Macroeconomic Risks and the Fama and French/Carhart Model

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1 Introduction

Several recent papers study the wide–spread empirical success of the Fama and French (hereafter FF) (1992; 1993) model and report evidence that the book–to–market (HML) and size (SMB) factors are associated with economic fundamentals likely to characterize the investment opportunity set, as defined in Merton's (1973) or Campbell's (1993) ICAPM (see, e.g., Brennan et al., 2004; Fama, 1998, 1996). Economic factors found to be related to HML and/or SMB include innovations in economic growth expectations (Kelly, 2004; Vassalou, 2003; Liew and Vassalou, 2000), default risk (Hahn and Lee, 2005; Petkova, 2005; Vassalou and Xing, 2004; He and Ng, 1994), the term structure of risk–free interest rates (Hahn and Lee, 2005; Petkova, 2005), and inflation (Kelly, 2004). Chen (1991) shows that these economic fundamentals can be interpreted as state variables, since they predict current and future consumption at various horizons.

We extend this prior literature in five main ways. First, we consider the possibility that characteristic–based factors capture information on a broader set of macroeconomic fundamentals than has been examined in earlier research. To this end, we estimate multivariate GMM models relating characteristic–based portfolio returns to macroeconomic fundamentals. The multivariate models help clarifying the fundamental roles played by correlated macroeconomic factors examined in prior research, as well as assessing the role of other factors. Second, we include the momentum factor (WML) as proposed by Carhart (hereafter C) (1997) and its underlying benchmark portfolios in our analysis, in addition to SMB and HML (and their underlying benchmark portfolios). The prior literature does not contain evidence that WML serves as a proxy for fundamental state variable(s) (or risk factors).[1] Third, we identify the incremental information contained in the market portfolio, after controlling for the selected macroeconomic fundamentals. This is important given the role of the market portfolio in the FF model. Fourth, we estimate the risk premia associated with the macroeconomic fundamentals, using both unconditional and conditional pricing tests. Fifth, we assess the pricing ability of a macroeconomic factor (hereafter MF) model relative to the FF and C models.

Our results suggest that the stock characteristics underlying the FF model and the C model are

[1]Prior research suggests that the association between realized returns and momentum most likely reflects market microstructure–related effects (Da and Gao, 2005) or market irrationality and investors' behavioral biases (Daniel and Titman, 2004; Daniel et al., 1998).

associated with strong (almost monotonic) cross–sectional differences in exposures to five of the six macroeconomic state variables included in our model. While we can confirm most of the associations reported in prior research, we also find some evidence counter that presented in previous studies, and we identify new effects of macroeconomic state variable proxies. In particular, book–to–market is associated with variation in exposures to changes in economic growth expectations, consistent with Vassalou (2003) and Liew and Vassalou (2000), and with variation in exposures to the term structure slope, in line with the findings in Hahn and Lee (2005) and Petkova (2005). This is despite changes in economic growth expectations and term structure slope being relatively highly correlated. However, contrary to Petkova (2005), we find that the inclusion of the term structure slope does not render the association between book–to–market and exposure to changes in economic growth expectations insignificant. In addition, we also obtain new evidence showing that book–to–market is associated with unexpected inflation and innovations in the U.S. dollar exchange rate. With regard to firm size, we find that market capitalization is negatively associated with exposures to changes in the survival probability, consistent with Hahn and Lee (2005) and Petkova (2005). Nevertheless, we also document differences in the exposures of size–sorted portfolios to innovations in the level and slope of the term structure, and the exchange rate. Finally and importantly, previous research has not established links between momentum–sorted portfolios and macroeconomic exposures. Here, our analysis reveals that momentum–sorted portfolios have very different exposures to both changes in the aggregate survival probability and changes in the slope of the term structure of risk–free interest rates.

Similar to Fama and French (1993) and Carhart (1997), we also construct factor–mimicking portfolios from the benchmark portfolios based on the three stock characteristics. Our analysis confirms that the mimicking portfolios constructed from benchmark portfolios two–way sorted on book–to–market and market capitalization (HML and SMB) and benchmark portfolios three–way sorted on book–to–market, market capitalization, and momentum (HML, SMB, and WML) are strongly related to the macroeconomic state variables. This leads us to extend the prior literature in two ways. First, we use unconditional and conditional asset pricing tests based on characteristic–sorted portfolios to examine whether the broad set of macroeconomic factors in our model are associated with significant risk premia. We find that shocks to investors' economic growth expectations, unexpected inflation, (weakly) the aggregate survival probability, the slope of the term structure, and changes in the U.S.

composite exchange rate are priced. We thus find weak evidence of a default risk premium, in contrast to Hahn and Lee (2005) and Petkova (2005), who find no evidence of a risk premium associated with this factor using different instruments to proxy for default risk.

Second, we employ model specification and comparison tests in order to investigate the extent to which the FF model and the C model capture information on macroeconomic state variables. This analysis provides insights how well book–to–market, market capitalization, and momentum effectively summarize exposures to macroeconomic fundamentals that are difficult to estimate directly at the stock level. Using unconditional tests, the FF and C models display almost identical ability as the MF model in pricing benchmark portfolios sorted on book–to–market and market capitalization. While the MF model is dominated by the C model in pricing benchmark portfolios sorted on book–to–market, market capitalization and momentum, it clearly outperforms the FF model on these test assets. These results suggest that the FF model does a good job at capturing the macroeconomic factors included in our model, but also that momentum may well proxy for as yet unidentified macroeconomic state variables, in addition to capturing information about changes in the aggregate survival probability and the slope of the term structure. Using conditional tests, we find strong evidence that the MF model markedly outperforms the FF and C models. This is important, as it indicates that the pricing performance of the MF model is more stable when alternative test assets are considered.

The remainder of the paper is organized as follows. In Section 2, we review the related literature and provide the motivation for our research. In Section 3, we describe our research design in terms of methodology and data, while Section 4 presents the results with regards to the estimated risk exposures, risk premia and model specification tests for conditional and unconditional settings. Finally, Section 5 concludes.

2 Prior literature

2.1 Asset pricing and macroeconomic pricing factors

Chan et al. (1985), Chen et al. (1986), and others[2] document that innovations in macroeconomic

[2]He and Ng (1994), McElroy and Burmeister (1988), Shanken and Weinstein (1987), Burmeister and Wall (1985) and McElroy and Burmeister (1985) further examine the relation between macroeconomic factors and

fundamentals can explain expected stock returns. However, until relatively recently, the possibility of cross–sectional patterns in exposures to macroeconomic pricing factors has not been explicitly considered. One reason for this is probably the difficulties associated in identifying proxies for macroeconomic risk factor exposures at the stock level. However, interest in this issue has been stimulated by attempts to develop economic explanations for the associations between the FF factors (HML and SMB) and expected stock returns. In particular, Liew and Vassalou (2000) were the first to suggest that HML and SMB contain information useful in predicting future GDP growth. Several recent papers have reported complementary results, either taking macroeconomic variables as the object of forecasting (see, e.g., Kelly, 2004), or in direct asset pricing tests based on macroeconomic factor–based risk models (see, e.g., Petkova, 2005).

Table 1 summarizes the main findings from asset pricing studies relating HML and SMB to a range of potential state variables, including innovations in GDP (industrial production) growth, unexpected inflation, the level and the slope of the term structure, default risk or the aggregate survival probability, and the dividend yield. The current consensus in the literature is that:

1. Evidence from predictive studies suggests that HML captures information relevant in predicting economic growth, while SMB is associated with innovations in economic growth expectations and inflation (Kelly, 2004; Liew and Vassalou, 2000). Even though the relevance of these factors has not been tested in an asset pricing framework, these studies (like earlier work by Chan et al. (1985), etc.) imply that innovations in growth expectations and inflation might usefully be considered for inclusion in a macroeconomic factor model.

2. When stock returns are modelled as a function of term structure innovations, the coefficients on innovations in the slope of the term structure increase across portfolios sorted on book–to–market, but not across portfolios sorted on market capitalization. Consistent with these findings, there is a significant positive association between innovations in the slope of the term structure and HML, but not SMB. Thus, HML serves as a proxy for interest rate term structure slope risk (Petkova, 2005; Hahn and Lee, 2005).

expected returns for the U.S. market; Hamao (1988) focuses on the Japanese market, and Poon and Taylor (1991) on the U.K. market.

3. When stock returns are modelled as a function of innovations in default risk, coefficients increase across portfolios sorted on size, but no association is found for portfolios sorted on book–to–market. Accordingly, the empirical findings reveal a significant negative association between innovations in the aggregate default probability and SMB, but not HML. Thus, SMB serves as a proxy for default risk (Petkova, 2005; Hahn and Lee, 2005; He and Ng, 1994; Chen et al., 1986; Chan et al., 1985).

4. Hahn and Lee (2005) and Petkova (2005) find a strongly significant risk premium on the slope of the term structure, but conclude that innovations in default risk are not associated with a significant risk premium. Vassalou (2003) reveals weak evidence that GDP growth risk is priced, i.e. the estimated risk premium is significant at the 10% significance level.

Table 1 indicates that individual studies in the prior literature relating SMB and HML to macroeconomic fundamentals have generally focused on quite limited sets of state variables. Factors found to have significant explanatory power for stock returns in other studies, such as changes in the exchange rate (Vassalou, 2000; Jorion, 1991) and the oil price (Panetta, 2002; Chen et al., 1986), have not been considered as possible correlates of SMB and HML. Therefore, we expand the set of macroeconomic state variables analyzed to include these variables. Moreover, Table 1 also reveals that the prior literature focuses on only partially overlapping sets of macroeconomic state variables. This is not a problem if the state variables included in different studies are uncorrelated. However, when the state variables studied are correlated, as indeed we show to be the case, the significance of included macroeconomic instruments as fundamental risk factors will be ambiguous and estimated beta risk exposures will potentially be biased, because of a correlated omitted variable problem. For example, if changes in GDP growth expectations are negatively correlated with changes in the level of interest rates, we cannot necessarily conclude that both GDP growth risk and term structure risk are relevant state variables, unless both are included in the same model and found to be significant in explaining expected returns. Table 1 is especially striking in revealing that no single study examines economic growth and inflation risk jointly with term structure and default risk, despite the likelihood that these factors are correlated. Our model addresses the possibility that macroeconomic factors serve as proxies for correlated omitted variables.

Several prior studies have also included the market portfolio as an additional pricing factor alongside macroeconomic factors. The market portfolio appears in the ICAPM to reward investors for bearing return variation unexplained by the state variables, i.e. the part of the market portfolio legitimately treated as a separate state variable is the variation in the market portfolio not explained by the other state variables (Fama, 1996, p. 460). Since the market portfolio is, however, itself an asset, a significant component of its return can be explained by variation in macroeconomic pricing factors. As a result, if the return on the market portfolio is treated as exogenous, its inclusion in a model might mask significant associations between the attribute–sorted portfolio returns (or FF factor returns) and the fundamental macroeconomic state variables. In this study, we therefore treat the return on the market portfolio as endogenous and focus on the component uncorrelated with included macroeconomic state variables. In the cross–sectional tests, we add an orthogonalized stock market index to the macroeconomic state variables, in order to account for the component of expected returns related to bearing return variation unexplained by the included state variables.

2.2 Risk factor exposures and stock characteristics

Valuation theory provides a framework suggesting why some stock–level characteristics should capture cross–sectional variation in exposures to common risk factors. Rubinstein (1976) shows that in a no–arbitrage economy, the equity value of a firm can be written as the present value of expected future dividends under the risk–adjusted probability measure, discounted using the term structure of risk–free interest rates:

$$MV_0 = \sum_{t=1}^{\infty} \left[\frac{E_0^Q(d_t)}{(1+r_t)^t} \right], \tag{1}$$

where MV_0 is the current market value of the firm, d_t is the dividend flow at time t under the risk–adjusted probability measure Q, and r_t is the t–period spot interest rate at time 0. Given (1), changes in market value (returns) are related to changes in expected future dividends, in the stochastic discount factor underlying E_0^Q, and in the term structure of risk–free interest rates.

Since changes in book value are (approximately) equal to earnings less dividends paid, we can replace dividends and rewrite valuation expression (1) as the sum of book value and discounted residual income (see, e.g., Ohlson, 1995; Lee et al., 1999):

$$MV_0 = B_0 + \sum_{t=1}^{\infty} \left[\frac{E_0^Q(RI_t)}{(1+r_t)^t} \right], \tag{2}$$

where B_0 is the book value of equity at time 0, and RI_t is residual income and equals net income minus a cost of capital charge based on beginning–of–period book value of equity. Note that residual income can be interpreted as a measure of excess profitability.

Valuation expression (2) indicates that the difference between the market value of equity and the book value of equity equals the discounted present value of risk–adjusted expected residual income. Moreover, we also see that changes in market value are related to changes in book value (i.e., current period earnings less dividends), in expected future residual income, in the stochastic discount factor underlying E_0^Q, and in the term structure of risk–free interest rates.

In turn, valuation expression (2) may be rewritten in terms of the risk–neutral present value of expected future residual income and the price of risk:

$$MV_0 = B_0 + \sum_{t=1}^{\infty} \left[\frac{E_0(RI_t)}{(1+r_t)^t} \right] - PR_0. \tag{3}$$

The price of risk (PR) in equation (3) depends on the covariances between priced fundamental risk factors and future residual income (Feltham and Ohlson, 1999). The second term on the right–hand side of (3) captures expected future growth in residual income. Holding future growth expectations and the price of risk constant, we expect market value to be sensitive to innovations in the term structure through the denominator in the second term in expression (3). The higher $\sum_{t=1}^{\infty} \left[\frac{E_0(RI_t)}{(1+r_t)^t} \right]$ is in relation to B_0, the greater the stock's term structure risk exposure. Because this second term is the present value of multi–period residual income flows, interest rate risk exposure also depends on the timing of the expected residual income flows and this term determines equity duration (Dechow et al., 2004; Leibowitz and Kogelman, 1993; Leibowitz, 1986; Lanstein and Sharpe, 1978).

Valuation expression (3) also helps us understand why fundamental macroeconomic factors beyond term structure changes might constitute sources of risk for equities. The third term on the right hand side of the equation is the uncertain component of the investment opportunity set and its value depends on beliefs concerning realizations of future cash flows (and hence future earnings and residual income realizations). In turn, these beliefs will be conditioned on observable macroeconomic state variables that are informative about systematic components of future cash flow realizations. From expression (3), the price of risk as a proportion of market value is given by:

$$\frac{PR_0}{MV_0} = \frac{B_0}{MV_0} + \frac{\sum_{t=1}^{\infty}\left[\frac{E_0(RI_t)}{(1+r_t)^t}\right]}{MV_0} - 1 \tag{4}$$

Expressions (3) and (4) imply that book–to–market is negatively associated with future profitability (growth) and positively associated with the price of risk. Thus, we expect book–to–market to capture information on exposures to fundamental risk factors. However, expression (4) also suggests why book–to–market cannot be fully informative about the price of risk and why variables, such as market capitalization and stock momentum, might also capture information about risk. If the second term on the right–hand side of (4) is not a constant, then any variable correlated with this term (and, in general, correlated with future residual income expectations) can play a role in identifying the price of risk and hence ultimately the cost of equity.[3]

3 Research design

3.1 Methodology

Our main objective is to assess the pricing ability of the FF model and the C model relative to the macroeconomic factor (MF) model that is based on pricing factors suggested by the prior macroeconomic asset pricing literature.[4] Our MF model is based on the following linear relation between

[3]Note that our reasoning is consistent with Campbell and Vuolteenaho (2004), who also argue that exposure to numerator (cash flow) and denominator (discount rate) shocks should command different risk premia.

