e_{i,t+1}) = \alpha_{i,0} + \beta_{i,M}\,\mathrm{E}(\mathrm{RM}_{t+1}) + \beta_{i,M,\mathrm{VS}}\,\mathrm{E}(\mathrm{RM}_{t+1}\mathrm{VS}_t) + \beta_{i,M,\mathrm{TB}}\,\mathrm{E}(\mathrm{RM}_{t+1}\mathrm{TB}_t)$$
$$+\beta_{i,M,\mathrm{IK}}\,\mathrm{E}(\mathrm{RM}_{t+1}\mathrm{IK}_t) + \beta_{i,M,\mathrm{RD}}\,\mathrm{E}(\mathrm{RM}_{t+1}\mathrm{RD}_t). \tag{23}$$

This means that to check the validity of the conditional models for unconditional risk premia, we need to test whether the intercept is zero ($\alpha_{i,0} = 0$), exactly as in the benchmark specification tested in the previous section. In other words, non-zero alpha coefficients on the instruments ($\alpha_{i,z} \neq 0$) do not affect the asset pricing implications of the conditional factor model for unconditional risk premia. Still, it could be the case that time-varying alphas can have an effect on the estimate of the average alpha ($\alpha_{i,0}$), which represents the unconditional pricing error, and also on the respective standard errors.

We redo the asset pricing tests for the joint 25 anomalies by using the augmented time-series regression presented above, which includes the four lagged instruments as regressors in each version of the conditional factor models. Untabulated results show that the estimated alphas (intercepts) and goodness-of-fit measures are very similar to the corresponding estimates in the benchmark tests. These results suggest that allowing alphas to be time-varying has a negligible impact in the fit of the conditional factor models for the cross-section of average stock returns.

VII. Restricted conditional models

A. Full cross-section

In this section, we estimate restricted versions of the scaled HXZ and FF models. In both groups of conditional models, only the scaled factors associated with the investment and profitability factors are included. The objective is to better disentangle the effect of conditioning information associated with the investment and profitability factors in terms of driving the explanatory power of each model for the cross-section of stock returns.

Specifically, the time-series regressions for the restricted HXZ model scaled by IK are given by

$$R^e_{i,t+1} = \alpha_i + \beta_{i,M}\mathrm{RM}_{t+1} + \beta_{i,\mathrm{ME}}\mathrm{ME}_{t+1} + \beta_{i,\mathrm{IA}}\mathrm{IA}_{t+1} + \beta_{i,\mathrm{IA,IK}}\mathrm{IA}_{t+1}\mathrm{IK}_t + \beta_{i,\mathrm{ROE}}\mathrm{ROE}_{t+1} + \beta_{i,\mathrm{ROE,IK}}\mathrm{ROE}_{t+1}\mathrm{IK}_t + \varepsilon_{i,t+1}, \tag{24}$$

and similarly for the models scaled by VS, TB, and RD. In the case of the restricted FF model based on VS, we have

$$R^e_{i,t+1} = \alpha_i + \beta_{i,M}\mathrm{RM}_{t+1} + \beta_{i,\mathrm{SMB}}\mathrm{SMB}_{t+1} + \beta_{i,\mathrm{HML}}\mathrm{HML}_{t+1} + \beta_{i,\mathrm{RMW}}\mathrm{RMW}_{t+1} + \beta_{i,\mathrm{RMW,VS}}\mathrm{RMW}_{t+1}\mathrm{VS}_t + \beta_{i,\mathrm{CMA}}\mathrm{CMA}_{t+1} + \beta_{i,\mathrm{CMA,VS}}\mathrm{CMA}_{t+1}\mathrm{VS}_t + \varepsilon_{i,t+1}, \tag{25}$$

and similarly for the models scaled by RREL, NTIS, and RD. Hence, each of these conditional models contains only two scaled factors. We also estimate restricted versions of the augmented scaled HXZ and FF models (based on all four instruments), which contain eight scaled factors.

The estimation results are presented in Table 10, which is similar to Table 7 above. We can see that the performance of the restricted scaled HXZ models is very similar to that of the corresponding models in Table 7. In particular, the MAA and R^2_C are almost identical to the corresponding estimates in the original scaled models. This suggests that the scaled factors associated with RM and ME do not add significant explanatory power in terms of pricing the large cross-section of equity risk premia. Importantly, it turns out that the gain in fit of the conditional model based on IK (relative to the baseline HXZ) is now significant at the 10% level. This suggests that excluding some noisy scaled factors can improve the power of the conditional asset pricing tests.

In the case of the scaled FF models there is a slightly larger difference in performance (relative to the benchmark scaled models) by excluding some of the scaled factors. Specifically, for both the augmented model and the model scaled by VS the explanatory ratios decline by around 5 percentage points. This implies that the gain in fit of the augmented model (relative to the baseline FF) is no longer significant at the 10% level (p-value of 11%). These results suggest that the performance of the scaled FF is more dependent of the other scaled factors. Moreover, the scaled HXZ model tends to achieve its performance with fewer scaled factors than the scaled FF model, which is consistent with the evidence from Section V..

We also assess the performance of the restricted conditional models across each anomaly group. Results presented in the online appendix show that the fit of the restricted HXZ models is quite similar to that of the corresponding unrestricted scaled models. In the case of the augmented model and the single-instrument models scaled by VS and IK the R_C^2 estimates are very close to the corresponding estimates for the unrestricted models: Only in the version based on VS when estimated on the investment group does the explanatory ratio decline by more than 5 percentage points. Excluding some of the scaled factors has a slightly larger negative impact on the performance of the scaled FF models, in line with the results for the full cross-section. Specifically, the explanatory ratio declines by more than 5 percentage points for both the FF version based on VS and augmented model (when tested on the momentum group) and the model based on NTIS (in terms of pricing the profitability group). This implies that the gain in fit (relative to the unconditional FF) is no longer significant (at the 10% level) for the FF scaled by VS (whereas in the case of the augmented model there is significance (for the difference in R_C^2) only at the 10% level) when it comes to explain the group of momentum anomalies.

