New evidence on conditional factor models

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This version: January 2016[2]

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[2]I thank Frederico Belo for helpful comments. I am grateful to Kenneth French, Robert Shiller, and Lu Zhang for providing stock market data. Any remaining errors are mine.

Abstract

I estimate conditional multifactor models over a large cross-section of stock returns associated with 25 CAPM anomalies. The four-factor model of Hou, Xue, and Zhang (2015a, 2015b) clearly outperforms the competing models in pricing the extreme portfolio deciles and the cross-sectional dispersion in equity risk premia. Yet, the five-factor model of Fama and French (2015, 2016) outperforms in pricing the intermediate deciles. Therefore, 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. The HML factor is largely redundant within the five-factor model when using conditioning information.

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; HML

JEL classification: G10; G12

1 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 with 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 (2015b) 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 Hou, Xue, and Zhang (2015a) and Maio (2015), the performance of the two models varies widely when it comes to price 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. 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 from Sharpe (1964) and Lintner (1965) when it comes to explain 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 (2013). Yet, most of this literature focuses on the conditional CAPM and neglects the role of conditioning information for multifactor models (with He, Kan, Ng, and Zhang (1996), Ferson and Harvey (1999), Wang (2003), and Maio (2013) representing notable exceptions).

Following Hou, Xue, and Zhang (2015a, 2015b), I test conditional factor models over a large cross-section of stock returns associated with 25 different CAPM anomalies. These anomalies can be broadly classified in strategies related with value, momentum, investment, profitability, and intangibles. In the benchmark test, the portfolios are value-weighted and all the groups include decile portfolios, except “industry momentum” and “number of quarters with earnings increases” with nine portfolios each. Following the conditional CAPM literature, I use four conditioning variables in the construction of the scaled risk factors—the term spread, default spread, log dividend yield, and the one-month T-bill rate. In line with the related literature, I employ the time-series regression approach to evaluate the alternative factor models.

By conducting Wald tests on the joint significance of the scaled factors associated with each of the original factors, it follows that the factor loadings are time-varying in most cases, and thus, it makes sense to conduct conditional tests to evaluate the alternative multifactor models. The analysis of the alphas for the 25 “high-minus-low” spreads in returns suggests that using conditioning information has a relevant impact on the performance of the factor models. The model that registers the greatest improvement relative to the unconditional test is the five-factor model of Fama and French (2015, 2016) (FF5 henceforth), although the four-factor model of Hou, Xue, and Zhang (2015a, 2015b) (HXZ4) shows the best overall performance, similarly to the unconditional tests. Specifically, the four-factor model produces a mean absolute alpha of 0.19% among the 25 spreads, compared to 0.28% for FF5 and 0.29% for the four-factor model of Carhart (1997) (C4). There are seven (out of 25) statistically significant alphas for HXZ4, compared to 12 for FF5 and 13 for C4.

When one tests the alternative models over the full cross-section of stock returns (for a total of 248 portfolios), it turns out that the three models register a similar average mispricing. Specifically, the root mean squared alpha is the same across C4, HXZ4, and FF5 (0.13%), whereas the mean absolute alpha estimates are 0.09% for FF5 compared to 0.10% for both C4 and HXZ4. Yet, both HXZ4 and FF5 have a much lower number of individual significant alphas than C4 (around 33 versus 51 for C4). The fact that FF5 produces an average mispricing that is similar to that of HXZ4 stems from the former model doing better in pricing the middle deciles, while HXZ4 clearly dominates when it comes to price the extreme deciles. Moreover, this pattern is robust across the different classes of anomalies.

Across categories, it turns out that the three-factor model of Fama and French (1993) (FF3), C4, and FF5 clearly dominate the HXZ4 model in terms of pricing the value anomalies. On the other hand, both C4 and HXZ4 significantly outperform FF5 when it comes to price the momentum-based anomalies, while HXZ4 is the clear winner in the group of profitability anomalies. In the group of 11 investment-based anomalies, FF5 produces an average alpha of 0.11% compared to 0.12% for both C4 and HXZ4. Yet, the number of deciles with significant alphas in HXZ4 and FF5 (around 15) is slightly lower than for C4 (22). In the estimation within the intangibles category, we observe a similar performance for both HXZ4 and FF5. By conducting a decomposition of equity risk premia for nine of the most important individual anomalies (those with spreads above 0.50% in magnitude), one observes that the most relevant conditioning variables in driving the fit of both HXZ4 and FF5 are the TERM spread and the T-bill rate. Thus, both the dividend yield, and especially the default spread, seem to play a less relevant role in pricing these nine spreads in returns.

I repeat the asset pricing tests by using equal-weighted portfolios, following previous evidence that small stocks represent the major challenge for asset pricing models (e.g., Fama and French (2012, 2015)). The results indicate that all factor models, and especially HXZ4, have greater difficulty in pricing the equal-weighted portfolios than the value-weighted portfolios. Yet, HXZ4 continues to beat the alternative models when it comes to price the spreads high-minus-low, with a mean absolute alpha (across the 25 spreads) of 0.27%, compared to 0.37% for FF5 and 0.39% for C4. In contrast, the five-factor model produces the best fit in the estimation with all 248 portfolios. Specifically, the root mean squared alpha is 0.16% for FF5 compared to 0.16% and 0.17% for C4 and HXZ4, respectively, while the mean absolute alpha estimates are 0.12%, 0.13%, and 0.15% for FF5, C4, and HXZ4, respectively. However, FF5 produces a smaller number of significant alphas than the other models by a great margin (62 compared to 102 and 125 for HXZ4 and C4, respectively). This shows that, similarly to the benchmark test based on value-weighted portfolios, HXZ4 does a better job in pricing the extreme deciles, while FF5 outperforms when it comes to explaining the intermediate deciles.

I estimate a conditional restricted version of FF5 that excludes the HML factor. The results show that in most cases the restricted model is not dominated by FF5. Specifically, the mean absolute alpha across the 25 value-weighted spreads is 0.28% (the same as for FF5). The average alpha across the 248 portfolios is 0.12% (compared to 0.13% for FF5), and the model produces 30 significant alphas (compared to 34 for FF5). In the estimation containing all 248 equal-weighted portfolios, the model that excludes HML produces an average mispricing of 0.15%, versus 0.16% for FF5. These results largely confirm the previous evidence for unconditional asset pricing tests (e.g., Fama and French (2015, 2016), Hou, Xue, and Zhang (2015a)) that HML is redundant when in the presence of the investment and profitability factors.

Following Maio (2015), I compute a cross-sectional R^2 metric to evaluate the cross-sectional dispersion in equity risk premia based on all portfolios, and not just the spreads high-minus-low. This metric is based on the constraint that the factor risk price estimates are equal to the corresponding factor sample means. The results confirm that the HXZ4 model outperforms the competing models in terms of explaining the cross-sectional dispersion in equity risk premia for a large number of anomalies, and these results hold for both value- and equal-weighted portfolios. Specifically, in the estimation with 248 value-weighted portfolios the R^2 estimates are 53% for HXZ4, compared to 35% for both C4 and FF5. In the estimation with all equal-weighted portfolios, the fit of HXZ4 is 69% versus 45% and 46% for C4 and FF5, respectively.

Overall, the results of this paper show that the HXZ4 model outperforms the competing models when it comes to price the extreme portfolio deciles and the cross-sectional dispersion in equity risk premia. Yet, the FF5 model performs slightly better in terms of pricing the intermediate deciles. 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. Moreover, the HML factor continues to be largely redundant within the five-factor model when using conditioning information.

The paper proceeds as follows. Section 2 shows the theoretical background, while Section 3 describes the data and methodology. The main empirical analysis is presented in Section 4. Section 5 shows the empirical results for equal-weighted portfolios, while in Section 6, I analyze further the cross-sectional dispersion in equity risk premia. Finally, Section 7 concludes.

2 Conditional factor models

In this section, I present the theoretical background and the conditional factor models estimated in the following sections.

2.1 Theoretical background

Consider the usual asset pricing equation in conditional form,

$$0 = \mathrm{E}_t(M_{t+1} R^e_{i,t+1}), \tag{1}$$

where $R^e_{i,t+1}$ denotes the excess return on an arbitrary risky asset i and M_{t+1} is the stochastic discount factor (SDF).

Following Cochrane (1996, 2005) and Lettau and Ludvigson (2001), I define an SDF that is linear on K original factors $(f_{j,t+1})$, but with coefficients that are linear functions of a predetermined instrument with zero mean (z_t):[1]

$$
\begin{aligned}
M_{t+1} &= a_t + \sum_{j=1}^{K} b_{j,t} f_{j,t+1}, && (2)\\
a_t &= a_0 + a_1 z_t, && (3)\\
b_{j,t} &= b_{j,0} + b_{j,1} z_t, j = 1, ..., K. && (4)
\end{aligned}
$$

In this specification, I am using a single instrument to simplify the algebra presented below, but the analysis can be generalized in a straightforward way to the case of multiple conditioning variables.

By applying the law of total expectations, we obtain the unconditional pricing equation,

$$0 = \mathrm{E}(M_{t+1} R^e_{i,t+1}), \tag{5}$$

which can be defined in expected return-covariance representation as

$$\mathrm{E}(R^e_{i,t+1}) = -\frac{\mathrm{Cov}(R^e_{i,t+1}, M_{t+1})}{\mathrm{E}(M_{t+1})}. \tag{6}$$

By substituting the expression for the SDF in the expected return-covariance equation above, we obtain the SDF as a function of the instrument and the scaled factors ($f_{j,t+1} z_t$):

$$M_{t+1} = a_0 + a_1 z_t + \sum_{j=1}^{K} b_{j,0} f_{j,t+1} + \sum_{j=1}^{K} b_{j,1} f_{j,t+1} z_t. \tag{7}$$

The scaled factor is often interpreted as the return on a "managed portfolio" (see Hansen and Richard (1987), Cochrane (1996, 2005), Bekaert and Liu (2004), and Brandt and Santa-Clara

[1] In a conditional pricing equation, even if one specifies an SDF with fixed coefficients it follows that by forcing the model to price an arbitrary set of test assets (e.g., its factors if they represent returns) the coefficients will be a function of conditional moments of the testing returns (and thus, will be time-varying). Cochrane (2005) (Chapter 8) provides a simple example with the CAPM, in which the model is forced to price the market return and the risk-free rate. This originates SDF coefficients that depend on the conditional mean and variance of the market return and also on the time-varying risk-free rate.

(2006)).

It can be shown that, by substituting the new expression of the SDF into the expected return-covariance equation, one obtains the following multifactor model in expected return-beta form,[2]

$$\mathrm{E}(R^e_{i,t+1}) = \sum_{j=1}^{K} \beta_{i,j}\lambda_j + \sum_{j=1}^{K} \beta_{i,jz}\lambda_{jz}, \tag{8}$$

where the factor loadings are obtained from the following time-series regression:

$$R^e_{i,t+1} = \alpha_i + \sum_{j=1}^{K} \beta_{i,j} f_{j,t+1} + \sum_{j=1}^{K} \beta_{i,jz} f_{j,t+1} z_t + \varepsilon_{i,t+1}. \tag{9}$$

This regression 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:

$$R^e_{i,t+1} = \alpha_i + \sum_{j=1}^{K} (\beta_{i,j} + \beta_{i,jz} z_t) f_{j,t+1} + \varepsilon_{i,t+1}. \tag{10}$$

Thus, a K-factor conditional model is equivalent to a $2K$-factor model in the equivalent unconditional representation.[3] Moreover, specifying a SDF with time-varying coefficients is equivalent to modelling a beta representation with time-varying factor loadings.

As noted in Cochrane (2005) and Maio (2015), when the factors represent excess returns, the risk prices are restricted to be equal to the corresponding factor means,

$$\mathrm{E}(f_{j,t+1}) = \lambda_j, \tag{11}$$

$$\mathrm{E}(f_{j,t+1} z_t) = \lambda_{jz}, j = 1, ..., K. \tag{12}$$

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

[2]The full derivation is available upon request.

[3]I 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.

on all the other factors.[4] By substituting the restrictions on the factor risk prices back into the beta equation, we obtain the following multifactor model:

$$\mathrm{E}(R^e_{i,t+1}) = \sum_{j=1}^{K} \beta_{i,j}\,\mathrm{E}(f_{j,t+1}) + \sum_{j=1}^{K} \beta_{i,jz}\,\mathrm{E}(f_{j,t+1} z_t). \tag{13}$$

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

2.2 Models

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

$$\mathrm{E}(R^e_{i,t+1}) = \mathrm{E}(RM_{t+1})\beta_{i,M} + \mathrm{E}(RM_{t+1} z_t)\beta_{i,Mz}, \tag{14}$$

where RM denotes the excess market return.

The second model is a conditional version of the Fama and French (1993, 1996) three-factor model (henceforth FF3),

$$\begin{aligned}\mathrm{E}(R^e_{i,t+1}) = {} & \mathrm{E}(RM_{t+1})\beta_{i,M} + \mathrm{E}(RM_{t+1} z_t)\beta_{i,Mz} + \mathrm{E}(SMB_{t+1})\beta_{i,SMB} + \mathrm{E}(SMB_{t+1} z_t)\beta_{i,SMBz} \\ & + \mathrm{E}(HML_{t+1})\beta_{i,HML} + \mathrm{E}(HML_{t+1} z_t)\beta_{i,HMLz},\end{aligned} \tag{15}$$

where SMB and HML represent the size and value factors, respectively.

The third model analyzed is the conditional four-factor model from Carhart (1997) (C4,

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

henceforth), which adds a momentum factor (UMD) to FF3:

$$\begin{aligned}
\mathrm{E}(R^e_{i,t+1}) &= \mathrm{E}(RM_{t+1})\beta_{i,M} + \mathrm{E}(RM_{t+1}z_t)\beta_{i,Mz} + \mathrm{E}(SMB_{t+1})\beta_{i,SMB} + \mathrm{E}(SMB_{t+1}z_t)\beta_{i,SMBz} \\
&+ \mathrm{E}(HML_{t+1})\beta_{i,HML} + \mathrm{E}(HML_{t+1}z_t)\beta_{i,HMLz} + \mathrm{E}(UMD_{t+1})\beta_{i,UMD} + \mathrm{E}(UMD_{t+1}z_t)\beta_{i,UMDz}.
\end{aligned} \tag{16}$$

The fourth model is a conditional version of the four-factor model of Hou, Xue, and Zhang (2015a, 2015b) (HXZ4),

$$\begin{aligned}
\mathrm{E}(R^e_{i,t+1}) &= \mathrm{E}(RM_{t+1})\beta_{i,M} + \mathrm{E}(RM_{t+1}z_t)\beta_{i,Mz} + \mathrm{E}(ME_{t+1})\beta_{i,ME} + \mathrm{E}(ME_{t+1}z_t)\beta_{i,MEz} \\
&+ \mathrm{E}(IA_{t+1})\beta_{i,IA} + \mathrm{E}(IA_{t+1}z_t)\beta_{i,IAz} + \mathrm{E}(ROE_{t+1})\beta_{i,ROE} + \mathrm{E}(ROE_{t+1}z_t)\beta_{i,ROEz},
\end{aligned} \tag{17}$$

where ME, IA, and ROE represent the size, investment (investment-to-assets), and profitability (return-on-equity) factors, respectively.