[4]In its time–series representation, the FF (C) model can be stated as follows:

$$R^E_{t-1,tp} = \beta_{0p} + \beta_{1p}RM_{t-1,t} + \beta_{2p}SMB_{t-1,t} + \beta_{3p}HML_{t-1,t}(+\beta_{4p}WML_{t-1,t}) + \varepsilon_{t-1,tp}, \tag{5}$$

where $R^E_{t-1,tp}$ represents a test asset's return in excess of the risk–free rate, $RM_{t-1,t}$ stands for the return on a value–weighted stock market index minus the risk–free rate, $SMB_{t-1,t}$ for the return on a zero investment portfolio long on large and short on small market capitalization stocks, and $HML_{t-1,t}$ for the return on a zero investment portfolio long on high and short on low book–to–market ratio stocks. The C model adds to the former pricing factors the return on a zero investment portfolio long on winner and short on loser stocks, denoted here by $WML_{t-1,t}$.

realized excess test asset returns and macroeconomic pricing factors:

$$R^E_{t-1,tp} = \beta_{0p} + \beta_{1p}MYP_{t,t+12} + \beta_{2p}UI_{t-1,t} + \beta_{3p}DSV_{t-1,t} + \beta_{4p}ATS_{t-1,t} \\ +\beta_{5p}STS_{t-1,t} + \beta_{6p}FX_{t-1,t} + \beta_{7p}OIL_{t-1,t} + \varepsilon_{t-1,tp}, \quad (6)$$

where $MYP_{t,t+12}$ is the change in expectations of one year ahead industrial production growth over month t, $UI_{t-1,t}$ is unexpected inflation in month t, $DSV_{t-1,t}$ is the change in the aggregate survival probability in month t, $ATS_{t-1,t}$ and $STS_{t-1,t}$ are changes over month t in, respectively, the average level and the slope of the term structure. $FX_{t-1,t}$ is the change in a multilateral U.S. dollar exchange rate and $OIL_{t-1,t}$ represents the change in a raw materials price index (largely comprising oil and petroleum derivatives). This model nests the majority of the asset pricing models used in prior studies described in Table 1, and it includes additional factors such as exchange rate risk and oil price risk identified by Panetta (2002), Vassalou (2000), De Santis and Gérard (1998), Dumas and Solnik (1995), Jorion (1991), and Chen et al. (1986). An augmented version of this model, which we call augmented macroeconomic factor (AMF) model, also includes the orthogonalized excess market return, $RM^*_{t-1,t}$, to address the point raised by Fama (1996). We orthogonalize the excess market return by regressing it on our set of state variables, and we then use the residual from this regression as $RM^*_{t-1,t}$.

Next, we use cross–sectional tests to check whether the spreads in risk exposures translate into statistically significant MF factor risk premia. More importantly, we also wish to compare the pricing performance of the FF model, the C model, and the MF model. To achieve these objectives, we study the asset pricing models in stochastic discount factor language. As test assets, we use both two–way (5x5) and three–way (4x4x4) sorted portfolios based on firm fundamentals (book–to–market, size and momentum). The stochastic discount factor representation is:

$$p_{t,p} = E_t(m_{t+1}R^E_{t+1,p}) \quad (7)$$

where $p_{t,p}$ is the market price of portfolio p at time t (zero in the case of excess returns), $E_t(.)$ is the expectation operator conditional on time t information, m_{t+1} is the linear stochastic discount factor at time t+1, i.e. $m_{t+1} = 1 - b'f_{t+1}$, where f_{t+1} are the pricing factors used in the different models, and

$R^E_{t+1,p}$ represents the excess returns of portfolio p at time t+1. Equation (7) can be rearranged to give the prices of factor risk. The statistical significance of the factor risk premia can be easily assessed using the *delta*–method (see Cochrane, 2001).

We also follow Cochrane (1996), Hodrick and Zhang (2001) and other recent studies and assess the pricing ability of the models on conditional assets, i.e. on test assets with time–varying weights equivalent to dynamic trading strategies. In particular, we multiply the three–way sorted benchmark portfolios by a set of economy–wide lagged instruments, including the dividend yield on the S&P500 index, the default yield spread, and the government bond term spread, and then repeat the cross–sectional tests. To avoid an excessive number of test assets, we use (2x2x2) three–way sorted portfolios as test assets in this exercise. Note that the instrumental variables are lagged by two periods to avoid overlap with the test portfolios. In the final section of the paper, we also scale the pricing factors by the dividend yield, in order to allow for dependence of the stochastic discount factor on the business cycle (see, e.g., Fama and French, 1988).

3.2 Test assets

Our initial test assets in the time–series regressions are portfolios one–way sorted on size, prior fiscal year book–to–market, and momentum. Since one–way sorted portfolios are, however, often unstable on other firm characteristics, we also examine the associations between the risk exposures and portfolios independently three–way sorted on book–to–market, size, and momentum.[5] One–way sorted portfolios are constructed in a manner exactly analogous to Fama and French (1993). In particular, we first obtain the size decile breakpoints for all NYSE firms as at June of year t. In the same manner, we derive the book–to–market decile breakpoints in December of each year $t-1$ for all NYSE firms. In line with Carhart (1997), in June of each year t we also compute the breakpoints for the compounded return over the prior eleven months for the same firms.[6] Having identified the portfolio breakpoints, we construct value–weighted portfolios comprising all stocks within each relevant range of the sorting variable. Portfolio composition remains fixed from July of year t to June of year t+1, when portfolios

[5]There is a tendency for very large firms to have low book–to–market and high momentum (and vice versa).

[6]Note that, in order to avoid measurement problems associated with returns, such as infrequent trading, non–synchronous trading, and the "bid–ask" bounce, we leave a one–month gap between the computation of momentum and the initiation of the trading strategy. This is in line with the findings of Da and Gao (2005).

are reformed using the same algorithm.

Three–way independently sorted portfolios are formed using a similar approach and the same decile breakpoints. However, in order to limit the number of test assets, we assign the firms to (1) eight (2x2x2) portfolios based on the median, (2) twenty–seven (3x3x3) portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30%, and, finally, (3) sixty–four (4x4x4) portfolios based on the breakpoints for the bottom 20%, the two middle 30%s, and the top 20% of the ranked values. As in Liew and Vassalou (2000), the three–way sorted benchmark factor portfolios, i.e. SMB, HML, and WML, are created from the (3x3x3) benchmark portfolios (see Appendix A for details, including summary statistics of these portfolios in Table A1).

3.3 Macroeconomic factors

Innovations in the macroeconomic factors included in the model are defined in ways consistent with the prior literature. Our analysis is conducted using monthly asset return series. Therefore, we employ industrial production data as our proxy for economic growth (MYP), since such data is reported monthly, whereas GDP data is only reported quarterly. Directly observed expectations of industrial production are not available. One solution would be to use future *realized* economic growth as a proxy for innovation in economic growth expectations. This, however, creates an errors–in–variables problem rendering model parameter estimates unreliable (Petkova and Zhang, 2004; Greene, 2003).[7] To avoid this problem, we adopt an approach similar to Vassalou (2003) by creating a factor–mimicking portfolio to capture the change in industrial production growth expectations over the next year. The factor mimicking portfolio is constructed by regressing log changes in realized industrial production growth over the next year on the excess returns of a set of base assets and a set control variables capturing information on expected asset returns and growth (see, e.g., Lamont, 2001; Breeden et al., 1989). The portfolio weights in the factor–mimicking portfolio correspond to the estimated parameters on the vector of base asset returns.

[7]Substituting realized industrial production growth for changes in expectations into statistical model (6), we obtain $R^E_{tp} = \beta_{1p} + \beta_{2p} YP_{t,t+12} + \beta_{3p} UI_t + \ldots + u_{tp}$, where $u_{tp} = \varepsilon_{tp} - \beta_{2p}(E_{t-1}(YP_{t,t+12}) + \eta_{t,t+12})$. Thus, $cov(u_{tp}, YP_{t,t+12}) = cov(\varepsilon_{tp} - \beta_{2p}(E_{t-1}(YP_{t,t+12}) + \eta_{t,t+12}), E_{t-1}(YP_{t,t+12}) + \Delta E_{t-1,t}(YP_{t,t+12}) + \eta_{t,t+12}) = -\beta_{2p} var(E_{t-1}(YP_{t,t+12}) + \eta_{t,t+12})$. The unbiasedness of the OLS parameter estimates, however, depends crucially on the assumption that regressors and error term are orthogonal to each other.

While the choice of base assets should span the space of asset returns, the theoretical literature offers little guidance on the selection of base assets. This potentially explains why previous studies use a wide variety of assets.[8] We include in the set of base assets the market portfolio, portfolios of long–term, intermediate–term, and short–term government bonds and a corporate bond portfolio.[9] As control variables, we employ a set of lagged instrumental variables used in prior studies to capture time–variation in expected returns, including the risk–free rate, the difference between long–term and short–term government bond yields, the default yield spread, the dividend yield on the S&P500 stock index, plus one year lagged industrial production growth, inflation, and the excess market return.[10]

Our model further includes a proxy for the aggregate survival probability that is derived as in Vassalou and Xing (2004) using the contingent claims methodology of Black and Scholes (1973) and Merton (1974). We compute unexpected inflation as actual inflation minus the predicted value from an MA(1)–process (Fama and Gibbons, 1984).[11] We employ two proxies in order to capture term structure risk. First, the average level of the term structure is an arithmetic mean of the monthly change in the 3–month Treasury bill yield and the change in the 10–year Treasury bond yield. Second, the change in the slope of the term structure is the difference between the monthly change in the 10–year Treasury bond yield and the monthly change in the 3–month Treasury bill yield. Finally, in order to capture risk related to unexpected changes in foreign exchange rates as well as oil and other raw material prices, we assume that innovations in these macroeconomic variables equal the monthly changes in the underlying time–series. We estimate the free parameters of model (6) and (7) using Hansen (1982)'s Generalized Method of Moments (GMM). Using the GMM has the advantage that

[8]Vassalou (2003) reports evidence that the benchmark portfolios underlying HML and SMB contain useful information for predicting GDP growth. However, we avoid using these benchmark portfolios, because there is a risk of inducing a mechanical relation between HML, SMB, and WML and the growth factor. If the factor–mimicking portfolio for the growth factor is just a linear combination of the benchmark portfolios underlying HML, SMB and WML, we would expect that HML, SMB and WML, which are themselves linear combinations of the benchmark portfolios, should be related to the factor mimicking portfolio return.

[9]We also experimented with a set of industry equity portfolios, but found that these were less powerful in capturing changes in economic growth expectations.

[10]The ability of these instrumental variables to predict time–variation in expected returns has been documented by Ferson and Harvey (1991), Breen et al. (1989), Ferson (1989), Harvey (1989), Fama and French (1989, 1988), Campbell (1987), and Keim and Stambaugh (1986). In two alternative specifications, we also add the one–month or one–year lagged base assets' excess returns as control variables. Results are qualitatively similar.

[11]Thus, unexpected inflation is also a generated regressor. Pagan (1984), however, shows that, if the generated regressor is the residual from a first–stage estimation, the standard errors in the second–stage estimation are usually not biased. Petkova (2005) makes a similar point.

we can easily correct the standard errors of both models for the additional uncertainty induced by the generated regressor, i.e. the mimicking portfolio for changes in economic growth expectations. Details on the implementation of the GMM methodology can be found in Appendix B.

3.4 Data and sample

We obtain the data required to form the three–way sorted benchmark portfolios and factors on size, book–to–market, and momentum from the intersection of CRSP and COMPUSTAT. We exclude firms with negative book values and issues other than ordinary common equity. As in Fama and French (1993), we define the book value of a firm as the COMPUSTAT book value of stockholders' equity, plus balance–sheet deferred taxes and investment tax credits, minus the book–value of preferred stock, where the value of preferred stock is either the redemption, liquidation, or par value (in this order). The original Fama–and–French benchmark portfolios, i.e. the 25 portfolios two–way sorted on size and book–to–market, and factors, i.e. the market portfolio, SMB, and HML, and, finally, the risk–free rate of return are from Kenneth French's website.[12] The dividend yield on the S&P 500 index is from Robert Shiller's website.[13] We obtain the change in the aggregate survival probability (default risk) from Maria Vassalou's website.[14] Yield data on the 3–month U.S. government Treasury bill, the 10–year Treasury bond, and Aaa and Baa–rated corporate bond portfolios and the exchange rate (in U.S. dollar per unit of foreign currency) between the U.S. dollar and a trade–weighted G10 composite currency index are from the Federal Reserve Bank's website.[15] Return data on long–term, intermediate–term, and 1–year U.S. government bond portfolios and the yield on 1–year U.S. government bond notes are from Ibbotson Associates. We obtain the seasonally–adjusted levels of the U.S. industrial production index, the consumer price index, and the HWWA index of raw material prices from DataStream. All variables are in monthly frequency, and have non–missing data for the

[12] We thank Ken French for making these variables available on his website. The website can be found at: <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html>.

[13] We thank Robert Shiller for making this variable available on his website. The website can be found at: <http://www.econ.yale.edu/ shiller/index.html>

[14] We thank Maria Vassalou for making this variable available on her website. The website can be found at: < http://www-1.gsb.columbia.edu/faculty/mvassalou.html>

[15] <http://www.federalreserve.gov/releases/h15/data.htm#top>

sample period from February 1971 to December 1998.[16]

3.5 Summary statistics

Table 2 summarizes the OLS–regressions underlying the factor–mimicking portfolio for changes in expectations of industrial production growth. Since monthly industrial production growth is measured over rolling one–year windows, t–statistics are corrected for the induced moving average error in residuals using the Newey and West (1987) correction with l = 11. Overall, the portfolio weights are very similar across the three alternative specifications. The individual t–statistics and the exclusion tests both indicate that of the base assets, the market portfolio proxy and the government bond portfolios are significantly related to future industrial production growth, whereas the default bond return is insignificant. While the parameter estimates on the lagged control variables are not easily interpretable, we note that most of them are also significant. Finally, at least 6.22% of the variation in changes in industrial production growth expectations is explained by the excess returns on the selected base assets, which is reasonable in light of the prior literature (see Lamont, 2001). In the interests of parsimony, for the remainder of the paper we employ the factor–mimicking portfolio specification that excludes all lagged base assets.[17]

We report summary statistics on the macroeconomic pricing factors and the one–way sorted benchmark portfolios in Table 3. The sample mean of the factor–mimicking portfolio for industrial production growth is positive with a t–statistic of 5.22 (not reported). This suggests that, if industrial production growth is a factor that can explain the cross-section of asset returns, its associated risk premium is positive (Vassalou, 2003, p. 58).[18] Summary statistics on the benchmark portfolios and factors used in the paper are provided in Table A1 in the Appendix. Panel B of Table 3 indicates that some of the macroeconomic factors are quite highly correlated. Particularly noteworthy are the correlations between the change in industrial production growth expectations (MYP) with the

[16] Data on the aggregate survival probability (default risk) can only be obtained starting from February 1971. Data on the level of the HWWA index ends in December 1998. Even if we exclude the HWWA index, we could only lengthen our sample period by one year, since data on the aggregate survival probability ends in December 1999.

[17] We obtain nearly identical results in the subsequent analysis, if we use any of the two other specifications.

[18] We should, however, keep in mind that this t–statistics is not corrected for the fact that we obtain the weights of the factor–mimicking portfolio through a first–stage regression, and, second, that the realizations of this portfolio also correlate with other macroeconomic fundamentals (see Panel B).

term structure variables (ATS and STS) and with the aggregate survival probability (DSV). Growth, term structure, and default risk factors have all been proposed in the prior literature as potential fundamental risk factors underlying the FF model, but no prior model has considered these factors simultaneously. Therefore, it is possible that one or more of this group of factors is simply serving as a proxy for other factors in the group, providing a strong justification for developing a multivariate macroeconomic factor model that can disentangle potential proxy and fundamental risk factor effects.

Table 3 also shows that the correlations between the macroeconomic pricing factors and the one–way sorted benchmark portfolio returns are frequently high, suggesting that in a univariate setting the pricing factors are statistically significant in explaining the time–series of portfolio returns. Note, in particular, that generally MYP and DSV are strongly positively correlated with portfolios returns, UI, ATS and STS are strongly negatively associated with portfolios returns, and that FX and OIL are less strongly but negatively associated with portfolios returns. While correlations between the macroeconomic variables and the benchmark portfolios are only univariate and thus have to be interpreted with care, some interesting patterns can be observed. In particular, the relation between DSV and portfolio returns is monotonically decreasing with both size and momentum. Similarly, not controlling for other factors, there are negative relations between ATS and size, while STS and FX are positively (negatively) associated with book–to–market (size). The multivariate analysis below shows, however, that the preliminary evidence from these correlations cannot be taken at face value and may not be a good guide to the sign of beta exposures in a multifactor model that controls for important correlations between the included factors.