Finally, we estimate restricted scaled models containing only one scaled factor. These models represent special cases of the single-instrument HXZ models based on VS and IK on one hand and the single-instrument FF models based on VS and NTIS on the other hand. Assessing the fit of these lower-scale restricted models allows one to better discriminate which are the scaled factors (profitability versus investment) driving the pricing performance of the models estimated above. Untabulated results show that the explanatory ratios (for the full cross-section of stock returns) associated with the scaled HXZ models containing $\text{ROE}_{t+1}\text{IK}_t$ and $\text{IA}_{t+1}\text{VS}_t$ as the sole scaled factor are 36% in both cases. By comparing these values with the corresponding fit for the restricted models (based on two scaled factors) in Table 10, it follows that $\text{IA}_{t+1}\text{IK}_t$ has an important contribution in terms of pricing the average portfolio, while the incremental explanatory power driven by $\text{ROE}_{t+1}\text{VS}_t$ is relatively marginal. On the other hand, the R^2_C estimates for the scaled FF models based on $\text{CMA}_{t+1}\text{VS}_t$ and $\text{RMW}_{t+1}\text{NTIS}_t$ are 8% and 11%, respectively. This suggests that $\text{RMW}_{t+1}\text{VS}_t$ helps explaining equity risk premia of the average portfolio while $\text{CMA}_{t+1}\text{NTIS}_t$ has no incremental pricing power for a model that already contains $\text{RMW}_{t+1}\text{NTIS}_t$.

Overall, the results of this subsection suggest that the scaled profitability and investment factors are the most relevant in terms of driving the performance of both the conditional HXZ and FF models. This implies that the remaining scaled factors in these models are of second-order importance at explaining cross-sectional risk premia. This pattern is especially notable in the case of the conditional HXZ models, while in the case of the scaled FF the missing factors have some contribution in terms of pricing several anomalies (e.g., momentum anomalies). This suggests that the conditional HXZ model not only achieves better overall pricing performance than the scaled FF model (as shown in the previous sections), but it also does so with fewer scaled factors.

B. Decomposing return spreads

What is the role of conditioning information in terms of driving the fit of the conditional factor models? More specifically, which scaled factors contribute the most for the fit of each model? To answer this question, we conduct a decomposition for the spreads high-minus-low in average returns. Following Maio (2013b) and Maio and Santa-Clara (2017), for each spread in returns we estimate the contribution from each factor in producing the respective alpha, which arises from computing the respective risk premium (beta times risk price). For example, in the case of the high-minus-low spread associated with the BM deciles, the contribution of the scaled factor $\text{IA}_{t+1}\text{IK}_t$ from the HXZ model is given by

$$\text{E}(\text{IA}_{t+1}\text{IK}_t)\beta_{10-1,BM,\text{IA},\text{IK}}, \tag{26}$$

where $\beta_{10-1,BM,\text{IA},\text{IK}}$ denotes the loading on $\text{IA}_{t+1}\text{IK}_t$ for the high-minus-low BM return spread. For a given factor to help explaining the raw return spread, the risk premium associated with that factor needs to have a relevant magnitude and the same sign as the original spread.

We focus on the single-instrument restricted conditional models presented above in order to better disentangle the contribution of each scaled factor for the model's performance. The results tabulated in the online appendix indicate that the scaled factors $\text{ROE}_{t+1}\text{IK}_t$ and $\text{IA}_{t+1}\text{VS}_t$ contribute the most to explaining the raw risk premia for the conditional HXZ models based on IK and VS, respectively. In the case of the conditional FF model based on VS and NTIS, the most relevant scaled factors are $\text{CMA}_{t+1}\text{VS}_t$ and $\text{RMW}_{t+1}\text{NTIS}_t$, respectively, as indicated by the signs and magnitudes of the respective risk premiums.

To a large extent these results support a consistency in the time-series and cross-sectional dimensions of stock returns: an instrument produces a higher explanatory power for cross-sectional risk premia when combined (into a scaled factor) with a raw factor for which it has greater forecasting power in the time-series. Hence, this legitimates our method of selecting instruments based on the time-series (univariate) predictive performance of the conditioning variables for the equity factors. Nevertheless, the results of this subsection should be interpreted with some caution, since the high-minus-low return spreads represent a rather incomplete picture of the broad cross-section of equity risk premia.

VIII. Conclusion

In this paper, we test conditional factor models over a large cross-section of stock returns associated with 25 different CAPM anomalies. These anomalies can be broadly classified as strategies related with value, momentum, investment, profitability, and intangibles. We test conditional versions of the CAPM, four-factor model of Hou et al. (2015), (2017) (HXZ), and the five-factor model of Fama and French (2015), (2016) (FF). We employ alternative instruments in the construction of the scaled factors within the conditional HXZ and FF models.

The analysis of the alphas for the 25 "high-minus-low" spreads in returns suggests that using conditioning information has a positive impact on the performance of the two multifactor models mentioned above. When we test the alternative models over the full cross-section of stock returns (for a total of 248 portfolios), our results also indicate that using conditioning information improves the performance of the two multifactor models for the broad cross-section of stock returns. The increased explanatory power is similar across both multifactor models, however, the conditional

HXZ model clearly dominates when it comes to explaining the cross-sectional dispersion in risk premia as indicated by the substantially larger explanatory ratios. Our results also suggest that the investment-to-capital ratio is the most important instrument for the performance of the conditional HXZ model, while the value spread is the key instrument in terms of driving the fit of the augmented conditional FF model.

We find that there is significant heterogeneity in the performance of the two multifactor models across groups of anomalies. On one hand, using conditioning information improves the performance of HXZ for the investment (like operating accruals, net operating assets, investment-to-assets, or inventory growth), intangibles (like organizational capital-to-assets and operating leverage), and momentum (like earnings momentum) anomalies. The performance of FF also improves substantially in terms of explaining the momentum (like industry momentum) and investment-based anomalies (like accruals-related anomalies). On the other hand, the scaled factors do not help HXZ and FF (or even have a negative impact) in terms of explaining the value-growth and profitability anomalies, respectively. With regards to relative performance, our results suggest that the conditional HXZ model outperforms the scaled FF model in terms of explaining the momentum and profitability anomalies, while the inverse holds when it comes to pricing the group of value-growth anomalies. This suggests, that even after accounting for the role of conditioning information, the asset pricing implications of the different versions of the investment and profitability factors are quite different for a large cross-section of stock returns.