The fifth model is a conditional version of the five-factor model of Fama and French (2015, 2016) (FF5), which adds an investment (CMA) and a profitability (RMW) factor to the FF3 model:

$$\begin{aligned}
\mathrm{E}(R^e_{i,t+1}) &= \mathrm{E}(RM_{t+1})\beta_{i,M} + \mathrm{E}(RM_{t+1}z_t)\beta_{i,Mz} + \mathrm{E}(SMB_{t+1})\beta_{i,SMB} + \mathrm{E}(SMB_{t+1}z_t)\beta_{i,SMBz} \\
&+ \mathrm{E}(HML_{t+1})\beta_{i,HML} + \mathrm{E}(HML_{t+1}z_t)\beta_{i,HMLz} + \mathrm{E}(RMW_{t+1})\beta_{i,RMW} + \mathrm{E}(RMW_{t+1}z_t)\beta_{i,RMWz} \\
&+ \mathrm{E}(CMA_{t+1})\beta_{i,CMA} + \mathrm{E}(CMA_{t+1}z_t)\beta_{i,CMAz}.
\end{aligned} \tag{18}$$

Both RMW and CMA are constructed in a different way than the investment and profitability factors in Hou, Xue, and Zhang (2015b).

Finally, I estimate a restricted version of FF5 that excludes the HML factor (FF4):

$$\mathrm{E}(R^e_{i,t+1}) = \mathrm{E}(RM_{t+1})\beta_{i,M} + \mathrm{E}(RM_{t+1}z_t)\beta_{i,Mz} + \mathrm{E}(SMB_{t+1})\beta_{i,SMB} + \mathrm{E}(SMB_{t+1}z_t)\beta_{i,SMBz}$$
$$+ \mathrm{E}(RMW_{t+1})\beta_{i,RMW} + \mathrm{E}(RMW_{t+1}z_t)\beta_{i,RMWz} + \mathrm{E}(CMA_{t+1})\beta_{i,CMA} + \mathrm{E}(CMA_{t+1}z_t)\beta_{i,CMAz}. \quad (19)$$

The estimation of this model is related with previous evidence showing that the HML factor is redundant within the FF5 model (see Fama and French (2015, 2016) and Hou, Xue, and Zhang (2015a)).

3 Data and methodology

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

3.1 Data

The data on the risk factors associated with the CAPM, FF3, C4, and FF5 models (RM, SMB, HML, UMD, 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 factor with the largest mean is UMD (0.71% per month), followed by ROE and RM (with means above 0.50% per month). On the other hand, the factor with the lowest mean is SMB (0.20% per month), followed by ME with an average of 0.31%. This confirms previous evidence showing that the size premium has declined over time. The factors with the highest volatility are the equity premium and UMD, with standard deviations around or 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). Both investment factors are positively correlated with HML (around 0.70). On the other hand, both profitability factors show weak negative correlations with both size factors as shown by the correlation coefficients between -0.31 and -0.44. Moreover, ROE is positively correlated with UMD (0.50), yet, there is no such pattern for RMW. Hence, the two profitability factors do not seem to exhibit a large degree of overlapping.

I use four conditioning variables in the construction of the scaled risk factors. The instruments are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and the one-month T-bill rate (TB). These variables have been widely used in cross-sectional tests of conditional factor models (e.g., Harvey (1989), Jagannathan and Wang (1996), Ferson and Harvey (1999), Petkova and Zhang (2005), and Maio (2013)).[5] $TERM$ represents the yield spread between the ten-year and the one-year Treasury bonds, while DEF denotes the yield spread between BAA and AAA corporate bonds from Moody's. The bond yield data are available from the St. Louis Fed Web page. TB is the annualized one-month T-bill rate, available from Kenneth French's website. dp is computed as the log ratio of annual dividends to the level of the S&P 500 index, where the dividend and price data are obtained from Robert Shiller's website.[6]

The portfolio return data used in the cross-sectional asset pricing tests are associated with some of the most relevant market anomalies. I employ a total of 25 anomalies or portfolio sorts, which correspond roughly to the portfolios used in Maio (2015) and represents a subset of the anomalies considered in Hou, Xue, and Zhang (2015a, 2015b). Table 2 contains the list and description of the anomalies included in my analysis. Following Hou, Xue, and Zhang (2015b), these anomalies can be broadly classified in strategies related with value

[5]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)).

[6]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)).

(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, Xue, and Zhang (2015b), I do not use portfolios sorted on earnings-to-price ratio since these deciles are strongly correlated with the book-to-market (BM) deciles. Similarly, I do not consider the return on assets deciles because they are strongly correlated with the return on equity deciles (ROE). Moreover, I use only one measure of price momentum (MOM) and earnings surprise (SUE), since the other related anomalies used in Hou, Xue, and Zhang (2015b) are strongly correlated with either MOM or SUE. I also exclude all portfolio sorts used in Table 4 of Hou, Xue, and Zhang (2015b) that start after 1972:01. In contrast to Hou, Xue, and Zhang (2015b), I 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, I 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 decile 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.

3.2 Methodology

I use time-series regressions to test the alternative factor models. This methodology is adequate when all the factors in the model represent excess stock returns as 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.[7] With four instruments, the time-series regression for the conditional CAPM is as follows,

$$
\begin{aligned}
R^e_{i,t+1} = \alpha_i + \beta_{i,M} RM_{t+1} + \beta_{i,M,TERM} RM_{t+1} TERM_t + \beta_{i,M,DEF} RM_{t+1} DEF_t \\
+\beta_{i,M,dp} RM_{t+1} dp_t + \beta_{i,M,TB} RM_{t+1} TB_t + \varepsilon_{i,t+1},
\end{aligned} \tag{20}
$$

and similarly for the other models. Taking expectations on both sides of the regression above, one obtains,

$$
\begin{aligned}
\mathrm{E}(R^e_{i,t+1}) = \alpha_i + \beta_{i,M}\,\mathrm{E}(RM_{t+1}) + \beta_{i,M,TERM}\,\mathrm{E}(RM_{t+1} TERM_t) + \beta_{i,M,DEF}\,\mathrm{E}(RM_{t+1} DEF_t) \\
+\beta_{i,M,dp}\,\mathrm{E}(RM_{t+1} dp_t) + \beta_{i,M,TB}\,\mathrm{E}(RM_{t+1} TB_t),
\end{aligned} \tag{21}
$$

thus, for the conditional CAPM to be valid one needs to impose the condition that the intercepts are zero for every testing asset i ($\alpha_i = 0$). It is important to note that the conditional CAPM (or any conditional factor model) does not necessarily outperform the corresponding unconditional specification. The reason is that adding additional factors to the regression above does not imply lower intercept estimates (alphas).[8]

A formal statistical test for the null hypothesis that the alphas are jointly equal to zero is provided by Gibbons, Ross, and Shanken (1989) (GRS henceforth):

$$
\frac{T-N-K}{N}\left[1+\mathrm{E}(\mathbf{f})'\widehat{\mathbf{\Omega}}^{-1}\,\mathrm{E}(\mathbf{f})\right]^{-1} \widehat{\boldsymbol{\alpha}}'\widehat{\mathbf{\Sigma}}^{-1}\widehat{\boldsymbol{\alpha}} \sim F_{N,T-N-K}, \tag{22}
$$

[7] This avoids the critique of implausible risk price estimates (see Lewellen and Nagel (2006) and Lewellen, Nagel, and Shanken (2010)).

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

where

$$\widehat{\mathbf{\Omega}} = \frac{1}{T}\sum_{t=1}^{T}\left[\mathbf{f}_t - \mathrm{E}(\mathbf{f})\right]\left[\mathbf{f}_t - \mathrm{E}(\mathbf{f})\right]', \tag{23}$$

$$\widehat{\mathbf{\Sigma}} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\boldsymbol{\varepsilon}}_t\widehat{\boldsymbol{\varepsilon}}_t', \tag{24}$$

represent the covariance matrices of the factors ($\mathbf{f}_t \equiv (f_{1,t}, ..., f_{K,t})'$) and residuals from the time-series regressions ($\widehat{\boldsymbol{\varepsilon}}_t \equiv (\widehat{\varepsilon}_{1,t}, ..., \widehat{\varepsilon}_{N,t})'$). In the expressions above, 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 $\widehat{\boldsymbol{\alpha}} \equiv (\widehat{\alpha}_i, ..., \widehat{\alpha}_N)$ denotes the vector of alphas.

This statistic relies on the OLS classical distribution, and thus, is based on 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.

An alternative test that avoids these restrictive assumptions is the following Wald test,

$$T\left[1 + \mathrm{E}(\mathbf{f})'\widehat{\mathbf{\Omega}}^{-1}\,\mathrm{E}(\mathbf{f})\right]^{-1}\widehat{\boldsymbol{\alpha}}'\widehat{\mathbf{\Sigma}}^{-1}\widehat{\boldsymbol{\alpha}} \sim \boldsymbol{\chi}^2(N), \tag{25}$$

which is based on the GMM distribution and thus, is only valid asymptotically (see Cochrane (2005), Chapter 12 for details).

Although these two statistics represent a formal test of the validity of a given model for explaining a given cross-section of average returns, they are in general not robust and may produce perverse results. The reason hinges on the problematic inversion of $\widehat{\mathbf{\Sigma}}$, especially when there is a large number of testing assets. Thus, in some cases one might reject a model (i.e., the value of both statistics is large) because of a large estimate of $\widehat{\mathbf{\Sigma}}^{-1}$ even with low magnitudes of the alphas. In other cases, one might accept a model with large alphas because the estimate of $\widehat{\mathbf{\Sigma}}^{-1}$ is too small. These problems might be accentuated by the term involving $\widehat{\mathbf{\Omega}}^{-1}$, 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, I also report the number of alphas that are individually statistically significant (at the 5% level) in each cross-sectional test.

Compared to the previous statistics, a more robust goodness-of-fit measure to evaluate factor models is the mean absolute alpha,

$$\text{MAA} = \frac{1}{N}\sum_{i=1}^{N}|\widehat{\alpha}_i|. \tag{26}$$

A related measure is the root mean squared alpha,

$$\text{RMSA} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\widehat{\alpha}_i^2}, \tag{27}$$

where $RMSA$ is always above MAA, due to a Jensen's inequality effect.

4 Main results

In this section, I test the alternative conditional multifactor models by using a large cross-section of stock returns.

4.1 Time-varying betas

As a motivation exercise, I assess whether the loadings associated with the original equity factors are time-varying. Hence, I conduct Wald tests to assess if the loadings on the four scaled factors associated with a given factor (e.g., IA) are jointly statistically significant. The testing assets employed are the spreads high-minus-low for each of the 25 anomalies. To save space, I restrict the analysis to the C4, HXZ4, and FF5 models.

The p-values for the Wald statistics associated with the C4 model are reported in Table

4. There is significant time variation in the loadings associated with HML as the four betas for the scaled factors corresponding to the value factor are jointly statistically significant for 17 (out of the 25) spreads high-minus-low. There is slightly less evidence of time variation in the loadings for the market and momentum factors as the corresponding scaled factors are jointly significant for 12 and 13 spreads, respectively. The factor with the least evidence of time-varying betas is SMB with the respective scaled factors being jointly significant for only nine anomalies. There are four anomalies (MOM, SUE, ABR, and CEI) in which none of the four groups of scaled factors are jointly significant. This result is not totally surprising in the case of the momentum anomalies since the UMD factor should drive most of the model's explanatory power for those portfolios. The Wald tests associated with the original factors in the model (RM, SMB, HML, UMD) indicate that these factors are jointly significant for all 25 spreads.

The results for the HXZ4 model are reported in Table 5. The scaled factors associated with ME and IA are jointly significant for 16 of the 25 spreads high-minus-low. In comparison, the scaled factors corresponding to ROE are significant for 14 anomalies, whereas for the market factor there is less evidence of time-variation in the betas (11 anomalies with significant loadings on the respective scaled factors). It turns out that for all 25 spreads in average returns at least one of the groups of scaled factors is statistically significant. This points to a sharper evidence of time-variation in the original factor loadings than in the C4 model.

The results for the FF5 model presented in Table 6 show a weaker evidence of time-variation in the original factor loadings when compared to the other models. The scaled factors that appear to be more significant are those associated with RM and HML, whose slopes are significant for 12 and 13 anomalies, respectively. Still, there is less evidence of time-variation in the loadings for HML than in the C4 model. On the other hand, the scaled factors associated with CMA and RMW are significant less times (that is, for fewer anomalies) than the scaled factors corresponding to IA and ROE, respectively. Despite the weaker evidence of time variation in the factor betas, still only for three anomalies (ABR*, CEI, and IVG) one can not find any evidence of time-varying factor loadings associated with the five-factor model. On the other hand, the Wald tests associated with the original factors in the model (RM, SMB, HML, RMW, CMA) show that these are not jointly significant for the momentum-based anomalies (MOM, SUE, ABR, IM, ABR*) as indicated by the p-values above 5%. This is related with the fact that this model cannot explain the momentum anomalies as shown below.

Overall, the results from Tables 4, 5, and 6 suggest that the factor loadings are time-varying in most cases, and thus, it makes sense to conduct conditional tests to evaluate the alternative multifactor models.

4.2 Spreads high-minus-low

I estimate time-series regressions for each factor model applied to the spreads high-minus-low in average returns. For comparison purposes, I start to present results for the baseline unconditional models. The alphas for the spreads high-minus-low associated with the unconditional models are presented in Table 7. We can see that all the 25 alphas associated with the CAPM are statistically significant, thus confirming that the model in its unconditional form cannot explain any of these 25 anomalies in returns.[9] The FF3 model provides a small improvement relative to the CAPM. In fact, only the spreads associated with the value-based anomalies (BM, DUR, and CFP) and also those associated with some investment-based anomalies (IA, IG, and IVG) are not statistically significant at the 5% level.

The performance of the C4 and FF5 models seems similar in terms of overall explanatory power for the large cross-section of stock returns as both models produce 14 significant alphas out of the original 25 spreads in returns. Both models struggle in pricing the profitability-based anomalies (ROE, GPA, NEI, and RS), since only in one case (FF5 for the GPA spread) is the respective alpha insignificant. On the other hand, the five-factor model performs rather

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

poorly when it comes to price the spreads associated with the momentum-based anomalies (MOM, SUE, ABR, IM, ABR*) as the respective alphas are significant in all cases. As expected, the C4 model is successful in terms of explaining price momentum (MOM and IM), which stems from the UMD factor (since this factor is mechanically related with the MOM and IM deciles). Yet, the model is not successful in explaining earnings momentum (SUE, ABR, ABR*). Both models are also not able to price several investment-related anomalies. Interestingly, the FF4 model that excludes HML does at least as well as the five-factor model in terms of average explanatory power with 14 significant alphas. This suggests that HML is redundant when in the presence of both RMW and CMA, which confirms the evidence from Fama and French (2015, 2016) and Hou, Xue, and Zhang (2015a).