4 Results

4.1 Macroeconomic risk exposures

In order to investigate the relation between the book–to–market, size, and momentum portfolios and the macroeconomic fundamentals in a multivariate framework, we first perform time–series regressions of the one–way sorted book–to–market deciles' excess returns on the macroeconomic pricing factors (see equation 6). The results in Panel A of Table 4 show that the adjusted R^2 statistics lie between

51% and 67%, suggesting that the macroeconomic pricing factors are able to explain a substantial proportion of the variation in the portfolios' excess returns. Generally, results indicate that MYP, DSV, STS and OIL play statistically important roles. However, comparisons of the risk exposures across portfolios are the most interesting aspect of Table 4. Of the statistically significant pricing factors, the beta estimates for MYP decline nearly monotonically with the book–to–market ratio, while those for STS increase (become less negative) almost monotonically. At the bottom of panel A, we report tests of differences in risk exposures across different definitions of high and low book–to–market portfolios. These tests reveal that differences in the MYP betas are significant at the ten percent level for comparison of the top three (five) versus bottom three (five) portfolios, while differences in STS exposures are highly significant in all tests. While other pricing factors play a significant role in explaining portfolio returns, we find no evidence of statistically significant differences in risk exposures across book–to–market portfolios.

Panel B repeats the analysis for size–sorted portfolios. As in the case of the book–to–market sorted portfolios, the MF model does a good job in explaining size–sorted portfolio returns – adjusted R^2 statistics range from 61% to 71%. Results again indicate that the same factors (MYP, DSV, STS and OIL) play statistically important roles in explaining size–sorted portfolio returns. In contrast to the book–to–market sorted portfolios, MYP betas display, however, no pattern across portfolios, and there is no significant difference in betas for small firm and large firms portfolios. Results for OIL are qualitatively similar. In contrast, risk exposures to DSV decline monotonically as firm size increases, and differences are highly statistically significant. For example, the risk exposure on the portfolio of smallest firms is nearly three times as high as the risk exposure on the portfolio of largest firms. Similarly, the (negative) beta for STS decreases almost monotonically as firm size increases and, again, the differences in betas between small and large firms are significant. The results for ATS and FX betas are more difficult to interpret. Each of these factors is insignificant in each individual portfolio regression, but in the cases of both factors, statistical tests of differences in betas between small firm and large firm portfolios indicate that the differences in betas are significant.

Panel C provides a comparable analysis for momentum–sorted portfolios. Explanatory power is similar to Panels A and B and the same factors (MYP, DSV, STS and OIL) are statistically significant for at least some of the portfolios. DSV betas decline almost monotonically with momentum, and the differences of coefficients across portfolios are statistically significant. Similarly, the STS betas become more negative as momentum increases and again differences are highly significant. There are no other significant beta differences across momentum portfolios. Indeed, the evidence suggests that the MYP and ATS betas have non–linear, U–shaped patterns across momentum sorted portfolios.

Overall, the results in Panels A to C of Table 4 suggest that the FF and C model factors are derived from firm characteristics associated with large spreads in exposures to macroeconomic factors. However, these characteristics are themselves correlated. For example, because the denominator of book–to–market depends on market value, larger firms tend to have lower book–to–market values (Fama and French, 1993). Similarly, momentum is correlated with firm size, because high (low) momentum firms have experienced relative stock price appreciation (decline). Since firm characteristics are correlated, Fama and French (1993) employ two–way sorts on market value and book–to–market in forming the benchmark portfolios used to construct benchmark factors. We follow similar procedures here and create portfolios that allow one firm characteristic to vary, while holding the other characteristics constant. Two–way sorted book–to–market and size benchmark portfolios ensure that HML and SMB are (approximately) orthogonal. Similarly, three–way sorted book–to–market, size, and momentum benchmark portfolios ensure that HML, SMB, and WML are (approximately) orthogonal. We then examine the risk exposures of these benchmark factors. The estimated betas are a better reflection of the "true" risk exposures associated with the characteristics.

Panel D of Table 4 reports the risk exposures of our three–way sorted benchmark portfolios and the derived factor portfolios. In the vast majority of cases, the risk exposures are consistent with findings in Panels A–C, but generally the picture that emerges is sharper. There are some important differences between our results and those obtained from less comprehensive macroeconomic factor models in the prior literature.[19]

Consistent with Panel A of Table 4, HML is significantly negatively related to MYP, confirming that growth stocks have higher exposure to economic growth risk than value stocks (see Section 2.2). We also find some evidence of HML exposure to other factors that does not show up in the one–way sorted book–to–market portfolios, i.e. HML is weakly positively associated with UI and weakly

[19] For comparative purposes, we also analyze the Fama and French (1993) benchmark factors and find that the beta estimates from using the original Fama and French (1993) benchmark factors based on two–way sorts do not differ dramatically from the parameter estimates obtained from our benchmark factors.

negatively associated with ATS (both at the 10 percent significance level). It is interesting to compare these results with prior research. First, the negative beta on MYP is especially noteworthy. This result contrasts with Liew and Vassalou (2000) and Kelly (2004). Using research designs with reversed causality and only the market portfolio as additional factor, they report that future GDP growth is *positively* related to HML. We believe that this result arises, because these studies do not control for simultaneous term structure innovations which are highly correlated with MYP (see Table 3).[20] Consistent with this explanation, when we drop the term structure variables from our set of pricing factors (and control for the excess market return — as they do), we obtain a positive and significant association. While the HML beta on ATS is only weakly significant, the beta on STS is positive and significant, reflecting the higher negative exposure of growth stocks to changes in the slope of the term structure, as predicted in Section 2.2. Similar results for term structure innovations are reported by Petkova (2005), although she does not control for innovations in economic growth expectations.

It is also interesting to note that while all but one benchmark portfolio have significant betas on DSV, the DSV beta for HML is insignificant. In other words, after controlling for other macroeconomic factors, HML is not directly associated with default risk. This finding corroborates results in Hahn and Lee (2005), who control only for term structure slope risk, but it is contrary to conjectures in Fama and French (1996) and is inconsistent with Vassalou and Xing (2004), who show that in a bivariate regression HML is *negatively* associated with DSV. However, Vassalou and Xing (2004) do not control for simultaneous innovations in other macroeconomic factors. Table 3 indicates that MYP is positively correlated with DSV. When we drop MYP from our model, the coefficient on DSV becomes negative and significant, with a t–statistic slightly above 2, which is consistent with Vassalou and Xing (2004).

The results for the SMB benchmark factor regression in Panel D of Table 4 also contain interesting insights to the multivariate relation between SMB and the macroeconomic factors. Generally, the same factors for which the one–way size–sorted portfolios display spreads in betas in Panel B are also significantly associated with SMB, i.e. DSV, ATS, STS and FX, and the signs of the betas are consistent.[21] The finding that SMB is positively related to DSV is consistent with small capitalization

[20] Specifically, the correlation of MYP with ATS is -0.659 and with STS is 0.432.

[21] Note that SMB is based on a hedge portfolios comprising long positions in small stocks and short positions in big stocks, whereas the differences in betas tested in Table 4, Panel B relate to the differences between big stock betas (e.g., portfolio 10) and small stocks (e.g., portfolio 1).

stocks having higher exposure to default risk, as conjectured by Fama and French (1996) and consistent with the univariate regression results in Vassalou and Xing (2004) and findings in Hahn and Lee (2005), who control only for changes in the term spread (equivalent to our STS variable). Thus, we are able to confirm that the association between SMB and changes in default risk reported in prior research is robust to inclusion of other correlated macroeconomic factors. In other words, default risk appears to be a fundamental factor underlying SMB and not a proxy for another factor.

The significance of the ATS and STS betas in the SMB regression indicates that small firm returns are more sensitive to interest rate changes than large firm returns.[22] This result contrasts with Petkova (2005), who finds that betas on innovations in the term structure level and slope are *not* significantly related to SMB. Note, however, that Petkova (2005) does not include MYP (or an alternative economic growth proxy) in the set of macroeconomic factors. If we make our model specification more similar to Petkova (2005), i.e. if we exclude MYP, yet include RM, then we also no longer find evidence that SMB captures term structure effects. The final noteworthy result from the SMB regression is the significance of the FX beta. Again, consistent with the size–sorted portfolio results in Panel B, the individual FX betas on the benchmark portfolios are only in one case marginally significant. Since the small and large market capitalization portfolios, however, exhibit opposite signs on the FX betas, we still find a strongly significant relationship between FX and SMB.

The WML regression contains further new evidence to the literature. It shows that the momentum factor is strongly negatively associated with changes in the aggregate survival probability (DSV) (t-statistic = 3.54) and with changes in the slope of the term structure (STS) (t-statistic = 3.04). Other macroeconomic factors are not significantly related to the momentum factor. As for book-to-market and size portfolios, results are consistent with the analysis of one–way sorted momentum portfolios in Panel C.

Overall, our findings provide convincing evidence that there are large spreads in the exposures on our macroeconomic factors across the one–way sorted firm characteristic portfolios, and also that these spreads are reflected in the benchmark factors of the FF and C models. It thus seems that the book–to–market, market capitalization, and momentum characteristics are parsimonious summary measures

[22]Notice that the ATS beta is positive (but not significantly different from zero) for *all* benchmark portfolios, i.e. controlling for other factors, an increase in the level of interest rates is associated with positive stock returns.

of exposures to macroeconomic risk factors, which would be difficult to estimate directly at the firm level. The results also suggest that the FF and C models capture information on the macroeconomic risk factors in our model. We consider whether the FF and C models capture additional information beyond the MF model factors, or vice versa, in Section 4.4.

We also obtain evidence that some of the conclusions of prior research on the association between the FF factors and our macroeconomic factors are sensitive to the specification of the model tested. In three cases, our results show that the sign of beta estimates can be reversed or that previously significant associations can turn out to be indistinguishable from zero. The evidence suggests that correlations between the macroeconomic factors account for these results. In other words, beta estimates are vulnerable to specification problems of correlated omitted variables. Of course, while we include a large set of theoretically motivated macroeconomic factors, we acknowledge that it is possible that our own model is similarly incomplete and thus vulnerable.

4.2 Unconditional pricing ability of models

Since the identification of significant betas for macroeconomic variables does not imply that these factors are priced, we now turn to an examination of whether the MF model factors are associated with statistically significant risk premia in the cross–section of equity returns. We use the stochastic discount factor/GMM methodology to examine the relative pricing performance of the MF model, the augmented MF model (AMF) (which includes an orthogonalized market portfolio, see Section 2), the FF and the C model (see Cochrane, 2001).[23] We estimate both unconditional and conditional versions of the pricing models. The tests are based on two sets of assets: 25 two–way sorted portfolios based on book–to–market and size; and 60 three–way sorted portfolios based on book–to–market, size, and momentum.[24] We include results based on the smaller set of test assets to enable more direct comparisons with prior literature. The second set of test assets is expected to yield more powerful results, because test assets exhibit a larger spread in expected returns and because the sample size is larger. Therefore, our discussion centers mainly on the findings for the 60 portfolios.

[23]This methodology enables us to easily avoid or correct 'generated regressor' biases, which would make the standard errors unreliable. Appendix B contains more details on the GMM methodology.

[24]We lose four of the sixty–four three–way sorted portfolios due to missing data in the early sample period.

Table 5 reports the cross–sectional pricing tests of the unconditional versions of the MF model, the AMF model, the FF model, and the C model. Panel A examines the 25 two–way sorted test assets, while Panel B investigates the 60 three–way sorted test assets. In both Panels, we first show the explanatory power of the model factors for the stochastic discount factor. Significant coefficients indicate that a factor helps to price assets given the other factors. The results below the factor loadings are the estimated risk premia that indicate whether a factor is priced. Note that the significance of factor loadings on the stochastic discount factor and the significance of estimated risk premia will be consistent only if the pricing factors are orthogonal to one another (see Cochrane, 2001, pp. 260–262). This is approximately true for the FF model and the C model, but not for the MF model. To evaluate the performance of the individual models, we also report Hansen's (1982) J–test and the adjusted R–Square from a regression of expected returns on risk exposures (see Appendix B).

Results for the two versions of the MF model in Panels A and B of Table 5 indicate that the models are relatively successful in pricing the test assets. Several macroeconomic factors load significantly on the stochastic discount factor, estimated risk premia are strongly significant, and the J–tests fails to reject the models at all conventional levels. Results based on the 25 benchmark portfolios indicate that MYP, DSV, and FX are significantly associated with the stochastic discount factor. However, only STS (at the ten percent level) and FX obtain significant risk premia. When we use the 60 benchmark portfolios as test assets, stochastic discount factor results are qualitatively similar, with the exception that the loading of UI on the stochastic discount factor now turns significant. However, we find that in addition to FX, both STS and UI now have highly significant risk premia. The premium on MYP is now significant at the ten percent level. Note that for the AMF model neither the loading on the stochastic discount factor nor the risk premium on RM* are significant at conventional levels.

These results confirm and extend the recent results reported in Petkova (2005). First, Petkova (2005) finds that, while spreads in default risk betas may be significant, default risk is not priced. Our results based on a different default risk proxy, i.e. the change in the aggregate survival probability, are only slightly better; the premium on DSV is close to significant at the 10 percent level. Petkova (2005) also finds that innovations in the term structure command a significant risk premium, which is consistent with the results for our STS variable. In contrast, while Petkova (2005) also reports significance for innovations in the T-bill yield, the related evidence from our ATS variable does not support this result. Interestingly, unreported results show that the inclusion of U.S. exchange rate risk, a factor which obtains a highly significant risk premium in our model, renders the risk premium on ATS insignificant. Finally, Petkova (2005) shows that when a proxy for innovations in economic growth expectations (derived using a similar tracking portfolio approach) is added to her model, the growth proxy does not command a significant risk premium. Nevertheless, our model indicates that, while information on MYP is contained in the term structure innovation STS (i.e. MYP and STS are highly correlated), STS does not simply serve as a proxy for economic growth, as the risk premium on MYP is marginally significant.

Our results extend the analysis of Petkova (2005), because our MF model spans a broader set of macroeconomic pricing factors considered by the prior literature. Our analysis shows that inflation innovations (UI) and exchange rate innovations (FX) are important additional pricing factors. In particular, if we jointly drop these two factors from the macroeconomic pricing model, we observe sharp increases (decreases) in the J–test statistics (R^2s) and the fit of the models worsens markedly.

In order to examine whether the FF and C models contain additional information for asset pricing beyond the MF models, or vice versa, we first examine the relative pricing ability of these models for our test assets. Subsequently, we examine the incremental pricing ability of the FF and C factors beyond the MF model factors. Panel A of Table 5 shows that the FF model does a good job in pricing the 25 benchmark portfolios. The market portfolio and HML load significantly on the stochastic discount factor, the risk premia on the same factors are strongly significant, and the J–test fails to reject the model at all conventional levels. Around 50% of the variation in expected returns is captured by variation in the FF risk exposures. The FF model is slightly more successful than the MF models based on adjusted R^2 statistics. Consistent with Petkova (2005) and others, SMB does not appear to be a priced risk factor. In the tests based on the 60 benchmark portfolios, factor loadings and risk premia are consistent with the results based on the smaller set of test assets. However, the explanatory power of the FF model is considerably lower than for the MF models for this expanded set of test assets.

The FF model is nested by the C model, which contains the additional pricing factor WML. This factor ensures that the C model prices momentum–sorted portfolios more successfully. Thus, results in Panel A and B of Table 5 indicate that the estimated risk premia of the FF factors are consistent with the FF model estimates, but that WML also loads significantly and commands a significant risk premium. Based on adjusted R^2 statistics, the C model slightly outperforms the FF model in pricing the 25 benchmark portfolios and dramatically outperforms the FF model in pricing the 60 benchmark portfolios. This is to be expected given that the expanded set of test assets is also sorted on momentum. The striking increase in fit of the C model can also be seen from Figure 1, which plots the pricing performance of all four models.