In the last part of the paper, we estimate restricted versions of the conditional HXZ and FF models in which only the scaled factors associated with the investment and profitability factors are included. The results suggest that the scaled profitability and investment factors are the most relevant in terms of driving the performance of both the conditional HXZ and FF models. This pattern is especially notable in the case of the conditional HXZ models, while in the case of the scaled FF the missing factors have some contribution in terms of pricing several anomalies (e.g., momentum anomalies). This suggests that the conditional HXZ model not only achieves better overall pricing performance than the scaled FF model, but it also does so with fewer scaled factors.

Table 1: Descriptive Statistics for Equity Factors

This table reports descriptive statistics for the equity factors from alternative factor models. RM, SMB, and HML denote the market, size, and value factors, respectively. ME, IA, and ROE represent the Hou–Xue–Zhang size, investment, and profitability factors, respectively. RMW and CMA denote the Fama–French profitability and investment factors. The sample is 1972:01–2013:12. ϕ designates the first-order autocorrelation coefficient. The correlations between the factors are presented in Panel B.

Panel A. Basic Statistics

	Mean (%)	Std. Dev. (%)	Min. (%)	Max. (%)	ϕ
RM	0.53	4.61	−23.24	16.10	0.08
ME	0.31	3.14	−14.45	22.41	0.03
IA	0.44	1.87	−7.13	9.41	0.06
ROE	0.57	2.62	−13.85	10.39	0.10
SMB	0.23	3.07	−15.26	19.05	0.03
HML	0.40	3.00	−12.61	13.88	0.15
RMW	0.29	2.25	−17.60	12.24	0.18
CMA	0.37	1.96	−6.76	8.93	0.14

Panel B. Correlations

	RM	ME	IA	ROE	SMB	HML	RMW	CMA
RM	1.00	0.25	−0.36	−0.18	0.25	−0.32	−0.23	−0.39
ME		1.00	−0.12	−0.31	0.98	−0.07	−0.38	−0.01
IA			1.00	0.06	−0.15	0.69	0.10	0.90
ROE				1.00	−0.38	−0.09	0.67	−0.09
SMB					1.00	−0.11	−0.39	−0.05
HML						1.00	0.15	0.70
RMW							1.00	−0.03
CMA								1.00

Table 2: List of Portfolio Sorts

This table lists the 25 alternative anomalies or portfolio sorts employed in the empirical analysis. "Category" refers to the broad classification employed by Hou et al. (2015), and "#" represents the number of portfolios in each group. "Reference" shows the paper that represents the source of the anomaly.

Symbol	Anomaly	Category	#	Reference
BM	Book-to-market equity	Value-growth	10	Rosenberg, Reid, and Lanstein (1985)
MOM	Price momentum (11-month prior returns)	Momentum	10	Fama and French (1996)
IA	Investment-to-assets	Investment	10	Cooper, Gulen, and Schill (2008)
ROE	Return on equity	Profitability	10	Haugen and Baker (1996)
SUE	Earnings surprise (1-month holding period)	Momentum	10	Foster, Olsen, and Shevlin (1984)
GPA	Gross profits-to-assets	Profitability	10	Novy-Marx (2013)
NSI	Net stock issues	Investment	10	Pontiff and Woodgate (2008)
OCA	Organizational capital-to-assets	Intangibles	10	Eisfeldt and Papanikolaou (2013)
OL	Operating leverage	Intangibles	10	Novy-Marx (2011)
ABR	Cumulative abnormal stock returns around earnings announcements (1-month)	Momentum	10	Chan, Jegadeesh, and Lakonishok (1996)
CEI	Composite issuance	Investment	10	Daniel and Titman (2006)
PIA	Changes in property, plant, and equipment scaled by assets	Investment	10	Lyandres, Sun, and Zhang (2008)
DUR	Equity duration	Value-growth	10	Dechow, Sloan, and Soliman (2004)
IG	Investment growth	Investment	10	Xing (2008)
IVC	Inventory changes	Investment	10	Thomas and Zhang (2002)
IVG	Inventory growth	Investment	10	Belo and Lin (2011)
NOA	Net operating assets	Investment	10	Hirshleifer, Hou, Teoh, and Zhang (2004)
OA	Operating accruals	Investment	10	Sloan (1996)
POA	Percent operating accruals	Investment	10	Hafzalla, Lundholm, and Van Winkle (2011)
PTA	Percent total accruals	Investment	10	Hafzalla et al. (2011)
IM	Industry momentum	Momentum	9	Moskowitz and Grinblatt (1999)
NEI	Number of consecutive quarters with earnings increases	Profitability	9	Barth, Elliott, and Finn (1999)
ABR*	Cumulative abnormal stock returns around earnings announcements (6-month)	Momentum	10	Chan et al. (1996)
CFP	Cash flow-to-price	Value-growth	10	Lakonishok, Shleifer, and Vishny (1994)
RS	Revenue surprise	Profitability	10	Jegadeesh and Livnat (2006)

Table 3: Descriptive Statistics for Spreads in Returns

This table reports descriptive statistics for the "high-minus-low" spreads in returns associated with different portfolio classes. See Table 2 for a description of the different portfolio sorts. The sample is 1972:01–2013:12. ϕ designates the first-order autocorrelation coefficient.

	Mean (%)	Std. Dev. (%)	Min. (%)	Max. (%)	ϕ
BM	0.69	4.86	−14.18	20.45	0.11
DUR	−0.52	4.34	−21.38	15.77	0.09
CFP	0.49	4.66	−18.95	16.26	0.02
MOM	1.17	7.21	−61.35	26.30	0.05
SUE	0.44	3.05	−14.27	12.09	−0.00
ABR	0.73	3.17	−15.80	15.32	−0.10
IM	0.54	5.09	−33.33	20.27	0.05
ABR*	0.30	2.08	−10.45	9.86	−0.01
ROE	0.75	5.28	−26.37	29.30	0.16
GPA	0.34	3.36	−13.55	12.35	0.04
NEI	0.36	2.79	−12.10	12.21	0.00
RS	0.30	3.46	−12.85	20.08	0.07
IA	−0.42	3.62	−14.39	11.83	0.04
NSI	−0.69	3.28	−20.47	12.88	0.10
CEI	−0.55	4.06	−16.34	17.94	0.06
PIA	−0.49	3.00	−10.37	8.60	0.08
IG	−0.38	2.83	−12.81	9.67	0.07
IVC	−0.43	3.19	−12.21	11.64	0.06
IVG	−0.36	3.15	−9.69	12.04	0.07
NOA	−0.39	3.11	−14.26	13.45	0.02
OA	−0.27	3.10	−10.39	12.81	−0.01
POA	−0.43	3.12	−11.84	19.87	0.06
PTA	−0.40	3.38	−11.25	19.13	0.01
OCA	0.55	3.13	−13.68	13.60	−0.02
OL	0.39	3.86	−10.34	17.37	0.11

Table 4: Univariate Predictive Regressions for Equity Factors

This table presents the slopes and respective t-ratios (in parentheses) in single regressions of equity factors on lagged predictors. The second row contains the R^2 associated with each regression (in %). IA and ROE represent the Hou–Xue–Zhang investment and profitability factors, respectively. RMW and CMA denote the Fama–French profitability and investment factors, respectively. The sample is 1972:01–2013:12. The t-ratios are heteroskedasticity-robust. Bold t-ratios indicate statistical significance at the 5% level. For a description of the variables see the text in Section 4.