By far the best performing model is the four-factor model of Hou, Xue, and Zhang (2015a, 2015b). Out of the 25 spreads in average returns only in five cases do we obtain significant alphas. This mispricing refers to two of the momentum anomalies (ABR and ABR*) and three investment anomalies (NSI, NOA, and OA). In fact, the alphas associated with these spreads are statistically significance across all six factor models, which suggests that these anomalies are particularly difficult to explain. The mean absolute alpha across the 25 spreads (not tabulated) is 0.20% for HXZ4, compared to 0.30% for C4 and 0.32% for FF5. These results are largely consistent with the evidence provided in Hou, Xue, and Zhang (2015a, 2015b) showing that their multifactor model outperforms significantly the alternative models in terms of explaining the spreads in average returns among a large number of anomalies.

The alphas for the spreads high-minus-low associated with the conditional models are presented in Table 8. The conditional CAPM does not significantly improve the corresponding baseline model as only in one case (GPA) 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 justifying that the conditional CAPM is not a valid answer for explaining cross-sectional equity risk premia (e.g., Lewellen and Nagel (2006)). With 16 significant alphas, the FF3 model outperforms the conditional CAPM by a good margin, and also improves marginally the fit of the respective unconditional model. Specifically, the alphas associated with the spreads corresponding to the accrual anomalies (OA, POA, PTA) are no longer significant at the 5% level. This suggests that using conditioning information in the three-factor model helps explaining the accruals-related anomalies.[10]

C4, and especially FF5, respectively with 13 and 12 significant alphas, register a small improvement in comparison to the respective unconditional models. Specifically, in the case of C4, the alphas associated with the OA and PTA spreads are no longer significant, which is in line with the evidence for the three-factor model. In opposite direction, the spread associated with OL produces a significant alpha in the conditional test. Turning to FF5, the main improvements occur for the IM and NSI spreads, whose alphas become insignificant in the conditional test. The mean absolute alpha (across the 25 spreads) for FF5 is 0.28%, compared to 0.29% for C4, showing that the five-factor model benefits the most from using conditioning information when pricing the spreads in returns. Yet, the FF4 model performs even better than the five-factor model with 11 significant alphas and the same average mispricing. The reason hinges on the fact that the alpha for PIA within FF4 is not significant at the 5% level (although it is significant at the 10% level).

Perhaps the most salient fact in the conditional tests is that the dominance of the HXZ4 model against the alternative models narrows down in comparison to the unconditional tests. This can be inferred from the seven significant alphas in HXZ4, compared to 11 significant alphas for FF4 and 12 for FF5. This suggests that using conditioning information does not improve the performance of this model as much as for some of the alternative multifactor models. The alphas associated with some value anomalies (BM and CFP), in addition to CEI and OCA, are significant in the conditional version of HXZ4. In opposite direction, the mispricing associated with ABR* and OA are no longer significant in the conditional four-factor model. Still, the four-factor model produces an average mispricing of 0.19% among the 25 spreads, which continues to compare quite favorably with the alternative models.

[10]This result is consistent with the evidence in Guo and Maio (2015) showing that most multifactor models (in its unconditional form) fail to price portfolios sorted on the accruals anomalies.

The alphas associated with the ABR, NOA, and OCA spreads are significant across all models. Thus, in contrast with the unconditional tests, some models are able to price the spreads associated with ABR*, NSI, and OA. In opposite direction, the OCA spread is much more challengeable for the conditional models. Overall, the evidence from Table 8 suggests that using conditioning information has a relevant impact on the performance of the alternative factor models. The model that registers the greatest improvement relative to the unconditional test is the five-factor model, although HXZ4 continues to show the best overall performance.

4.3 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. Still, this represents an incomplete picture of the cross-section of average returns since it ignores all the remaining deciles within each anomaly. For this reason, I assess the explanatory power of the different factor models for all the deciles associated with each anomaly.

The results for the unconditional models are presented in Table 9. In the test including all 25 anomalies (Panel F), the average mispricing is similar across C4, HXZ4, and FF5. The C4 model produces an average alpha ($RMSA$) of 0.13%, marginally below the mispricing for HXZ4 (0.14%) and FF5 (0.15%). Similarly, the estimate of MAA is 0.10% for C4, compared to 0.11% for both HXZ4 and FF5. However, the HXZ4 model has a lower number of deciles with significant alphas (39 versus 48 for C4 and 54 for FF5). These results are consistent with the evidence in Hou, Xue, and Zhang (2015a, 2015b) showing that the average mispricing is similar across the three models, with a marginal outperformance of HXZ4.[11] The fit of the FF4 model for the joint 25 anomalies is basically the same as that from FF5. As expected,

[11] Specifically, Hou, Xue, and Zhang (2015a) report a mean absolute alpha of 0.11% for HXZ4, compared to 0.12% for both C4 and FF5. The slightly different results should be related with the fact that Hou, Xue, and Zhang (2015a) use 36 portfolio groups compared to the 25 groups used in this paper.

given the large number of portfolios considered, all models are clearly rejected by both the GRS and χ^2 tests.

Across categories, we can see that FF3 ($RMSA$ of 0.09%), C4 (0.08%), and FF5 (0.09%) clearly outperform HXZ4 (0.13%) in pricing the three value-based anomalies. In fact, these three models (FF3, C4, and FF5) pass both the GRS and χ^2 specification tests applied to the joint value anomalies, while HXZ4 is clearly rejected by both tests (p-values below 5%). In contrast, both C4 and HXZ4 produce by far the best fit among the five momentum-based anomalies, with average pricing errors of 0.13% and 0.14%, respectively, compared to 0.21% for FF5. The HXZ4 model produces seven significant alphas (out of 49 deciles) compared to 11 in the case of C4 and 15 for FF5. All factor models are rejected by both specification tests in the estimation with all momentum strategies.

HXZ4 clearly outperforms the remaining factor models when it comes to price the four profitability-based anomalies with a $RMSA$ of 0.12%, which compares to 0.15% for FF5 and 0.16% for C4. Both HXZ4 (marginally so) and FF5 pass the GRS test in the estimation with all the profitability deciles, although these two models are rejected by the more stringent χ^2-test. The three models (C4, HXZ4, and FF5) have a similar fit for the eleven investment anomalies, with $RMSA$ estimates of 0.14% for HXZ4 and 0.13% for both C4 and FF5. The number of deciles with significant alphas are 20, 23, and 26 for HXZ4, C4, and FF5, respectively. Not surprisingly, all models are rejected by the GRS test applied to the joint investment anomalies given the relatively large number of portfolios considered (110). Regarding the intangibles category (OL and OCA deciles), it turns out that FF5 produces an average alpha of 0.12% compared to 0.13% for C4 and 0.15% for HXZ4. Both HXZ4 and FF5 (this one marginally) are not rejected by the GRS test. The performance of FF4 is similar to that of FF5 across all the categories as indicated by the average alphas, confirming the previous evidence that HML is redundant. Furthermore, the FF4 model passes marginally the Wald test in the estimation with the profitability and intangibles anomalies, in contrast to the five-factor model.

The results for the conditional models are presented in Table 10. When we consider all 25 anomalies (Panel F), the average pricing error ($RMSA$) is the same across C4, HXZ4, and FF5 (0.13%). The estimates of MAA are 0.09% for FF5 compared to 0.10% for both C4 and HXZ4. Yet, both HXZ4 and FF5 outperform C4 since those models have a much lower number of significant alphas (around 33 versus 51 for C4). Interestingly, the best performing model in aggregate terms is FF4 with $RMSA$ and MAA estimates of 0.12% and 0.09%, respectively, and 30 significant alphas. Thus, the inclusion of HML actually seems to hurt the FF5 model in the conditional test containing all portfolios. When one compares the global fit of each conditional model with the respective unconditional versions, it follows that most models register a slight increase in explanatory power. The exception is C4, as indicated by average alphas that are the same as in the unconditional test, and a marginally higher number of significant alphas. Hence, these results suggest that adding scaled factors to the pricing equation of C4 hurts the model's global performance.

Across categories, it turns out that FF3 ($RMSA$ of 0.09%), C4 (0.08%), and FF5 (0.07%) clearly dominate the HXZ4 model (0.16%) in terms of pricing the value anomalies. Moreover, all four models pass both specification tests applied to the joint 30 value portfolios. In the case of the momentum anomalies, we have an opposite pattern. Both C4 and HXZ4, with average alphas of 0.13% and 0.12%, respectively, clearly dominate FF5 (with an average mispricing of 0.16%). There are only five significant alphas (out of 49 momentum-based portfolios) in the HXZ4 model, compared to 8 for FF5 and 11 for C4.

Similarly to the unconditional tests, HXZ4 ($RMSA$ of 0.11%) dominates both C4 (0.17%) and FF5 (0.16%) in terms of explaining the four profitability anomalies. Moreover, HXZ4 is not rejected by the GRS test in the estimation with the 40 profitability deciles, although it fails to pass the χ^2-test. Overall, the relative performance of the three models (C4, HXZ4, and FF5) in the conditional tests associated with the value, momentum, and profitability anomalies is qualitatively similar to the corresponding results from the unconditional tests discussed above.

In the large group of investment-based anomalies, FF5 produces an average alpha of 0.11% compared to 0.12% for both C4 and HXZ4. Yet, the number of deciles with significant alphas in HXZ4 and FF5 (around 15) is slightly lower than for C4 (22). As in the unconditional test on the investment portfolios, all models are rejected by the two specification tests. In the estimation with the OL and OCA deciles, we observe a similar performance for both HXZ4 ($RMSA$ of 0.12%) and FF5 (0.11%), which compare with a mispricing of 0.14% for C4. Both HXZ4 and FF5 pass the GRS test applied to the 20 intangibles deciles.

Across categories, the fit of FF4 is similar to the five-factor model in most cases. In contrast to the results for the unconditional tests, it turns out that FF4 outperforms marginally FF5 in explaining the profitability anomalies as indicated by the $RMSA$ and MAA estimates of 0.15% and 0.11%, respectively. One can also conclude that using conditioning information helps improving the fit of the factor models in global terms. This can be seen, for example, from the fact that the average alphas associated with the best conditional model across each group of anomalies is marginally below the corresponding mispricing for the best performing unconditional model.

How do we reconcile the evidence that the conditional HXZ4 model dominates the other conditional models in pricing the spreads high-minus-low with the results showing that both FF5 and FF4 produce similar (or even marginally lower) average alphas than HXZ4 when one considers the full cross-section of stock returns? This pattern suggests that HXZ4 has larger explanatory power for the extreme deciles across the average anomaly, while both FF5 and FF4 outperform when it comes to explain the intermediate deciles.

Table 11 presents the results for the joint tests by groups of anomalies in which only the first and last decile among each anomaly is considered. In the estimation including all 25 anomalies (Panel F), we can see that the HXZ4 model outperforms significantly the alternative models in pricing the extreme deciles, with an average alpha of 0.15% compared to 0.20% for C4 and 0.21% for FF5. In the case of HXZ4 there are only six extreme deciles (out of 50 portfolios) with significant alphas, compared to 17 for FF5 and 19 for C4. The performance of FF4 is marginally better to that of FF5 as indicated by the $RMSA$ of 0.20% and 14 significant alphas. Despite the lower number of portfolios included in the estimation (50 versus 248 in the benchmark case) all models are rejected by the corresponding GRS tests, thus confirming that the extreme portfolios are particularly challengeable to price.

Across categories, HXZ4 clearly dominates the other models in pricing the extreme deciles associated with the momentum, profitability, and intangibles categories. This is especially notable in the profitability group as indicated by the $RMSA$ of 0.11% for HXZ4 compared to 0.29% for both C4 and FF5 and 0.26% for FF4. Moreover, the four-factor model is not rejected by both specification tests in the estimation with the profitability and intangibles portfolios. In contrast, HXZ4 clearly underperforms the alternative models (except the CAPM) when it comes to price the extreme deciles associated with the three joint value anomalies. On the other hand, both HXZ4 and FF5 have a similar performance in explaining the extreme deciles for the investment anomalies as indicated by the average alpha of 0.12% in both cases. Yet, only the four-factor model passes both specification tests in the estimation with the extreme investment deciles. In sum, the fact that HXZ4 does better in pricing the extreme deciles than the other models is entirely consistent with the results for the spreads high-minus-low discussed above.

The results for the intermediate deciles (that is, excluding the first and last deciles associated with each anomaly) are presented in Table 12. In the test including all anomalies (202 portfolios, Panel F), we can see that FF5 does slightly better in terms of pricing the intermediate deciles, with an average alpha of 0.10% versus 0.11% for C4 and 0.12% for HXZ4. The number of significant intermediate alphas is 17 (out of 202) for FF5 compared to 27 for HXZ4 and 32 for C4. The overall performance of FF4 for the intermediate deciles is basically the same as for FF5. Interestingly, both FF5 and FF4 pass the GRS test (although both models are rejected by the χ^2-test) applied on the 202 portfolios, which shows that the intermediate deciles are less difficult to explain jointly than the extreme deciles.

Across categories, we can see that both FF5 and FF4 outperform the alternative models (marginally so in some groups) in explaining the intermediate deciles within all groups. This is especially remarkable in the momentum anomalies where both FF5 and FF4 produce an average alpha of 0.08%, compared to 0.11% for both C4 and HXZ4. In the profitability group, the average alphas for FF5 and FF4 are 0.11% and 0.10%, respectively, which compare with 0.12% for both C4 and HXZ4. Thus, the results above showing that FF5 (and FF4) underperform HXZ4 when it comes to pricing the momentum and profitability-based portfolios relies on the lack of explanatory power for the extreme deciles associated with these anomalies. Furthermore, both FF5 and FF4 pass the two specification tests in the estimation with the value, profitability, and intangibles categories.

Overall, the results from this subsection indicate that both FF5 and FF4 produce an average mispricing that is similar to that of HXZ4 because those models do better in pricing the middle deciles, while the model of Hou, Xue, and Zhang (2015a, 2015b) dominates significantly when it comes to price the extreme deciles. Moreover, this pattern is robust across classes of anomalies.

4.4 Selected anomalies

Next, I compare the performance of the alternative factor models for a selected number of relevant individual anomalies. Following Maio (2015), I select nine anomalies with magnitudes of spreads high-minus-low above 0.50% (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 the previous section. In principle, these anomalies are more difficult to explain than the remaining anomalies given the largest spreads in average returns between the extreme deciles.

The results for the conditional models tested on each of the nine anomalies referred above are presented in Table 13. The HXZ4 model outperforms the other models in pricing the deciles associated with MOM and ROE, whereas both HXZ4 and C4 produce a similar fit for the ABR and IM portfolios. This is in line with the evidence above showing that both four-factor models produce the best fit for the momentum-based anomalies, whereas HXZ4 is the clear winner among the profitability-related anomalies. FF5 outperforms marginally HXZ4 when it comes to price NSI and CEI, while both models have a similar fir for explaining the OCA deciles. The BM deciles are equally explained by FF3, C4, and FF5, while the five-factor model produces the largest explanatory power for the DUR deciles.