4.3 Conditional pricing ability of models

Table 6 reports the results from the cross–sectional tests of the two versions of the MF model, the FF and the C model, using 36 conditional (managed) portfolios, i.e. the eight (2x2x2) unconditional size, book–to–market, and momentum benchmark portfolios multiplied with in turn a vector of ones, the dividend yield on the S&P500 index, the yield spread between Aaa and Baa–rated corporate bond portfolios, and, finally, the yield spread between long–term and short–term government bonds, all instruments lagged by two periods. We ensure that the scale of the individual test portfolios is approximately equal by subtracting 0.04 from the dividend yield, and multiplying all instruments by 100 (see Cochrane, 1996, p. 588).

The MF model clearly outperforms the FF and C models in pricing the 36 conditional benchmark portfolios. The significant loadings on the stochastic discount factor do not differ vastly from the unconditional setting, except for UI. Moreover, all risk premia (with the same exception as before) remain close to the unconditional values. The larger spread in expected returns on the conditional assets, however, strongly increases the power of the tests. We thus find now significant risk premia on changes in economic growth expectations, the aggregate survival probability, the average level and the slope of the term structure, and the exchange rate. All of the above provides robustness for our previous findings. The superior fit of the MF model can also be seen in Figure 2 or from the adjusted R^2 of nearly 80%. Augmenting the MF model with RM* does not lead to any improvement over the original model.

Results for the FF and C models are in line with the unconditional tests in Table 5, insofar as the market portfolio, HML and WML attract significant risk premia. Notwithstanding these findings, the FF model still prices the conditional three–way sorted portfolios far more efficiently than the unconditional ones, i.e. around 50% of the expected return variation can be captured by the risk exposures and the J–test fails to reject the model. The increased fit can also be seen from Figure 2. The C model, on the other hand, shows a comparable ability to price the managed portfolios as it did for the unconditional two–way or three–way sorted portfolios.

As a last step, we would like to allow the stochastic discount factor to depend on conditional information, too. We thus multiply the pricing factors of each model by a vector of ones and the two–times lagged dividend yield on the S&P500 index. We use the dividend yield as the only instrumental variable, since its realizations can be easily interpreted in terms of business conditions. For example, as the dividend yield is approximately equal to the level of expected returns (see Fama and French, 1988), and high expected return levels imply depressed prices, a high dividend yield entails a recession state of nature, and vice versa. Finally, note that after scaling the models' pricing factors by the instrumental variables, we can no longer compute the factor risk premia (Lettau and Ludvigson, 2001). Table 7 reports the results of the cross–sectional tests with conditional test assets and scaled pricing factors.

The results on the MF model are mixed, i.e. at the 10% significance level, UI, DSV, and FX show time–invariant loadings on the stochastic discount factor. While MYP, ATS, and OIL do not associate significantly with the pricing kernel, STS varies significantly with the business cycle. In particular, when the dividend yield increases (when the economy moves into a recession), the stochastic discount factor relates more positively with changes in the slope of the term structure. The J–test fails to reject the model at all conventional significance levels. Our conclusions are not materially altered if we add the orthogonalized market portfolio to the macroeconomic pricing factors. Note that the orthogonalized market portfolio again fails to relate to the stochastic discount factor. The good fit of the two models can be seen from Figure 3.

The loadings of the FF pricing factors on the stochastic discount factor show significant signs of time–variation. In particular, moving into a recession state of nature, the pricing kernel relates significantly more negatively with RM and HML, yet more positively with SMB. In contrast to our former findings, SMB plays now a significant role in pricing the test assets. From Figure 3, we see that the scaling of the factors has improved the performance of the FF model. Lastly, the J–test cannot reject the model. The findings on the C model are in line with those of the FF model, yet now also WML shows signs of time–variation in its loading on the stochastic discount factor, i.e. when the dividend yield increases, the stochastic discount factor associates more negatively with WML. Figure 3 indicates that the scaling of the factors also improves the fit of the C model. As before, the J–test cannot reject the model.

4.4 Incremental pricing ability of models

In Table 8, we report comparative statistics on the asset pricing models tested in Tables 5, 6, and 7. Starting with the unconditional tests, we see that for all models, the loadings on the stochastic discount factor of the models' pricing factors are jointly significant. If added to the MF factors, the risk premia on HML and SMB are still jointly significant, based on the smaller set of 25 benchmark portfolios, yet they are not jointly significant based on the 60 benchmark portfolios. On the other hand, if added to the MF model factors, the risk premia on HML, SMB, and WML are always jointly significant when examining the 60 benchmark portfolios. This indicates that models containing 'asset' pricing factors usually relate more strongly to expected returns than macroeconomic data models. The parsimonious way in which the FF and the C model summarize macroeconomic risk factors might well be seen as one of the major advantages of these models. Nonetheless, the HJ–distance rejects all four models at all conventional significance levels.

Turning to the conditional models with non–scaled pricing factors, we find that the loadings on the stochastic discount factor of all four models are again jointly strongly significant. Adding HML and SMB to the pricing factors of the MF model, we see that the risk premia on the added spread portfolios obtain joint significance at the 5% significance level, yet not at the 1% significance level. If we instead add HML, SMB, and WML to the macroeconomic pricing factors, we can reject the joint insignificance of the risk premia of these factors at all conventional levels. While the stochastic discount factor specified by the MF model is the least far away from one true stochastic discount factor, unfortunately, the HJ–distance rejects again all models. The final column reports the comparative statistics on the scaled factor models. Again, the loadings on the pricing kernel are jointly significant for all models. Our findings furthermore show that we cannot reject time–variation in the pricing factors of the two versions of the MF model, the FF and the C model at the 5% significance level. At the 1% level, however, the loadings on the stochastic discount factor of the MF model do not exhibit significant time–variation. While scaling the pricing factors of the models by the two–times lagged dividend yield does help to lower the HJ–distances, all of them are still strongly significant, and thus again reject the models.

5 Conclusion

While the unconditional Fama and French (FF) and Carhart (C) model are empirical successes (Fama and French, 2004, 1997, 1996), the economic rationales underlying SMB, HML, and WML are still not completely resolved. As a result, this paper pursues an attempt to link the FF and C benchmark factors to innovations in the investment opportunity set. Based on valuation theory, we conjecture that the book–to–market, size, and momentum properties of stocks systematically reflect their exposure to changes in investors' economic growth expectations, unexpected inflation, the aggregate survival probability, the term structure, the U.S. dollar exchange rate, and raw material prices. In a similar vein, recent related work indicates that book–to–market and size are associated with changes in economic growth expectations (Kelly, 2004; Vassalou, 2003; Liew and Vassalou, 2000), default risk (Hahn and Lee, 2005; Petkova, 2005; He and Ng, 1994; Vassalou and Xing, 2004), the term structure of risk–free interest rates (Hahn and Lee, 2005; Petkova, 2005), and inflation (Kelly, 2004).

We extend this literature by clarifying the fundamental roles played by the correlated macroeconomic factors examined in prior research, as well as by assessing the role of other factors that have not been related to HML and SMB. We include the momentum factor and its underlying benchmark portfolios in our analysis, since the prior literature does not contain evidence that WML serves as a proxy for fundamental state variable(s) (or risk factors). Moreover, we identify the incremental information contained in the market portfolio, after controlling for the selected macroeconomic fundamentals. In our asset pricing tests, we estimate the risk premia associated with these macroeconomic fundamentals, using both unconditional and conditional pricing tests, and assess the pricing ability of a macroeconomic factor model relative to the FF and the C model.

Based on U.S. data, we find the following:

1. HML is significantly associated with with changes in economic growth expectations, unexpected

inflation, the average level and the slope of the term structure, and – for two–way sorted benchmark portfolios – the exchange rate.

2. SMB picks up changes in the aggregate survival probability, the average level and the slope of the term structure, and the exchange rate.

3. WML strongly reflects changes in the aggregate survival probability and the slope of the term structure.

Unconditional cross–sectional tests show that shocks to investors' economic growth expectations (weak support), unexpected inflation, the slope of the term structure, and the U.S. dollar exchange rate are priced. In comparison with the FF model and the C model, the MF model exhibits a nearly identical fit for the 25 two–way sorted benchmark portfolios. While it cannot compete with the C model on the 60 three–way sorted portfolios, the MF model clearly outperforms the FF model for these test assets. Using conditional test portfolios, we find that the MF model is superior to both the FF model and the C model, while the loadings on the stochastic discount factor, the risk premia, and the significance levels do not change materially.

Our results have implications for long term investors (e.g. pension funds) seeking to hedge liabilities with macroeconomic risk exposures through the equities markets. Our results suggest that style–based equity investment strategies are associated with fundamentally different macroeconomic risk exposures. If the value of an investor's liabilities depends on the macroeconomic factors considered here, style investing can have a dramatic impact on whether an equity portfolio provides a hedge against, or exacerbates, such risks.

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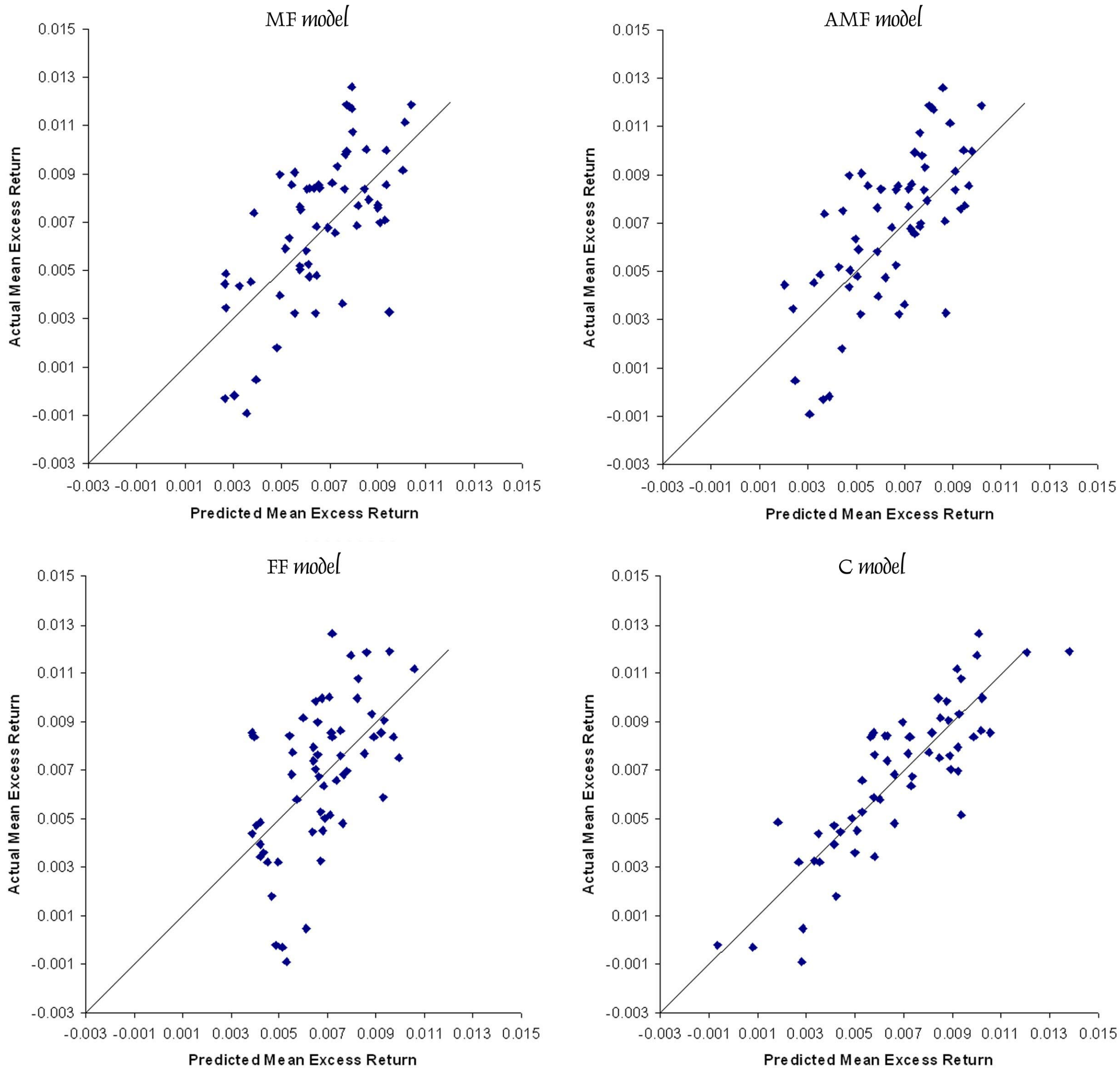

Figure 1: These figures show the predicted versus the actual mean excess return of the 60 three–way sorted size, book–to–market, and momentum portfolios for the macroeconomic factor model (top left), the augmented macroeconomic factor model (top right), the 3–factor Fama and French model (bottom left), and the 4–factor Carhart model (bottom right).

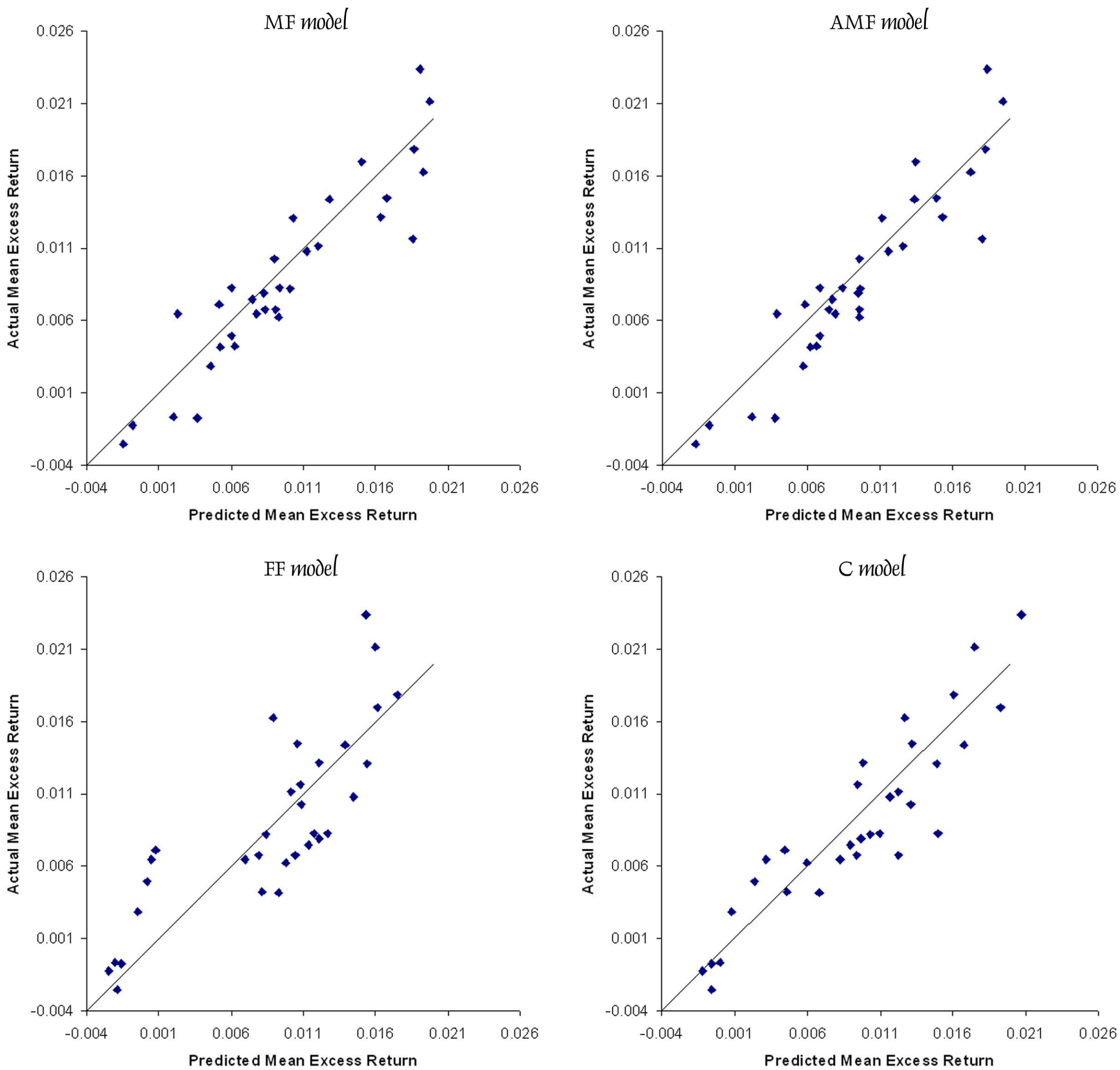

Figure 2: These figures show the predicted versus the actual mean excess return of the 36 conditional three–way sorted size, book–to–market, and momentum portfolios for the macroeconomic factor model (top left), the augmented macroeconomic factor model (top right), the 3–factor Fama and French model (bottom left), and the 4–factor Carhart model (bottom right).

