Macro factors and the cross-section of stock returns

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Abstract

We evaluate whether macroeconomic variables are valid risk factors that explain the cross-section of stock returns. We use "pure" macroeconomic variables, which are not based on asset prices, and employ information from a large panel of macro variables by estimating four common factors with principal component analysis. Most macro models are not successful in explaining cross-sectional risk premia, with the conditional CAPM offering the highest fit. Alternative multifactor models, based on interest rate and bond yield factors, outperform the macro models. Thus, factors related to asset prices seem to provide better information for equity risk premia than "pure" macro variables.

Keywords: asset pricing; cross-section of stock returns; risk-return tradeoff; macro risk factors; linear multifactor models; Intertemporal CAPM; conditional CAPM; predictability of stock returns; value premium; long-term reversal in returns; factor analysis; principal components

JEL classification: E44; G10; G12

1 Introduction

In rational asset pricing models, the dispersion in expected returns across different assets (e.g., stocks or portfolios of stocks) should be linked to a corresponding dispersion in the sensitivities (factor loadings) to a set of common risk factors. These risk factors represent a measure of the systematic risk in the economy; that is, risk that is not stock-specific and thus cannot be diversified away by forming arbitrarily large portfolios. Macroeconomic variables are a natural choice for such common systematic risk factors since they represent a direct measure of business cycle fluctuations, which affect all the firms in the economy, although to different degrees. Moreover, in contrast to portfolio-based risk factors, macro risk factors are not likely to be "mechanically related" to the test assets, and thus the respective asset pricing models are likely to provide more economic content.[1]

Given the Roll's critique that a broad stock index is a not a valid proxy for aggregate wealth (Roll (1977)), the inclusion of macro factors—in addition to the market factor associated with the Capital Asset Pricing Model (CAPM) from Sharpe (1964) and Lintner (1965)—seems a valid approach to incorporate other proxies of aggregate wealth. In such a setup, if an asset is positively correlated with a given macroeconomic variable (that measures economic activity), a representative rational risk-averse investor will require a higher risk premium to invest in such an asset compared to a second asset that is uncorrelated with this factor. The reason is that the first asset does not provide a hedge against macroeconomic or business cycle risk, since it pays high returns in times of good economic conditions (economic booms), precisely when the wealth (financial and non-financial) of the investor is at relatively high levels.

This paper evaluates whether macroeconomic variables are valid candidates for risk fac-

[1]This is especially notorious in the cases of the multifactor models from Fama and French (1993) (when tested on size/book-to-market portfolios) and Carhart (1997) (when tested on size-momentum portfolios), since in these two models both the factors and the test assets are based on the same sorting variables.) In recent work, Kogan and Tian (2013) show that it is relatively easy for characteristic-based factors (constructed as long-short positions in the extreme decile characteristic-based portfolios) to price the cross-section of stock returns.

tors in multifactor asset pricing models, which help to price the cross-section of stock returns. We depart from the existing asset pricing literature in two major aspects. First, we use "pure" macroeconomic variables, which are directly related to economic activity; that is, we exclude variables that are based on asset prices. In fact, many of the multifactor models presented in the empirical cross-sectional asset pricing literature, which do not rely on portfolio-based factors, use as risk factors (transformations of) aggregate financial ratios (e.g., dividend yield, earnings yield, book-to-market ratio, consumption-to-wealth ratio), bond yields (e.g., slope of the Treasury yield curve, credit risk spread), short-term interest rates (e.g., Treasury bill rate, Fed funds rate), or stock market volatility.[2] Second, we use the information from a large panel of macro variables to construct our risk factors, rather than selecting a few macro variables. The motivation for this procedure is two-fold. First, in making their investment decisions, thereby affecting stock valuations and required stock returns, investors use all the public information available, including all the macroeconomic data. Second, this procedure allows us to evaluate empirically which macro variables are relevant in pricing the cross-section of stock returns, instead of making a prior on which macro variables are relevant.