	IA		ROE		RMW		CMA	
DP	0.000	(0.14)	0.001	(0.53)	−0.001	(−0.73)	−0.001	(−0.75)
	0.01		0.09		0.22		0.18	
TERM	−0.001	(−0.91)	−0.002	(−1.49)	0.002	(1.68)	−0.001	(−1.05)
	0.17		0.49		0.56		0.24	
TB	0.001	(1.34)	0.003	(**2.22**)	−0.000	(−0.17)	0.001	(0.84)
	0.28		1.04		0.00		0.13	
DE	0.001	(0.60)	−0.003	(−1.56)	0.000	(0.03)	−0.000	(−0.13)
	0.08		1.35		0.00		0.00	
NTIS	0.001	(0.76)	−0.000	(−0.30)	−0.002	(**−1.98**)	0.000	(0.42)
	0.10		0.02		0.53		0.03	
RD	0.002	(1.66)	0.001	(0.26)	0.002	(0.96)	0.003	(1.82)
	1.32		0.05		1.07		1.91	
DEF	0.000	(0.09)	−0.002	(−1.49)	−0.001	(−0.54)	−0.000	(−0.40)
	0.00		0.78		0.05		0.03	
DFR	0.000	(0.04)	0.000	(0.11)	−0.001	(−0.85)	0.000	(0.02)
	0.00		0.01		0.20		0.00	
VS	0.003	(**2.61**)	−0.001	(−0.38)	0.001	(0.44)	0.003	(**3.08**)
	1.93		0.07		0.15		2.70	
SVAR	−0.001	(−0.79)	−0.001	(−0.75)	−0.000	(−0.02)	0.000	(0.46)
	0.07		0.22		0.00		0.02	
INF	0.001	(1.22)	0.001	(0.93)	0.000	(0.05)	0.001	(0.76)
	0.24		0.16		0.00		0.10	
ΔFFR	0.001	(1.45)	−0.000	(−0.37)	−0.001	(−1.08)	0.001	(0.88)
	0.29		0.03		0.19		0.15	
RREL	0.000	(0.49)	−0.001	(−0.89)	−0.003	(**−3.00**)	0.001	(1.18)
	0.04		0.15		1.32		0.26	
CSV	0.001	(0.46)	−0.001	(−0.67)	−0.000	(−0.07)	0.001	(0.83)
	0.12		0.28		0.01		0.39	
YG	−0.000	(−0.32)	0.003	(1.56)	−0.001	(−0.88)	−0.001	(−0.70)
	0.03		1.13		0.21		0.13	
IPG	0.000	(0.43)	0.000	(0.18)	−0.002	(−1.73)	−0.000	(−0.07)
	0.03		0.01		0.52		0.00	
EP	−0.000	(−0.25)	0.003	(1.61)	−0.001	(−0.84)	−0.001	(−0.66)
	0.02		1.18		0.19		0.11	
PE	−0.000	(−0.44)	−0.000	(−0.25)	0.001	(0.71)	0.000	(0.32)
	0.06		0.02		0.20		0.03	
BM	0.001	(0.69)	0.001	(0.83)	−0.001	(−1.35)	−0.000	(−0.08)
	0.11		0.18		0.43		0.00	
CAY	−0.001	(−1.10)	0.001	(1.34)	0.002	(**2.13**)	−0.001	(−1.56)
	0.20		0.22		0.53		0.40	
IK	0.001	(0.48)	0.003	(1.92)	0.001	(0.42)	0.001	(0.92)
	0.08		1.12		0.08		0.27	

Table 5: Multivariate Predictive Regressions for Equity Factors

This table presents the results for regressions of equity factors on lagged predictors. In Panel A, the lagged instruments are the value spread (VS), one-month T-bill rate (TB), investment-capital ratio (IK), and stock return dispersion (RD). In Panel B, the instruments are VS, RD, relative T-bill rate (RREL), and net equity expansion (NTIS). RM, SMB, and HML denote the market, size, and value factors, respectively. ME, IA, and ROE represent the Hou–Xue–Zhang size, investment, and profitability factors, respectively. RMW and CMA denote the Fama–French profitability and investment factors. The sample is 1972:01–2013:12. For each regression, the first row presents the coefficient estimates and the second row reports GMM-based t-ratios. R^2 denotes the coefficient of determination. The column labeled χ^2 presents the Wald statistic (first line) and associated p-value (in parenthesis) for the test on the joint significance of the four predictors. Bold t-ratios indicate statistical significance at the 5% level.

Panel A. HXZ (VS,TB,IK,RD)

	VS	TB	IK	RD	R^2	χ^2
RM	−0.001	−0.001	−0.004	−0.001	0.01	4.74
	(−0.46)	(−0.29)	(−1.43)	(−0.48)		(0.32)
ME	0.002	−0.000	0.000	−0.001	0.01	2.22
	(1.21)	(−0.13)	(0.03)	(−0.32)		(0.69)
IA	0.003	0.002	−0.001	0.001	0.03	14.32
	(**2.33**)	(**2.33**)	(−0.56)	(0.82)		(0.01)
ROE	−0.000	0.002	0.002	0.000	0.01	6.63
	(−0.06)	(1.29)	(1.25)	(0.04)		(0.16)

Panel B. FF (VS,RREL,NTIS,RD)