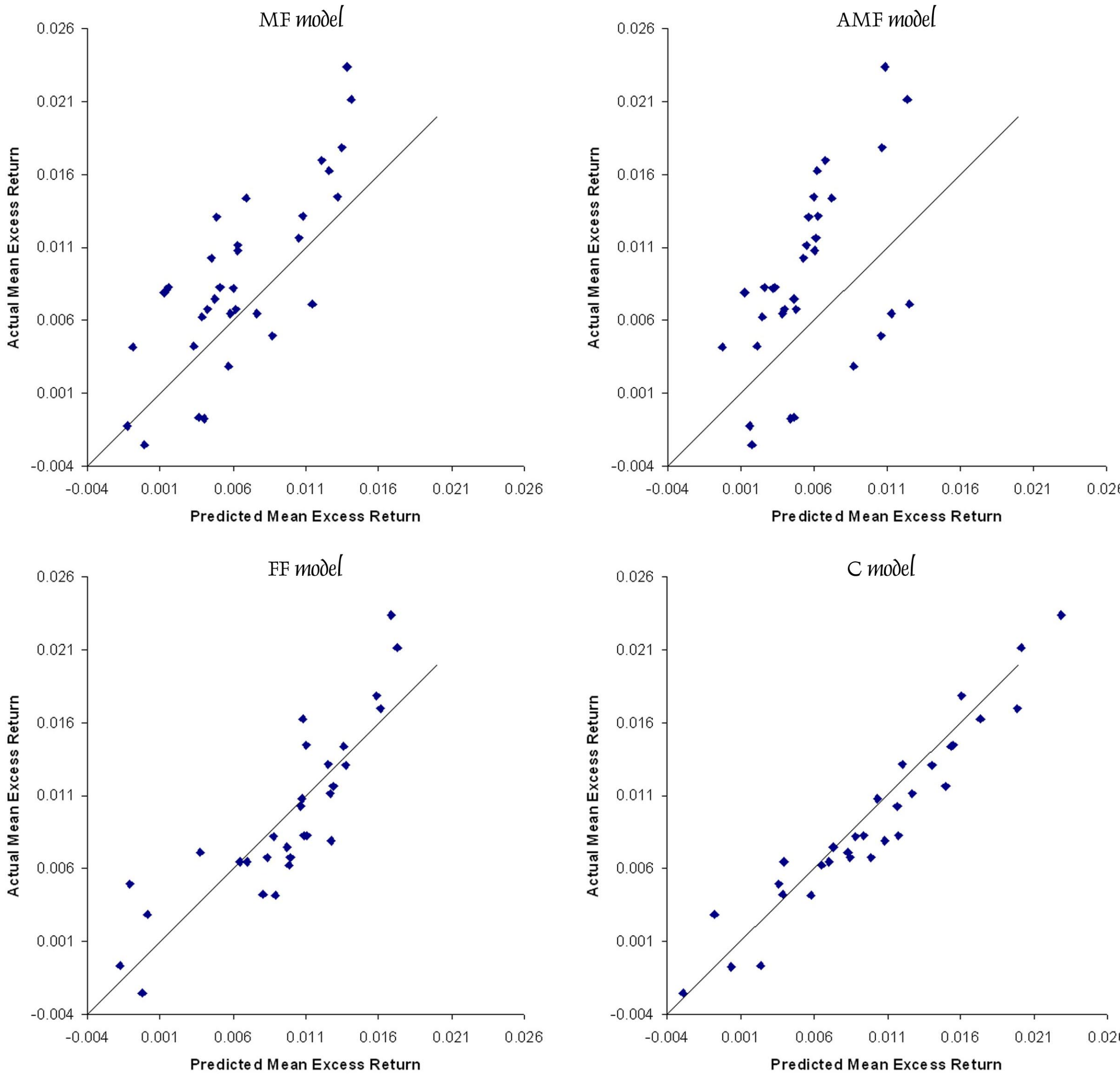

Figure 3: These figures show the predicted versus the actual mean excess return of the 36 conditional three–way sorted size, book–to–market, and momentum portfolios for the scaled macroeconomic factor model (top left), the scaled augmented macroeconomic factor model (top right), the scaled 3–factor Fama and French model (bottom left), and the scaled 4–factor Carhart model (bottom right).

Table 1: Previous work on the association between HML/SMB and macroeconomic fundamentals[a]

Paper (year of publication and journal)	Data	Risk premia estimated	Dependent variable	Independent variables							
				RM	HML	SMB	GDP/IP growth	Term level	Term slope	Default	Other
Petkova (2005, JF *forthcoming)*	Monthly data 1963-2001	yes	HML	-				N/S	+	N/S	DivYield N/S
			SMB	+				N/S	N/S	-	DivYield N/S
Hahn & Lee (2005, JFQA *forthcoming)*	Monthly data 1963-2001	yes	HML	-					+	N/S	
			SMB	+					N/S	-	
Kelly (2004, WP)	Annual data 1956-2001	no	Real GDP growth	+	+	+					
			Inflation	-	N/S	-					
Vassalou and Xing (2004, JF)	Monthly data 1971-1999	yes	HML							+	
			SMB							-	
Vassalou (2003, JFE)	Quarterly data 1953-1998	yes	HML				+				
			SMB				+				
Liew & Vassalou (2000, JFE)	Quarterly data 1978-1996	no	Nominal GDP growth	+	+	+					

[a] This table provides an overview of previous studies relating the Fama–and–French benchmark portfolios and/or factors to macroeconomic fundamentals. The column labelled as "Paper (year of publication and journal)" indicates the name(s) of the study's author(s), the year of publication, and the title of the journal. "Data" describes the frequency of the data studied and the sample period, whereas "Risk premia estimated" indicates whether the study uses cross–sectional tests to estimate the risk premia on the studied pricing factors. The remaining columns, which are the main part of the table, form a matrix with the "Dependent variables" analyzed in the individual studies on the vertical axis and the corresponding "Independent variables" on the horizontal axis. A + sign in this matrix indicates a significant multivariate positive relationship between the associated dependent and independent variable, while a − sign indicates a negative relationship. *N/S* stands for "not significant" associations. It is important to realize that Vassalou and Xing (2004) use innovations in the aggregate survival probability rather than innovations in default risk. To make their results comparable to the other studies, we switch the signs on their findings in this table, i.e. a positive association between innovations in the aggregate survival probability and SMB in their paper is reported in this table as a negative association between innovations in default risk and SMB. JF stands for the *Journal of Finance*, JFE for the *Journal of Financial Economics*, and JFQA for the *Journal of Financial and Quantitative Analysis*. Finally, WP represents a working paper.

Table 2: Estimation of the mimicking portfolio for industrial production growth[a]

Panel A: Parameter estimates

	Parms	t-statistic	Parms	t-statistic	Parms	t-statistic
Base assets						
Market portfolio excess return $(RM)_{t-1,t}$	**0.09**	[2.60]	**0.09**	[2.58]	**-0.05**	[1.25]
Baa minus Aaa (default) bond portfolio $\text{return}_{t-1,t}$	**-0.15**	[1.95]	**-0.17**	[1.93]	**-0.12**	[1.33]
Longterm government bond excess $\text{return}_{t-1,t}$	**0.05**	[0.29]	**0.11**	[0.56]	**0.24**	[1.31]
Medium–term government bond excess $\text{return}_{t-1,t}$	**1.30**	[3.52]	**1.26**	[3.46]	**0.99**	[2.24]
1-year government bond excess $\text{return}_{t-1,t}$	**0.01**	[0.05]	**0.01**	[0.10]	**0.04**	[0.43]
Control variables						
Intercept	**0.05**	[2.99]	**0.05**	[2.92]	**0.06**	[3.54]
$RF_{t-1,t}$	**-18.15**	[7.67]	**-18.02**	[7.49]	**-20.50**	[7.24]
10 year minus 3 month government bond yield_{t-1}	**-0.61**	[1.50]	**-0.57**	[1.32]	**-0.88**	[2.12]
1 year minus 3 month government bond yield_{t-1}	**1.51**	[3.27]	**1.33**	[1.87]	**1.20**	[2.72]
Baa minus Aaa corporate bond yield_{t-1}	**4.47**	[4.57]	**4.48**	[4.66]	**4.76**	[4.11]
Dividend yield_{t-1}	**0.74**	[1.00]	**0.75**	[0.98]	**1.25**	[1.76]
Production $\text{growth}_{t-13,t-1}$	**0.07**	[0.87]	**0.07**	[0.95]	**0.05**	[0.75]
$\text{Inflation}_{t-13,t-1}$	**-0.34**	[1.72]	**-0.34**	[1.71]	**-0.57**	[2.41]
Market portfolio excess return $(RM)_{t-13,t-1}$	**0.11**	[5.80]	**0.11**	[5.85]	**0.02**	[0.64]
1-month lagged base asset returns		no		yes		no
1-year lagged (compounded) base asset returns		no		no		yes
Adjusted R-Square		68.79%		68.52%		70.79%
Adjusted R-Square (base assets only)		4.98%		4.98%		4.98%
Lower bound adjusted R-Square		6.22%		6.32%		5.59%

Panel B: Exclusion tests

	F-Stat	p-value	F-Stat	p-value	F-Stat	p-value
All base assets	4.26	*(0.00)*	4.27	*(0.00)*	3.75	*(0.00)*
All base assets except the market portfolio	3.19	*(0.01)*	3.32	*(0.01)*	4.68	*(0.00)*
All government bond returns	3.66	*(0.01)*	3.80	*(0.01)*	4.70	*(0.00)*

[a] The table shows the OLS–estimations of the log–change in industrial production over the next year regressed on a set of base assets' excess returns and a set of lagged control variables (Panel A). Our base assets consist out of the return on the market portfolio, on a default bond portfolio, and on three government bond portfolios. All base asset returns (except the second) are in excess of the risk–free rate of return. We control for the expected level of returns by including a set of lagged control variables, such as the risk–free rate, the yield spread between long–term and short–term government bonds, the yield spread between one–year and short–term government bonds, the yield spread between Baa–rated and Aaa–rated corporate bonds, and the dividend yield on the S&P500. We also include industrial production growth, inflation, and excess market returns compounded over the last year. The specifications in column (2) and (3) add to the former variables the one–month or one–year lagged base assets' excess returns. Since realized industrial production growth has an overlap with its lagged value of eleven months, we correct for heteroskedasticity and autocorrelation using the Newey and West (1987) correction with $l = 11$. To measure how well the set of base assets captures changes in industrial production over the next year, we compute the adjusted R^2s for all three specifications with and without control variables. The lower–bound adjusted R^2s from the regression of changes in industrial production growth expectations on unexpected stock returns is computed according to Lamont (2001). In particular, we first regress realized industrial production growth onto our control variables. Subsequently, we regress the mimicking portfolio return onto our control variables. Finally, regressing the residuals from the former regression onto the residuals from the latter regression we obtain the lower–bound adjusted R^2. The F-statistics in Panel B test the hypothesis that a subset of the parameter estimates is zero. The sample period extends from February 1971 to December 1998.

Table 3: Summary statistics and cross–correlations[a]

Panel A: Summary statistics

Variable symbol	Mean ($x10^3$)	Median ($x10^3$)	StDev ($x10^3$)	Skew	Kurt	Min ($x10^3$)	Max ($x10^3$)
MYP	1.83	1.64	6.84	0.59	8.09	-26.44	40.66
UI	-0.04	-0.08	2.23	0.30	8.35	-9.76	13.61
DSV	0.00	0.22	10.19	0.12	15.99	-58.17	61.01
ATS	-0.02	0.10	4.54	-0.98	10.62	-28.65	18.00
STS	-0.05	-0.30	4.91	0.91	8.57	-18.30	26.40
FX	-0.77	-0.30	22.25	-0.20	4.06	-85.80	60.00
OIL	0.78	0.64	13.76	1.20	10.17	-46.16	80.50

Panel B: Correlations

	HML	SMB	WML	RM	MYP	UI	DSV	ATS	STS	FX	OIL
MYP	-0.16	0.16	-0.08	0.65							
UI	0.16	-0.13	0.03	-0.23	-0.21						
DSV	-0.20	0.44	-0.28	0.57	0.32	-0.22					
ATS	-0.09	0.10	0.04	-0.18	-0.66	0.15	0.02				
STS	0.22	0.07	-0.19	-0.12	0.43	-0.02	-0.05	-0.50			
FX	0.07	0.09	-0.02	-0.07	-0.10	0.02	-0.04	0.11	-0.06		
OIL	0.04	0.03	-0.05	-0.11	-0.04	0.25	0.03	0.07	0.03	-0.14	
BM decile 1 (low)	-0.59	0.15	0.11	0.93	0.57	-0.23	0.50	-0.12	-0.20	-0.10	-0.12
BM decile 2	-0.48	0.20	0.05	0.97	0.63	-0.24	0.55	-0.17	-0.11	-0.08	-0.13
BM decile 3	-0.40	0.21	0.02	0.96	0.63	-0.23	0.57	-0.17	-0.11	-0.06	-0.11
BM decile 4	-0.31	0.21	-0.01	0.94	0.59	-0.20	0.54	-0.17	-0.07	-0.06	-0.07
BM decile 5	-0.30	0.17	0.07	0.94	0.58	-0.18	0.48	-0.16	-0.11	-0.06	-0.05
BM decile 6	-0.21	0.21	-0.04	0.93	0.61	-0.19	0.54	-0.19	-0.08	-0.09	-0.07
BM decile 7	-0.14	0.19	-0.12	0.90	0.62	-0.24	0.53	-0.25	-0.02	-0.04	-0.11
BM decile 8	-0.11	0.25	-0.12	0.91	0.63	-0.19	0.58	-0.20	-0.02	-0.04	-0.09
BM decile 9	-0.05	0.28	-0.12	0.88	0.59	-0.19	0.55	-0.17	-0.03	-0.03	-0.13
BM decile 10 (high)	-0.02	0.39	-0.10	0.84	0.57	-0.20	0.56	-0.13	-0.01	-0.04	-0.07
Size decile 1 (small)	-0.24	0.70	-0.14	0.80	0.53	-0.22	0.67	-0.06	-0.02	0.00	-0.06
Size decile 2	-0.30	0.62	-0.10	0.87	0.59	-0.25	0.67	-0.12	-0.02	-0.02	-0.09
Size decile 3	-0.33	0.57	-0.09	0.90	0.60	-0.24	0.65	-0.13	-0.04	-0.03	-0.08
Size decile 4	-0.34	0.54	-0.07	0.91	0.61	-0.25	0.64	-0.15	-0.03	-0.04	-0.09
Size decile 5	-0.34	0.49	-0.06	0.92	0.62	-0.26	0.63	-0.15	-0.03	-0.03	-0.11
Size decile 6	-0.34	0.44	-0.05	0.94	0.64	-0.26	0.61	-0.17	-0.04	-0.05	-0.11
Size decile 7	-0.36	0.38	-0.03	0.96	0.65	-0.25	0.61	-0.19	-0.04	-0.08	-0.09
Size decile 8	-0.34	0.30	-0.02	0.97	0.67	-0.24	0.60	-0.20	-0.05	-0.07	-0.10
Size decile 9	-0.36	0.20	0.01	0.98	0.65	-0.23	0.56	-0.21	-0.09	-0.07	-0.10
Size decile 10 (big)	-0.42	0.03	0.07	0.97	0.59	-0.20	0.50	-0.15	-0.17	-0.09	-0.10
Momentum decile 1 (low)	-0.33	0.38	-0.34	0.86	0.60	-0.22	0.67	-0.13	0.00	-0.06	-0.04
Momentum decile 2	-0.31	0.26	-0.31	0.89	0.61	-0.23	0.63	-0.14	-0.05	-0.04	-0.09
Momentum decile 3	-0.27	0.20	-0.32	0.90	0.61	-0.24	0.64	-0.17	-0.06	-0.05	-0.09
Momentum decile 4	-0.31	0.18	-0.20	0.93	0.64	-0.26	0.59	-0.21	-0.07	-0.07	-0.10
Momentum decile 5	-0.34	0.15	-0.12	0.93	0.61	-0.24	0.60	-0.19	-0.14	-0.06	-0.12
Momentum decile 6	-0.36	0.17	-0.05	0.95	0.62	-0.23	0.59	-0.19	-0.13	-0.06	-0.11
Momentum decile 7	-0.38	0.18	0.06	0.96	0.63	-0.25	0.54	-0.19	-0.13	-0.07	-0.10
Momentum decile 8	-0.39	0.18	0.21	0.94	0.59	-0.20	0.48	-0.14	-0.14	-0.10	-0.08
Momentum decile 9	-0.41	0.19	0.26	0.94	0.57	-0.21	0.49	-0.12	-0.13	-0.08	-0.11
Momentum decile 10 (high)	-0.45	0.27	0.29	0.90	0.54	-0.20	0.48	-0.12	-0.13	-0.08	-0.12

[a] Panel A shows the mean, the median, the standard deviation, skewness, kurtosis, the minimum, and the maximum for all regressors used in the analysis, i.e. the factor–mimicking portfolio on industrial production growth (MYP), unexpected inflation (UI), changes in the survival probability (default risk) (DSV), changes in the average level of the term structure of risk–free interest rate yields (ATS), changes in the slope of the term structure of risk–free interest yields (STS), changes in the exchange rate between the U.S. dollar and a trade–weighted composite currency (FX), and, finally, changes in the price of raw materials (OIL). Panel B provides the cross–correlations between our set of macroeconomic pricing factors, the benchmark factors, i.e. HML, SMB, and WML, and the one–way sorted book–to–market, size, and momentum benchmark portfolios. The sample period extends from February 1971 to December 1998.