All three models (C4, HXZ4, and FF5) pass both the GRS and χ^2 tests when the testing deciles are BM, DUR, and IM as indicated by the p-values above 5%. On the other hand, HXZ4 is not rejected in the case of the CEI and OCA deciles, while the same occurs for FF5 in the case of CEI. The performance of the FF4 model is close to that of FF5. The restricted model does slightly worse than the five-factor model for the DUR and IM portfolios, while the opposite pattern holds in the estimation with the MOM, ROE, and OCA deciles. Moreover, the FF4 model passes the GRS test in four cases (BM, DUR, CEI, and OCA).

Table 14 presents the results for the joint nine anomalies. The estimates of both $RMSA$ and MAA indicate that C4, HXZ4, and FF5 have a similar explanatory power for the joint nine groups of portfolios. Yet, both HXZ4 (with 15 significant alphas) and FF5 (11) outperform C4 (24) in terms of the number of portfolios with significant alphas. All factor models are rejected by the specification tests associated with the joint 89 portfolios, confirming that these portfolios impose a high hurdle for the formal statistical tests.

4.5 Decomposition of equity risk premia

What is the role of conditioning information in 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, I conduct a decomposition for the spreads high-minus-low in average returns. Following Maio (2013) and Lioui and Maio (2014), for each spread in returns I 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 $IA_{t+1}dp_t$ from the HXZ4 model is given by

$$\text{E}(IA_{t+1}dp_t)\beta_{10-1,BM,IAdp}, \tag{28}$$

where $\beta_{10-1,BM,IAdp}$ denotes the loading on $IA_{t+1}dp_t$ for the high-minus-low BM portfolio.

To save space, I only report the results for the nine individual anomalies described in the previous sub-section. Table 15 present the results for the C4 model. We can see that the driving forces in explaining the raw spreads in average returns are the original factors (mainly HML and UMD), with the scaled factors playing a secondary role. The scaled factors that are more relevant in helping the model explaining the spreads in returns are $RM_{t+1}dp_t$ (for the OCA spread) and $HML_{t+1}TB_t$ (for ROE and NSI). This result is consistent with the evidence above shoing that the performance of the conditional version of C4 is basically the same as the baseline unconditional model.

The results in Table 16 show that conditioning information is more important in the case of the HXZ4 model. Specifically, several scaled factors help the model in explaining the raw spreads in average returns. This includes $RM_{t+1}dp_t$ (for the OCA spread), $ME_{t+1}TERM_t$ (for MOM and IM), $ME_{t+1}TB_t$ (for DUR), $IA_{t+1}TB_t$ (for DUR), and $ROE_{t+1}TERM_t$ (for MOM). Thus, scaled factors associated with the lagged term spread help the model in explaining price momentum. On the other hand, scaled factors associated with the lagged T-bill rate help pricing the equity duration anomaly.

The case in which the scaled factors have a greater contribution for the model's fit is clearly FF5, as shown in Table 17. Specifically, the spreads associated with MOM, ABR, and IM are partially explained by the scaled factors $SMB_{t+1}TERM_t$, $RMW_{t+1}TERM_t$, and $CMA_{t+1}TB_t$ (in this case, only for MOM and IM). On the other hand, the scaled factor $HML_{t+1}TB_t$ also has a relevant contribution in pricing the BM, ABR, ROE, and NSI spreads, while $RMW_{t+1}TERM_t$ helps to price the DUR, ROE, and OCA spreads. These results indicate that the most relevant conditioning variable for the fit of the five-factor model is the TERM spread, followed by the T-bill rate, which is consistent with the evidence for HXZ4. Thus, both dp, and especially DEF, seem to play a less relevant role in pricing these nine spreads in returns.

5 Equal-weighted portfolios

In this section, I repeat the cross-sectional tests conducted in the last section by using equal-weighted portfolios. It is well known that value-weighted portfolios overweight large capitalization stocks, and thus, one must check if the results documented above also hold for small stocks and not only for large caps. In fact, Fama and French (2012, 2015) show that small caps represent the biggest challenge for asset pricing models.

I use the data on equal-weighted portfolios employed in Hou, Xue, and Zhang (2015b) (see their internet appendix). Hou, Xue, and Zhang (2015b) show that there are more statistically significant anomalies (i.e. spreads high-minus-low) based on equal-weighted than on value-weighted portfolios. Yet, to be consistent and facilitate the comparison with the analysis conducted above, I use the same 25 anomalies as in the previous section.

Table 18 shows the descriptive statistics associated with the spreads high-minus-low based on the equal-weighted portfolios. There are 15 anomalies with spreads in average returns above 0.50% in magnitude, compared to nine spreads in the case of value-weighted portfolios. Specifically, the spreads associated with CFP, SUE, GPA, RS, IA, PIA, and NOA all have magnitudes above 50 basis points, clearly above the corresponding magnitudes based on value-weighted portfolios. The most pronounced anomalies seem to be BM, CFP, MOM, SUE, ABR, ROE, IA, and NSI, all with spreads above 0.70% in magnitude. In fact, most equal-weighted spreads have larger magnitudes in average returns than the counterparts based on value-weighted portfolios. The few exceptions are the spreads based on POA, OCA, and OL. These results suggest that the equal-weighted portfolios represent a significantly bigger challenge to the conditional multifactor models than the value-weighted portfolios.

I estimate the time-series regressions for each of the 25 spreads high-minus-low based on the equal-weighted portfolios, whose results appear in Table 19. The results show a significant deterioration in the explanatory power of all multifactor models relative to the benchmark test with value-weighted portfolios.[12] There are 12 spreads with significant alphas across all models, compared to only three anomalies in the benchmark case. These significant alphas are associated with three momentum anomalies (SUE, ABR, and ABR*), two profitability spreads (ROE and RS), six investment anomalies (IA, CEI, PIA, IVC, NOA, and PTA), and the spread associated with OCA.

The decline in performance is especially notable in the case of HXZ4 as indicated by the 16 (out of 25) significant alphas, compared to only seven significant alphas in the estimation based on value-weighted portfolios. In addition to the 12 anomalies already referred, the four-factor model is not able to price the spreads corresponding to BM, CFP, NSI, and OA. With 15 significant alphas, the five-factor model performs only marginally better than HXZ4 in this dimension. In addition to the 12 groups mentioned above, the model struggles in pricing the spreads associated with the MOM, NEI, and OA anomalies. In terms of average mispricing, HXZ4 dominates the other models with a MAA (computed over the 25 spreads) of 0.27%, compared to 0.37% for FF5 and 0.39% for C4.

In contrast to the benchmark case, FF4 performs slightly worse than FF5 with 17 spreads registering significant alphas (compared to 11 in the estimation with value-weighted portfolios). Relative to FF5, the four-factor model cannot price the NSI and IVG spreads. This suggests that HML plays a more important role in the tests with equal-weighted portfolios. Yet, the mean absolute error is the same for the two models (0.37%). The C4 model produces 17 significant alphas, compared to 13 in the benchmark case. In addition to the 12 anomalies already referred, the model cannot explain the spreads associated with GPA, NEI, NSI, and more surprisingly, MOM (t-ratio of 2.02). This indicates that the UMD factor does not help to eliminate the price momentum based on equal-weighted portfolios. In other words, there

[12] This is consistent with the evidence presented in the internet appendix of Hou, Xue, and Zhang (2015b).

seems to be a relevant size effect embedded in the price momentum anomaly.

Next, I present the results for the asset pricing tests containing all 248 portfolios. The results in table 20 indicate that when it comes to price simultaneously all the deciles (Panel F), the FF5 model outperforms both C4 and HXZ4. Specifically, the $RMSA$ estimate is 0.16% for FF5 compared to 0.16% and 0.17% for C4 and HXZ4, respectively. The MAA estimates are 0.12%, 0.13%, and 0.15% for FF5, C4, and HXZ4, respectively. However, FF5 produces a smaller number of significant alphas than the other models by a great margin (62 compared to 102 and 125 for HXZ4 and C4, respectively). The performance of FF4 is basically the same as FF5, with a marginally lower $RMSA$ (0.15%).[13] When we compare with the joint tests based on the value-weighted portfolios it is evident that the fit is significantly lower in the estimation with the equal-weighted portfolios.

Across categories, we have roughly similar results to the benchmark estimation with value-weighted portfolios. Specifically, both HXZ4 ($RMSA$ of 0.16%) and C4 (0.15%) outperform the remaining models in pricing momentum-based anomalies, while HXZ4 provides by a good margin the best fit for the profitability anomalies with an average alpha of 0.16% (compared to 0.20% for FF5). On the other hand, the five-factor model dominates the other models in explaining portfolios related with value, investment, and intangibles strategies. In the case of the investment portfolios, the five-factor model produces an average alpha of 0.13%, compared to 0.16% for C4 and 0.18% for HXZ4. Regarding the two anomalies related with intangibles, the average alpha for FF5 is 0.11%, which compares to 0.13% for C4 and 0.15% for HXZ4. Only in the estimation with the three value strategies do any of the three models (C4, HXZ4, and FF5) pass the GRS test. As in the benchmark case based on value-weighted portfolios, FF4 is not dominated by FF5. Specifically, the four-factor model generates marginally lower average alphas than FF5 in all categories except the group of investment-based anomalies.

[13]The results in Hou, Xue, and Zhang (2015a) for unconditional factor models tested on 50 groups of equal-weighted portfolios also indicate a small dominance of FF5. Specifically, they report mean absolute alphas of 0.11% and 0.13% for FF5 and HXZ4, respectively.

The results from this section indicate that all factor models, and especially HXZ4, have greater difficulty in pricing the equal-weighted portfolios than the value-weighted portfolios. Yet, the four-factor model continues to beat the alternative models when it comes to price the spreads high-minus-low, while the five-factor model produces the lowest average alpha in the estimation with all portfolios. This suggests that, similarly to the benchmark test based on value-weighted portfolios, HXZ4 does a better job in pricing the extreme deciles, while FF5 outperforms in explaining the intermediate deciles.

6 Cross-sectional dispersion in risk premia

In this section, I investigate further the explanatory power of the conditional multifactor models for the cross-section of average excess stock returns. The spreads high-minus-low in average returns represent an incomplete picture of the dispersion in cross-sectional risk premia since they exclude the intermediate eight deciles in each portfolio group. For this reason, I compute the (constrained) cross-sectional R^2 proposed in Maio (2015),

$$R_C^2 = 1 - \frac{\mathrm{Var}_N(\hat{\alpha}_i)}{\mathrm{Var}_N(\overline{R_i^e})}, \tag{29}$$

where $\mathrm{Var}_N(\cdot)$ stands for the cross-sectional variance (with N denoting the number of test assets), and $\overline{R_i^e}$ is the sample mean of the excess return for asset i. R_C^2 represents a proxy for the proportion of the cross-sectional variance of average excess returns on the test assets explained by the factor loadings associated with a given model. Maio (2015) uses the above measure to evaluate the fit of factor models from a constrained cross-sectional regression of average excess returns on factor betas in which the factor risk price estimates correspond to the factor means. For example, in the case of the conditional CAPM this constrained regression is given by

$$\overline{R_i^e} = \overline{RM}\beta_{i,M} + \overline{RMTERM}\beta_{i,M,TERM} + \overline{RMDEF}\beta_{i,M,DEF} + \overline{RMdp}\beta_{i,M,dp} + \overline{RMTB}\beta_{i,M,TB}, \tag{30}$$

where $\overline{RM}$ denotes the sample mean of the market factor, and $\overline{RMz}$, $z \equiv TERM, DEF, dp, TB$ represents the sample mean of each of the scaled factors. 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 in which the factor risk prices are equal to the factor means is equivalent to the time-series regression approach. This 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 explaining cross-sectional variation in risk premia, that is, the model performs worse than a model that predicts constant risk premia in the cross-section of average returns.

Table 21 presents the R_C^2 estimates for the conditional tests based on both the value- and equal-weighted portfolios. Starting with the value-weighted portfolios, we can see that both the CAPM and FF3 models produce negative estimates in the estimation including all portfolios (Panel F), which indicates that both models perform worse than a trivial model containing just an intercept. Both C4 and FF5 clearly outperform FF3 as indicated by the explanatory ratio of 35% in both cases. Yet, HXZ4 has the best overall performance, with 53% of the cross-sectional variation in equity risk premia being explained by the factor loadings associated with this model.

Across categories of anomalies, HXZ4 clearly underperforms the alternative multifactor models in pricing the value-growth portfolios, as indicated by the R^2 of 37%, compared to values around 80% for the other models. However, this four-factor model shows the best performance when it comes to price the portfolios within the momentum, profitability, and intangibles categories, with explanatory ratios above or around 50%. Specifically, among the profitability-based portfolios all factor models, apart from HXZ4, produce negative R^2_C estimates, which shows that they perform worse than a trivial model that predicts constant cross-sectional risk premia. In the case of the investment anomalies, both HXZ4 and FF5 show a good performance (47%), which is above the fit of C4 (31%). We can also see that FF4 is never dominated by FF5, except in the test with the value-growth portfolios.

Turning to the tests with equal-weighted portfolios, the fit of HXZ4 in the estimation with all portfolios achieves a level close to 70%, clearly above the explanatory ratios for both C4 and FF5 (around 45%). Thus, the fit of HXZ4 is even higher than in the estimation with value-weighted portfolios. Part of the increased explanatory power of this model comes from a better fit in driving cross-sectional risk premia among the value-based portfolios as indicated by the R^2 of 83%, which is only marginally below the fit of C4 (89%). In the remaining categories, HXZ4 tends to dominates the competing models, especially among the profitability-based portfolios. The exception is the group of investment anomalies, in which both HXZ4 and FF5 have a similar fit (around 60%), outperforming C4 (38%) by a significant margin.

With the exception of the investment anomalies, the FF4 is not outperformed by FF5. Specifically, within the profitability anomalies, the restricted model produces a larger fit than the five-factor model (38% versus 25%). Overall, the results of this section confirm the evidence from the previous sections that the HXZ4 model outperforms the competing models in terms of explaining the cross-sectional dispersion in equity risk premia for a large number of anomalies, and these results hold for both value- and equal-weighted portfolios.

7 Conclusion

In this paper, I test conditional factor models over a large cross-section of stock returns associated with 25 different CAPM anomalies. These anomalies can be broadly classified in strategies related with value, momentum, investment, profitability, and intangibles. The analysis of the alphas for the 25 "high-minus-low" spreads in returns suggests that using conditioning information has a relevant impact on the performance of the factor models. The model that registers the greatest improvement relative to the unconditional test is the five-factor model of Fama and French (2015, 2016) (FF5), although the four-factor model of Hou, Xue, and Zhang (2015a, 2015b) (HXZ4) shows the best overall performance, similarly to the unconditional tests.

When one tests the alternative models over the full cross-section of stock returns (for a total of 248 portfolios), it turns out that the three models register a similar average mispricing. Specifically, the root mean squared alpha is the same across C4, HXZ4, and FF5 (0.13%), whereas the mean absolute alpha estimates are 0.09% for FF5 compared to 0.10% for both C4 and HXZ4. Yet, both HXZ4 and FF5 have a much lower number of individual significant alphas than C4 (around 33 versus 51 for C4). Across categories, it turns out that the three-factor model of Fama and French (1993) (FF3), C4, and FF5 clearly dominate the HXZ4 model in terms of pricing the value anomalies. On the other hand, both C4 and HXZ4 significantly outperform FF5 when it comes to price the momentum-based anomalies, while HXZ4 is the clear winner in the group of profitability anomalies.

