Conditional Asset Pricing and Stock Market Anomalies in Europe

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Abstract

This study provides European evidence on the ability of static and dynamic specifications of the Fama-French (1993) three-factor model to price 25 size-B/M portfolios. In contrast to US evidence, we detect a small-growth premium and find that the size effect is still present in Europe. Furthermore, we document strong time variation in factor risk loadings. Incorporating these risk fluctuations in conditional specifications of the three-factor model clearly improves its ability to explain time variation in expected returns. However, the model still fails to completely capture cross-sectional variation in returns as it is unable to explain the momentum effect.

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1. Introduction

The Capital Asset Pricing Model (CAPM) has been one of the cornerstones of modern finance since its development in the 1960s. However, starting in the eighties several patterns in the cross-section of average returns have been detected that question the validity of the model, including the size effect (Banz, 1981), value premium (Basu, 1977) and momentum effect (Jegadeesh and Titman, 1993). In addition, Fama and French (1992) show that size and book-to-market equity (B/M) are better able to capture the cross-section of returns than market beta. While the Fama-French (1993) three-factor model seems to be able to repair most of the cracks in the building of modern finance, Fama and French (1996) show that it is unable to explain the momentum effect. Apart from these cross-sectional anomalies, prior research has also found that firm characteristics (Lewellen, 1999) and macroeconomic variables (Ferson and Harvey, 1999) predict significant time variation in expected returns on size-B/M sorted portfolios.

Rational asset pricing theory posits that these variables have predictive power because they capture information about time-varying risk. Accordingly, static models fail to explain the cross-section of average returns because they ignore risk dynamics across stocks. Therefore, much recent work has focused on *conditional* asset pricing models, in which risk loadings are allowed to vary over time. Since the empirical results of these studies are mixed and primarily based on US data, our main goal in this paper is to provide out-of-sample evidence on the performance of the conditional three-factor model. Specifically, we test whether factor loadings are time-varying and if so, to what extent dynamic specifications of the model explain time variation and cross-sectional variation in returns on 25 size-B/M portfolios constructed using stocks from 16 European markets.

We first examine the predictive power of a set of macroeconomic and portfolio-specific variables for European size-B/M portfolios. Next, we test whether portfolio betas are time-varying by modeling variation in risk loadings as a function of the predictive variables. Subsequently, we investigate whether conditional models completely explain conditional expected returns, i.e. whether conditional alphas are zero. We also test the weaker hypothesis that conditional alphas are unrelated to the predictors. Finally, we calculate risk-adjusted portfolio returns and perform a cross-sectional analysis to examine whether cross-sectional variation in pricing errors is related to size, B/M and past returns.

We extend existing work in several ways. First, by using a large data set of European stocks we provide out-of-sample empirical evidence on the time-varying behavior of risk and the performance of conditional asset pricing models. Following Fama and French (2006), we construct the 25 size-B/M portfolios and the risk factors using merged data from the markets of interest, which enables us to form well-diversified portfolios. Thus, we adopt a pan-European approach motivated by the increasing integration between European markets that started in the mid-1980s, which coincides with the beginning of our sample (Bekaert, Hodrick and Zhang, 2005; Eiling and Gerard, 2006). We find that for our sample period the explanatory power of the three-factor model in Europe is higher than in the US, providing further support for the pan-European perspective we take.

On the methodology side, the time-series tests we employ avoid the problems associated with cross-sectional tests discussed by Lewellen, Nagel and Shanken (2006) because they impose the theoretical restrictions that risk premia equal expected excess factor returns and that the zero-beta rate equals the risk-free rate. We combine the time-series tests with the cross-sectional framework developed by Brennan, Chordia and

Subrahmanyam (1998). This cross-sectional procedure is useful to identify the sources of mispricing if the time-series tests reject an asset pricing model.

Our empirical results show substantial differences between US and European data, which motivates the analysis of the performance of conditional asset pricing models in Europe. In particular, we find that the size effect, which has vanished in the US after its discovery, is still present in Europe. In addition, our time-series analysis reveals that the unconditional three-factor model leaves significant pricing errors. Strikingly, the small-growth portfolio, known to be hard to price in the US because it generates significant negative alphas, produces significant *positive* pricing errors in Europe. We also find that macroeconomic and portfolio-specific variables have substantial predictive power for returns on the size-B/M portfolios. Using these variables as instruments for conditional betas, we document strong evidence of time-varying risk. Incorporating these fluctuations in risk improves the performance of the three-factor model in explaining time variation in portfolio returns. Nevertheless, even after allowing for variation in loadings the three-factor model does not completely explain conditional expected returns as pricing errors for some portfolios remain predictable.

Our cross-sectional findings show that the rejection of the three-factor model is due to strong momentum effects in returns on the 25 size-B/M portfolios. Both the static and dynamic three-factor model do not capture the explanatory power of past return (momentum) variables for the cross-section of portfolio returns. Our European evidence supports findings for the US by Ferson and Harvey (1999), Avramov and Chordia (2006), Lewellen and Nagel (2006) and Petkova and Zhang (2005). In particular, although betas do vary over time, these fluctuations are too small to explain the momentum effect.

The remainder of this paper is organized as follows. Section 2 provides the rationale for conditional asset pricing models and reviews existing empirical evidence. Section 3 explains our methodology and section 4 describes the data set. In section 5 we present our empirical findings and discuss the robustness of the results. Section 6 concludes.

2. Conditional Asset Pricing: Theory and Evidence

Proponents of conditional asset pricing argue that the failure of unconditional models to explain the cross-section of average returns might be due to their assumption that risk loadings remain constant over time. Santos and Veronesi (2004) show within a general equilibrium model that market betas vary substantially when the covariation between a firm's cash flows and the aggregate economy is large. If true betas are time-varying, static models will be misspecified and will give an incomplete description of stock returns. Indeed, abundant empirical evidence of time variation in beta has been found, which in turn has motivated the development and testing of conditional asset pricing models that allow factor loadings to vary. Theoretical support for dynamic models is given by Hansen and Richard (1987), who show that a conditional version of the CAPM can hold perfectly even if its unconditional counterpart fails.

According to conditional asset pricing theory, a significant relation between predictive variables and the time series and cross-section of returns must be due to their association with risk. In particular, the variables must contain information about time variation in risk, and consequently, in expected returns. Furthermore, differences in risk dynamics across stocks induce cross-sectional variation in conditional expected returns. This implies that the power of the predictors should disappear once we adequately control for fluctuations in risk. Gomes, Kogan and Zhang (2003) show theoretically that the ability of size and B/M to explain cross-sectional variation in returns is due to their correlation with the true conditional market beta. Zhang (2005) extends this work and argues that because of costly reversibility of capital value firms have countercyclical betas while betas of growth stocks are procyclical. Because the price of risk is also countercyclical his model can explain the value premium within a rational framework.