	VS	RREL	NTIS	RD	R^2	χ^2
RM	−0.001	−0.004	0.000	−0.003	0.01	5.63
	(−0.43)	(**−2.04**)	(0.18)	(−1.02)		(0.23)
SMB	0.001	−0.003	0.001	−0.001	0.01	7.25
	(0.74)	(**−2.15**)	(0.56)	(−0.41)		(0.12)
HML	0.001	0.004	0.001	0.004	0.04	12.79
	(0.74)	(**2.68**)	(0.45)	(1.89)		(0.01)
RMW	−0.001	−0.002	−0.001	0.002	0.03	15.59
	(−0.32)	(**−2.12**)	(−1.24)	(1.02)		(0.00)
CMA	0.003	0.002	−0.001	0.001	0.04	12.36
	(**2.69**)	(**2.13**)	(−0.81)	(0.90)		(0.01)

Table 6: Spreads "High-minus-Low"

This table presents alphas for "high-minus-low" portfolio return spreads associated with unconditional and conditional factor models. See Table 2 for a description of the different portfolio sorts. The models are the Hou–Xue–Zhang four-factor model (HXZ) and Fama–French five-factor model (FF). In the conditional HXZ models, the lagged instruments are the value spread (VS), one-month T-bill rate (TB), investment-capital ratio (IK), and stock return dispersion (RD). In the conditional FF models, the lagged instruments are VS, RD, relative T-bill rate (RREL), and net equity expansion (NTIS). "All" refers to conditional models in which all the corresponding four instruments are employed. The sample is 1972:01–2013:12. Bold values indicate statistical significance at the 5% level.

	HXZ	VS	TB	RD	IK	All	FF	RREL	NTIS	RD	VS	All
BM	0.23	**0.38**	0.22	0.32	0.36	**0.42**	0.04	0.06	−0.03	0.03	0.02	0.01
DUR	−0.27	**−0.49**	−0.26	−0.32	**−0.39**	**−0.42**	−0.15	−0.12	−0.13	−0.10	−0.12	−0.06
CFP	0.22	0.36	0.21	0.31	0.34	0.36	0.07	0.10	0.03	0.03	−0.03	−0.06
MOM	0.26	0.03	0.29	0.21	0.08	0.04	**1.22**	**1.31**	**1.13**	**1.21**	**1.02**	**1.00**
SUE	0.16	0.09	0.15	0.17	0.09	−0.01	**0.44**	**0.44**	**0.39**	**0.48**	**0.48**	**0.42**
ABR	**0.64**	**0.58**	**0.63**	**0.63**	**0.59**	**0.50**	**0.84**	**0.84**	**0.81**	**0.85**	**0.83**	**0.78**
IM	0.05	−0.09	0.03	−0.02	−0.03	−0.11	**0.60**	**0.58**	**0.50**	**0.57**	0.46	0.31
ABR*	**0.26**	0.18	**0.25**	**0.24**	0.20	0.11	**0.44**	**0.42**	**0.42**	**0.44**	**0.43**	**0.39**
ROE	0.02	0.10	0.05	0.10	0.11	0.19	**0.54**	**0.57**	**0.52**	**0.60**	**0.63**	**0.67**
GPA	0.11	0.12	0.07	0.11	0.11	0.11	0.11	0.11	0.14	0.09	0.09	0.11
NEI	0.15	0.10	0.13	0.10	0.12	0.05	**0.44**	**0.44**	**0.44**	**0.45**	**0.47**	**0.45**
RS	0.18	0.09	0.15	0.14	0.14	0.03	**0.50**	**0.50**	**0.48**	**0.51**	**0.55**	**0.50**
IA	0.13	0.03	0.10	0.05	0.09	0.01	0.11	0.10	0.11	0.09	0.08	0.05
NSI	**−0.26**	**−0.37**	**−0.28**	**−0.37**	**−0.32**	**−0.42**	**−0.26**	**−0.27**	**−0.25**	**−0.28**	**−0.26**	−0.23
CEI	−0.21	−0.26	−0.22	−0.23	−0.24	−0.27	−0.20	−0.20	−0.15	−0.16	−0.13	−0.05
PIA	−0.24	**−0.25**	**−0.26**	−0.21	−0.12	−0.18	**−0.30**	**−0.32**	**−0.28**	**−0.30**	**−0.32**	**−0.31**
IG	0.07	0.03	0.02	0.09	0.08	0.01	−0.02	−0.04	−0.06	−0.01	−0.02	−0.07
IVC	−0.26	−0.26	**−0.30**	−0.23	−0.16	−0.22	**−0.34**	**−0.37**	**−0.36**	**−0.33**	**−0.36**	**−0.38**
IVG	0.02	−0.02	0.01	0.02	0.06	0.03	−0.08	−0.09	−0.09	−0.10	−0.08	−0.09
NOA	**−0.37**	−0.24	−0.32	**−0.35**	−0.27	−0.18	**−0.43**	**−0.48**	**−0.46**	**−0.43**	**−0.32**	**−0.39**
OA	**−0.53**	**−0.40**	**−0.49**	**−0.47**	**−0.43**	**−0.33**	**−0.51**	**−0.52**	**−0.46**	**−0.51**	**−0.48**	**−0.41**
POA	−0.11	−0.13	−0.10	−0.15	−0.13	−0.14	−0.12	−0.13	−0.09	−0.14	−0.11	−0.11
PTA	−0.11	−0.21	−0.14	−0.16	−0.16	−0.21	−0.06	−0.07	−0.04	−0.05	−0.06	−0.03
OCA	0.11	0.17	0.14	0.12	0.14	0.23	**0.30**	**0.33**	**0.32**	**0.31**	**0.33**	**0.41**
OL	−0.06	0.09	−0.04	0.04	0.02	0.05	0.02	−0.01	0.02	0.05	0.09	0.07

Table 7: Joint Time-Series Tests

This table presents joint time-series tests of unconditional and conditional factor models. The test portfolios are the 25 different portfolios sorts defined in Table 2. The unconditional models are the CAPM, Hou–Xue–Zhang four-factor model (HXZ), and Fama–French five-factor model (FF). In Panel A, the lagged variables used in the (single-instrument) conditional specifications of HXZ are the value spread (VS), one-month T-bill rate (TB), investment-capital ratio (IK), and stock return dispersion (RD). In Panel B, the lagged variables used in the (single-instrument) conditional specifications of FF are VS, RD, relative T-bill rate (RREL), and net equity expansion (NTIS). "All" refers to conditional HXZ and FF models in which all the corresponding four instruments are employed. "CAPM(All)" denotes the conditional CAPM containing all four instruments. The sample is 1972:01–2013:12. MAA denotes the mean absolute alpha. $\# < 0.05$ represents the number of portfolios in which the alphas are significant at the 5% level. $\#\chi^2$ denotes the number of portfolio groups in which the model is not rejected by the χ^2 specification test. R^2_C is the cross-sectional constrained R^2. The numbers in parentheses represent empirical p-values (obtained from a bootstrap simulation) for testing the null hypothesis that the difference in R^2_C between each conditional multifactor model (and the corresponding unconditional model) is equal to zero.