The results for equal-weighted portfolios indicate that all factor models, and especially HXZ4, have greater difficulty in pricing the equal-weighted portfolios than the value-weighted portfolios. Yet, HXZ4 continues to beat the alternative models when it comes to price the spreads high-minus-low, with a mean absolute alpha (across the 25 spreads) of 0.27%, compared to 0.37% for FF5 and 0.39% for C4. In contrast, the five-factor model produces the best fit in the estimation with all 248 portfolios. Specifically, the root mean squared alpha is 0.16% for FF5 compared to 0.16% and 0.17% for C4 and HXZ4. However, FF5 produces a smaller number of significant alphas than the other models by a great margin (62 compared to 102 and 125 for HXZ4 and C4, respectively). This shows that, similarly to the benchmark test based on value-weighted portfolios, HXZ4 does a better job in pricing the extreme deciles, while FF5 outperforms when it comes to explaining the intermediate deciles.

I estimate a conditional restricted version of FF5 that excludes the HML factor. The results show that in most cases the restricted model is not dominated by FF5. Specifically, the mean absolute alpha across the 25 value-weighted spreads is 0.28% (the same as for FF5). The average alpha across the 248 portfolios is 0.12% (compared to 0.13% for FF5), and the model produces 30 significant alphas (compared to 34 for FF5). In the estimation containing all 248 equal-weighted portfolios, the model that excludes HML produces an average mispricing of 0.15%, versus 0.16% for FF5.

I also compute a cross-sectional R^2 metric to evaluate the cross-sectional dispersion in equity risk premia based on all portfolios, and not just the spreads high-minus-low. This metric is based on the constraint that the factor risk price estimates are equal to the corresponding factor sample means. The results confirm that the HXZ4 model outperforms the competing models in terms of explaining the cross-sectional dispersion in equity risk premia for a large number of anomalies, and these results hold for both value- and equal-weighted portfolios.

Overall, the results of this paper show that the HXZ4 model outperforms the competing models when it comes to price the extreme portfolio deciles and the cross-sectional dispersion in equity risk premia. Yet, the FF5 model performs slightly better in terms of pricing the intermediate deciles. 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. Moreover, the HML factor continues to be largely redundant within the five-factor model when using conditioning information.

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Table 1: Descriptive statistics for equity factors

This table reports descriptive statistics for the equity factors from alternative factor models. RM, SMB, HML, and UMD denote the market, size, value, and momentum 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

	Mean (%)	Stdev. (%)	Min. (%)	Max. (%)	ϕ
RM	0.53	4.61	−23.24	16.10	0.08
SMB	0.20	3.13	−16.39	22.02	0.01
HML	0.39	3.01	−12.68	13.83	0.15
UMD	0.71	4.46	−34.72	18.39	0.07
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
RMW	0.29	2.25	−17.60	12.24	0.18
CMA	0.37	1.96	−6.76	8.93	0.14

Panel B

	RM	SMB	HML	UMD	ME	IA	ROE	RMW	CMA
RM	1.00	0.28	−0.32	−0.14	0.25	−0.36	−0.18	−0.23	−0.39
SMB		1.00	−0.23	−0.01	0.95	−0.23	−0.39	−0.44	−0.12
HML			1.00	−0.15	−0.07	0.69	−0.09	0.15	0.70
UMD				1.00	0.00	0.04	0.50	0.09	0.02
ME					1.00	−0.12	−0.31	−0.38	−0.01
IA						1.00	0.06	0.10	0.90
ROE							1.00	0.67	−0.09
RMW								1.00	−0.04
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, Xue, and Zhang (2015b), 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 et al. (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, Lundholm, and Van Winkle (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, Jegadeesh, and Lakonishok (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 (%)	Stdev. (%)	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: Wald tests for factor loadings: C4

This table presents the p-values of Wald tests for combinations of factor loadings associated with the Carhart four-factor model (C4). The test assets are "high-minus-low" portfolio return spreads associated with 25 anomalies. See Table 2 for a description of the different portfolio sorts. RM, SMB, HML, and UMD represent the Fama-French market, size, value, and momentum factors, respectively. The lagged instruments (z) used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. Bold p-values indicate rejection of the null hypothesis (that the slopes are jointly equal to zero) at the 5% level.

	$RM_{t+1}z_t$	$SMB_{t+1}z_t$	$HML_{t+1}z_t$	$UMD_{t+1}z_t$	(RM, SMB, HML, UMD)
BM	0.29	0.13	**0.00**	**0.03**	**0.00**
DUR	**0.00**	0.14	**0.00**	0.08	**0.00**
CFP	**0.00**	**0.00**	0.16	0.21	**0.00**
MOM	0.81	0.22	0.90	0.27	**0.00**
SUE	0.10	0.22	0.09	0.21	**0.00**
ABR	0.93	0.58	0.10	0.12	**0.00**
IM	**0.04**	0.17	0.83	**0.03**	**0.00**
ABR*	**0.04**	0.30	0.33	**0.04**	**0.00**
ROE	**0.00**	0.14	**0.00**	**0.00**	**0.00**
GPA	0.06	**0.01**	**0.00**	**0.05**	**0.00**
NEI	0.62	**0.00**	**0.00**	**0.00**	**0.00**
RS	**0.04**	0.16	**0.00**	0.18	**0.00**
IA	0.23	**0.05**	0.39	**0.01**	**0.00**
NSI	0.24	0.25	**0.00**	**0.01**	**0.00**
CEI	0.24	0.19	0.14	0.16	**0.00**
PIA	**0.02**	0.16	**0.00**	**0.00**	**0.00**
IG	**0.00**	0.25	**0.02**	0.16	**0.00**
IVC	0.48	0.19	**0.00**	0.09	**0.00**
IVG	0.06	0.12	**0.00**	**0.00**	**0.00**
NOA	**0.00**	0.08	**0.00**	**0.00**	**0.00**
OA	0.85	**0.00**	**0.00**	**0.00**	**0.00**
POA	0.25	**0.01**	**0.01**	0.14	**0.00**
PTA	**0.00**	**0.00**	**0.00**	0.07	**0.00**
OCA	**0.00**	**0.03**	**0.00**	0.58	**0.00**
OL	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

Table 5: Wald tests for factor loadings: HXZ4

This table presents the p-values of Wald tests for combinations of factor loadings associated with the Hou-Xue-Zhang four-factor model (HXZ4). The test assets are "high-minus-low" portfolio return spreads associated with 25 anomalies. See Table 2 for a description of the different portfolio sorts. RM, ME, IA, and ROE represent the Hou-Xue-Zhang market, size, investment, and profitability factors, respectively. The lagged instruments (z) used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. Bold p-values indicate rejection of the null hypothesis (that the slopes are jointly equal to zero) at the 5% level.

	$RM_{t+1}z_t$	$ME_{t+1}z_t$	$IA_{t+1}z_t$	$ROE_{t+1}z_t$	(RM, ME, IA, ROE)
BM	**0.01**	**0.03**	0.08	**0.01**	**0.00**
DUR	0.06	**0.00**	**0.00**	**0.00**	**0.00**
CFP	0.57	**0.00**	0.08	**0.00**	**0.00**
MOM	0.76	**0.01**	**0.01**	**0.00**	**0.00**
SUE	**0.00**	0.07	0.56	0.05	**0.00**
ABR	0.75	**0.04**	**0.02**	0.23	**0.00**
IM	0.13	**0.00**	**0.01**	0.22	**0.00**
ABR*	**0.04**	**0.00**	**0.01**	0.16	**0.00**
ROE	0.12	0.58	**0.00**	0.12	**0.00**
GPA	**0.01**	**0.05**	**0.01**	0.11	**0.00**
NEI	0.09	**0.00**	0.88	**0.00**	**0.00**
RS	**0.03**	**0.01**	**0.02**	0.06	**0.00**
IA	0.74	0.10	0.08	**0.03**	**0.00**
NSI	0.34	0.25	0.17	**0.00**	**0.00**
CEI	0.91	0.14	0.77	**0.04**	**0.00**
PIA	0.08	**0.04**	**0.04**	**0.00**	**0.00**
IG	**0.00**	0.17	**0.00**	0.30	**0.00**
IVC	0.73	0.12	**0.00**	0.27	**0.00**
IVG	**0.03**	0.18	**0.02**	**0.00**	**0.00**
NOA	**0.03**	0.11	**0.00**	0.60	**0.03**
OA	0.56	**0.00**	**0.00**	**0.02**	**0.00**
POA	0.26	**0.00**	0.13	**0.02**	**0.00**
PTA	**0.00**	**0.00**	**0.02**	0.10	**0.00**
OCA	**0.00**	**0.05**	0.15	**0.04**	**0.00**
OL	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

Table 6: Wald tests for factor loadings: FF5

This table presents the p-values of Wald tests for combinations of factor loadings associated with the Fama-French five-factor model (FF5). The test assets are "high-minus-low" portfolio return spreads associated with 25 anomalies. See Table 2 for a description of the different portfolio sorts. RM, SMB, HML, RMW, and CMA represent the Fama-French market, size, value, profitability, and investment factors, respectively. The lagged instruments (z) used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. Bold p-values indicate rejection of the null hypothesis (that the slopes are jointly equal to zero) at the 5% level.

	$RM_{t+1}z_t$	$SMB_{t+1}z_t$	$HML_{t+1}z_t$	$RMW_{t+1}z_t$	$CMA_{t+1}z_t$	(RM, SMB, HML, RMW, CMA)
BM	0.47	0.25	**0.01**	0.06	**0.04**	**0.00**
DUR	**0.01**	0.22	**0.00**	**0.00**	0.46	**0.00**
CFP	**0.00**	**0.00**	0.36	**0.01**	0.38	**0.00**
MOM	**0.04**	0.06	0.15	**0.00**	**0.01**	0.08
SUE	**0.02**	**0.02**	0.09	0.12	0.45	0.77
ABR	0.17	0.34	**0.01**	0.08	0.14	0.09
IM	0.07	0.14	0.22	**0.00**	0.08	0.85
ABR*	0.10	0.08	0.15	0.06	0.05	0.13
ROE	**0.00**	0.64	**0.05**	**0.00**	0.48	**0.00**
GPA	**0.01**	**0.04**	**0.02**	0.43	**0.00**	**0.00**
NEI	0.27	**0.00**	0.09	0.10	0.53	**0.00**
RS	0.06	0.24	**0.02**	0.77	0.11	**0.00**
IA	0.43	**0.00**	**0.03**	0.21	**0.00**	**0.00**
NSI	**0.02**	0.53	**0.00**	0.33	0.76	**0.00**
CEI	0.16	0.21	0.16	0.37	0.24	**0.00**
PIA	**0.00**	**0.01**	0.05	0.82	**0.05**	**0.00**
IG	**0.00**	0.28	0.70	0.23	0.05	**0.00**
IVC	0.40	**0.01**	**0.01**	0.94	**0.03**	**0.00**
IVG	0.14	0.08	0.08	0.77	0.29	**0.00**
NOA	0.20	0.08	**0.00**	**0.00**	**0.00**	**0.00**
OA	0.60	**0.00**	0.54	**0.04**	**0.01**	**0.00**
POA	0.42	**0.00**	0.80	0.47	0.21	**0.00**
PTA	**0.03**	**0.00**	**0.04**	0.29	0.13	**0.00**
OCA	**0.00**	0.78	**0.03**	**0.00**	0.27	**0.00**
OL	**0.00**	0.10	**0.01**	0.15	**0.01**	**0.00**

Table 7: Spreads "high-minus-low": unconditional models

This table presents alphas for "high-minus-low" portfolio return spreads associated with unconditional factor models. See Table 2 for a description of the different portfolio sorts. The models are the CAPM; Fama-French three-factor model (FF3); Carhart four-factor model (C4); Hou-Xue-Zhang four-factor model (HXZ4); Fama-French five-factor model (FF5); and a restricted version of FF5 (FF4). The sample is 1972:01–2013:12. For each model, the first column shows the alphas whereas the second column presents the associated GMM-based t-ratios. Bold t-ratios indicate statistical significance at the 5% level.

	CAPM	t	FF3	t	C4	t	HXZ4	t	FF5	t	FF4	t
BM	0.75	**3.48**	0.01	0.07	−0.00	−0.01	0.23	1.25	0.02	0.20	−0.03	−0.17
DUR	−0.61	**−3.24**	−0.05	−0.37	−0.07	−0.51	−0.27	−1.38	−0.14	−0.97	−0.09	−0.46
CFP	0.63	**3.10**	0.00	0.03	−0.06	−0.40	0.22	1.08	0.06	0.43	0.01	0.03
MOM	1.29	**4.22**	1.51	**4.84**	0.09	0.63	0.26	0.68	1.22	**3.31**	1.25	**3.34**
SUE	0.50	**3.87**	0.55	**4.06**	0.34	**2.50**	0.16	1.11	0.44	**3.00**	0.45	**3.03**
ABR	0.76	**5.51**	0.84	**5.77**	0.61	**4.34**	0.64	**4.17**	0.85	**5.65**	0.85	**5.59**
IM	0.61	**2.70**	0.71	**3.16**	−0.15	−0.92	0.05	0.19	0.59	**2.32**	0.61	**2.38**
ABR*	0.30	**3.41**	0.37	**4.01**	0.18	**2.08**	0.26	**2.47**	0.43	**4.42**	0.44	**4.44**
ROE	0.93	**4.16**	1.14	**5.79**	0.81	**4.33**	0.02	0.16	0.56	**3.65**	0.57	**3.66**
GPA	0.32	**2.13**	0.50	**3.40**	0.44	**2.93**	0.11	0.72	0.10	0.74	0.12	0.85
NEI	0.37	**3.07**	0.60	**5.39**	0.39	**3.58**	0.15	1.39	0.45	**4.03**	0.46	**3.92**
RS	0.31	**2.10**	0.61	**4.20**	0.44	**2.92**	0.18	1.19	0.51	**3.38**	0.53	**3.36**
IA	−0.52	**−3.29**	−0.16	−1.20	−0.10	−0.71	0.13	0.97	0.10	0.80	0.11	0.85
NSI	−0.79	**−5.51**	−0.65	**−5.04**	−0.55	**−4.20**	−0.26	**−2.01**	−0.26	**−2.19**	−0.26	**−2.16**
CEI	−0.79	**−5.02**	−0.50	**−3.95**	−0.40	**−3.12**	−0.21	−1.49	−0.21	−1.75	−0.20	−1.52
PIA	−0.56	**−4.23**	−0.40	**−3.04**	−0.34	**−2.51**	−0.24	−1.79	−0.30	**−2.33**	−0.30	**−2.34**
IG	−0.43	**−3.34**	−0.24	−1.95	−0.17	−1.42	0.07	0.55	−0.02	−0.15	−0.01	−0.12
IVC	−0.49	**−3.46**	−0.37	**−2.56**	−0.28	−1.91	−0.26	−1.81	−0.34	**−2.45**	−0.35	**−2.46**
IVG	−0.43	**−3.13**	−0.25	−1.91	−0.15	−1.14	0.02	0.13	−0.09	−0.70	−0.09	−0.69
NOA	−0.38	**−2.76**	−0.52	**−3.66**	−0.41	**−2.90**	−0.37	**−2.15**	−0.42	**−2.67**	−0.44	**−2.63**
OA	−0.30	**−2.19**	−0.35	**−2.54**	−0.31	**−2.12**	−0.53	**−3.60**	−0.52	**−3.71**	−0.52	**−3.71**
POA	−0.51	**−3.82**	−0.31	**−2.46**	−0.24	−1.94	−0.11	−0.77	−0.13	−0.97	−0.12	−0.92
PTA	−0.51	**−3.59**	−0.30	**−2.22**	−0.28	**−1.98**	−0.11	−0.71	−0.06	−0.45	−0.06	−0.39
OCA	0.65	**4.64**	0.61	**4.38**	0.40	**2.83**	0.11	0.80	0.29	**2.15**	0.30	**2.18**
OL	0.43	**2.49**	0.36	**2.09**	0.32	1.83	−0.06	−0.34	−0.00	−0.01	−0.01	−0.04

Table 8: Spreads “high-minus-low”: conditional models

This table presents alphas for “high-minus-low” portfolio return spreads associated with conditional factor models. See Table 2 for a description of the different portfolio sorts. The models are the CAPM; Fama-French three-factor model (FF3); Carhart four-factor model (C4); Hou-Xue-Zhang four-factor model (HXZ4); Fama-French five-factor model (FF5); and a restricted version of FF5 (FF4). The lagged instruments used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. For each model, the first column shows the alphas whereas the second column presents the associated GMM-based t-ratios. Bold t-ratios indicate statistical significance at the 5% level.