In contrast, the mispricing view put forward by Lakonishok, Shleifer and Vishny (1994) and Daniel and Titman (1997) asserts that the significant association between predictive variables and expected returns is related to investor cognitive biases. Specifically, this story says that the predictors contain information about mispricing of securities and, consequently, that their predictive power will persist even when risk fluctuations are taken into account.

Hitherto, empirical evidence on the performance of conditional asset pricing models is inconclusive and primarily based on US data. Favorable results are documented by Jagannathan and Wang (1996), who find that a conditional CAPM extended by a proxy for the return on human capital leaves insignificant pricing errors when applied to portfolios sorted on size and beta. Lewellen (1999) shows that after controlling for its role as determinant of conditional betas B/M contains little incremental information about time variation in expected returns. Ferson and Harvey (1998) argue that the cross-sectional explanatory power of firm-specific attributes like book-to-market mainly arises from their role as instruments for risk instead of their relation to mispricing.

More recently, Ang and Chen (2005) document strong evidence of time variation in betas of portfolios sorted on B/M and find that a conditional CAPM in which time-varying betas are treated as latent state variables is able to capture the book-to-market effect. Adrian and Franzoni (2005) propose a conditional CAPM in which investors learn about unobserved time-varying risk by observing realizations of returns. Their learning CAPM cannot be rejected when applied to size-B/M portfolios.

In contrast, results found by other studies are less favorable. Ferson and Harvey (1999) show that even in a conditional three-factor model proxies for time variation in expected returns based on macroeconomic instruments have significant cross-sectional explanatory power for returns on size-B/M sorted portfolios. Petkova and Zhang (2005) confirm empirically the theoretical prediction of Zhang (2005) that value firms are riskier than growth firms in economic downturns when the expected market premium is high. However, they note that the covariance between beta and the price of risk is too small to explain the magnitude of the value premium. Lewellen and Nagel (2006) also find that this covariance is insufficient to explain the large unconditional alphas produced by book-to-market and momentum portfolios.

Using individual stocks as test assets, Avramov and Chordia (2006) find that conditional multifactor models can explain size and value anomalies but are unable to capture momentum and turnover effects in returns. Lewellen, Nagel and Shanken (2006) argue that the favorable evidence on the ability of conditional models to price size-B/M sorted portfolios is largely due to the low power of the cross-sectional tests employed in many papers. In particular, they show that when risk premia are unrestricted, *any* factor that is only weakly correlated with SMB and HML will price the size-B/M portfolios due to their strong factor structure.

3. Methodology

3.1 Time-Series Test Methodology

The conditional three-factor model can be written as

$$E_t(R_{it+1}) = \alpha_{it} + \sum_{k=1}^{3} \beta_{ikt} E_t(FF_{kt+1}), \tag{1}$$

where R_i is the excess return on asset *i*, *FF* is a vector containing the three Fama-French factors R_M, *SMB* and *HML*, $E_t(.)$ is the conditional expectation, given the public information set at time *t*, and β_{ikt} is the conditional beta with respect to the k'th factor.

Following Shanken (1990), we model time variation in alphas and betas by allowing them to depend linearly on a set of predetermined instruments (conditioning variables). This approach explicitly links conditional betas to observable state variables, consistent with the economic motivation for conditional models. In particular, in this framework conditional betas are given by

$$\beta_{ikt} = \gamma_{ik0} + \gamma_{ik1} Z_{it}, \tag{2}$$

where γ_{ik0} is a scalar, γ_{ik1} a vector of *N* parameters and Z_{it} a vector of *N* instruments. We test the hypothesis that risk loadings are constant over time by examining whether the γ_{ik1} parameters are equal to zero. Analogous to the specification of conditional betas, the conditional alpha is

$$\alpha_{it} = \alpha_{i0} + \alpha_{i1} W_{it}, \tag{3}$$

where W_{it} is a vector of instruments for alpha.

We test the hypothesis that the three-factor model completely explains conditional expected portfolio returns, which corresponds to the null hypothesis that the conditional alpha in equation (1) is equal to zero. Thus, rational asset pricing theory predicts that the

α_{i0} and α_{i1} parameters in equation (3) should all be zero. We also test the weaker condition that alpha is constant over time, i.e. that α_{i1} is zero. Under this null hypothesis the instruments do not predict expected portfolio returns after their role as instrumental variables for conditional risk loadings is taken into account. The alternative hypothesis is that the conditioning variables are related to time-varying mispricing.

Combining equations (1), (2), and (3) leads to the econometric model

$$R_{it+1} = \alpha_{i0} + \alpha_{i1} W_{it} + (\gamma_{ik0} + \gamma_{ik1} Z_{it}) FF_{kt+1} + \varepsilon_{it+1} \, . \tag{4}$$

We evaluate alternative model specifications based on (4), with both constant and time-varying alphas and betas and various combinations of instrumental variables, using the adjusted R^2 and Akaike information criterion.

3.2 Cross-Sectional Framework

In the cross-sectional tests we examine the predictive power of various non-risk characteristics. Rational asset pricing theory predicts that non-risk security characteristics like size and B/M should not have any cross-sectional explanatory power for returns incremental to the risk factors included in the asset pricing model. This hypothesis can be tested using the following equation,

$$R_{it+1} = c_{0t+1} + \sum_{k=1}^{3} \lambda_{kt+1} \hat{\beta}_{ikt} + \sum_{m=1}^{M} c_{mt+1} P_{mit} + v_{it+1} \, , \tag{5}$$

where λ_k is the risk premium for factor k, c_m is the reward to non-risk characteristic m and P_{mit} is the value of characteristic m for portfolio i at time t. The null hypothesis that expected returns on portfolio i only depend on its sensitivity to the risk factors in the model, measured by $\hat{\beta}_{ik}$, implies that all loadings c_m on the non-risk factors must be zero.

The Fama-MacBeth (1973) two-step procedure often used to test this hypothesis suffers from an errors-in-variables problem, since the betas included as regressors in the second stage cross-sectional regressions are estimated with error in the time-series regressions.

In order to circumvent this problem we follow Brennan, Chordia and Subrahmanyam (1998) and Avramov and Chordia (2006) by regressing *risk-adjusted* returns obtained from the time-series regression (4) on the portfolio characteristics size, book-to-market and cumulative past returns. The estimated risk-adjusted return is given by

$$R_{it+1}^{*} \equiv R_{it+1} - \sum_{k=1}^{3} \hat{\beta}_{ikt} FF_{kt+1}. \tag{6}$$

We calculate the risk-adjusted return $R_{\mathrm{it+1}}^{*}$ in (6) as the sum of the intercept α_{i0} and the error term ε_{it+1} obtained from the first-pass time-series regression (4). This risk-adjusted return is then used as dependent variable in the second-stage cross-sectional regression,

$$R_{it+1}^{*} = c_{0t+1} + \sum_{m=1}^{M} c_{mt+1} P_{mit} + \eta_{it+1}. \tag{7}$$

This approach avoids any errors-in-variables bias because betas estimated in the time-series regressions do not show up as regressors in the cross-sectional regressions. The relation between the time-series tests and the cross-sectional analysis is as follows: if the time-series regressions indicate that a model produces significant pricing errors, the cross-sectional tests reveal whether this mispricing is related to size, value or momentum effects.