Since we cannot include all the available macroeconomic series as alternative risk factors within a multifactor model due to a dimensionality issue, we estimate common macroeconomic factors using the asymptotic principal component analysis developed by Connor and Korajczyk (1986) and widely implemented for large macroeconomic panels (see, for example, Stock and Watson (2002a, 2002b)). These factors summarize the information from a panel

[2] An incomplete list of multifactor models that rely on factors related to asset prices includes Campbell (1996), Lettau and Ludvigson (2001), Brennan, Wang, and Xia (2004), Ang, Hodrick, Xing, and Zhang (2006), Guo (2006), Hahn and Lee (2006), Petkova (2006), Guo and Savickas (2008), Maio and Santa-Clara (2012, 2013), and Koijen, Lustig, and Van Nieuwerburgh (2012). In related work, several papers test versions or extensions of the Campbell (1993) version of the Merton (1973) Intertemporal CAPM (ICAPM) by using as risk factors expectations about future market returns (discount rate news) and future aggregate cash flows (cash-flow news). These in turn represent linear combinations of the original state variables (financial ratios, bond yield spreads, short-term interest rates, or market volatility). An incomplete list of this branch of the empirical asset pricing literature includes Chen (2003), Campbell and Vuolteenaho (2004), Chen and Zhao (2009), Botshekan, Kraeussl, and Lucas (2012), Campbell, Giglio, Polk, and Turley (2013), and Maio (2013b, 2013c).

of 107 macro variables from 1964:01 to 2010:09, which can be broadly classified into different economic categories: output and income; employment and labor force; housing; manufacturing, inventories and sales; money and credit; exchange rates; and price indices. We estimate four macro factors from the panel of 107 raw variables. The first factor is an output factor since it is strongly correlated with the categories of output and income; employment and labor force; and manufacturing, inventories, and sales. The second factor represents an inflation factor since it shows a high correlation with price indices. The third factor is an output and housing factor, since it is highly correlated with these categories. Finally, the fourth factor represents a real estate factor since it is most correlated with the housing category.

We derive and test multifactor models containing the macro factors as additional sources of risk beyond the market factor, which help to price the cross-section of stock returns. The test assets are the standard 25 size/book-to-market portfolios, and also 25 portfolios sorted by both size and past long-term returns. First, we test a two-factor model (augmented CAPM), which contains the beta relative to each macro factor in addition to the market beta. This two-factor model is not successful in pricing either set of equity portfolios. Second, we test a two-factor conditional CAPM in which each of the macro factors appears as a conditioning variable that drives a time-varying market price of risk or a time-varying market beta. The results indicate that the two-factor conditional CAPM clearly outperforms the two-factor augmented CAPM in pricing the cross-section of average returns. Specifically, the specifications based on the first two macro factors have explanatory power for the size-BM portfolios. Finally, we take to the data a two-factor Intertemporal CAPM (ICAPM, Merton (1973)), in which the second factor is the innovation in each of the macro factors. The results show that the two-factor ICAPM does not do better than the two-factor CAPM in pricing the size-BM portfolios, while it outperforms slightly in the test with the size-return reversal portfolios. Overall, the two-factor models containing the macro factors are not very successful in explaining the cross-section of stock returns. Five-factor versions (containing all macro factors) of the augmented CAPM (for the size-BM portfolios) and the conditional CAPM (for both portfolios) produce greater explanatory power for cross-sectional risk premia. However, it is not always clear which of the macro factors drive the model's fit.

Our results show that the multifactor models based on the macro factors tend to perform worse than the Fama and French (1993) three-factor model in pricing both sets of equity portfolios. We also show that alternative conditional CAPM and ICAPM specifications, based on interest rate and bond yield factors, perform better than the multifactor models based on the "economic activity" factors. In sum, these results seem to indicate that risk factors related to asset prices (such as short-term interest rates or bond yield spreads) provide better information in explaining cross-sectional risk premia than "pure" macro factors directly related to real economic activity.

The results are reasonably robust to estimating the models in covariance form; specifying the ICAPM with alternative proxies for the innovations in the macro variables; adding bond returns and industry portfolio returns to the test assets; and using alternative macro factors (individual macro variables). On the other hand, our results show that the macro models perform better with GLS cross-sectional regressions, that is; they do a better job in pricing an efficient combination of the original equity portfolios than the actual original portfolios. Moreover, some of the macro factors in the conditional CAPM help to price size-momentum portfolios, while the augmented CAPM tends to perform better when we use factor-mimicking portfolios.