Table 4: Macroeconomic risk exposures[a]

Panel A: One way–sorted book–to–market (BM) benchmark portfolios

Dependent variable		Independent variables								Adjusted R-Square
		Constant	MYP	UI	DSV	ATS	STS	FX	OIL	
Regression results:										
BM decile 1 (low)	Estimate	**-0.01**	**6.42**	**-0.86**	**1.10**	**2.56**	**-4.68**	**-0.13**	**-0.41**	64.2%
	t–stat	[2.41]	[3.21]	[0.80]	[1.71]	[1.02]	[3.45]	[1.63]	[2.74]	
BM decile 2	Estimate	**0.00**	**5.88**	**-0.62**	**1.22**	**2.21**	**-3.56**	**-0.10**	**-0.43**	67.0%
	t–stat	[1.44]	[3.27]	[0.76]	[1.85]	[0.89]	[2.68]	[1.23]	[3.09]	
BM decile 3	Estimate	**0.00**	**5.81**	**-0.08**	**1.43**	**2.20**	**-3.54**	**-0.06**	**-0.38**	67.2%
	t–stat	[1.44]	[3.31]	[0.09]	[2.01]	[0.88]	[2.63]	[0.83]	[2.56]	
BM decile 4	Estimate	**0.00**	**5.30**	**0.12**	**1.37**	**1.95**	**-2.92**	**-0.03**	**-0.19**	58.4%
	t–stat	[0.99]	[3.21]	[0.13]	[1.84]	[0.81]	[2.19]	[0.41]	[1.25]	
BM decile 5	Estimate	**0.00**	**5.31**	**0.14**	**0.95**	**1.96**	**-3.23**	**-0.01**	**-0.16**	57.2%
	t–stat	[1.41]	[3.30]	[0.16]	[1.24]	[0.80]	[2.50]	[0.17]	[1.07]	
BM decile 6	Estimate	**0.00**	**4.99**	**0.41**	**1.14**	**1.46**	**-3.04**	**-0.02**	**-0.23**	58.9%
	t–stat	[0.70]	[3.29]	[0.45]	[1.56]	[0.65]	[2.45]	[0.38]	[1.82]	
BM decile 7	Estimate	**0.00**	**4.66**	**0.01**	**1.16**	**1.09**	**-2.31**	**0.01**	**-0.27**	57.6%
	t–stat	[0.36]	[3.47]	[0.02]	[1.65]	[0.55]	[2.07]	[0.10]	[1.75]	
BM decile 8	Estimate	**0.00**	**4.50**	**0.27**	**1.43**	**1.19**	**-2.20**	**0.04**	**-0.26**	60.8%
	t–stat	[0.30]	[3.38]	[0.40]	[2.44]	[0.64]	[2.03]	[0.64]	[2.23]	
BM decile 9	Estimate	**0.00**	**4.59**	**0.48**	**1.51**	**1.19**	**-2.08**	**-0.02**	**-0.34**	57.9%
	t–stat	[0.19]	[3.25]	[0.68]	[2.48]	[0.60]	[1.78]	[0.19]	[3.22]	
BM decile 10 (high)	Estimate	**0.00**	**5.12**	**0.51**	**1.77**	**2.01**	**-1.98**	**0.02**	**-0.42**	50.7%
	t–stat	[0.32]	[3.44]	[0.48]	[2.25]	[0.89]	[1.59]	[0.15]	[2.72]	
χ^2–difference test statistics:										
BM decile 10 - BM decile 1	Estimate		**-1.30**	**1.37**	**0.68**	**-0.55**	**2.70**	**0.14**	**-0.01**	
	χ^2–stat		1.21	1.14	2.82	0.21	15.06	1.49	0.00	
	p–value		*(0.27)*	*(0.29)*	*(0.09)*	*(0.65)*	*(0.00)*	*(0.22)*	*(0.95)*	
Mean(BM deciles 10-7) - mean(BM deciles 1-3)	Estimate		**-1.30**	**0.94**	**0.32**	**-0.86**	**1.84**	**0.11**	**0.07**	
	χ^2–stat		2.87	1.37	2.46	1.02	12.02	2.53	0.45	
	p–value		*(0.09)*	*(0.24)*	*(0.12)*	*(0.31)*	*(0.00)*	*(0.11)*	*(0.50)*	
Mean(BM deciles 10-6) - mean(BM deciles 1-5)	Estimate		**-0.97**	**0.59**	**0.19**	**-0.79**	**1.26**	**0.07**	**0.01**	
	χ^2–stat		2.86	1.08	1.30	1.41	9.91	2.56	0.02	
	p–value		*(0.09)*	*(0.30)*	*(0.25)*	*(0.24)*	*(0.00)*	*(0.11)*	*(0.89)*	

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[a] The table shows the results of the regressions of the one–way sorted book–to–market (Panel A), size (Panel B), and momentum (Panel C) benchmark portfolios and of the three–way sorted book–to–market, size, and momentum benchmark portfolios plus the market portfolio and the three–way sorted HML, SMB, and WML benchmark factors (Panel D) on changes in industrial production growth expectations (MYP), contemporaneous, unexpected inflation (UI), changes in the aggregate survival probability (DSV), changes in the average level and the slope of the term structure of risk–free interest rate yields (ATS and STS, respectively), changes in a multilateral U.S. dollar exchange rate (in U.S. dollar per unit of foreign currency) (FX), and changes in the price of raw materials (OIL). Bold numbers are parameter estimates, and the numbers in square brackets are t–statistics. In Panel A, B, and C, the χ^2–tests reported below the regression results check whether the (average) differences in parameter values on the same pricing factor across the one–way sorted portfolios are statistically different. Here, *(continued on next page)*

Table 4: Macroeconomic risk exposures (continued)[a]

Panel B: One way–sorted size benchmark portfolios

Dependent variable		Independent variables								Adjusted R-Square
		Constant	MYP	UI	DSV	ATS	STS	FX	OIL	
Regression results:										
Size decile 1 (low)	Estimate	**0.00**	**5.36**	**-0.37**	**2.67**	**3.77**	**-1.35**	**0.12**	**-0.25**	61.4%
	t–stat	[1.52]	[3.75]	[0.41]	[3.22]	[1.73]	[0.88]	[1.10]	[1.56]	
Size decile 2	Estimate	**-0.01**	**5.99**	**-1.01**	**2.46**	**3.44**	**-1.91**	**0.06**	**-0.33**	66.7%
	t–stat	[1.65]	[3.74]	[1.08]	[2.97]	[1.45]	[1.20]	[0.59]	[1.96]	
Size decile 3	Estimate	**0.00**	**5.96**	**-0.82**	**2.30**	**3.05**	**-2.29**	**0.05**	**-0.28**	65.5%
	t–stat	[1.43]	[3.61]	[0.86]	[2.78]	[1.26]	[1.46]	[0.52]	[1.56]	
Size decile 4	Estimate	**0.00**	**5.94**	**-0.96**	**2.17**	**2.92**	**-2.29**	**0.02**	**-0.35**	66.6%
	t–stat	[1.33]	[3.60]	[1.02]	[2.70]	[1.22]	[1.50]	[0.16]	[1.96]	
Size decile 5	Estimate	**0.00**	**5.89**	**-0.96**	**2.02**	**2.81**	**-2.26**	**0.04**	**-0.40**	67.7%
	t–stat	[1.16]	[3.62]	[1.09]	[2.53]	[1.18]	[1.55]	[0.49]	[2.29]	
Size decile 6	Estimate	**0.00**	**5.93**	**-1.13**	**1.77**	**2.50**	**-2.70**	**-0.01**	**-0.33**	68.5%
	t–stat	[1.52]	[3.68]	[1.22]	[2.31]	[1.06]	[1.94]	[0.19]	[2.13]	
Size decile 7	Estimate	**0.00**	**5.96**	**-0.59**	**1.74**	**2.38**	**-2.87**	**-0.06**	**-0.31**	70.8%
	t–stat	[1.49]	[3.59]	[0.65]	[2.37]	[0.97]	[2.05]	[0.76]	[2.13]	
Size decile 8	Estimate	**0.00**	**5.91**	**-0.44**	**1.54**	**2.06**	**-2.99**	**-0.04**	**-0.33**	70.5%
	t–stat	[1.69]	[3.55]	[0.56]	[2.08]	[0.85]	[2.23]	[0.54]	[2.31]	
Size decile 9	Estimate	**0.00**	**5.63**	**-0.14**	**1.31**	**1.70**	**-3.45**	**-0.05**	**-0.31**	69.1%
	t–stat	[1.55]	[3.47]	[0.17]	[1.92]	[0.72]	[2.72]	[0.72]	[2.26]	
Size decile 10 (high)	Estimate	**0.00**	**5.21**	**0.26**	**0.93**	**1.65**	**-3.73**	**-0.10**	**-0.31**	63.9%
	t–stat	[1.33]	[3.19]	[0.32]	[1.51]	[0.74]	[3.29]	[1.55]	[2.55]	
χ^2–difference test statistics:										
Size decile 10 - size decile 1	Estimate		**-0.15**	**0.63**	**-1.74**	**-2.12**	**-2.37**	**-0.22**	**-0.05**	
	χ^2–stat		0.02	0.45	11.63	6.00	6.16	6.29	0.13	
	p–value		*(0.88)*	*(0.50)*	*(0.00)*	*(0.01)*	*(0.01)*	*(0.01)*	*(0.72)*	
Mean(size deciles 10-7) - mean(size deciles 1-3)	Estimate		**-0.19**	**0.63**	**-1.22**	**-1.62**	**-1.54**	**-0.14**	**-0.03**	
	χ^2–stat		0.09	1.09	13.99	8.84	5.12	5.38	0.10	
	p–value		*(0.76)*	*(0.30)*	*(0.00)*	*(0.00)*	*(0.02)*	*(0.02)*	*(0.75)*	
Mean(size deciles 10-6) - mean(size deciles 1-5)	Estimate		**-0.10**	**0.42**	**-0.87**	**-1.14**	**-1.12**	**-0.11**	**0.00**	
	χ^2–stat		0.06	1.02	14.15	8.84	5.62	5.96	0.00	
	p–value		*(0.81)*	*(0.31)*	*(0.00)*	*(0.00)*	*(0.02)*	*(0.01)*	*(0.96)*	

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[a] *(continued)* the bold number is the (average) difference in parameter values, the second number the test statistic, and the number in round brackets the associated p–value. In Panel D, the first element in the portfolio's name indicates the book–to–market category, the second the size category, and the final element the momentum category the respective test asset belongs to (with the fundamentals again increasing from 1 to 2). In the one–step GMM procedure, we stack the moment conditions of the mimicking portfolio on the moment conditions of the asset–pricing model. Since the system is exactly identified, we obtain the same parameter estimates as if we had used a two–stage regression approach. The one–step GMM procedure, however, corrects standard errors for the additional uncertainty created by the generated regressor. All estimation procedures correct for heteroskedasticity and autocorrelation by using the Newey and West correction with l = 12. The sample period extends from February 1971 to December 1998.

Table 4: Macroeconomic risk exposures (continued)

Panel C: One way–sorted momentum benchmark portfolios

Dependent variable		Independent variables: Constant	MYP	UI	DSV	ATS	STS	FX	OIL	Adjusted R-Square
Regression results:										
Momentum decile 1 (low)	Estimate	**-0.01**	**6.39**	**-0.16**	**2.78**	**3.40**	**-1.95**	**-0.03**	**-0.18**	66.7%
	t–stat	[2.84]	[3.63]	[0.14]	[3.31]	[1.40]	[1.36]	[0.23]	[0.84]	
Momentum decile 2	Estimate	**-0.01**	**5.76**	**-0.20**	**2.00**	**2.65**	**-2.60**	**-0.01**	**-0.31**	67.4%
	t–stat	[2.49]	[3.59]	[0.23]	[2.89]	[1.22]	[2.12]	[0.11]	[1.36]	
Momentum decile 3	Estimate	**0.00**	**5.00**	**-0.43**	**1.95**	**1.78**	**-2.54**	**-0.02**	**-0.27**	66.9%
	t–stat	[1.46]	[3.58]	[0.51]	[3.45]	[0.92]	[2.31]	[0.25]	[1.85]	
Momentum decile 4	Estimate	**0.00**	**4.91**	**-0.71**	**1.48**	**1.25**	**-2.84**	**-0.04**	**-0.25**	66.6%
	t–stat	[1.53]	[3.48]	[0.90]	[2.63]	[0.67]	[2.64]	[0.51]	[1.97]	
Momentum decile 5	Estimate	**0.00**	**4.60**	**-0.03**	**1.48**	**0.97**	**-3.39**	**-0.05**	**-0.33**	69.0%
	t–stat	[1.02]	[3.53]	[0.04]	[2.87]	[0.54]	[3.41]	[0.73]	[2.86]	
Momentum decile 6	Estimate	**0.00**	**4.90**	**0.07**	**1.40**	**1.18**	**-3.45**	**-0.04**	**-0.29**	68.8%
	t–stat	[1.35]	[3.47]	[0.10]	[2.48]	[0.59]	[3.11]	[0.53]	[2.47]	
Momentum decile 7	Estimate	**0.00**	**5.27**	**-0.66**	**1.08**	**1.59**	**-3.51**	**-0.05**	**-0.22**	66.7%
	t–stat	[1.87]	[3.17]	[0.89]	[1.92]	[0.71]	[2.86]	[0.89]	[1.93]	
Momentum decile 8	Estimate	**0.00**	**5.65**	**-0.22**	**0.86**	**2.31**	**-3.60**	**-0.13**	**-0.22**	60.0%
	t–stat	[1.35]	[3.15]	[0.25]	[1.29]	[0.93]	[2.81]	[1.86]	[1.81]	
Momentum decile 9	Estimate	**0.00**	**6.29**	**-0.24**	**1.04**	**2.90**	**-3.79**	**-0.12**	**-0.37**	58.6%
	t–stat	[1.16]	[3.28]	[0.29]	[1.36]	[1.02]	[2.54]	[1.48]	[2.53]	
Momentum decile 10 (high)	Estimate	**0.00**	**6.65**	**-0.13**	**1.33**	**2.88**	**-4.15**	**-0.15**	**-0.49**	53.3%
	t–stat	[0.59]	[3.20]	[0.12]	[1.42]	[0.99]	[2.60]	[1.50]	[2.44]	
χ^2–difference test statistics:										
Mom decile 10 -	Estimate		**0.26**	**0.03**	**-1.44**	**-0.52**	**-2.20**	**-0.13**	**-0.31**	
Mom decile 1	χ^2–stat		0.07	0.00	4.86	0.32	8.59	1.23	2.01	
	p–value		*(0.79)*	*(0.98)*	*(0.03)*	*(0.57)*	*(0.00)*	*(0.27)*	*(0.16)*	
Mean(Mom deciles 10-7) -	Estimate		**0.48**	**0.07**	**-1.16**	**0.09**	**-1.48**	**-0.12**	**-0.11**	
mean(Mom deciles 1-3)	χ^2–stat		0.36	0.01	6.56	0.01	5.77	2.38	0.34	
	p–value		*(0.55)*	*(0.93)*	*(0.01)*	*(0.93)*	*(0.02)*	*(0.12)*	*(0.56)*	
Mean(Mom deciles 10-6) -	Estimate		**0.42**	**0.07**	**-0.79**	**0.16**	**-1.03**	**-0.07**	**-0.05**	
mean(Mom deciles 1-5)	χ^2–stat		0.49	0.02	7.46	0.05	5.80	1.75	0.15	
	p–value		*(0.48)*	*(0.89)*	*(0.01)*	*(0.82)*	*(0.02)*	*(0.19)*	*(0.70)*	