We test the hypothesis that expected returns only depend on the risk characteristics of returns by calculating the Fama-MacBeth (FM) estimator for the non-risk characteristics, which is the time-series average of the monthly parameter estimates $c_{mt.}$ The standard error of the FM estimator is calculated from the time series of these monthly estimates.

4. Data and Descriptive Statistics

The MSCI data set we use consists of the monthly return and book and market value for a sample of common stocks from 16 European countries that covers approximately 80% of European stock market capitalization. All variables are denominated in Euros. The raw data set includes 2503 firms and covers the period from February 1985 to June 2002. The stocks are listed on the exchanges of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, The Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the UK. The number of stocks per country ranges from 37 for Ireland to 519 for the UK. The MSCI data is free from survivorship bias as it includes historical data for firms that are delisted over time. Furthermore, historical data for newly included stocks is not added to the data set, which should prevent any backfilling bias.

A stock is used in our analysis for a given month t if it satisfies the following criteria: (i) data should be available in month $t-1$ for size as measured by market capitalization and for the book-to-market ratio. This condition is imposed because returns for month t are calculated for portfolios formed at the end of month $t-1$ on size and book-to-market; (ii) its book-to-market equity is non-negative. This last requirement follows Fama and French (1993). The screening process leads to a sample that contains on average 1315 stocks per month. The total number of stocks over the full sample period is 2165. Since we need portfolio returns over the past 12 months to calculate cumulative lagged returns as a proxy for momentum, the analysis starts in February 1986 and ends in June 2002.

Our test assets are 25 portfolios formed on size and B/M, which have become standard in asset pricing tests after the failure of CAPM to explain size and B/M effects in returns. Following Fama and French (2006), we use merged data from all countries for constructing the size-B/M portfolios. The upper left corner of table 1 presents summary statistics for the 25 European size-B/M portfolios. For comparison, in the upper right corner we also report statistics for the 25 US size-B/M portfolios for the same period.[1] Strikingly, in the European sample the small growth portfolio (S1/B1) has the highest average return. In contrast, Fama and French (1996) find for the US that the return on the small growth portfolio is the lowest of all 25 portfolios, which is confirmed by the statistics we report for the US portfolios. Table 1 also shows the presence of a size effect in the European sample, which is absent in the US data. The value premium is positive in both samples but insignificant. In general, table 1 reveals important differences between US and European data, which motivates our analysis of the performance of conditional asset pricing models in Europe.

An important issue when applying asset pricing models to European stock markets is whether country-specific or pan-European versions of the models should be used. Bekaert, Hodrick and Zhang (2005) and Eiling and Gerard (2006) find evidence of capital market integration between European markets from the mid 1980s onwards, which coincides with the beginning of our sample period. This motivates the construction of the Fama-French risk factors on a pan-European level, consistent with our portfolio formation procedure. We choose the MSCI Europe index as a proxy for the market portfolio because of its broad coverage of European stock market capitalization and subtract the three-month German FIBOR rate as a proxy for the risk-free rate to obtain the market premium R_M. We follow the procedure outlined by Fama and French (1993) for constructing the SMB and HML factors on a European level.

[1] Return data for the 25 US size-B/M portfolios are obtained from Kenneth French’s data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

We consider both macroeconomic and portfolio-specific variables as potential instruments for conditional alphas and betas because of their documented predictive power for returns. Macroeconomic variables shown to predict returns include the default spread (DEF; Keim and Stambaugh, 1986), the risk-free rate (R_F; Fama and Schwert, 1977) and the term spread (TERM; Fama and French, 1989). The default spread is defined as the yield spread between Moody's Baa- and Aaa-corporate bonds and the term spread as the spread between ten-year German government bonds and the three-month FIBOR rate. The theoretical motivation for choosing the portfolio-specific variables size and book-to-market as instruments is given by Gomes, Kogan, and Zhang (2003), who show that the ability of size and B/M to explain the cross-section of returns is due to their correlation with the true conditional market beta. In particular, they demonstrate that size captures the component of a firm's systematic risk related to its growth options whereas the book-to-market ratio is a measure of the risk of the firm's assets in place.

Jagannathan and Wang (1996) stress that, although several variables may help predict the business cycle, we have to restrict ourselves to a small number of such variables to ensure some precision in the estimation of the model parameters. We use the adjusted R^2 and Akaike information criterion to determine the optimal set of conditioning variables. These model selection criteria prefer the default spread, size, B/M and interaction terms between default spread and size and between default spread and B/M as instruments for conditional factor loadings. For modeling conditional alphas the preferred specification includes the default spread, risk-free rate, term spread and the two portfolio-specific instruments size and B/M.[2]

[2] Our main conclusions are robust to the choice of conditioning variables.

For every portfolio the following non-risk characteristics are calculated each month as possible determinants of the cross-section of risk-adjusted returns:

- **SIZE**: average market value of equity of the firms in the portfolio in billions of euros, included to assess the significance of the size effect
- **B/M:** sum of book equity for the firms in the portfolio divided by the sum of their market capitalization, included to examine the significance of the value premium.
- **RET2-3, RET4-6, RET7-12:** cumulative portfolio returns over the second through third, fourth through sixth, and seventh through twelfth months prior to the current month, respectively, included to analyze the significance of the relation between past performance and expected returns.

Because the distributions of these characteristics display considerable skewness we use their logarithmic transformations. Following Brennan, Chordia and Subrahmanyam (1998), in the cross-sectional analysis we normalize the characteristics by expressing them as deviations from their cross-sectional means. Thus, for the *average* portfolio the value of the characteristics is zero. Consequently, under both the null hypothesis that non-risk characteristics do not have significant incremental power for capturing the cross-section of returns and the alternative hypothesis that they do have significant explanatory power, the return on the *average* portfolio is determined by its risk characteristics only.

5. Empirical Results

5.1 Time-Series Evidence on the Unconditional Three-Factor Model

As a benchmark we first consider time-series regression results for the unconditional three-factor model, shown in table 2. The explanatory power of the model in terms of adjusted R^2 is high, ranging from 73% to 89%. In fact, for our sample period the three-factor model has higher explanatory power in Europe than in the US. This result lends support to the assumption that European financial markets are fairly integrated and justifies our use of a pan-European version of the model.