Our work is closely related to the cross-sectional asset pricing literature that uses macroeconomic variables related with economic activity as risk factors within multifactor models. Specifically, Chen, Roll, and Ross (1986) use industrial production growth, unanticipated inflation, and the change in expected inflation to help pricing size portfolios in a five-factor model. Griffin, Ji, and Martin (2003) find that a restricted version of the Chen, Roll, and Ross (1986) model cannot explain momentum profits, while Liu and Zhang (2008) find that the growth in industrial production helps to price the cross-section of momentum portfolios. Shanken and Weinstein (2006) examine the robustness of the explanatory power of the five-factor model in explaining risk premia among size portfolios. Burmeister and McElroy (1988) use unanticipated inflation and the growth in final sales to explain the cross-section of individual stock returns. Ferson and Harvey (1994) use both expected and unexpected inflation and the growth in industrial production to help pricing equity risk premia in an international setting. Campbell (1996) tests a version of the Campbell (1993) ICAPM, which includes labor income growth as one of the risk factors, while Jagannathan and Wang (1996) also use labor income growth in their conditional CAPM. In related work, Maio (2013b) presents a conditional version of the Campbell and Vuolteenaho (2004) two-factor model, in which one of the conditioning variables is the CPI inflation rate. Building on the theoretical framework of Campbell and Cochrane (1999), Brandt and Wang (2003) specify a model in which the risk factors are the innovations to consumption growth and inflation. Vassalou (2003) uses a factor-mimicking portfolio related to news about future GDP growth to help explain risk premia among portfolios sorted by size and book-to-market. Following a production-based approach to asset pricing, Cochrane (1996), Gomes, Yaron, and Zhang (2006), and Li, Vassalou, and Xing (2006) use aggregate investment returns to price the cross-section of stock returns. In related work, Balvers and Huang (2007) use an aggregate productivity shock as risk factor, while Belo (2010) uses the nondurable minus durable spreads in output and price growth to explain cross-sectional risk premia.

As noted above, our main contribution relative to this literature is that our macro risk factors are constructed from a large panel of macro variables, rather than associated with a few macroeconomic indicators. Our second innovation is that we analyze the role of macro risk factors within three alternative frameworks—an augmented CAPM, the conditional CAPM, and the ICAPM—rather than relying on a single framework. For example, a specific macro factor might not be relevant in driving future aggregate investment opportunities (i.e., it is not priced within the ICAPM), but still be relevant in driving variation in the current market beta or market price of risk (i.e., it is priced within the conditional CAPM).

Another important literature concerns the cross-sectional tests of the consumption-CAPM from Breeden (1979), or extensions of this model, in which a key risk factor is aggregate consumption growth.[3] This paper is also related to previous work using macro factors that summarize the information from a large data set of macro variables in order to study the interaction between stock returns and the economy (e.g., Ludvigson and Ng (2007), Maio and Philip (2013)). The key difference relative to these papers is that we use the macro factors in cross-sectional asset pricing tests to assess whether the macro variables are priced risk factors, while these papers focus on the time-series predictive power of the macro factors for the (excess) stock market return.

The paper proceeds as follows. In Section 2, we estimate the common macroeconomic factors. Section 3 presents the analysis of multifactor models containing macro factors, in extensions of the baseline CAPM. In Section 4, we evaluate whether the macro factors are priced in the ICAPM framework. Section 5 contains the results for alternative macro models, and Section 6 provides several robustness checks. Finally, Section 7 concludes.

2 Macroeconomic variables and estimation of common factors

We consider a large set of macroeconomic time series, originally used by Stock and Watson (2002b, 2006), consisting of seven broad categories, namely: output and income; employment and labor force; housing; manufacturing, inventories and sales; money and credit; exchange rates; and prices. The data are collected from both the Global Insights Basic Economics and the Conference Board databases.