Panel A. HXZ (VS,TB,IK,RD)

	CAPM	CAPM(All)	HXZ	VS	TB	IK	RD	All
MAA	0.15	0.13	0.11	0.10	0.10	0.10	0.11	0.09
$\# < 0.05$	82	67	39	30	37	31	38	28
$\#\chi^2$	4	6	7	8	7	12	9	13
R^2_C	−0.46	−0.20	0.30	0.41	0.33	0.48	0.39	0.52
				(0.21)	(0.41)	(0.12)	(0.25)	(0.07)

Panel B. FF (VS,RREL,NTIS,RD)

	CAPM	CAPM(All)	FF	VS	RREL	NTIS	RD	All
MAA	0.15	0.14	0.11	0.11	0.11	0.11	0.11	0.10
$\# < 0.05$	82	77	56	46	56	55	50	43
$\#\chi^2$	4	6	8	9	8	11	8	9
R^2_C	−0.46	−0.34	0.07	0.19	0.04	0.12	0.10	0.27
				(0.16)	(0.43)	(0.32)	(0.41)	(0.06)

Table 8: Joint Time-Series Tests by Category

This table presents joint time-series tests of unconditional and conditional factor models. The test portfolios are combinations of 25 different portfolios sorts that correspond to the categories defined in Table 2. For example, the value-growth category contains the BM, DUR, and CFP deciles. The models are the Hou–Xue–Zhang four-factor model (HXZ) and the Fama–French five-factor model (FF). In the conditional HXZ models, the lagged instruments are the value spread (VS), one-month T-bill rate (TB), investment-capital ratio (IK), and stock return dispersion (RD). In the conditional FF models, the lagged instruments are VS, RD, relative T-bill rate (RREL), and net equity expansion (NTIS). "All" refers to conditional HXZ and FF models in which all the corresponding four instruments are employed. MAA denotes the mean absolute alpha. $\# < 0.05$ represents the number of portfolios in which the alphas are significant at the 5% level. $\#\chi^2$ denotes the number of portfolio groups in which the model is not rejected by the χ^2 specification test. R^2_C is the cross-sectional constrained R^2. The numbers in parentheses represent empirical p-values (obtained from a bootstrap simulation) for testing the null hypothesis that the difference in R^2_C between each conditional multifactor model (and the corresponding unconditional model) is equal to zero.

	HXZ	FF	HXZ(TB)	HXZ(RD)	HXZ(VS)	HXZ(IK)	HXZ(All)	FF(RREL)	FF(RD)	FF(NTIS)	FF(VS)	FF(All)
Panel A. Value-Growth												
MAA	0.10	0.08	0.10	0.12	0.13	0.12	0.13	0.07	0.07	0.08	0.07	0.06
$\# < 0.05$	2	1	2	6	5	5	9	1	1	2	1	1
$\#\chi^2$	2	3	2	2	2	2	1	3	3	3	3	3
R^2_C	0.36	0.66	0.41	0.30	0.09	0.25	0.20	0.67	0.72	0.66	0.74	0.79
			(0.45)	(0.44)	(0.24)	(0.37)	(0.36)	(0.47)	(0.41)	(0.51)	(0.37)	(0.30)
Panel B. Momentum												
MAA	0.10	0.16	0.10	0.10	0.09	0.10	0.09	0.16	0.16	0.16	0.14	0.13
$\# < 0.05$	7	16	7	7	5	6	3	16	16	18	12	12
$\#\chi^2$	1	0	2	2	2	2	3	0	0	1	0	0
R^2_C	0.42	−0.33	0.46	0.53	0.57	0.56	0.66	−0.41	−0.30	−0.20	−0.05	0.07
			(0.42)	(0.31)	(0.26)	(0.28)	(0.16)	(0.37)	(0.41)	(0.26)	(0.09)	(0.04)
Panel C. Profitability												
MAA	0.09	0.12	0.10	0.10	0.10	0.08	0.09	0.12	0.12	0.11	0.12	0.11
$\# < 0.05$	7	9	7	5	4	6	3	10	9	9	9	7
$\#\chi^2$	1	1	2	2	1	3	3	2	2	2	1	1
R^2_C	0.48	−0.06	0.45	0.49	0.48	0.58	0.56	−0.14	−0.10	0.02	−0.16	−0.07
			(0.47)	(0.46)	(0.52)	(0.33)	(0.33)	(0.40)	(0.45)	(0.33)	(0.36)	(0.56)
Panel D. Investment												
MAA	0.11	0.10	0.11	0.11	0.10	0.10	0.09	0.10	0.10	0.10	0.10	0.10
$\# < 0.05$	20	27	18	17	14	11	13	24	21	23	21	20
$\#\chi^2$	2	3	1	2	2	3	4	2	2	3	4	4
R^2_C	0.10	0.18	0.15	0.25	0.33	0.40	0.48	0.16	0.20	0.18	0.26	0.31
			(0.36)	(0.19)	(0.10)	(0.05)	(0.02)	(0.48)	(0.42)	(0.47)	(0.28)	(0.17)
Panel E. Intangibles												
MAA	0.12	0.10	0.12	0.10	0.11	0.09	0.09	0.10	0.10	0.10	0.10	0.08
$\# < 0.05$	3	3	3	3	2	3	0	5	3	3	3	3
$\#\chi^2$	1	1	0	1	1	2	2	1	1	1	1	1
R^2_C	0.11	0.18	0.07	0.35	0.42	0.54	0.65	0.21	0.21	0.24	0.15	0.35
			(0.47)	(0.17)	(0.11)	(0.05)	(0.02)	(0.40)	(0.43)	(0.36)	(0.48)	(0.18)