The intercept in the time-series regressions is the pricing error, which represents the portion of the excess portfolio return left unexplained by the risk factors in the model. If the three-factor model completely explains the cross-section of average returns the intercepts in the time-series regressions should all be zero. The empirical results show that the intercept is significant at the 5% level for four out of 25 portfolios.

Notably, the pricing error of the small-growth portfolio is significantly *positive* and large in economic terms, whereas in the US this portfolio produces significant *negative* pricing errors (Fama and French, 1996). Thus, the small-growth anomaly we observe in Europe is exactly opposite to that in the United States. Furthermore, the small-growth premium is remarkably stable over time and not driven by large return outliers in the portfolio. In section 5.6 we show that the premium is also not due to country or sector tilts. Another striking feature of this portfolio is the high first order autocorrelation of its monthly return ($\rho = 0.41$), which could be due to thin trading. In turn, infrequent trading might lead to market inefficiency.

In general, several pricing errors are quite large in absolute value, particularly for some of the small portfolios. This is confirmed by the Gibbons, Ross and Shanken (1989) test, which strongly rejects the hypothesis that the intercepts for the 25 size-B/M portfolios are jointly equal to zero. These results motivate the extension of the model to conditional specifications.

5.2 Predictability of Size and Book-to-Market Portfolio Returns

Before turning to the analysis of the conditional three-factor model, we first examine the time-series relation between expected returns on the 25 size-B/M portfolios and the predictive variables R_F, DEF, TERM, SIZE and B/M. Table 3 summarizes time-series regressions of portfolio returns on this set of lagged variables. The results confirm that the variables are significant predictors of time variation in expected portfolio returns. The explanatory power of the predictive variables in terms of adjusted R^2 ranges from 2% for some of the large-cap portfolios to 11% for some small-cap portfolios, consistent with results documented for the US by Ferson and Harvey (1999). Moreover, the coefficients on the predictors vary considerably across portfolios, suggesting that they do have explanatory power for the cross-section of portfolio returns. Table 3 also reports regression results for the three Fama-French factors. The predictive power for R_M and SMB is in line with that for the 25 portfolios. However, HML seems not very predictable, suggesting that it contributes little to explaining time-varying expected returns.

5.3 Time-Varying Betas in the Three-Factor Model

Conditional asset pricing theory asserts that the significant relation between the predictors and expected returns should disappear when their role as determinant of time-varying risk is recognized. In contrast, the mispricing view argues that their predictive power will persist even when fluctuations in risk have been taken into account. Thus, in order to distinguish between both views, we model time variation in risk loadings as a function of the instruments and assess whether the alphas produced by conditional specifications of the Fama-French three-factor model are constant.

Table 4 reports regression results for the conditional three-factor model. The table shows the explanatory power of the model in terms of adjusted R^2. It also provides p-values of F-tests performed to investigate whether the lagged instruments pick up significant variation in risk loadings. The null hypothesis for these tests is that the loadings on the interaction terms between the risk factors and the conditioning variables are jointly equal to zero. P-values are below 5% for 24 portfolios in the constant alpha case and 22 portfolios when alpha is allowed to vary. The joint Bonferroni test strongly rejects the null hypothesis of constant betas.[3] Thus, betas exhibit strong time variation, which can be captured by a set of lagged instruments. For most portfolios the adjusted R^2 rises considerably when risk loadings are allowed to fluctuate over time. The explanatory power of the model also increases for many portfolios when time variation in alphas is modeled. This suggests that alphas may not be constant over time, even in a model with time-varying betas. We test this hypothesis in the next section.

5.4 Conditional Alphas in the Three-Factor Model

In table 5 results are shown for tests of the hypothesis that pricing errors are zero and for the weaker hypothesis that alphas are constant through time. We test whether conditional alphas are zero by performing an F-test for the hypothesis that the intercept and the slopes on the lagged instruments are jointly equal to zero. Columns two and three show that the hypothesis of a zero conditional alpha is rejected at the 5% level for 15 portfolios in the constant beta case and 12 portfolios in the conditional three-factor model. The Bonferroni adjusted p-value for a joint test across portfolios is 0.000.

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[3] The Bonferroni correction is a multiple-comparison adjustment for dependence across portfolios.

When testing whether alphas are constant the null hypothesis of the F-test is that the instruments for the conditional alpha can be excluded from the model. Results reported in column four indicate that the weaker hypothesis that alphas are constant is rejected at the 5% level for 15 of the 25 portfolios in a model with constant betas. This implies that the static three-factor model does not adequately explain the dynamics of conditional expected returns. In contrast, column five shows that when betas are allowed to vary the null hypothesis is rejected for only eight portfolios. Thus, the ability of the instruments to predict mispricing diminishes when allowing for time variation in factor loadings. Nevertheless, the joint Bonferroni test still rejects the null hypothesis of constant alphas.

In sum, the main conclusion drawn from the time-series analysis is that betas are time-varying and that these fluctuations in risk can be picked up by a combination of macroeconomic and portfolio-specific instruments. Conditional specifications of the three-factor model outperform their unconditional counterpart in explaining time variation in expected returns. However, even after taking time variation in betas into account the model does not fully explain conditional expected returns on the portfolios. Predictable patterns in pricing errors remain, consistent with results documented by Ferson and Harvey (1999) for the US but contradicting the conclusion of Lewellen (1999) that modeling time variation in risk eliminates the predictive power of B/M.

5.5 Cross-Sectional Evidence on the Three-Factor Model

Having found evidence of substantial fluctuations in betas we now examine whether incorporating time variation in risk is sufficient to eliminate the cross-sectional explanatory power of size, B/M and momentum variables. The cross-sectional analysis is useful to identify the sources of the mispricing detected by the time-series regressions. Following Avramov and Chordia (2006), we evaluate the pricing abilities of the model by looking at the significance of Fama-MacBeth parameter estimates for the size, book-to-market and momentum variables. In addition, we use the time-series average of the cross-sectional adjusted R^2 as an informal measure of model performance. In short, a low R^2 and insignificant coefficients can be interpreted as support for the model used to risk-adjust returns, since these imply that the explanatory power of the portfolio characteristics is limited. In contrast, a high average adjusted R^2 and significant Fama-MacBeth coefficient estimates suggest that size, book-to-market and momentum effects are not adequately captured by the asset pricing model.[4]

We start off by considering results for Fama-MacBeth regressions of raw returns (i.e. *not* adjusted for risk) on a constant and the portfolio characteristics size, B/M and the past return variables RET2-3, RET4-6 and RET7-12. Average cross-sectional regression coefficients are reported in column two of table 6 along with their t-ratios and the time-series average of the monthly adjusted R^2. The intercept is significant at a 5% level, suggesting the presence of time-invariant pricing errors. The coefficient on size is negative and significant. Thus, a size effect is present in the cross-section of portfolio returns. The book-to-market coefficient is positive but insignificant, which means that the value premium is absent. Loadings on all three past return variables are positive and significant. Strong momentum effects in size-B/M portfolios have also been found in the

[4] As noted by Avramov and Chordia (2006), a zero R^2 does not necessarily imply that the model completely explains the cross-section of average portfolio returns. A significant intercept would imply that the model produces time-invariant pricing errors unrelated to the portfolio characteristics.