The financial variables, including stock market variables, interest rates, and interest rate spreads are not considered in our macroeconomic variables list, as the purpose of this paper

[3] An incomplete list of papers that test this class of models on the cross-section of stock returns includes Breeden, Gibbons, and Litzenberger (1989), Lettau and Ludvigson (2001), Aït-Sahalia, Parker, and Yogo (2004), Lustig and Van Nieuwerburgh (2005), Parker and Julliard (2005), Yogo (2006), Jagannathan and Wang (2007), Savov (2011), and Lioui and Maio (2012).

is to separate the impact of the pure macroeconomic variables from that of the financial variables in explaining the cross-section of stock returns. Some series were discontinued[4] and the variable entitled "Non-borrowed reserves of depository institutions" (*fmrnba*) was measured with errors during 2008.[5] Hence, such variables are excluded from our list. Our final macroeconomic dataset consists of 107 macro variables from 1964:01 to 2010:09.

To make the variables stationary we transform the macro time series by using growth rates for real variables, and changes in growth rates for prices following Stock and Watson (2002b). In our sample period some variables, such as the housing group variables, are still non-stationary after using the original transformations of Stock and Watson, and hence appropriate transformations were carried out to ensure stationarity. After these transformations the variables are further standardized (zero mean and variance of one) before undertaking the common factors estimation. The description of the list of macroeconomic variables and the transformations employed are detailed in Table A.1 located in the internet appendix.

To estimate the common macroeconomic factors, we use asymptotic principal component analysis developed by Connor and Korajczyk (1986), and widely implemented for large macroeconomic panels (see Stock and Watson (2002a, 2002b, 2006), Ludvigson and Ng (2007, 2009, 2010), among others). Consider the stationary representation for a macroeconomic time series panel with cross-sectional, N, and time series, T, dimensions and with r static factors,

$$y_{it} = \mathbf{f}_t' \boldsymbol{\theta}_i + \varepsilon_{it}, \tag{1}$$

where y_{it} is the ith cross-sectional unit from the macroeconomic panel at time period t; $\mathbf{f}_t$ is

[4]The list of discontinued variables includes "Index of help-wanted advertising in newspapers" (*lhel*), "Employment ratio" (*lhelx*), and "Employee hours in nonagricultural establishments" (*a0m048*).

[5]We exclude the variable *fmrnba* since it shows negative values during 2008. Non-borrowed reserves by definition are equal to total reserves minus borrowed reserves. From 2008:01 to 2008:11 the non-borrowed reserves are negative, indicating that the borrowed reserves have exceeded the total reserves, which contradicts its original definition. Barnett and Chauvet (2011) note that this is a consequence of including the new Term Auction Facility borrowing from the Fed into the non-borrowed reserves, even though these funds were not held as reserves.

the r-dimensional vector of latent common factors for all cross-sectional units at t; $\boldsymbol{\theta}_i$ is the r-dimensional vector of factor loadings for the cross-sectional unit i; and ε_{it} stands for the idiosyncratic $i.i.d.$ errors, allowed to have limited correlation among units.

This model captures the main sources of variations and covariations among the N macroeconomic variables with a set of r common factors ($r << N$). The framework is frequently referred to as the approximate factor structure, and usually estimated by principal component analysis, which is an eigen decomposition of the sample covariance matrix. The estimated $(T \times r)$ factors matrix, $\hat{\mathbf{f}} = \left(\hat{\mathbf{f}}_1, ..., \hat{\mathbf{f}}_r\right)$, is equal to $\sqrt{T}$ multiplied by the r eigenvectors corresponding to the first r largest eigenvalues of the $T \times T$ matrix, $\mathbf{yy}'/(NT)$, where $\mathbf{y}$ is a $(T \times N)$ data matrix. The normalization $\hat{\mathbf{f}}'\hat{\mathbf{f}} = \mathbf{I}_r$ is imposed, where $\mathbf{I}_r$ is the $r-$dimensional identity matrix. This normalization is necessary since $\mathbf{f}$ and the factors loading matrix, $\boldsymbol{\Theta} = (\boldsymbol{\theta}_1', ..., \boldsymbol{\theta}_N')'$, are not separately identifiable. The factor loadings matrix can be obtained as $\hat{\boldsymbol{\Theta}} = \mathbf{y}'\hat{\mathbf{f}}/T$. For a large number of macroeconomic time series this methodology can effectively distinguish noise from signal and summarize information into a small number of estimated common factors.