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Table 4: Macroeconomic risk exposures (continued)

Panel D: Three way–sorted BM, size, and momentum benchmark portfolios and factors

Dependent variable		Independent variables								Adjusted R-Square
		Constant	MYP	UI	DSV	ATS	STS	FX	OIL	
Regression results:										
BM1Size1Momentum1	Estimate	**-0.01**	**6.17**	**-0.58**	**2.71**	**3.71**	**-1.88**	**0.04**	**-0.28**	67.4%
	t–stat	[2.40]	[3.64]	[0.61]	[3.18]	[1.53]	[1.15]	[0.36]	[1.50]	
BM1Size1Momentum2	Estimate	**-0.01**	**6.90**	**-1.35**	**2.09**	**3.88**	**-3.05**	**0.04**	**-0.36**	63.7%
	t–stat	[1.58]	[3.77]	[1.26]	[2.29]	[1.39]	[1.79]	[0.37]	[1.67]	
BM1Size2Momentum1	Estimate	**-0.01**	**5.41**	**-0.61**	**1.57**	**1.82**	**-3.22**	**-0.08**	**-0.27**	67.2%
	t–stat	[2.15]	[3.48]	[0.66]	[2.62]	[0.87]	[2.75]	[1.11]	[1.95]	
BM1Size2Momentum2	Estimate	**0.00**	**5.77**	**-0.35**	**0.97**	**2.20**	**-4.04**	**-0.12**	**-0.35**	62.7%
	t–stat	[1.43]	[3.16]	[0.42]	[1.43]	[0.87]	[3.10]	[1.72]	[2.57]	
BM2Size1Momentum1	Estimate	**0.00**	**4.86**	**-0.43**	**2.63**	**2.63**	**-0.99**	**0.12**	**-0.26**	66.3%
	t–stat	[0.13]	[3.59]	[0.49]	[3.64]	[1.35]	[0.76]	[1.30]	[1.82]	
BM2Size1Momentum2	Estimate	**0.00**	**5.27**	**-0.59**	**1.94**	**2.21**	**-2.08**	**0.06**	**-0.27**	63.7%
	t–stat	[0.29]	[3.51]	[0.67]	[2.72]	[1.00]	[1.54]	[0.63]	[1.92]	
BM2Size2Momentum1	Estimate	**0.00**	**4.39**	**0.20**	**1.68**	**0.86**	**-2.10**	**0.03**	**-0.23**	60.4%
	t–stat	[0.23]	[3.33]	[0.26]	[3.11]	[0.50]	[1.99]	[0.42]	[1.48]	
BM2Size2Momentum2	Estimate	**0.00**	**5.01**	**0.27**	**1.03**	**1.63**	**-2.92**	**-0.05**	**-0.26**	54.3%
	t–stat	[0.86]	[3.27]	[0.35]	[1.42]	[0.71]	[2.33]	[0.72]	[2.03]	
RM	Estimate	**0.00**	**5.56**	**-0.11**	**1.20**	**2.02**	**-3.35**	**-0.05**	**-0.30**	70.9%
	t–stat	[0.50]	[3.40]	[0.15]	[1.84]	[0.87]	[2.73]	[0.81]	[2.39]	
HML	Estimate	**0.01**	**-1.36**	**1.10**	**-0.07**	**-1.22**	**1.34**	**0.07**	**0.03**	15.7%
	t–stat	[5.24]	[2.53]	[1.84]	[0.41]	[1.88]	[2.89]	[1.34]	[0.25]	
SMB	Estimate	**0.00**	**0.57**	**-0.79**	**1.21**	**1.74**	**1.09**	**0.15**	**0.07**	23.3%
	t–stat	[0.09]	[0.93]	[1.34]	[3.81]	[3.23]	[1.91]	[2.26]	[0.63]	
WML	Estimate	**0.00**	**0.64**	**-0.15**	**-0.93**	**0.17**	**-1.45**	**-0.05**	**-0.07**	12.3%
	t–stat	[1.19]	[1.28]	[0.25]	[3.54]	[0.25]	[3.04]	[0.79]	[0.58]	

Table 5: Unconditional cross–sectional tests of alternative asset pricing models[a]

Panel A: 25 benchmark portfolios two way–sorted on book–to–market and size

	Pricing factors													
	MYP	UI	DSV	ATS	STS	FX	OIL	RM*	RM	SMB	HML	WML	J–test	Adj.R^2
Macroeconomic factor (MF) model														
b–estimate (stochastic discount factor)	**109.94**	**93.04**	**-38.35**	**81.23**	**39.21**	**27.68**	**-5.87**						17.00	48.7%
t–stat	[2.48]	[1.02]	[2.13]	[1.28]	[1.00]	[2.28]	[0.35]						(0.52)	
Risk premia (x10^2)	**0.30**	**0.05**	**-0.27**	**-0.08**	**0.18**	**1.59**	**-0.20**							
t–stat	[1.38]	[0.99]	[1.30]	[0.61]	[1.79]	[2.22]	[0.63]							
Augmented macroeconomic factor (AMF) model														
b–estimate (stochastic discount factor)	**141.22**	**116.73**	**-47.64**	**105.48**	**27.95**	**26.85**	**-3.41**	**-4.91**					17.29	46.9%
t–stat	[2.73]	[1.27]	[2.32]	[1.41]	[0.62]	[2.01]	[0.19]	[0.53]					(0.43)	
Risk premia (x10^2)	**0.39**	**0.07**	**-0.33**	**-0.08**	**0.19**	**1.63**	**-0.14**	**-0.40**						
t–stat	[1.23]	[1.25]	[1.27]	[0.46]	[1.59]	[1.95]	[0.36]	[0.57]						
Fama and French (FF) model														
b–estimate (stochastic discount factor)									**5.05**	**-0.32**	**8.47**		19.58	52.7%
t–stat									[5.96]	[0.20]	[5.46]		(0.61)	
Risk premia (x10^2)									**0.61**	**0.09**	**0.39**			
t–stat									[3.21]	[0.65]	[3.25]			
Carhart (C) model														
b–estimate (stochastic discount factor)									**4.80**	**2.00**	**14.38**	**9.23**	19.03	56.9%
t–stat									[4.94]	[1.26]	[7.77]	[2.86]	(0.58)	
Risk premia (x10^2)									**0.53**	**0.14**	**0.51**	**0.52**		
t–stat									[2.28]	[0.85]	[4.39]	[1.96]		

(continued on next page)

[a] The table shows the stochastic discount factor estimations and risk premia of the macroeconomic factor (MF) model, an augmented macroeconomic factor (AMF) model, the Fama and French (FF) model, and the Carhart (C) model, using 25 two–way sorted book–to–market and size portfolios (Panel A) or 60 three–way sorted book–to–market, size, and momentum portfolios (Panel B) as test assets. The pricing factors of the MF model are changes in industrial production growth expectations (MYP), contemporaneous, unexpected inflation (UI), changes in the aggregate survival probability (DSV), changes in the average level and the slope of the term structure of risk–free interest rate yields (ATS and STS, respectively), changes in the exchange rate between the U.S. dollar and a trade–weighted composite currency (FX), and changes in the price of raw materials (OIL). The pricing factors of the AMF model are the former factors plus the orthogonalized excess return on the market portfolio (RM*). The pricing factors of the FF model are the excess return on the market portfolio, the return on the SMB zero investment portfolio, and the return on the HML zero investment portfolio. The pricing factors of the C model are the former factors plus the return on the WML zero investment portfolio. In the one–step GMM procedure, we *(continued on next page)*

Table 5: Unconditional cross–sectional tests of alternative asset pricing models (continued)[a]

Panel B: 60 benchmark portfolios three way–sorted on book–to–market, size, and momentum

	Pricing factors													
	MYP	UI	DSV	ATS	STS	FX	OIL	RM*	RM	SMB	HML	WML	J–test	Adj.R^2
Macroeconomic factor (MF) model														
b–estimate (stochastic discount factor)	**157.55**	**217.07**	**-56.69**	**79.52**	**54.37**	**37.97**	**-6.15**						23.73	17.2%
t–stat	[3.43]	[3.06]	[2.89]	[1.12]	[0.97]	[4.10]	[1.13]						(1.00)	
Risk premia (x10^2)	**0.52**	**0.12**	**-0.51**	**-0.20**	**0.34**	**2.34**	**-0.19**							
t–stat	[1.77]	[2.68]	[1.58]	[1.31]	[2.63]	[4.25]	[1.30]							
Augmented macroeconomic factor (AMF) model														
b–estimate (stochastic discount factor)	**205.91**	**252.01**	**-67.21**	**109.94**	**23.16**	**23.45**	**-0.53**	**-11.65**					22.19	17.5%
t–stat	[3.82]	[3.68]	[2.58]	[1.10]	[0.39]	[4.10]	[0.08]	[1.38]					(1.00)	
Risk premia (x10^2)	**0.76**	**0.16**	**-0.56**	**-0.24**	**0.34**	**1.53**	**0.06**	**-1.07**						
t–stat	[1.68]	[3.56]	[1.23]	[1.04]	[2.06]	[3.50]	[0.28]	[1.54]						
Fama and French (FF) model														
b–estimate (stochastic discount factor)									**5.26**	**-1.60**	**9.15**		25.52	11.1%
t–stat									[9.56]	[1.56]	[9.17]		(1.00)	
Risk premia (x10^2)									**0.57**	**-0.02**	**0.45**			
t–stat									[4.91]	[0.24]	[6.07]			
Carhart (C) model														
b–estimate (stochastic discount factor)									**5.05**	**1.07**	**14.36**	**6.86**	25.30	62.0%
t–stat									[9.28]	[1.23]	[13.21]	[9.07]	(1.00)	
Risk premia (x10^2)									**0.55**	**0.07**	**0.54**	**0.33**		
t–stat									[4.26]	[0.69]	[7.97]	[5.20]		

[a] *(continued)* stack the moment conditions of the mimicking portfolio on the moment conditions of the asset pricing model, and then use a specific weighting matrix A to ensure that the coefficients of this approach are exactly equal to those of a two–stage approach (see Appendix). The one–step GMM approach corrects standard errors for the additional uncertainty of the generated regressor. The J–test is Hansen's (1982) test of the over–identifying restrictions. The sample period extends from February 1971 to December 1998.

Table 6: Conditional cross–sectional tests of alternative asset pricing models[a]

	Pricing factors												J–test	Adj.R^2
	MYP	UI	DSV	ATS	STS	FX	OIL	RM*	RM	SMB	HML	WML		
Macroeconomic factor (MF) model														
b–estimate (stochastic discount factor)	**142.85**	**-127.11**	**-76.08**	**63.58**	**46.54**	**21.57**	**-1.13**						21.27	79.0%
t–stat	[2.59]	[1.44]	[3.45]	[0.72]	[1.54]	[2.40]	[0.13]						(0.85)	
Risk premia ($x10^2$)	**0.59**	**-0.08**	**-0.57**	**-0.29**	**0.34**	**1.24**	**-0.34**							
t–stat	[1.91]	[1.63]	[1.87]	[1.71]	[3.06]	[2.15]	[1.58]							
Augmented macroeconomic factor (AMF) model														
b–estimate (stochastic discount factor)	**189.47**	**-7.95**	**-75.20**	**121.67**	**19.69**	**12.67**	**-2.77**	**-11.14**					19.22	78.2%
t–stat	[3.20]	[0.06]	[4.55]	[1.26]	[0.49]	[1.61]	[0.26]	[1.26]					(0.92)	
Risk premia ($x10^2$)	**0.71**	**-0.02**	**-0.52**	**-0.23**	**0.29**	**0.76**	**-0.22**	**-1.00**						
t–stat	[1.62]	[0.19]	[1.84]	[0.98]	[1.84]	[1.20]	[0.71]	[1.37]						
Fama and French (FF) model														
b–estimate (stochastic discount factor)									**7.02**	**-1.37**	**11.31**		24.11	52.2%
t–stat									[11.42]	[0.96]	[8.75]		(0.87)	
Risk premia ($x10^2$)									**0.87**	**0.05**	**0.53**			
t–stat									[5.18]	[0.38]	[4.86]			
Carhart (C) model														
b–estimate (stochastic discount factor)									**6.85**	**1.30**	**17.77**	**8.32**	22.93	71.1%
t–stat									[9.98]	[1.14]	[12.51]	[5.34]	(0.88)	
Risk premia ($x10^2$)									**0.87**	**0.11**	**0.68**	**0.42**		
t–stat									[4.66]	[0.78]	[6.61]	[2.86]		

[a] The table shows the stochastic discount factor estimations and risk premia of the macroeconomic factor (MF) model, an augmented macroeconomic factor (AMF) model, the Fama and French (FF) model, and the Carhart (C) model, using 36 conditional (managed) portfolios as test assets, i.e. eight three–way sorted book–to–market, size, and momentum benchmark portfolios, plus the same portfolios multiplied by the dividend yield on the S&P500 stock index, the yield spread between Baa and Aaa–rated corporate bond portfolios, and the yield spread between long–term and short–term government bond portfolios. All instruments are lagged by 2 months. The pricing factors of the tested models are the same as in Table 5. In the one–step GMM procedure, we stack the moment conditions of the mimicking portfolio on the moment conditions of the asset pricing model, and then use a specific weighting matrix A to ensure that the coefficients of this approach are exactly equal to those of a two–stage approach (see Appendix). The one–step GMM approach corrects standard errors for the additional uncertainty of the generated regressor. The J–test is Hansen's (1982) test of the over–identifying restrictions. The sample period extends from February 1971 to December 1998.