US by Lewellen (2002). The average adjusted R^2 is 38.0%, indicating that the characteristics explain a substantial part of cross-sectional variation in returns.

In order to examine whether the high explanatory power and significance of the size and momentum variables persist when cross-sectional differences in risk are taken into account, we risk-adjust returns in first-pass three-factor regressions. Fama-MacBeth parameter estimates are shown in column three. The coefficient on size is no longer significant at the 5% level. The intercept has also become insignificant and the adjusted R^2 has fallen sharply to 12.1%. However, all three momentum variables are still significant, confirming the finding of Fama and French (1996) that their three-factor model does not capture the momentum effect.

Results for the conditional Fama-French model are presented in column four. As in the case of the unconditional model, coefficients on both the size characteristic and the B/M variable are insignificant. More important, however, is that the loadings on all three past return variables are still significant at the 5% level, suggesting that even a dynamic three-factor model cannot capture the momentum effect. Furthermore, although the conditional model produces the lowest average adjusted R^2, it still exceeds 10%, reflecting the strong cross-sectional predictive power of the past return variables.

In conclusion, results presented in table 6 indicate that the Fama-French model eliminates the cross-sectional explanatory power of size. Allowing for time variation in risk loadings only leads to a marginal improvement in the pricing ability of the model specification we consider. In particular, both static and dynamic three-factor models are unable to explain the impact of past returns on the cross-section of portfolio returns.

5.6 Robustness of Empirical Results

As a first robustness check we purge the 25 size-B/M portfolios from possible country and sector effects to determine whether our results are affected by country and/or sector tilts in the portfolios. In particular, we control for country and sector effects by first performing cross-sectional regressions of firm size and B/M on country and sector dummies,

$$x_{it} = \kappa_t + \sum_{j=1}^{J-1} \theta_{jt} S_{ij} + \sum_{h=1}^{H-1} \psi_{ht} C_{ih} + \tau_{it}, \tag{8}$$

where x_{it} is a vector that contains the size and book-to-market characteristics of firm i at date t, S_{ij} a sector dummy variable equal to one if firm i belongs to sector j and zero otherwise, and C_{ih} a dummy variable that equals one if firm i belongs to country h. By leaving out the sector (country) dummies we can purge the characteristics from country (sector) effects only. Subsequently, the vector of residuals τ_{it} from (8) is used to sort the stocks into 25 size-B/M portfolios.

The bottom half of table 1 reports value-weighted returns for the 25 size-B/M portfolios constructed using country- or sector-neutral characteristics. Similar to the original portfolios shown in the upper left corner, the purged portfolios exhibit a significant average size effect but insignificant value premium, although for some individual size quintiles a significant B/M effect can be observed. In general, however, returns on the country-neutral and/or sector-neutral portfolios do not deviate strongly from the returns on the original portfolios. We can confirm that using these portfolios as test assets in the empirical analysis does not alter our conclusions.[5]

[5] Results for all robustness checks are omitted in the interest of parsimony and available upon request.

The second check on our results deals with possible correlation between errors in the factor loadings estimated in first-pass time-series regressions and the non-risk portfolio characteristics used as predictors in the second-stage cross-sectional regression (7). Although factor loadings are correlated with the portfolio characteristics included in P_t in equation (7), Brennan, Chordia and Subrahmanyam (1998) argue that there is no a priori reason to believe that the *errors* in the estimated loadings will be correlated with the characteristics. Nevertheless, if they are not independent the cross-sectional regression coefficients on the portfolio characteristics will be correlated with the factor returns and consequently, the standard Fama-MacBeth estimator will be biased.

Therefore, Brennan et al. (1998) propose to calculate a purged estimator for each of the characteristics. This estimator is unbiased when errors in the estimated factor loadings and the characteristics in P_t are correlated, provided that factor premia are serially uncorrelated. The purged estimator is the intercept in an OLS regression of the original monthly cross-sectional parameter estimates on a constant and the time series of factor realizations FF_{kt}. It turns out that our empirical results are almost unchanged when the purged estimator is used instead of the standard Fama-MacBeth estimator.

A third check is motivated by Shanken (1992), who points out that the Fama-MacBeth procedure overstates the precision of parameter estimates in the second-stage cross-sectional regressions by ignoring estimation errors in factor loadings obtained from first-pass time-series regressions. Shanken suggests a solution for this problem that explicitly adjusts the standard errors, assuming conditional homoskedasticity of returns. Applying this correction leads to t-statistics that are only slightly lower than standard OLS t-statistics. Hence, our conclusions from the cross-sectional analysis still hold.

Fourth, instead of estimating the time-series regressions by ordinary least squares (OLS) regressions, we also perform seemingly unrelated regressions (SUR) to account for contemporaneous correlation in residuals across portfolios. However, estimation results are very similar and all main conclusions remain unchanged.

Finally, we repeat the empirical analysis for the CAPM and the Carhart (1997) four-factor model, which adds a momentum factor to the three-factor model. As expected the three-factor model is clearly superior to the CAPM in terms of time series and cross-sectional explanatory power. Although we find evidence of significant time variation in CAPM betas, a conditional CAPM is not able to capture size and momentum effects in portfolio returns. These results are consistent with findings documented by Lewellen and Nagel (2006) for the US, who conclude that allowing for time variation in beta does little to salvage the CAPM. Results for the Carhart four-factor model are very similar to those reported for the Fama-French model. Most importantly, the Carhart model also fails to eliminate the strong momentum effects in the 25 size-B/M portfolios.

6. Conclusion

This paper investigates whether risk loadings in the Fama-French (1993) three-factor model are time-varying and if so, to what extent conditional specifications of the model can eliminate well-known anomalies in European stock markets. Our work is motivated by mixed empirical evidence on the performance of conditional asset pricing models in the United States. Prior research shows that several firm characteristics like size, book-to-market, and past returns have explanatory power for the cross-section of returns. Furthermore, it has been found that size, B/M and macroeconomic variables predict significant time variation in expected returns. This paper combines these findings to examine whether the predictive power of these variables is due to their association with time-varying risk, as suggested by conditional asset pricing theory, or to mispricing. Specifically, we test the ability of static and dynamic specifications of the three-factor model to price 25 size-B/M portfolios using merged data from 16 European markets, thereby providing out-of-sample empirical evidence on conditional asset pricing models.