	CAPM	t	FF3	t	C4	t	HXZ4	t	FF5	t	FF4	t
BM	0.62	**3.00**	−0.07	−0.59	−0.11	−0.80	0.38	**2.08**	−0.01	−0.11	0.12	0.72
DUR	−0.59	**−3.14**	−0.05	−0.36	−0.01	−0.08	−0.32	−1.84	0.07	0.48	−0.06	−0.32
CFP	0.57	**2.89**	0.03	0.23	−0.04	−0.25	0.40	**2.05**	−0.08	−0.54	0.05	0.24
MOM	1.35	**4.43**	1.40	**4.46**	0.10	0.76	0.07	0.22	0.93	**2.61**	0.89	**2.57**
SUE	0.48	**3.71**	0.47	**3.57**	0.30	**2.23**	0.04	0.28	0.40	**2.80**	0.38	**2.70**
ABR	0.77	**5.53**	0.81	**5.63**	0.62	**4.44**	0.54	**3.51**	0.80	**5.56**	0.77	**5.21**
IM	0.64	**2.86**	0.63	**2.75**	−0.19	−1.23	−0.16	−0.67	0.34	1.31	0.34	1.35
ABR*	0.34	**3.78**	0.36	**3.95**	0.20	**2.21**	0.13	1.34	0.36	**3.63**	0.33	**3.38**
ROE	0.87	**4.28**	1.20	**7.97**	0.87	**6.39**	0.21	1.71	0.84	**5.64**	0.78	**5.16**
GPA	0.27	1.83	0.54	**4.18**	0.45	**3.37**	0.10	0.72	0.12	0.93	0.04	0.33
NEI	0.37	**3.08**	0.59	**5.42**	0.33	**3.12**	−0.01	−0.06	0.41	**3.72**	0.36	**3.17**
RS	0.33	**2.18**	0.63	**4.64**	0.45	**3.22**	0.01	0.08	0.53	**3.57**	0.44	**2.88**
IA	−0.41	**−2.72**	−0.10	−0.77	−0.08	−0.59	−0.02	−0.17	0.03	0.26	0.04	0.38
NSI	−0.75	**−5.30**	−0.62	**−4.94**	−0.58	**−4.64**	−0.41	**−3.17**	−0.19	−1.59	−0.22	−1.87
CEI	−0.73	**−4.61**	−0.47	**−3.75**	−0.38	**−2.99**	−0.28	**−2.00**	−0.07	−0.59	−0.12	−0.92
PIA	−0.53	**−4.00**	−0.31	**−2.48**	−0.30	**−2.32**	−0.15	−1.24	−0.23	**−1.99**	−0.23	−1.95
IG	−0.41	**−3.23**	−0.18	−1.55	−0.14	−1.18	0.03	0.26	−0.07	−0.62	−0.08	−0.71
IVC	−0.49	**−3.43**	−0.33	**−2.36**	−0.26	−1.83	−0.18	−1.27	−0.28	**−2.07**	−0.27	**−2.00**
IVG	−0.41	**−2.99**	−0.19	−1.41	−0.08	−0.66	0.01	0.11	−0.06	−0.50	−0.10	−0.85
NOA	−0.39	**−2.79**	−0.48	**−3.61**	−0.44	**−3.28**	−0.32	**−2.00**	−0.39	**−2.71**	−0.40	**−2.69**
OA	−0.32	**−2.42**	−0.22	−1.68	−0.14	−1.07	−0.27	−1.90	−0.28	**−2.02**	−0.30	**−2.21**
POA	−0.44	**−3.33**	−0.23	−1.89	−0.14	−1.20	−0.17	−1.28	−0.11	−0.85	−0.12	−0.95
PTA	−0.43	**−2.98**	−0.21	−1.61	−0.20	−1.49	−0.20	−1.43	0.00	0.00	−0.04	−0.32
OCA	0.59	**4.82**	0.64	**5.14**	0.49	**3.94**	0.28	**2.08**	0.43	**3.27**	0.38	**2.92**
OL	0.36	**2.19**	0.33	**2.16**	0.38	**2.47**	0.13	0.77	0.06	0.41	0.09	0.61

Table 9: Joint time-series tests by category: unconditional models

This table presents joint time-series tests of unconditional 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. In Panel F all the 25 sorts are included simultaneously as test assets. See Table 2 for a description of the different portfolio sorts and categories. The models are the CAPM; Fama-French three-factor model (FF3); Carhart four-factor model (C4); Hou-Xue-Zhang four-factor model (HXZ4); Fama-French five-factor model (FF5); and a restricted version of FF5 (FF4). The sample is 1972:01–2013:12. MAA denotes the mean absolute alpha and $RMSA$ is the root mean squared alpha. $\# < 0.05$ represents the number of portfolios in which the alphas are significant at the 5% level. F and χ^2 denote the p-values associated with the GRS and robust χ^2 model specification tests, respectively.

	CAPM	FF3	C4	HXZ4	FF5	FF4
Panel A (Value-growth)						
MAA	0.21	0.08	0.07	0.10	0.07	0.07
$RMSA$	0.25	0.09	0.08	0.13	0.09	0.09
$\# < 0.05$	16	3	2	2	1	1
F	0.05	0.10	0.38	0.03	0.14	0.15
χ^2	0.02	0.05	0.27	0.01	0.08	0.09
Panel B (Momentum)						
MAA	0.15	0.17	0.09	0.10	0.16	0.17
$RMSA$	0.21	0.24	0.13	0.14	0.21	0.22
$\# < 0.05$	17	20	11	7	15	15
F	0.00	0.00	0.00	0.00	0.00	0.00
χ^2	0.00	0.00	0.00	0.00	0.00	0.00
Panel C (Profitability)						
MAA	0.12	0.18	0.13	0.09	0.12	0.12
$RMSA$	0.16	0.22	0.16	0.12	0.15	0.15
$\# < 0.05$	7	18	8	7	9	9
F	0.03	0.00	0.01	0.05	0.06	0.12
χ^2	0.01	0.00	0.00	0.02	0.02	0.05
Panel D (Investment)						
MAA	0.15	0.12	0.11	0.11	0.10	0.10
$RMSA$	0.18	0.15	0.13	0.14	0.13	0.13
$\# < 0.05$	37	28	23	20	26	27
F	0.01	0.00	0.04	0.00	0.00	0.00
χ^2	0.00	0.00	0.00	0.00	0.00	0.00
Panel E (Intangibles)						
MAA	0.12	0.12	0.11	0.12	0.10	0.10
$RMSA$	0.15	0.15	0.13	0.15	0.12	0.12
$\# < 0.05$	5	6	4	3	3	4
F	0.03	0.00	0.02	0.08	0.05	0.08
χ^2	0.02	0.00	0.01	0.05	0.03	0.05
Panel F (All)						
MAA	0.15	0.13	0.10	0.11	0.11	0.11
$RMSA$	0.19	0.18	0.13	0.14	0.15	0.15
$\# < 0.05$	82	75	48	39	54	56
F	0.00	0.00	0.00	0.00	0.00	0.00
χ^2	0.00	0.00	0.00	0.00	0.00	0.00

Table 10: Joint time-series tests by category: conditional models

This table presents joint time-series tests of 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. In Panel F all the 25 sorts are included simultaneously as test assets. See Table 2 for a description of the different portfolio sorts and categories. The models are the CAPM; Fama-French three-factor model (FF3); Carhart four-factor model (C4); Hou-Xue-Zhang four-factor model (HXZ4); Fama-French five-factor model (FF5); and a restricted version of FF5 (FF4). The lagged instruments used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. MAA denotes the mean absolute alpha and $RMSA$ is the root mean squared alpha. $\# < 0.05$ represents the number of portfolios in which the alphas are significant at the 5% level. F and χ^2 denote the p-values associated with the GRS and robust χ^2 model specification tests, respectively.

	CAPM	FF3	C4	HXZ4	FF5	FF4
Panel A (Value-growth)						
MAA	0.18	0.07	0.06	0.13	0.06	0.07
$RMSA$	0.21	0.09	0.08	0.16	0.07	0.08
$\# < 0.05$	11	4	3	7	1	0
F	0.06	0.13	0.22	0.18	0.78	0.75
χ^2	0.03	0.05	0.11	0.08	0.64	0.62
Panel B (Momentum)						
MAA	0.14	0.15	0.09	0.09	0.11	0.11
$RMSA$	0.21	0.22	0.13	0.12	0.16	0.15
$\# < 0.05$	14	19	11	5	8	9
F	0.00	0.00	0.00	0.01	0.00	0.00
χ^2	0.00	0.00	0.00	0.00	0.00	0.00
Panel C (Profitability)						
MAA	0.12	0.18	0.14	0.09	0.13	0.11
$RMSA$	0.16	0.23	0.17	0.11	0.16	0.15
$\# < 0.05$	7	19	10	6	8	8
F	0.02	0.00	0.00	0.06	0.00	0.03
χ^2	0.00	0.00	0.00	0.01	0.00	0.00
Panel D (Investment)						
MAA	0.13	0.10	0.10	0.10	0.08	0.09
$RMSA$	0.16	0.13	0.12	0.12	0.11	0.11
$\# < 0.05$	31	28	22	14	15	12
F	0.01	0.01	0.05	0.01	0.02	0.02
χ^2	0.00	0.00	0.00	0.00	0.00	0.00
Panel E (Intangibles)						
MAA	0.10	0.11	0.11	0.10	0.09	0.08
$RMSA$	0.13	0.15	0.14	0.12	0.11	0.10
$\# < 0.05$	4	5	5	1	2	1
F	0.01	0.00	0.00	0.09	0.08	0.23
χ^2	0.01	0.00	0.00	0.05	0.04	0.14
Panel F (All)						
MAA	0.13	0.12	0.10	0.10	0.09	0.09
$RMSA$	0.18	0.17	0.13	0.13	0.13	0.12
$\# < 0.05$	67	75	51	33	34	30
F	0.00	0.00	0.00	0.00	0.00	0.00
χ^2	0.00	0.00	0.00	0.00	0.00	0.00

Table 11: Time-series tests by category: extreme deciles

This table presents joint time-series tests of 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. For each anomaly, only the extreme first and last deciles are considered. In Panel F all the 25 sorts are included simultaneously as test assets. See Table 2 for a description of the different portfolio sorts and categories. The models are the CAPM; Fama-French three-factor model (FF3); Carhart four-factor model (C4); Hou-Xue-Zhang four-factor model (HXZ4); Fama-French five-factor model (FF5); and a restricted version of FF5 (FF4). The lagged instruments used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. MAA denotes the mean absolute alpha and $RMSA$ is the root mean squared alpha. $\# < 0.05$ represents the number of portfolios in which the alphas are significant at the 5% level. F and χ^2 denote the p-values associated with the GRS and robust χ^2 model specification tests, respectively.

	CAPM	FF3	C4	HXZ4	FF5	FF4
Panel A (Value-growth)						
MAA	0.30	0.09	0.08	0.18	0.08	0.08
$RMSA$	0.31	0.10	0.09	0.23	0.09	0.10
$\# < 0.05$	3	1	0	2	1	0
F	0.00	0.00	0.01	0.01	0.06	0.11
χ^2	0.00	0.00	0.00	0.01	0.04	0.09
Panel B (Momentum)						
MAA	0.36	0.37	0.14	0.13	0.28	0.27
$RMSA$	0.41	0.42	0.18	0.16	0.31	0.30
$\# < 0.05$	7	8	3	2	5	5
F	0.00	0.00	0.00	0.01	0.00	0.00
χ^2	0.00	0.00	0.00	0.00	0.00	0.00
Panel C (Profitability)						
MAA	0.23	0.37	0.26	0.10	0.26	0.24
$RMSA$	0.28	0.40	0.29	0.11	0.29	0.26
$\# < 0.05$	4	8	5	0	7	6
F	0.01	0.00	0.00	0.07	0.00	0.00
χ^2	0.01	0.00	0.00	0.05	0.00	0.00
Panel D (Investment)						
MAA	0.25	0.17	0.14	0.11	0.10	0.11
$RMSA$	0.27	0.20	0.17	0.12	0.12	0.12
$\# < 0.05$	14	9	8	2	3	2
F	0.00	0.00	0.01	0.29	0.10	0.15
χ^2	0.00	0.00	0.00	0.19	0.04	0.08
Panel E (Intangibles)						
MAA	0.24	0.24	0.22	0.10	0.13	0.12
$RMSA$	0.25	0.26	0.22	0.12	0.16	0.16
$\# < 0.05$	2	3	3	0	1	1
F	0.00	0.00	0.00	0.15	0.01	0.02
χ^2	0.00	0.00	0.00	0.13	0.01	0.02
Panel F (All)						
MAA	0.27	0.24	0.16	0.12	0.16	0.16
$RMSA$	0.31	0.29	0.20	0.15	0.21	0.20
$\# < 0.05$	30	29	19	6	17	14
F	0.00	0.00	0.00	0.00	0.00	0.00
χ^2	0.00	0.00	0.00	0.00	0.00	0.00

Table 12: Time-series tests by category: intermediate deciles

This table presents joint time-series tests of 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. For each anomaly, all the portfolios are included except the extreme first and last deciles. In Panel F all the 25 sorts are included simultaneously as test assets. See Table 2 for a description of the different portfolio sorts and categories. The models are the CAPM; Fama-French three-factor model (FF3); Carhart four-factor model (C4); Hou-Xue-Zhang four-factor model (HXZ4); Fama-French five-factor model (FF5); and a restricted version of FF5 (FF4). The lagged instruments used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. MAA denotes the mean absolute alpha and $RMSA$ is the root mean squared alpha. $\# < 0.05$ represents the number of portfolios in which the alphas are significant at the 5% level. F and χ^2 denote the p-values associated with the GRS and robust χ^2 model specification tests, respectively.