Table 9: Time-Series Tests for Selected Anomalies

This table presents time-series tests of unconditional and conditional factor models for selected individual anomalies. The portfolios are sorted on BM, MOM, ROE, NSI, OCA, ABR, CEI, DUR, IM, ABR*, NOA, and OA. See Table 2 in the paper for a description of the different portfolio sorts. The models are the Hou–Xue–Zhang four-factor model (HXZ) and the Fama–French five-factor model (FF). In the conditional HXZ models, the lagged instruments are the value spread (VS), one-month T-bill rate (TB), investment-capital ratio (IK), and stock return dispersion (RD). In the conditional FF models, the lagged instruments are VS, RD, relative T-bill rate (RREL), and net equity expansion (NTIS). The sample is 1972:01–2013:12. MAA denotes the mean absolute alpha. $\# < 0.05$ represents the number of portfolios in which the alphas are significant at the 5% level. χ^2 denotes the p-value associated with the χ^2 specification test. R^2_C is the cross-sectional constrained R^2. The numbers in parentheses represent empirical p-values (obtained from a bootstrap simulation) for testing the null hypothesis that the difference in R^2_C between each conditional multifactor model (and the corresponding unconditional model) is equal to zero.

	BM	DUR	MOM	ABR	IM	ABR*	ROE	NSI	CEI	NOA	OA	OCA
Panel A. HXZ (Uncond.)												
MAA	0.09	0.08	0.13	0.13	0.13	0.07	0.09	0.11	0.11	0.12	0.15	0.12
$\# < 0.05$	0	0	0	2	3	1	2	1	2	2	3	2
χ^2	0.22	0.60	0.01	0.00	0.04	0.00	0.02	0.01	0.01	0.00	0.00	0.01
R^2_C	0.60	0.62	0.67	−0.08	0.79	0.01	0.77	0.57	0.33	0.09	−1.05	0.16
Panel B. HXZ (IK)												
MAA	0.12	0.13	0.15	0.11	0.07	0.07	0.10	0.11	0.12	0.09	0.12	0.10
$\# < 0.05$	1	2	0	3	1	1	3	2	0	1	2	2
χ^2	0.12	0.14	0.01	0.00	0.18	0.02	0.00	0.01	0.03	0.01	0.00	0.09
R^2_C	0.51	0.39	0.64	0.18	0.83	0.45	0.67	0.63	0.55	0.47	−0.22	0.55
	(0.40)	(0.28)	(0.47)	(0.14)	(0.46)	(0.12)	(0.39)	(0.41)	(0.22)	(0.06)	(0.02)	(0.10)
Panel C. HXZ (VS)												
MAA	0.12	0.14	0.15	0.12	0.06	0.07	0.10	0.11	0.12	0.11	0.13	0.11
$\# < 0.05$	1	2	0	3	1	0	2	1	0	2	1	2
χ^2	0.07	0.12	0.01	0.00	0.11	0.03	0.00	0.00	0.02	0.00	0.00	0.03
R^2_C	0.34	0.17	0.67	0.14	0.83	0.44	0.65	0.63	0.58	0.31	−0.59	0.36
	(0.24)	(0.13)	(0.49)	(0.18)	(0.46)	(0.13)	(0.37)	(0.40)	(0.19)	(0.18)	(0.09)	(0.24)
Panel D. HXZ (VS,TB,IK,RD)												
MAA	0.12	0.15	0.15	0.10	0.05	0.06	0.11	0.11	0.10	0.09	0.11	0.10
$\# < 0.05$	2	5	0	2	0	1	2	1	1	1	1	0
χ^2	0.05	0.07	0.02	0.01	0.25	0.05	0.00	0.00	0.08	0.01	0.00	0.14
R^2_C	0.40	0.30	0.69	0.44	0.80	0.55	0.60	0.56	0.70	0.54	0.05	0.64
	(0.33)	(0.25)	(0.48)	(0.02)	(0.46)	(0.08)	(0.36)	(0.51)	(0.11)	(0.04)	(0.01)	(0.05)
Panel E. FF (Uncond.)												
MAA	0.05	0.05	0.23	0.16	0.23	0.08	0.11	0.11	0.10	0.11	0.13	0.11
$\# < 0.05$	0	0	3	3	6	3	2	3	2	4	5	2
χ^2	0.72	0.84	0.00	0.00	0.00	0.00	0.03	0.01	0.03	0.01	0.01	0.01
R^2_C	0.83	0.84	−0.10	−0.52	−0.36	−1.18	0.46	0.54	0.43	0.22	−0.60	0.26
Panel F. FF (VS)												
MAA	0.05	0.06	0.18	0.16	0.15	0.08	0.11	0.13	0.10	0.10	0.13	0.12
$\# < 0.05$	0	0	1	4	3	2	2	3	1	3	3	2
χ^2	0.60	0.87	0.00	0.00	0.01	0.00	0.00	0.00	0.03	0.01	0.01	0.00
R^2_C	0.83	0.88	0.21	−0.51	0.18	−1.21	0.34	0.50	0.50	0.41	−0.56	0.26
	(0.47)	(0.43)	(0.16)	(0.47)	(0.10)	(0.50)	(0.36)	(0.45)	(0.39)	(0.18)	(0.42)	(0.48)
Panel G. FF (NTIS)												
MAA	0.07	0.05	0.22	0.16	0.22	0.08	0.10	0.11	0.10	0.12	0.12	0.11
$\# < 0.05$	0	0	4	3	7	3	2	3	2	4	3	2
χ^2	0.80	0.64	0.00	0.00	0.00	0.00	0.08	0.01	0.05	0.01	0.02	0.02
R^2_C	0.85	0.81	0.02	−0.45	−0.07	−1.15	0.52	0.51	0.46	0.11	−0.33	0.31
	(0.45)	(0.48)	(0.35)	(0.36)	(0.23)	(0.44)	(0.41)	(0.44)	(0.44)	(0.32)	(0.18)	(0.39)
Panel H. FF (VS,RREL,NTIS,RD)												
MAA	0.04	0.05	0.17	0.15	0.14	0.07	0.13	0.13	0.10	0.10	0.11	0.10
$\# < 0.05$	0	0	1	4	4	2	2	4	1	3	2	2
χ^2	0.92	0.79	0.00	0.00	0.02	0.00	0.00	0.00	0.03	0.01	0.02	0.01
R^2_C	0.89	0.85	0.21	−0.31	0.53	−0.91	0.26	0.44	0.51	0.30	−0.08	0.35
	(0.41)	(0.45)	(0.17)	(0.15)	(0.03)	(0.19)	(0.31)	(0.37)	(0.35)	(0.32)	(0.05)	(0.30)