We identify important differences between US and European data. In particular, while the size effect has vanished in the US after its discovery, we document that it is still present in Europe. Moreover, in contrast to US evidence, we find that the notoriously hard to price small-growth portfolio displays significant *positive* pricing errors. We also show that a set of macroeconomic and portfolio-specific variables has substantial predictive power for European size-B/M portfolios. Our time-series tests reveal that these variables pick up significant time variation in risk. Conditional specifications of the three-factor model outperform their static counterpart in explaining time variation in expected returns. Nevertheless, even after allowing for fluctuations in factor loadings pricing errors for some portfolios are still significant and predictable to some extent.

In order to identify the sources of mispricing we apply the cross-sectional testing framework of Avramov and Chordia (2006). While the three-factor model captures the size effect, both static and dynamic specifications of the model fail to eliminate the strong cross-sectional predictive power of momentum variables. Conditioning does little to improve the cross-sectional pricing ability of the model. Thus, although the evidence of time-varying risk motivates the use of conditional asset pricing models, more is needed to revive modern finance.

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Table 1

Average Monthly Returns for European, US and Country or Sector-Neutral European Size-B/M Portfolios

This table presents average monthly value-weighted returns for 25 size-B/M stock portfolios for the period February 1986 through June 2002. The portfolios in the upper left corner are the original European portfolios constructed by sorting stocks each month independently into size and B/M quintiles. The 25 size-B/M portfolios are formed as the intersections of the five size and the five B/M quintiles. The portfolios in the upper right corner are 25 US size-B/M portfolios for the same period. The bottom left and bottom right corners show returns for European size-B/M portfolios constructed using country-neutral and sector-neutral firm size and book-to-market, respectively. Value weighted returns for month *t+1* are calculated for portfolios formed at the end of month *t* as the value weighted average of the excess returns of the individual stocks in the portfolios. H-L is the value premium for a given size quintile defined as the average of the time-series of monthly differences between the return for the highest B/M quintile and the return for the lowest B/M quintile within a size group. Similarly S-B is the size premium for a given B/M quintile defined as the average of the time-series of monthly differences between the return for the smallest size quintile and the return for the largest size quintile within a B/M group. The numbers in the columns (rows) denoted "mean" refer to the time-series means of the five individual average H-L (S-B) returns. t(H-L) and t(S-B) are the average monthly differences divided by their standard error.

	Europe								United States							
	Low	2	3	4	High	Mean	H-L	t(H-L)	Low	2	3	4	High	Mean	H-L	t(H-L)
Small	2.35	1.19	0.60	0.92	1.20		-1.15	-2.19	-0.24	0.72	0.86	1.11	0.98		1.22	3.34
2	1.00	0.70	0.54	0.87	1.19		0.19	0.48	0.22	0.60	0.87	0.92	0.84		0.62	1.84
3	0.48	0.44	0.36	0.79	1.16		0.68	2.06	0.39	0.69	0.70	0.80	1.03		0.64	1.57
4	0.41	0.34	0.56	0.87	1.08		0.67	2.04	0.74	0.75	0.75	0.90	0.85		0.11	0.30
Big	0.52	0.45	0.55	0.72	0.82		0.30	0.82	0.76	0.79	0.71	0.73	0.65		-0.10	-0.34
Mean							0.14	0.43							0.50	1.56
S-B	1.83	0.73	0.05	0.20	0.38	0.64			-0.99	-0.06	0.15	0.39	0.33	-0.04		
t(S-B)	3.82	2.34	0.17	0.86	1.17	2.63			-2.08	-0.13	0.40	1.05	0.91	-0.10		

	Europe: Country-Neutral								Europe: Sector-Neutral							
	Low	2	3	4	High	Mean	H-L	t(H-L)	Low	2	3	4	High	Mean	H-L	t(H-L)
Small	2.18	0.81	0.80	0.76	0.98		-1.20	-2.58	2.26	1.21	1.02	0.90	1.17		-1.09	-2.32
2	0.83	0.47	0.44	0.65	0.97		0.14	0.40	1.08	0.66	0.87	0.89	1.15		0.07	0.20
3	0.51	0.49	0.27	0.70	0.91		0.40	1.29	0.34	0.54	0.61	0.78	1.19		0.84	2.61
4	0.43	0.44	0.57	0.81	0.76		0.34	0.99	0.35	0.51	0.51	0.83	0.84		0.49	1.63
Big	0.56	0.51	0.58	0.71	0.57		0.02	0.06	0.45	0.50	0.76	0.57	0.45		0.00	0.01
Mean							-0.06	-0.21							0.07	0.23
S-B	1.63	0.30	0.22	0.05	0.40	0.52			1.81	0.71	0.26	0.33	0.72	0.77		
t(S-B)	3.82	1.06	0.88	0.20	1.35	2.37			4.29	2.36	1.06	1.30	2.55	3.64		

Table 2

Unconditional Three-Factor Model Regressions

This table reports parameter estimates for unconditional least squares three-factor regressions

$$r_{it} = \alpha_i + \beta_i r_{Mt} + \delta_i SMB_t + \varphi_i HML_t + \varepsilon_{it}$$

Monthly excess returns on 25 size-B/M portfolios are regressed on a constant, the market premium R_M and SMB and HML. RMSE is the root mean squared pricing error. # > |2| denotes the number of t-statistics larger than 2 in absolute value. GRS F is the Gibbons, Ross and Shanken (1989) test statistic for the null hypothesis that the intercepts in the regressions for the 25 size-B/M portfolios are jointly equal to zero.

$$GRS = \frac{T-N-K}{N}\left[1+E_T(f)'\hat{\Omega}^{-1}E_T(f)\right]^{-1}\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}\sim F_{N,T-N-K}$$

where T is the number of months, N the number of portfolios, K the number of factors f, α the vector of intercepts, Ω the covariance matrix of the factors, and Σ the covariance matrix of α.