Table 7: Conditional cross–sectional tests of alternative asset pricing models with scaled factors[a]

	Pricing factors												
	MYP	UI	DSV	ATS	STS	FX	OIL	RM*	RM	SMB	HML	WML	J–test
Macroeconomic factor (MF) model													
b–estimate (sdf pricing factors)	**49.49**	**-388.30**	**-51.14**	**-55.10**	**-23.51**	**40.32**	**-12.27**						16.12
t–stat	[0.92]	[1.82]	[2.36]	[0.56]	[0.60]	[4.53]	[0.54]						(0.58)
b–estimate (sdf pricing factors*instruments)	**-36.01**	**87.69**	**40.66**	**17.92**	**64.79**	**-7.06**	**0.02**						
t–stat	[1.00]	[0.70]	[1.56]	[0.22]	[1.90]	[0.85]	[0.00]						
Augmented macroeconomic factor (AMF) model													
b–estimate (sdf pricing factors)	**221.28**	**-247.45**	**-94.22**	**89.91**	**3.98**	**27.01**	**-11.50**	**-22.89**					15.30
t–stat	[2.60]	[1.21]	[4.41]	[0.74]	[0.07]	[2.12]	[0.57]	[2.00]					(0.50)
b–estimate (sdf pricing factors*instruments)	**-31.23**	**95.10**	**15.33**	**98.55**	**73.42**	**-1.27**	**-0.22**	**12.90**					
t–stat	[0.74]	[0.73]	[0.63]	[1.56]	[1.33]	[0.13]	[0.02]	[1.70]					
Fama and French (FF) model													
b–estimate (sdf pricing factors)									**4.57**	**3.85**	**5.75**		23.29
t–stat									[4.79]	[2.61]	[3.63]		(0.62)
b–estimate (sdf pricing factors*instruments)									**-3.88**	**4.14**	**-11.28**		
t–stat									[4.67]	[3.13]	[7.15]		
Carhart (C) model													
b–estimate (sdf pricing factors)									**4.35**	**5.03**	**10.49**	**5.79**	22.39
t–stat									[5.67]	[3.90]	[5.53]	[3.23]	(0.56)
b–estimate (sdf pricing factors*instruments)									**-2.60**	**2.55**	**-8.10**	**-8.95**	
t–stat									[3.55]	[2.07]	[3.91]	[5.56]	

[a] The table shows the stochastic discount factor estimations of the macroeconomic factor (MF) model, an augmented macroeconomic factor (AMF) model, the Fama and French (FF) model, and the Carhart (C) model, using 36 conditional (managed) portfolios as test assets, i.e. eight three–way sorted book–to–market, size, and momentum benchmark portfolios, plus the same portfolios multiplied by the dividend yield on the S&P500 stock index, the yield spread between Baa and Aaa–rated corporate bond portfolios, and the yield spread between long–term and short–term government bond portfolios. All instruments are lagged by 2 months. The pricing factors of the tested models are the same as in Table 5, plus these pricing factors multiplied by the lagged dividend yield on the S&P500 stock index. In the one–step GMM procedure, we stack the moment conditions of the mimicking portfolio on the moment conditions of the asset pricing model, and then use a specific weighting matrix A to ensure that the coefficients of this approach are exactly equal to those of a two–stage approach (see Appendix). The one–step GMM approach corrects standard errors for the additional uncertainty of the generated regressor. The J–test is Hansen's (1982) test of the over–identifying restrictions. The sample period extends from February 1971 to December 1998.

Table 8: Model specification and comparison tests[a]

		Unconditional model 25 portfolios	Unconditional model 60 portfolios	Conditional model unscaled	Conditional model scaled
Panel A: Macroeconomic factor (MF) model					
Joint test factor loadings on sdf	χ^2 (# restrictions)	**17.27**	**150.26**	**59.87**	**84.05**
(All b parameters = 0)	p-value	*(0.016)*	*(0.000)*	*(0.000)*	*(0.000)*
Joint test SMB and HML premia	χ^2 (# restrictions)	**8.06**	**6.00**	**6.53**	
(λ_{SMB} and $\lambda_{HML} = 0$)	p-value	*(0.018)*	*(0.051)*	*(0.038)*	
Joint test SMB, HML, and WML premia	χ^2 (# restrictions)	**12.17**	**51.20**	**36.13**	
(λ_{SMB}, λ_{HML}, and $\lambda_{WML} = 0$)	p-value	*(0.007)*	*(0.000)*	*(0.000)*	
Joint test time variation	χ^2 (# restrictions)				**14.19**
(Interaction parameters = 0)	p-value				*(0.048)*
HJ statistic	Sum of (n-#) i.i.d $\chi^2(1)$	**0.385**	**0.595**	**1.783**	**1.577**
	p-value	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Panel B: Augmented macroeconomic factor (AMF) model					
Joint test factor loadings on sdf	χ^2 (# restrictions)	**18.05**	**122.12**	**50.39**	**54.49**
(All b parameters = 0)	p-value	*(0.021)*	*(0.000)*	*(0.000)*	*(0.000)*
Joint test SMB and HML premia	χ^2 (# restrictions)	**6.97**	**8.58**	**6.52**	
(λ_{SMB} and $\lambda_{HML} = 0$)	p-value	*(0.031)*	*(0.014)*	*(0.038)*	
Joint test SMB, HML, and WML premia	χ^2 (# restrictions)	**4.87**	**46.48**	**23.70**	
(λ_{SMB}, λ_{HML}, and $\lambda_{WML} = 0$)	p-value	*(0.182)*	*(0.000)*	*(0.000)*	
Joint test time variation	χ^2 (# restrictions)				**20.96**
(Interaction parameters = 0)	p-value				*(0.007)*
HJ statistic	Sum of (n-#) i.i.d $\chi^2(1)$	**0.384**	**0.595**	**1.766**	**1.560**
	p-value	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Panel C: Fama and French 3–factor (FF) model					
Joint test factor loadings on sdf	χ^2 (# restrictions)	**51.77**	**120.85**	**206.29**	**154.58**
(All b parameters = 0)	p-value	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Joint test SMB and HML premia	χ^2 (# restrictions)	**10.86**	**37.25**	**23.82**	
(λ_{SMB} and $\lambda_{HML} = 0$)	p-value	*(0.004)*	*(0.000)*	*(0.000)*	
Joint test time variation	χ^2 (# restrictions)				**84.68**
(Interaction parameters = 0)	p-value				*(0.000)*
HJ statistic	Sum of (n-#) i.i.d $\chi^2(1)$	**0.398**	**0.585**	**2.132**	**2.022**
	p-value	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Panel D: Carhart 4–factor (C) model					
Joint test factor loadings on sdf	χ^2 (# restrictions)	**52.52**	**237.71**	**212.21**	**97.67**
(All b parameters = 0)	p-value	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Joint test SMB, HML, and WML premia	χ^2 (# restrictions)	**16.25**	**122.77**	**92.82**	
(λ_{SMB}, λ_{HML}, and $\lambda_{WML} = 0$)	p-value	*(0.001)*	*(0.000)*	*(0.000)*	
Joint test time variation	χ^2 (# restrictions)				**47.27**
(Interaction parameters = 0)	p-value				*(0.000)*
HJ statistic	Sum of (n-#) i.i.d $\chi^2(1)$	**0.398**	**0.544**	**2.110**	**1.967**
	p-value	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*

[a] The table shows test statistics used to evaluate the macroeconomic factor (MF) model (Panel A), the augmented macroeconomic factor (AMF) model (Panel B), the Fama and French (FF) model (Panel C), and the Carhart (C) model (Panel D). The first Wald statistic (joint test factor loadings on sdf) tests whether all factor loadings on the pricing kernel of the specific model are jointly equal to zero. The subsequent two Wald statistics test whether the lambdas on the attribute–sorted spread portfolios, namely SMB and HML for the FF model (joint test SMB and HML premia) or SMB, HML, and WML for the C model (joint test SMB, HML, and WML premia), are jointly equal to zero. In case of the MF and the AMF models, we need to add the attribute–sorted spread portfolios to the other pricing factors to perform these tests. The final Wald test (joint test time variation) applies only to the models with conditional factors; it tests whether the pricing factors are time-varying with respect to the instrumental variable used, i.e. the dividend yield on the S&P500. Finally, we report the HJ distance and its empirical p–value.

Appendix A Creation of benchmark factors

Following Liew and Vassalou (2000), we construct the three benchmark factors, i.e. HML, SMB, and WML, from the 27 (3x3x3) three–way independently sorted size, book–to–market, and momentum portfolios at each point in time t through the following equations:

$$\begin{aligned} HML = \frac{1}{9}[&(B3S1M1 - B1S1M1) + (B3S1M2 - B1S1M2) + (B3S1M3 - B1S1M3) \\ &+(B3S2M1 - B1S2M1) + (B3S2M2 - B1S2M2) + (B3S2M3 - B1S2M3) \\ &+(B3S3M1 - B1S3M1) + (B3S3M2 - B1S3M2) + (B3S3M3 - B1S3M3)], \end{aligned} \tag{8}$$

$$\begin{aligned} SMB = \frac{1}{9}[&(B1S1M1 - B1S3M1) + (B1S1M2 - B1S3M2) + (B1S1M3 - B1S3M3) \\ &+(B2S1M1 - B2S3M1) + (B2S1M2 - B2S3M2) + (B2S1M3 - B2S3M3) \\ &+(B3S1M1 - B3S3M1) + (B3S1M2 - B3S3M2) + (B3S1M3 - B3S3M3)], \end{aligned} \tag{9}$$

$$\begin{aligned} WML = \frac{1}{9}[&(B1S1M3 - B1S1M1) + (B2S1M3 - B2S1M1) + (B3S1M3 - B3S1M1) \\ &+(B1S2M3 - B1S2M1) + (B2S2M3 - B2S2M1) + (B3S2M3 - B3S2M1) \\ &+(B1S3M3 - B1S3M1) + (B2S3M3 - B2S3M1) + (B3S3M3 - B3S3M1)], \end{aligned} \tag{10}$$

where the first two letters of the portfolio name indicate the book–to–market category the portfolio belongs to, the second two letters the size category, and the last two letters the momentum category, with size, book–to–market, and momentum increasing from one to three.

Table A1: Summary statistics on benchmark portfolios and factors[a]

Variable	Mean ($x10^3$)	Median ($x10^3$)	StDev ($x10^3$)	Skew	Kurt	Min ($x10^3$)	Max ($x10^3$)
Panel A: Benchmark factor returns							
HML	5.03	4.66	23.49	-0.08	5.21	-115.39	95.70
SMB	1.08	-0.11	31.28	0.23	4.04	-100.36	115.15
WML	2.97	3.45	26.85	-0.42	7.64	-156.28	106.18
Panel B: Benchmark portfolio excess returns							
BM decile 1 (low)	4.72	4.70	52.88	-0.12	4.77	-226.14	224.18
BM decile 2	6.62	8.66	49.07	-0.48	5.46	-250.93	182.61
BM decile 3	5.75	7.33	49.05	-0.66	6.17	-256.30	151.76
BM decile 4	6.01	9.36	48.26	-0.39	5.80	-245.58	193.47
BM decile 5	6.14	7.67	45.58	-0.58	6.78	-241.41	172.74
BM decile 6	5.67	8.01	44.80	-0.31	6.69	-213.38	212.97
BM decile 7	7.81	7.89	43.27	0.18	5.30	-168.95	195.25
BM decile 8	8.20	7.57	44.61	-0.08	6.32	-188.00	212.68
BM decile 9	8.79	13.19	46.99	-0.19	5.88	-193.00	204.57
BM decile 10 (high)	11.22	11.89	55.64	0.10	8.38	-255.42	305.21
Size decile 1 (small)	6.16	8.65	60.54	-0.38	6.87	-299.82	275.98
Size decile 2	6.08	11.99	59.44	-0.51	7.16	-305.08	278.00
Size decile 3	6.85	12.37	57.67	-0.64	6.78	-293.17	249.26
Size decile 4	6.69	10.60	55.74	-0.67	6.70	-291.40	238.03
Size decile 5	6.71	12.34	54.66	-0.71	7.09	-296.88	237.43
Size decile 6	6.26	8.83	52.52	-0.65	6.09	-262.75	204.86
Size decile 7	6.25	7.42	51.84	-0.52	6.31	-260.15	212.74
Size decile 8	6.15	8.30	50.32	-0.50	5.78	-247.54	189.26
Size decile 9	6.00	8.55	47.35	-0.34	5.16	-225.30	169.98
Size decile 10 (big)	5.97	7.38	43.75	-0.30	5.33	-200.08	176.75
Momentum decile 1 (low)	3.31	3.17	64.45	-0.21	5.15	-271.54	236.10
Momentum decile 2	4.01	2.57	53.60	-0.37	6.12	-255.32	174.72
Momentum decile 3	5.33	5.07	49.63	-0.06	6.58	-222.40	248.74
Momentum decile 4	5.58	6.67	45.84	-0.16	4.70	-184.78	159.13
Momentum decile 5	6.10	9.05	43.62	-0.20	5.42	-181.59	196.73
Momentum decile 6	5.97	8.11	44.31	-0.41	5.57	-200.98	187.84
Momentum decile 7	5.13	6.35	44.63	-0.66	5.99	-233.14	164.17
Momentum decile 8	6.50	7.58	46.87	-0.64	6.43	-250.16	157.30
Momentum decile 9	7.73	11.99	53.08	-0.60	5.81	-261.23	189.34
Momentum decile 10 (high)	9.84	11.65	61.39	-0.38	4.94	-236.47	219.16

[a] The table shows the mean, the median, the standard deviation, skewness, kurtosis, the minimum, and the maximum for the three–way sorted benchmark factors, namely HML, SMB, and WML, (Panel A) and the one–way sorted portfolios on size, book–to–market, and momentum (Panel B). The sample period extends from February 1971 to December 1998.

Appendix B GMM methodology

We use Hansen's (1982) Generalized Method of Moments (GMM) to estimate the asset pricing models in this study. In particular, in the tests in Table 4 we stack the moment conditions of the factor–mimicking portfolio onto the moment conditions of all the firm characteristic–sorted asset pricing models. Since these systems are exactly identified, i.e. since there are as many moment conditions as free–parameters, the OLS parameter estimates obtained from the individual time–series regressions also constitute the correct parameter estimates for the GMM systems. Still, this approach holds the advantage that the GMM formula for the variances of the parameter estimates takes the dependence of the latter asset pricing models on the first–stage mimicking portfolio estimation into account. In other words, the standard errors obtained for the asset pricing models are corrected for the fact that the factor–mimicking portfolio is a 'generated regressor'. Furthermore, the system estimation also easily allows performing Wald tests on the (average) differences between the beta exposures of two or more time–series regressions.

A similar approach is taken for the cross–sectional tests in Tables 5, 6, and 7. In this case, the only complicating fact is that the stochastic discount factor models are usually overidentified, i.e. there are more moment conditions than free–parameters, and, therefore, seperately estimating the factor–mimicking portfolio and then the stochastic discount factor model does not necessarily yield the same parameter estimates as a one–step system approach.[25] We can, however, ensure that the GMM system gives us the same parameter estimates as the two–stage estimations by requiring the GMM procedure to minimize the following linear combination of the moment conditions vector.

$$a = \begin{bmatrix} \mathrm{I}_{BA+CV} & 0 \\ 0 & \frac{\partial g_T}{\partial b'} W \end{bmatrix},$$

where I_{BA+CV} is an identity matrix of dimension equal to the number of base assets and control variables, $\frac{\partial g_T}{\partial b'}$ is the derivative of the moment conditions with respect to the free–parameters, and W is a weighting matrix. If we choose the weighting matrix W equal to the weighting matrix W used in the two–stage factor mimicking portfolio and stochastic discount factor estimations, then the usage of a in the system approach ensures that parameter estimates in both cases are equal. We decide on the

[25]Maria Vassalou (2003) makes a similar point.

inverse of the spectral density matrix as weighting matrix W in the individual estimations, which we compute via Newey and West (1987) with l = 12.

The validity of a particular asset pricing model can be assessed through Hansen's (1982) *test of the overidentifying restrictions*. Using the inverse of the spectral density matrix as weighting matrix, the formula for the test statistic is:

$$Tg_T(b)'S^{-1}g_T(b) \sim \chi^2(\text{\# of moments - \# of parameters}),$$

where T is the sample size, $g_T(b)$ is the vector of moment conditions evaluated at the parameter estimates, and S^{-1} is the estimated inverse of the spectral density matrix. This test statistic obviously focuses only on the evaluation of the asset pricing model, i.e. it completely ignores the factor mimicking portfolio estimation. While we could use a more general formula to assess the whole GMM system for the MF and the AMF model (see Cochrane, 2001), we feel that we should evaluate a model based on its pricing errors and not on how well its pricing factors are measured.

Once we have estimated the factor loadings on the stochastic discount factor, we can then easily compute the risk premia on the pricing factors. The significance levels of the factor risk premia can be calculated with the *delta*–method. For more details, see Cochrane (2001).