To determine the value of r, which is the number of statistically significant common factors, we use the IC_2 information criteria suggested by Bai and Ng (2002). We minimize over r the following criteria,

$$\ln(V_r) + r\left(\frac{N+T}{NT}\right)\ln(C_{NT}^2), \tag{2}$$

where $V_r = (NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it} - \sum_{j=1}^{r}\hat{F}_{jt}\hat{\theta}_{ji}\right)^2$ and $C_{NT}^2 = \min\{N, T\}$. We consider a maximum set of 20 factors when estimating the optimal r, as usually carried out in the related literature. The estimation results show that there are four common macroeconomic factors that are statistically significant over the sample period considered.

In Table 1, Panel A reports the summary statistics of the four estimated factors. After carrying out simple univariate regressions of the four factors against each of the 107 macroeconomic variables (belonging to the seven broad macroeconomic categories), Panel B reports the highest r-squares of the factors for the different categories. The first three factors show strong persistence with statistically significant first-order autocorrelation coefficients ranging from 0.71 (first factor) to -0.20 (second factor). We see that the first factor heavily loads on the categories of output and income; employment and labor force; and manufacturing, inventories, and sales, with highest r-squares of 63% (for the macroeconomic variable "Purchasing Managers index"), 75% (for the macroeconomic variable "Industrial Production") and 80% (for the macroeconomic variable "Employees") respectively. Hence the first factor captures the real activity. The second factor is clearly the inflation or prices factor with a highest r-square of 83% (for the macroeconomic variable "CPI"). The third factor represents output and housing with highest r-squares of 41% (for the macroeconomic variable "Ratio of mfg and trade inventories to sales") and 35% (for the macroeconomic variable "Houses authorized by building permits"). The fourth factor loads heavily on the housing variables with the highest r-squares of 33% (for the macroeconomic variable "Housing starts").

Figure 1 plots the r-squares from simple univariate regressions of the four factors against each of the 107 macroeconomic variables. We see that to some extent the four macro factors capture information from different groups of macroeconomic variables and hence provide a good representation of the economy. Figure 2 displays the time-series of each of the macro factors. We can see that the first factor is clearly pro-cyclical, declining in recessions and rising during economic expansions, as measured by the National Bureau of Economic Research (NBER). The remaining three macro factors display a less clear relation with the U.S. business cycle.

3 Macro factors and the CAPM

In this section, we analyze whether the macro factors derived in the previous section explain the cross-section of stock returns within the CAPM (Sharpe (1964) and Lintner (1965)) framework. First, we specify an augmented version of the CAPM, in which the macro factors appear as additional risk factors that help to price assets. Second, we specify a conditional version of the CAPM in which the macro factors act as conditioning variables that drive a time-varying market price of risk or a time-varying market beta.

3.1 An augmented CAPM

3.1.1 A two-factor model

We specify the following two-factor augmented CAPM in expected return-beta form for each of the four macro factors,

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_j \beta_{i,j}, j = 1, ..., 4, \tag{3}$$

where $R_{i,t+1}$ denotes the return on asset i; $R_{f,t+1}$ stands for the risk-free rate; λ_M and λ_j represent the risk prices for the market factor and the j-th macro factor, respectively; and $\beta_{i,M}$ and $\beta_{i,j}$ denote the betas associated with the market and macro factors, respectively.

One possible way to justify the inclusion of a macro factor as an additional risk factor in a two-beta CAPM lies in the Roll's critique (Roll (1977)). Since the stock index is not a perfect proxy for aggregate wealth, the inclusion of macro factors, which are related to the business cycle and hence non-financial wealth, represents a natural extension of the baseline CAPM.[6][7]

[6] Fama and Schwert (1977), Campbell (1996), Jagannathan and Wang (1996), and Santos and Veronesi (2006) use this rationale for the inclusion of aggregate labor income growth on their factor models. In related work, Eiling (2013) specify a multifactor model containing labor income growth associated with different industries as risk factors.

[7] An alternative motivation for a multifactor model including macro variables is the Arbitrage Pricing Theory (APT) from Ross (1976), in which the common factors span the covariance matrix of the returns of the test assets. However, this justification is more suitable for multifactor models that use portfolio-based factors representing mechanical transformations of the test assets, as the multifactor models presented in Fama and French (1993, 1996) and Carhart (1997).