Portfolio	α	β	δ	φ		t(α)	t(β)	t(δ)	t(φ)	Adj.R^2
S1/B1	1.47	1.24	1.73	-1.03		4.51	18.21	12.42	-10.92	0.74
S1/B2	0.38	1.04	1.05	-0.20		1.62	21.11	10.42	-2.93	0.73
S1/B3	-0.19	0.92	0.90	0.15		-0.94	21.68	10.38	2.50	0.73
S1/B4	0.10	0.93	0.81	0.32		0.60	26.50	11.30	6.57	0.81
S1/B5	0.15	1.09	1.06	0.59		0.80	28.25	13.41	10.97	0.84
S2/B1	0.25	1.10	1.22	-0.69		1.34	28.25	15.37	-12.72	0.85
S2/B2	-0.07	0.97	0.94	-0.09		-0.45	30.52	14.54	-2.11	0.84
S2/B3	-0.24	0.91	0.81	0.21		-1.68	30.85	13.53	5.08	0.85
S2/B4	0.05	0.90	0.77	0.39		0.38	31.95	13.40	9.93	0.86
S2/B5	0.24	0.99	0.78	0.69		1.53	30.31	11.72	15.19	0.86
S3/B1	-0.21	1.03	0.92	-0.44		-1.34	30.83	13.48	-9.55	0.85
S3/B2	-0.30	0.95	0.68	0.13		-2.38	36.19	12.79	3.45	0.88
S3/B3	-0.40	0.95	0.64	0.23		-2.88	32.82	10.84	5.64	0.85
S3/B4	-0.02	0.99	0.57	0.40		-0.12	33.21	9.28	9.60	0.86
S3/B5	0.20	1.00	0.83	0.68		1.17	28.14	11.47	13.82	0.84
S4/B1	-0.23	1.07	0.66	-0.45		-1.55	34.93	10.61	-10.59	0.88
S4/B2	-0.30	0.93	0.38	0.08		-2.47	37.36	7.39	2.23	0.88
S4/B3	-0.13	0.94	0.40	0.25		-0.93	32.35	6.75	6.32	0.85
S4/B4	0.12	0.99	0.33	0.44		0.82	32.84	5.40	10.62	0.86
S4/B5	0.23	1.04	0.43	0.60		1.29	28.27	5.71	11.77	0.82
S5/B1	0.21	0.99	-0.28	-0.51		1.29	29.78	-4.18	-11.06	0.85
S5/B2	-0.01	0.95	-0.13	-0.03		-0.11	38.97	-2.72	-0.92	0.89
S5/B3	0.01	1.00	-0.16	0.18		0.08	34.32	-2.77	4.52	0.86
S5/B4	0.13	1.00	-0.11	0.33		0.90	33.96	-1.89	8.01	0.86
S5/B5	0.14	1.08	-0.29	0.63		0.62	22.74	-3.03	9.59	0.76
RMSE	0.36									
GRS F	2.47				# >|2|	4	25	24	24	0.84
P-value	0.0003									

Table 3

Predictability of Size and Book-to-Market Portfolio Returns

Portfolio and factor excess returns are regressed on a set of lagged instruments. The instrumental variables include the risk-free rate R_F, default spread DEF, term spread TERM, portfolio market capitalization SIZE and portfolio book-to-market B/M. Both SIZE and B/M are expressed as natural logarithms. In the regressions of the three risk factors, SIZE and B/M are the cross-sectional sums of portfolio market capitalization and book-to-market. The sample period is February 1986 to June 2002 and the number of observations is 197. The table reports OLS estimates of the coefficients. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively. Also shown are p-values for an F-test of the null hypothesis that all coefficients are equal to zero. The explanatory power of the predictive variables is measured by the R^2 and adjusted R^2.

Portfolio	R_F	DEF	TERM	SIZE	B/M	P-Value F-test	R^2	Adj. R^2
S1/B1	-15.67*	-38.71	-7.89	-19.87***	-14.76***	0.0000	0.14	0.11
S1/B2	-19.29***	-45.69**	-15.30**	-14.25***	-9.59***	0.0001	0.13	0.11
S1/B3	-21.62***	-36.50**	-15.27**	-10.70***	-5.44	0.0000	0.14	0.11
S1/B4	-19.86***	-24.03	-18.40***	-9.79***	-4.19	0.0001	0.13	0.10
S1/B5	-18.21***	-24.33	-13.90*	-10.84***	-2.70	0.0031	0.09	0.06
S2/B1	-14.25**	-64.79***	-7.25	-19.35***	-8.21***	0.0001	0.13	0.11
S2/B2	-13.08***	-27.76	-10.81	-11.67***	-5.58	0.0020	0.09	0.07
S2/B3	-14.32***	-12.41	-13.27**	-9.25***	-2.67	0.0013	0.10	0.07
S2/B4	-15.61***	-2.65	-13.26**	-7.27***	-1.47	0.0032	0.09	0.06
S2/B5	-25.45***	-22.71	-26.84***	-12.37***	-2.70	0.0000	0.14	0.11
S3/B1	-16.02***	-35.42*	-12.28	-12.54***	-3.70	0.0003	0.11	0.09
S3/B2	-18.12***	-17.11	-17.54***	-8.37***	-3.13	0.0032	0.09	0.06
S3/B3	-17.20***	-7.84	-17.37***	-4.97***	1.24	0.0196	0.07	0.04
S3/B4	-21.22***	-3.73	-20.85***	-6.38***	2.71	0.0009	0.10	0.08
S3/B5	-25.04***	-17.45	-25.69***	-6.97***	1.50	0.0006	0.11	0.08
S4/B1	-22.15***	-58.09***	-20.18***	-7.27***	-0.63	0.0018	0.09	0.07
S4/B2	-15.19***	-23.94	-15.12**	-3.53**	2.42	0.0356	0.06	0.04
S4/B3	-15.06***	-21.75	-13.23*	-2.89*	4.02	0.0500	0.06	0.03
S4/B4	-21.25***	-24.26	-21.01***	-4.70***	4.74*	0.0033	0.09	0.06
S4/B5	-29.19***	-41.34*	-26.76***	-6.70***	5.73**	0.0001	0.13	0.11
S5/B1	-12.12**	-5.45	-16.86*	-7.97***	-0.08	0.0145	0.07	0.05
S5/B2	-12.88***	-22.43	-12.23*	-1.06	3.88*	0.1375	0.04	0.02
S5/B3	-12.81***	-47.18**	-12.26*	-1.77*	3.79	0.1013	0.05	0.02
S5/B4	-18.43***	-38.64**	-18.05***	-5.48***	3.11	0.0004	0.11	0.09
S5/B5	-22.17***	-23.87	-28.16***	-4.92***	0.24	0.0005	0.11	0.09
Average	-18.25***	-27.52***	-16.79***	-8.44***	-1.26		0.10	0.07
R_M	-17.72***	-19.51	-16.57***	-4.62***	2.77		0.09	0.06
SMB	-3.71	22.28***	-2.21	-0.30	-0.28		0.07	0.04
HML	-5.89	19.29	-8.94*	-0.49	-0.27		0.03	0.01

Table 4

Time-Varying Betas in the Three-Factor Model

Value-weighted excess returns on 25 size-B/M portfolios are regressed on a constant, lagged instruments, the three Fama-French risk factors and interaction terms between these factors and the lagged instruments. The second column shows the adjusted R-squared for a constant alpha, constant betas model, while the third column presents this statistic for a constant alpha, time-varying betas model. The fourth column reports the p-value of an F-test comparing the R-squared of these two models to test for time-varying betas. The last three columns contain results for a similar analysis but in this case the alphas are assumed to be time-varying. The sample period is February 1986 through June 2002. Bonferroni is the Bonferroni adjusted p-value for a joint test across portfolios of the null hypothesis that betas are constant. # < 0.05 is the number of p-values below 0.05.