Table 10: Joint Time-Series Tests: Restricted Conditional Models

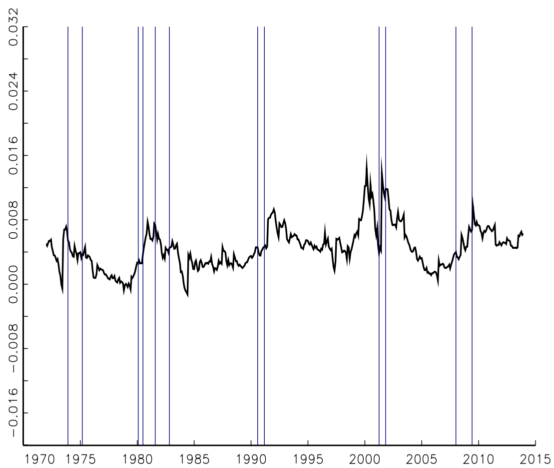
This table presents joint time-series tests of restricted conditional factor models. The test portfolios are the 25 different portfolios sorts defined in Table 2. The unconditional models are the Hou–Xue–Zhang four-factor model (HXZ) and Fama–French five-factor model (FF). In Panel A, the lagged variables used in the (single-instrument) conditional specifications of HXZ are the value spread (VS), one-month T-bill rate (TB), investment-capital ratio (IK), and stock return dispersion (RD). In Panel B, the lagged variables used in the (single-instrument) conditional specifications of FF are VS, RD, relative T-bill rate (RREL), and net equity expansion (NTIS). "All" refers to conditional HXZ and FF models in which all the corresponding four instruments are employed. Only the investment and profitability factors in both models are scaled. The sample is 1972:01–2013:12. MAA denotes the mean absolute alpha. $\# < 0.05$ represents the number of portfolios in which the alphas are significant at the 5% level. $\#\chi^2$ denotes the number of portfolio groups in which the model is not rejected by the χ^2 specification test. R^2_C is the cross-sectional constrained R^2. The numbers in parentheses represent empirical p-values (obtained from a bootstrap simulation) for testing the null hypothesis that the difference in R^2_C between each conditional multifactor model (and the corresponding unconditional model) is equal to zero.

Panel A. HXZ (VS,TB,IK,RD)

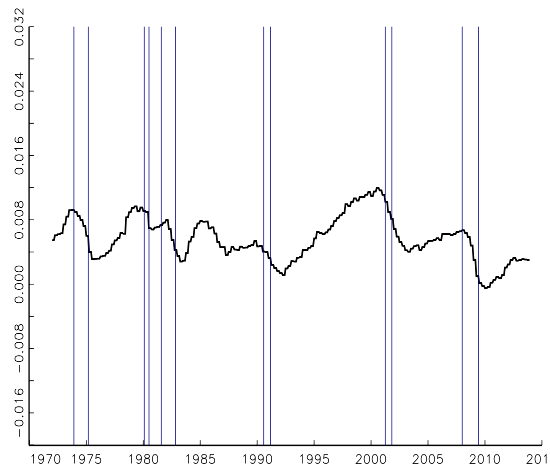
	HXZ	VS	TB	IK	RD	All
MAA	0.11	0.10	0.10	0.10	0.10	0.09
$\# < 0.05$	39	33	39	31	39	28
$\#\chi^2$	7	8	8	12	9	12
R^2_C	0.30	0.40	0.32	0.48	0.38	0.50
		(0.22)	(0.44)	(0.10)	(0.28)	(0.07)

Panel B. FF (VS,RREL,NTIS,RD)

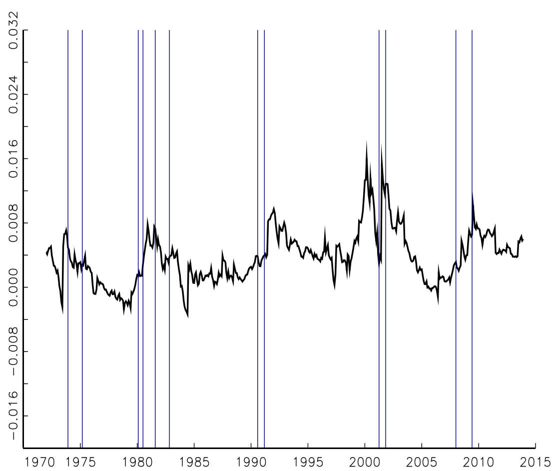
	FF	VS	RREL	NTIS	RD	All
MAA	0.11	0.11	0.11	0.11	0.11	0.10
$\# < 0.05$	56	50	56	53	50	46
$\#\chi^2$	8	8	8	8	8	9
R^2_C	0.07	0.15	0.11	0.10	0.10	0.22
		(0.25)	(0.38)	(0.40)	(0.40)	(0.11)



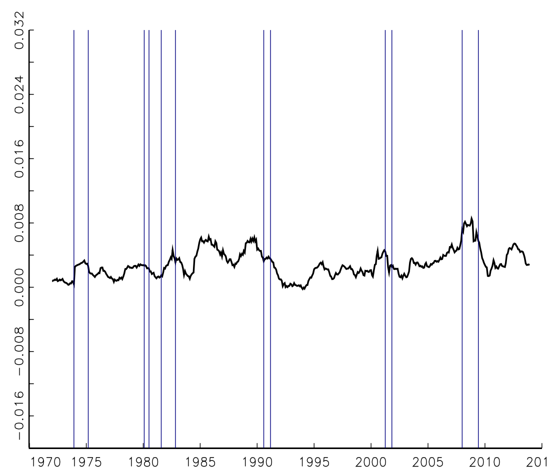
Graph A. IA



Graph B. ROE



Graph C. CMA



Graph D. RMW

Figure 1: Investment and Profitability Factor Premia

This figure plots the time-series for the fitted values of the equity factors, which are obtained from regressing the factors on a lagged instrument. The factors are the investment (IA and CMA) and profitability (ROE and RMW) factors. The instrument associated with both IA and CMA is the value spread (VS). In the regressions for ROE and RMW, the instruments are investment-capital ratio (IK) and net equity expansion (NTIS), respectively. The sample period is 1972:01–2013:12. The vertical lines indicate the NBER recession periods.

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