	CAPM	FF3	C4	HXZ4	FF5	FF4
Panel A (Value-growth)						
MAA	0.14	0.07	0.06	0.11	0.05	0.07
$RMSA$	0.18	0.08	0.08	0.14	0.06	0.08
$\# < 0.05$	8	3	3	5	0	0
F	0.04	0.19	0.31	0.15	0.84	0.71
χ^2	0.02	0.11	0.20	0.08	0.76	0.60
Panel B (Momentum)						
MAA	0.09	0.09	0.08	0.08	0.07	0.07
$RMSA$	0.11	0.11	0.11	0.11	0.08	0.08
$\# < 0.05$	7	11	8	3	3	4
F	0.09	0.00	0.00	0.08	0.04	0.06
χ^2	0.03	0.00	0.00	0.02	0.01	0.01
Panel C (Profitability)						
MAA	0.09	0.13	0.10	0.09	0.09	0.08
$RMSA$	0.11	0.16	0.12	0.12	0.11	0.10
$\# < 0.05$	3	11	5	6	1	2
F	0.36	0.01	0.04	0.06	0.21	0.39
χ^2	0.25	0.00	0.01	0.02	0.09	0.23
Panel D (Investment)						
MAA	0.10	0.09	0.09	0.09	0.08	0.08
$RMSA$	0.12	0.11	0.11	0.12	0.10	0.11
$\# < 0.05$	17	19	14	12	12	10
F	0.09	0.10	0.14	0.01	0.02	0.02
χ^2	0.00	0.00	0.00	0.00	0.00	0.00
Panel E (Intangibles)						
MAA	0.06	0.08	0.09	0.10	0.07	0.07
$RMSA$	0.08	0.11	0.11	0.11	0.09	0.08
$\# < 0.05$	2	2	2	1	1	0
F	0.00	0.12	0.29	0.47	0.53	0.72
χ^2	0.00	0.08	0.22	0.39	0.44	0.65
Panel F (All)						
MAA	0.10	0.09	0.08	0.09	0.08	0.08
$RMSA$	0.12	0.12	0.11	0.12	0.10	0.10
$\# < 0.05$	37	46	32	27	17	16
F	0.03	0.04	0.03	0.01	0.06	0.07
χ^2	0.00	0.00	0.00	0.00	0.00	0.00

Table 13: Time-series tests for conditional models: individual anomalies

This table presents time-series tests of conditional factor models for selected individual anomalies. The portfolios are sorted on BM, MOM, ROE, NSI, OCA, ABR, CEI, DUR, and IM. See Table 2 for a description of the different portfolio sorts. The models are the CAPM; Fama-French three-factor model (FF3); Carhart four-factor model (C4); Hou-Xue-Zhang four-factor model (HXZ4); Fama-French five-factor model (FF5); and a restricted version of FF5 (FF4). The lagged instruments used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. MAA denotes the mean absolute alpha and $RMSA$ is the root mean squared alpha. $\# < 0.05$ represents the number of portfolios in which the alphas are significant at the 5% level. F and χ^2 denote the p-values associated with the GRS and robust χ^2 model specification tests, respectively.

	BM	DUR	MOM	ABR	IM	ROE	NSI	CEI	OCA
Panel A (CAPM)									
MAA	0.17	0.20	0.22	0.13	0.14	0.16	0.16	0.16	0.12
$RMSA$	0.21	0.23	0.33	0.19	0.18	0.24	0.20	0.21	0.16
$\# < 0.05$	4	5	4	3	1	3	4	4	4
F	0.14	0.02	0.00	0.00	0.09	0.01	0.00	0.00	0.00
χ^2	0.12	0.02	0.00	0.00	0.08	0.00	0.00	0.00	0.00
Panel B (FF3)									
MAA	0.05	0.10	0.23	0.13	0.13	0.26	0.15	0.12	0.14
$RMSA$	0.06	0.11	0.34	0.20	0.18	0.34	0.18	0.16	0.19
$\# < 0.05$	0	3	4	3	4	7	4	3	4
F	0.23	0.06	0.00	0.00	0.21	0.00	0.00	0.00	0.00
χ^2	0.19	0.04	0.00	0.00	0.17	0.00	0.00	0.00	0.00
Panel C (C4)									
MAA	0.05	0.09	0.14	0.11	0.06	0.18	0.13	0.11	0.12
$RMSA$	0.06	0.10	0.19	0.16	0.07	0.23	0.16	0.14	0.15
$\# < 0.05$	0	2	4	3	1	4	3	3	4
F	0.31	0.14	0.00	0.00	0.31	0.00	0.00	0.00	0.00
χ^2	0.26	0.10	0.00	0.00	0.26	0.00	0.00	0.00	0.00
Panel D (HXZ4)									
MAA	0.13	0.13	0.14	0.10	0.06	0.12	0.11	0.11	0.11
$RMSA$	0.16	0.15	0.16	0.15	0.08	0.14	0.14	0.12	0.12
$\# < 0.05$	2	3	1	2	0	4	2	0	1
F	0.16	0.21	0.04	0.00	0.17	0.00	0.00	0.08	0.07
χ^2	0.13	0.17	0.02	0.00	0.14	0.00	0.00	0.06	0.05
Panel E (FF5)									
MAA	0.05	0.07	0.13	0.13	0.11	0.18	0.11	0.09	0.11
$RMSA$	0.05	0.07	0.22	0.19	0.13	0.23	0.12	0.10	0.13
$\# < 0.05$	0	0	1	3	1	2	2	1	1
F	0.89	0.74	0.00	0.00	0.10	0.00	0.01	0.10	0.03
χ^2	0.86	0.69	0.00	0.00	0.07	0.00	0.01	0.07	0.02
Panel F (FF4)									
MAA	0.07	0.07	0.12	0.12	0.13	0.16	0.10	0.09	0.10
$RMSA$	0.08	0.08	0.21	0.19	0.14	0.21	0.13	0.10	0.12
$\# < 0.05$	0	0	1	3	3	2	2	1	1
F	0.92	0.66	0.00	0.00	0.04	0.00	0.03	0.12	0.05
χ^2	0.91	0.61	0.00	0.00	0.03	0.00	0.01	0.09	0.03

Table 14: Joint time-series test for selected anomalies

This table presents joint time-series tests of conditional factor models. The test portfolios are portfolios sorted on book-to-market (BM), momentum (MOM), investment-to-assets (IA), return-on-equity (ROE), net stock issues (NSI), organizational capital-to-assets (OCA), cumulative abnormal stock returns around earnings announcements (ABR), composite issuance (CEI), equity duration (DUR), and industry momentum (IM). See Table 2 for a description of the different portfolio sorts. The models are the CAPM; Fama-French three-factor model (FF3); Carhart four-factor model (C4); Hou-Xue-Zhang four-factor model (HXZ4); Fama-French five-factor model (FF5); and a restricted version of FF5 (FF4). The lagged instruments used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. MAA denotes the mean absolute alpha and $RMSA$ is the root mean squared alpha. $\# < 0.05$ represents the number of portfolios in which the alphas are significant at the 5% level. F and χ^2 denote the p-values associated with the GRS and robust χ^2 model specification tests, respectively.

	CAPM	FF3	C4	HXZ4	FF5	FF4
MAA	0.16	0.15	0.11	0.11	0.11	0.11
$RMSA$	0.22	0.21	0.15	0.14	0.15	0.15
$\# < 0.05$	32	32	24	15	11	13
F	0.00	0.00	0.00	0.00	0.00	0.00
χ^2	0.00	0.00	0.00	0.00	0.00	0.00

Table 15: Decomposition of spreads high-minus-low: C4

This table reports the risk premium (beta times risk price) for each factor from the Carhart four-factor model (C4) when tested on the spreads high-minus-low in average returns. The spreads are associated with portfolios sorted on BM, MOM, ROE, NSI, OCA, ABR, CEI, DUR, and IM. See Table 2 for a description of the different portfolio sorts. E(R) denotes the original spread in average returns, and α represents the corresponding alpha. RM, SMB, HML, and UMD represent the market, size, value, and momentum factors, respectively. The lagged instruments used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. All the numbers are in %

	BM	DUR	MOM	ABR	IM	ROE	NSI	CEI	OCA
E(R)	0.69	-0.52	1.17	0.73	0.54	0.75	-0.69	-0.55	0.55
RM_{t+1}	0.04	0.00	0.00	-0.01	0.02	-0.12	0.02	0.11	-0.08
$RM_{t+1}TERM_t$	0.01	0.05	-0.02	0.00	-0.04	-0.04	0.01	0.00	-0.02
$RM_{t+1}DEF_t$	-0.01	-0.01	0.00	-0.01	-0.01	0.00	0.01	0.01	-0.04
$RM_{t+1}dp_t$	0.02	0.01	0.00	0.01	0.02	0.03	0.01	0.00	0.05
$RM_{t+1}TB_t$	0.00	0.01	0.00	0.00	0.04	0.00	0.02	0.02	0.03
SMB_{t+1}	0.12	-0.06	-0.01	-0.01	0.00	-0.14	0.04	0.06	0.02
$SMB_{t+1}TERM_t$	-0.03	0.04	0.04	0.04	0.03	-0.04	0.00	0.01	-0.06
$SMB_{t+1}DEF_t$	0.02	0.00	-0.01	-0.02	0.00	0.02	-0.01	-0.02	0.02
$SMB_{t+1}dp_t$	-0.01	-0.02	0.00	-0.01	-0.02	0.02	-0.01	0.01	0.01
$SMB_{t+1}TB_t$	0.01	-0.03	-0.01	-0.02	-0.03	0.03	-0.01	-0.01	0.03
HML_{t+1}	0.57	-0.44	0.02	-0.03	0.04	-0.17	-0.11	-0.28	0.01
$HML_{t+1}TERM_t$	0.00	-0.01	0.00	-0.01	0.00	-0.01	0.01	0.01	0.01
$HML_{t+1}DEF_t$	0.02	-0.01	-0.01	-0.01	0.01	-0.04	0.02	0.01	-0.01
$HML_{t+1}dp_t$	0.00	0.00	0.00	0.00	0.00	0.01	-0.01	0.00	0.00
$HML_{t+1}TB_t$	0.02	-0.01	0.01	0.03	0.01	0.06	-0.07	-0.04	-0.02
UMD_{t+1}	0.01	-0.03	1.05	0.16	0.64	0.27	-0.04	-0.07	0.13
$UMD_{t+1}TERM_t$	0.02	0.02	0.02	0.02	0.04	-0.03	0.01	-0.01	-0.01
$UMD_{t+1}DEF_t$	0.02	-0.02	0.01	0.03	0.04	0.00	0.05	0.00	-0.02
$UMD_{t+1}dp_t$	-0.01	0.01	0.00	-0.01	-0.01	-0.01	-0.01	0.01	0.01
$UMD_{t+1}TB_t$	-0.01	-0.02	-0.04	-0.05	-0.05	0.02	-0.03	0.01	0.02
α	-0.11	-0.01	0.10	0.62	-0.19	0.87	-0.58	-0.38	0.49

Table 16: Decomposition of spreads high-minus-low: HXZ4

This table reports the risk premium (beta times risk price) for each factor from the Hou-Xue-Zhang four-factor model (HXZ4) when tested on the spreads high-minus-low in average returns. The spreads are associated with portfolios sorted on BM, MOM, ROE, NSI, OCA, ABR, CEI, DUR, and IM. See Table 2 for a description of the different portfolio sorts. E(R) denotes the original spread in average returns, and α represents the corresponding alpha. RM, ME, IA, and ROE represent the market, size, investment, and profitability factors, respectively. The lagged instruments used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. All the numbers are in %

	BM	DUR	MOM	ABR	IM	ROE	NSI	CEI	OCA
E(R)	0.69	-0.52	1.17	0.73	0.54	0.75	-0.69	-0.55	0.55
RM_{t+1}	-0.02	0.06	0.04	0.00	0.03	-0.08	0.00	0.10	-0.06
$RM_{t+1}TERM_t$	0.00	0.04	-0.01	0.00	-0.04	-0.01	0.01	0.00	-0.03
$RM_{t+1}DEF_t$	-0.02	0.00	0.00	-0.01	-0.01	0.00	0.01	0.01	-0.04
$RM_{t+1}dp_t$	0.04	-0.01	-0.03	0.02	0.01	0.02	0.01	0.00	0.05
$RM_{t+1}TB_t$	0.01	0.00	-0.02	0.01	0.03	0.01	0.01	0.01	0.03
ME_{t+1}	0.14	-0.10	0.11	0.01	0.08	-0.13	0.05	0.08	0.06
$ME_{t+1}TERM_t$	-0.05	0.06	0.08	0.04	0.07	0.00	0.01	0.04	-0.03
$ME_{t+1}DEF_t$	0.03	-0.02	0.02	-0.01	0.01	0.02	-0.02	-0.03	0.03
$ME_{t+1}dp_t$	0.01	-0.03	-0.04	-0.01	-0.04	0.00	0.00	0.00	-0.01
$ME_{t+1}TB_t$	0.04	-0.05	-0.06	-0.04	-0.06	0.00	-0.01	-0.02	0.01
IA_{t+1}	0.54	-0.34	0.31	0.03	0.18	-0.08	-0.25	-0.45	0.09
$IA_{t+1}TERM_t$	-0.01	0.01	-0.02	0.00	-0.01	-0.01	0.01	0.01	0.00
$IA_{t+1}DEF_t$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$IA_{t+1}dp_t$	0.00	0.00	0.01	0.00	0.01	-0.01	0.00	0.00	0.00
$IA_{t+1}TB_t$	0.03	-0.05	0.01	0.00	0.00	0.01	-0.03	-0.02	-0.01
ROE_{t+1}	-0.39	0.19	0.87	0.18	0.51	0.77	-0.12	-0.04	0.18
$ROE_{t+1}TERM_t$	0.04	0.03	0.09	0.04	0.02	-0.01	-0.03	-0.01	-0.02
$ROE_{t+1}DEF_t$	-0.03	0.01	-0.09	-0.01	-0.04	0.00	0.02	0.02	-0.03
$ROE_{t+1}dp_t$	-0.02	0.02	0.00	0.00	0.00	0.00	0.01	0.01	-0.01
$ROE_{t+1}TB_t$	-0.03	-0.02	-0.17	-0.06	-0.04	0.04	0.06	0.03	0.04
α	0.38	-0.32	0.07	0.54	-0.16	0.21	-0.41	-0.28	0.28

Table 17: Decomposition of spreads high-minus-low: FF5

This table reports the risk premium (beta times risk price) for each factor from the Fama-French five-factor model (FF5) when tested on the spreads high-minus-low in average returns. The spreads are associated with portfolios sorted on BM, MOM, ROE, NSI, OCA, ABR, CEI, DUR, and IM. See Table 2 for a description of the different portfolio sorts. E(R) denotes the original spread in average returns, and α represents the corresponding alpha. RM, SMB, HML, RMW, and CMA represent the market, size, value, profitability, and investment factors, respectively. The lagged instruments used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. All the numbers are in %