	Constant Alphas			Time-Varying Alphas		
Portfolio	Adj. R^2 Constant Betas	Adj. R^2 Dynamic Betas	P-Value F-Test	Adj. R^2 Constant Betas	Adj. R^2 Dynamic Betas	P-Value F-Test
S1/B1	0.740	0.796	0.000	0.793	0.825	0.000
S1/B2	0.726	0.773	0.000	0.753	0.783	0.001
S1/B3	0.733	0.758	0.005	0.755	0.772	0.024
S1/B4	0.805	0.832	0.000	0.819	0.855	0.000
S1/B5	0.839	0.845	0.094	0.846	0.851	0.139
S2/B1	0.851	0.865	0.003	0.865	0.872	0.054
S2/B2	0.844	0.870	0.000	0.850	0.872	0.000
S2/B3	0.846	0.878	0.000	0.848	0.886	0.000
S2/B4	0.861	0.873	0.007	0.858	0.874	0.001
S2/B5	0.860	0.881	0.000	0.871	0.890	0.000
S3/B1	0.855	0.878	0.000	0.863	0.881	0.000
S3/B2	0.877	0.894	0.000	0.875	0.892	0.000
S3/B3	0.855	0.887	0.000	0.857	0.886	0.000
S3/B4	0.861	0.882	0.000	0.864	0.884	0.000
S3/B5	0.842	0.867	0.000	0.846	0.869	0.000
S4/B1	0.877	0.898	0.000	0.884	0.901	0.000
S4/B2	0.878	0.886	0.021	0.879	0.884	0.077
S4/B3	0.847	0.879	0.000	0.853	0.878	0.000
S4/B4	0.856	0.883	0.000	0.858	0.885	0.000
S4/B5	0.825	0.857	0.000	0.832	0.861	0.000
S5/B1	0.849	0.881	0.000	0.850	0.882	0.000
S5/B2	0.889	0.910	0.000	0.888	0.909	0.000
S5/B3	0.862	0.897	0.000	0.870	0.900	0.000
S5/B4	0.861	0.899	0.000	0.866	0.900	0.000
S5/B5	0.757	0.851	0.000	0.789	0.851	0.000
Bonferroni			0.000			0.000
# < 0.05			24			22

Table 5

Time-Varying Alphas in the Three-Factor Model

The second column in this table reports the p-value of an F-test for the hypothesis that the conditional alpha is zero in the constant beta three-factor model while in column three p-values are shown for the same hypothesis when betas are allowed to vary over time as a function of instrumental variables. Column four and five report p-values for the null hypothesis that alpha is constant in the constant beta three-factor model and a three-factor model with time-varying betas, respectively. The sample period is February 1986 through June 2002. Bonferroni is the Bonferroni adjusted p-value for a joint test across portfolios. # < 0.05 is the number of p-values below 0.05.

Portfolio	Test Zero Cond. α (Constant β)	Test Zero Cond. α (Time-varying β)	Test Constant α (Constant β)	Test Constant α (Time-varying β)
S1/B1	0.000	0.000	0.000	0.000
S1/B2	0.000	0.001	0.000	0.019
S1/B3	0.001	0.017	0.001	0.009
S1/B4	0.004	0.000	0.002	0.000
S1/B5	0.024	0.031	0.017	0.038
S2/B1	0.000	0.005	0.000	0.017
S2/B2	0.055	0.296	0.034	0.205
S2/B3	0.124	0.003	0.204	0.004
S2/B4	0.956	0.351	0.923	0.250
S2/B5	0.001	0.001	0.001	0.003
S3/B1	0.007	0.136	0.007	0.084
S3/B2	0.268	0.331	0.832	0.981
S3/B3	0.011	0.012	0.130	0.707
S3/B4	0.154	0.265	0.096	0.179
S3/B5	0.063	0.078	0.061	0.158
S4/B1	0.007	0.127	0.009	0.078
S4/B2	0.044	0.198	0.222	0.768
S4/B3	0.026	0.391	0.020	0.558
S4/B4	0.220	0.304	0.181	0.215
S4/B5	0.020	0.026	0.020	0.062
S5/B1	0.270	0.073	0.313	0.256
S5/B2	0.904	0.804	0.828	0.717
S5/B3	0.009	0.106	0.004	0.064
S5/B4	0.051	0.049	0.039	0.155
S5/B5	0.000	0.031	0.000	0.374
Bonferroni	0.000	0.000	0.000	0.001
# < 0.05	15	12	15	8

Table 6

Fama-MacBeth Regressions of Raw Returns and Three-Factor Risk-Adjusted Returns

This table reports Fama-MacBeth coefficient estimates. In the second column, the dependent variable is the excess portfolio return unadjusted for risk. In the third column the dependent variable is the excess return risk-adjusted using the Fama-French three-factor model with constant betas. In the fourth column the dependent variable is the excess portfolio return risk-adjusted using a conditional three-factor model, where factor loadings are scaled by the default spread, size, book-to-market and interaction terms between default spread and size and B/M,

$$\beta_{ikt} = \beta_{ik1} + \beta_{ik2}DEF_t + (\beta_{ik3} + \beta_{ik4}DEF_t)SIZE_{it} + (\beta_{ik5} + \beta_{ik6}DEF_t)B/M_{it},$$

where *DEF* is the default spread and *SIZE* and *B/M* are the logarithm of portfolio market capitalization in billions of euros and the logarithm of portfolio book-to-market ratio, respectively. Portfolio characteristics are the regressors in the cross-sectional regressions. SIZE and B/M are expressed as logarithms of market capitalization and book-to-market, respectively, and RET2-3, RET4-6 and RET7-12 are cumulative past returns. All five characteristics are measured as deviation from their cross-sectional mean in each month. The sample period is February 1986 through June 2002. Adj. R^2 is the time-series average of the monthly adjusted R^2. T-statistics are reported in parentheses.

	Raw Return	Static FF	Dynamic FF
Intercept	0.776	0.077	0.057
	(2.190)	(0.879)	(0.705)
SIZE	-0.093	-0.027	-0.024
	(-1.970)	(-0.978)	(-1.027)
B/M	0.006	-0.066	-0.005
	(0.051)	(-1.106)	(-0.084)
RET2-3	0.044	0.036	0.040
	(2.934)	(2.372)	(2.909)
RET4-6	0.029	0.028	0.027
	(2.308)	(2.164)	(2.293)
RET7-12	0.044	0.041	0.036
	(5.623)	(5.111)	(4.920)
Adj. R^2	0.380	0.121	0.106