	BM	DUR	MOM	ABR	IM	ROE	NSI	CEI	OCA
E(R)	0.69	-0.52	1.17	0.73	0.54	0.75	-0.69	-0.55	0.55
RM_{t+1}	0.04	0.00	-0.01	-0.03	0.00	-0.09	-0.03	0.05	-0.07
$RM_{t+1}TERM_t$	-0.01	0.04	0.03	0.02	-0.01	-0.03	0.01	0.01	-0.02
$RM_{t+1}DEF_t$	0.00	0.00	-0.06	-0.02	-0.05	-0.01	0.01	0.01	-0.05
$RM_{t+1}dp_t$	0.02	0.01	0.01	0.02	0.03	0.03	0.02	0.01	0.05
$RM_{t+1}TB_t$	0.01	0.01	-0.06	-0.01	0.01	0.01	0.02	0.02	0.02
SMB_{t+1}	0.10	-0.07	-0.02	-0.01	-0.01	-0.12	0.02	0.06	0.03
$SMB_{t+1}TERM_t$	-0.05	0.02	0.20	0.07	0.15	0.03	-0.03	-0.01	-0.02
$SMB_{t+1}DEF_t$	0.03	0.01	-0.09	-0.03	-0.05	-0.01	0.00	-0.01	0.01
$SMB_{t+1}dp_t$	0.01	-0.02	-0.02	-0.01	-0.04	-0.01	0.00	0.02	-0.01
$SMB_{t+1}TB_t$	0.02	-0.02	-0.07	-0.03	-0.07	-0.01	0.02	0.01	0.01
HML_{t+1}	0.53	-0.48	-0.09	-0.06	-0.02	-0.16	-0.05	-0.19	-0.07
$HML_{t+1}TERM_t$	-0.02	0.00	-0.01	-0.02	0.00	-0.01	0.00	0.00	0.00
$HML_{t+1}DEF_t$	0.02	0.00	0.01	-0.02	0.02	-0.02	0.02	0.01	-0.02
$HML_{t+1}dp_t$	0.00	0.00	-0.01	0.01	0.00	0.01	0.00	0.00	0.00
$HML_{t+1}TB_t$	0.06	-0.03	-0.09	0.05	-0.06	0.07	-0.05	-0.03	-0.02
RMW_{t+1}	-0.08	-0.05	0.13	-0.07	0.06	0.21	-0.23	-0.19	0.06
$RMW_{t+1}TERM_t$	-0.03	-0.07	0.11	0.05	0.12	0.06	0.00	0.01	0.06
$RMW_{t+1}DEF_t$	-0.01	0.00	-0.02	0.00	0.00	0.00	0.00	0.01	0.00
$RMW_{t+1}dp_t$	-0.02	-0.01	0.02	0.00	0.03	0.04	0.00	0.00	0.04
$RMW_{t+1}TB_t$	0.00	0.00	-0.01	0.00	-0.01	-0.01	0.00	0.00	-0.01
CMA_{t+1}	0.08	0.07	0.17	0.02	0.05	-0.03	-0.23	-0.28	0.12
$CMA_{t+1}TERM_t$	0.04	0.01	-0.04	0.01	-0.03	0.02	0.01	0.00	0.00
$CMA_{t+1}DEF_t$	0.00	-0.01	0.00	0.00	0.01	0.00	0.00	-0.01	0.01
$CMA_{t+1}dp_t$	-0.01	0.02	0.05	-0.01	0.03	0.00	0.01	0.02	0.00
$CMA_{t+1}TB_t$	-0.03	-0.01	0.10	0.01	0.06	-0.02	0.00	0.00	0.01
α	-0.01	0.07	0.93	0.80	0.34	0.84	-0.19	-0.07	0.43

Table 18: Descriptive statistics for spreads in returns: EW portfolios

This table reports descriptive statistics for the "high-minus-low" spreads in returns associated with different portfolio classes, in which the portfolios are equal-weighted. 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 (%)	Stdev. (%)	Min. (%)	Max. (%)	ϕ
BM	0.80	5.38	−28.19	30.47	0.09
DUR	−0.65	5.01	−19.03	26.18	0.13
CFP	0.73	4.98	−22.72	24.57	0.08
MOM	1.22	7.13	−50.09	38.42	0.03
SUE	0.74	2.57	−21.91	10.38	0.09
ABR	0.97	2.51	−9.52	10.68	−0.05
IM	0.68	4.94	−27.63	27.28	0.07
ABR*	0.46	1.88	−17.00	8.55	−0.02
ROE	1.00	4.98	−30.28	25.03	0.14
GPA	0.61	3.86	−12.50	20.75	0.20
NEI	0.45	2.53	−11.65	9.63	0.07
RS	0.60	3.06	−15.33	11.55	0.04
IA	−0.73	3.26	−12.23	15.48	0.14
NSI	−0.78	3.47	−17.30	22.40	0.08
CEI	−0.64	3.91	−17.23	21.84	0.06
PIA	−0.64	2.86	−11.92	12.46	0.10
IG	−0.40	2.46	−9.22	16.38	0.04
IVC	−0.48	2.33	−7.53	6.79	0.20
IVG	−0.47	2.61	−8.51	9.78	0.12
NOA	−0.55	3.33	−30.21	16.46	0.14
OA	−0.29	2.66	−14.32	7.77	0.09
POA	−0.41	2.48	−8.96	10.06	0.11
PTA	−0.47	2.37	−8.90	7.29	0.12
OCA	0.33	2.17	−12.05	8.81	0.05
OL	0.37	3.91	−14.37	14.29	0.18

Table 19: Spreads "high-minus-low" for conditional models: EW portfolios

This table presents alphas for "high-minus-low" portfolio return spreads associated with conditional factor models, in which the portfolios are equal-weighted. See Table 2 for a description of the different portfolio sorts. The models are the CAPM; Fama-French three-factor model (FF3); Carhart four-factor model (C4); Hou-Xue-Zhang four-factor model (HXZ4); Fama-French five-factor model (FF5); and a restricted version of FF5 (FF4). The lagged instruments used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. For each model, the first column shows the alphas whereas the second column presents the associated GMM-based t-ratios. Bold t-ratios indicate statistical significance at the 5% level.

	CAPM	t	FF3	t	C4	t	HXZ4	t	FF5	t	FF4	t
BM	0.82	**4.14**	0.21	1.89	0.10	0.93	0.32	**2.01**	−0.02	−0.17	0.09	0.60
DUR	−0.79	**−4.15**	−0.40	**−3.16**	−0.17	−1.36	−0.16	−0.97	0.11	0.88	−0.00	−0.01
CFP	0.84	**4.39**	0.34	**2.71**	0.16	1.31	0.38	**2.08**	−0.02	−0.12	0.12	0.69
MOM	1.37	**4.38**	1.51	**4.85**	0.26	**2.02**	0.20	0.63	0.96	**2.78**	0.94	**2.75**
SUE	0.77	**7.26**	0.82	**7.97**	0.56	**6.34**	0.25	**2.66**	0.70	**6.38**	0.66	**5.99**
ABR	1.00	**9.12**	1.03	**9.08**	0.88	**8.02**	0.79	**6.14**	1.03	**8.59**	1.00	**8.42**
IM	0.74	**3.40**	0.73	**3.26**	0.02	0.10	0.09	0.39	0.45	1.80	0.46	1.91
ABR*	0.47	**5.56**	0.52	**5.87**	0.34	**4.16**	0.24	**2.28**	0.48	**4.56**	0.45	**4.46**
ROE	1.04	**5.45**	1.24	**9.13**	0.95	**7.38**	0.35	**2.67**	0.80	**6.37**	0.73	**5.63**
GPA	0.52	**3.27**	0.64	**4.67**	0.50	**3.66**	0.05	0.37	0.02	0.17	−0.03	−0.22
NEI	0.45	**4.32**	0.64	**7.51**	0.43	**5.34**	0.05	0.68	0.42	**4.95**	0.37	**4.25**
RS	0.60	**4.76**	0.84	**8.29**	0.68	**6.70**	0.31	**3.16**	0.73	**6.69**	0.66	**5.78**
IA	−0.79	**−5.88**	−0.51	**−4.31**	−0.43	**−3.77**	−0.35	**−3.15**	−0.28	**−2.71**	−0.31	**−2.86**
NSI	−0.86	**−6.44**	−0.69	**−6.15**	−0.55	**−5.19**	−0.38	**−3.33**	−0.20	−1.88	−0.24	**−2.23**
CEI	−0.79	**−5.62**	−0.64	**−5.86**	−0.43	**−4.21**	−0.27	**−2.21**	−0.26	**−2.30**	−0.30	**−2.53**
PIA	−0.70	**−5.72**	−0.53	**−4.45**	−0.49	**−3.95**	−0.32	**−2.84**	−0.33	**−2.99**	−0.37	**−3.26**
IG	−0.43	**−4.03**	−0.24	**−2.47**	−0.18	−1.79	−0.02	−0.23	−0.06	−0.67	−0.08	−0.90
IVC	−0.55	**−5.63**	−0.47	**−5.13**	−0.39	**−4.12**	−0.27	**−2.65**	−0.38	**−4.41**	−0.39	**−4.28**
IVG	−0.55	**−5.02**	−0.37	**−3.60**	−0.26	**−2.49**	−0.19	−1.69	−0.16	−1.72	−0.21	**−2.18**
NOA	−0.61	**−4.18**	−0.64	**−4.85**	−0.64	**−4.83**	−0.57	**−3.58**	−0.59	**−4.70**	−0.62	**−4.48**
OA	−0.31	**−2.75**	−0.22	**−2.01**	−0.19	−1.69	−0.32	**−2.78**	−0.34	**−2.99**	−0.36	**−3.23**
POA	−0.45	**−4.33**	−0.29	**−3.14**	−0.14	−1.63	−0.13	−1.35	−0.15	−1.64	−0.16	−1.68
PTA	−0.53	**−5.36**	−0.34	**−3.83**	−0.33	**−3.65**	−0.32	**−3.51**	−0.20	**−2.30**	−0.24	**−2.72**
OCA	0.42	**4.64**	0.46	**5.49**	0.40	**4.39**	0.30	**3.11**	0.28	**3.12**	0.28	**2.99**
OL	0.34	**1.97**	0.28	1.71	0.30	1.90	−0.10	−0.56	−0.23	−1.42	−0.19	−1.19

Table 20: Joint time-series tests by category: EW portfolios

This table presents joint time-series tests of conditional factor models, in which the portfolios are equal-weighted. 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. In Panel F all the 25 sorts are included simultaneously as test assets. See Table 2 for a description of the different portfolio sorts and categories. The models are the CAPM; Fama-French three-factor model (FF3); Carhart four-factor model (C4); Hou-Xue-Zhang four-factor model (HXZ4); Fama-French five-factor model (FF5); and a restricted version of FF5 (FF4). The lagged instruments used in the time-series regressions are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12. MAA denotes the mean absolute alpha and $RMSA$ is the root mean squared alpha. $\# < 0.05$ represents the number of portfolios in which the alphas are significant at the 5% level. F and χ^2 denote the p-values associated with the GRS and robust χ^2 model specification tests, respectively.

	CAPM	FF3	C4	HXZ4	FF5	FF4
Panel A (Value-growth)						
MAA	0.24	0.07	0.10	0.15	0.07	0.07
$RMSA$	0.27	0.11	0.11	0.16	0.09	0.08
$\# < 0.05$	19	2	7	12	0	0
F	0.03	0.22	0.25	0.15	0.83	0.76
χ^2	0.01	0.11	0.13	0.06	0.72	0.63
Panel B (Momentum)						
MAA	0.22	0.20	0.11	0.12	0.16	0.15
$RMSA$	0.28	0.27	0.15	0.16	0.22	0.21
$\# < 0.05$	21	25	19	17	17	17
F	0.00	0.00	0.00	0.00	0.00	0.00
χ^2	0.00	0.00	0.00	0.00	0.00	0.00
Panel C (Profitability)						
MAA	0.20	0.20	0.17	0.13	0.16	0.15
$RMSA$	0.23	0.25	0.21	0.16	0.20	0.18
$\# < 0.05$	17	23	24	12	19	19
F	0.00	0.00	0.00	0.00	0.00	0.00
χ^2	0.00	0.00	0.00	0.00	0.00	0.00
Panel D (Investment)						
MAA	0.21	0.11	0.14	0.17	0.11	0.11
$RMSA$	0.23	0.16	0.16	0.18	0.13	0.13
$\# < 0.05$	62	31	69	56	25	25
F	0.00	0.00	0.00	0.00	0.00	0.00
χ^2	0.00	0.00	0.00	0.00	0.00	0.00
Panel E (Intangibles)						
MAA	0.11	0.09	0.11	0.13	0.10	0.09
$RMSA$	0.13	0.13	0.13	0.15	0.11	0.10
$\# < 0.05$	1	4	6	5	1	1
F	0.00	0.00	0.00	0.00	0.00	0.00
χ^2	0.00	0.00	0.00	0.00	0.00	0.00
Panel F (All)						
MAA	0.20	0.14	0.13	0.15	0.12	0.12
$RMSA$	0.24	0.20	0.16	0.17	0.16	0.15
$\# < 0.05$	120	85	125	102	62	62
F	0.00	0.00	0.00	0.00	0.00	0.00
χ^2	0.00	0.00	0.00	0.00	0.00	0.00

Table 21: Cross-sectional R^2 estimates

This table reports the cross-sectional constrained R^2 estimates for alternative conditional multi-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. In Panel F all the 25 sorts are included simultaneously as test assets. See Table 2 for a description of the different portfolio sorts and categories. The models are the CAPM; Fama-French three-factor model (FF3); Carhart four-factor model (C4); Hou-Xue-Zhang four-factor model (HXZ4); Fama-French five-factor model (FF5); and a restricted version of FF5 (FF4). VW and EW refer to tests based on value- and equal-weighted portfolios, respectively. The lagged instruments used in the construction of the scaled factors are the term spread ($TERM$), default spread (DEF), log dividend yield (dp), and one-month T-bill rate (TB). The sample is 1972:01–2013:12.

	CAPM	FF3	C4	HXZ4	FF5	FF4
Panel A (Value-growth)						
VW	−0.18	0.77	0.79	0.37	0.86	0.79
EW	−0.35	0.74	0.89	0.83	0.95	0.95
Panel B (Momentum)						
VW	−0.32	−0.39	0.53	0.65	0.24	0.28
EW	−0.22	−0.35	0.61	0.72	0.16	0.20
Panel C (Profitability)						
VW	−0.26	−1.72	−0.43	0.53	−0.36	−0.12
EW	0.01	−0.58	0.05	0.79	0.25	0.38
Panel D (Investment)						
VW	−0.28	0.19	0.31	0.47	0.47	0.47
EW	−0.43	0.10	0.38	0.60	0.63	0.56
Panel E (Intangibles)						
VW	−0.11	−0.27	0.15	0.50	0.27	0.35
EW	−0.11	−0.11	−0.02	0.27	0.16	0.24
Panel F (All)						
VW	−0.26	−0.16	0.35	0.53	0.35	0.38
EW	−0.28	−0.06	0.45	0.69	0.46	0.46