We also estimate a five-factor model including all four macro factors,

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_1 \beta_{i,1} + \lambda_2 \beta_{i,2} + \lambda_3 \beta_{i,3} + \lambda_4 \beta_{i,4}, \tag{4}$$

to assess the joint explanatory power of the macro factors for the cross-section of stock returns.

To put in perspective the results obtained for the two-factor model, we also estimate both the baseline CAPM,

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M}, \tag{5}$$

and the Fama and French (1993, 1996) three-factor model (FF3),

$$\mathrm{E}\left(R_{i,t+1} - R_{f,t+1}\right) = \lambda_M \beta_{i,M} + \lambda_{SMB} \beta_{i,SMB} + \lambda_{HML} \beta_{i,HML}, \tag{6}$$

where $(\lambda_{SMB}, \lambda_{HML})$ denote the risk prices associated with the size (SMB) and value (HML) factors respectively, and $(\beta_{i,SMB}, \beta_{i,HML})$ stand for the corresponding factor betas for asset i. The data on the Fama-French three factors are obtained from Kenneth French's webpage.

3.1.2 Econometric methodology

To test the models above, we employ the two-step procedure used in Jagannathan and Wang (1998), Cochrane (2005), Brennan, Wang, and Xia (2004), Campbell and Vuolteenaho (2004), and Maio and Santa-Clara (2013), among others. Specifically, for the two-factor model, in the first step the factor betas are estimated from the time-series multivariate regressions for each test asset,

$$R_{i,t+1} - R_{f,t+1} = \delta_i + \beta_{i,M} RM_{t+1} + \beta_{i,j} F_{j,t+1} + \varepsilon_{i,t}, j = 1, ..., 4, \tag{7}$$

where RM is the excess market return and F_j denotes the j-th macro factor.

In the second step, the expected return-beta representation is estimated by an OLS cross-sectional regression,

$$\overline{R_i - R_f} = \lambda_M \beta_{i,M} + \lambda_j \beta_{i,j} + \alpha_i, j = 1, ..., 4, \tag{8}$$

which allows us to obtain estimates for factor risk prices $(\widehat{\lambda})$ and pricing errors $(\hat{\alpha}_i)$. $\overline{R_i - R_f}$ represents the average time-series excess return for asset i.

A test for the null hypothesis that the N pricing errors are jointly equal to zero (that is, the model is perfectly specified) is given by

$$\hat{\boldsymbol{\alpha}}' \widehat{\text{Var}} \left(\hat{\boldsymbol{\alpha}} \right)^{-1} \hat{\boldsymbol{\alpha}} \sim \boldsymbol{\chi}^2 (N - K), \tag{9}$$

where K denotes the number of factors ($K = 2$ in the augmented CAPM), and $\hat{\boldsymbol{\alpha}}$ is the $(N \times 1)$ vector of cross-sectional pricing errors.

Both the t-statistics for the factor risk prices and the computation of $\text{Var}(\hat{\boldsymbol{\alpha}})$ are based on GMM-based standard errors. These standard errors can be interpreted as a generalization of the Shanken (1992) standard errors in the sense that they relax the implicit assumption of independence between the factors and the residuals from the time-series regressions (see Cochrane (2005), Chapter 12). Similarly to Shanken (1992), there is a correction for the estimation error in the factor betas from the time-series regressions. Thus, the standard errors account for the "error-in-variables" bias in the cross-sectional regression (see Cochrane (2005)). The full details are provided in Appendix A.

A simpler and more robust measure of the global fit of a given model over the cross-section of returns than the $\boldsymbol{\chi}^2$-test is the cross-sectional OLS coefficient of determination,

$$R^2 = 1 - \frac{\text{Var}_N(\hat{\alpha}_i)}{\text{Var}_N(\overline{R_i - R_f})}, \tag{10}$$

where $\text{Var}_N(\cdot)$ stands for the cross-sectional variance. R^2 represents a proxy for the proportion of the cross-sectional variance of average excess returns on the test assets explained by the factor loadings associated with a given model.

As an alternative to the GMM-based standard errors, we conduct a bootstrap simulation to produce more robust p-values for the tests of individual significance of the risk prices and also for the χ^2-test. The bootstrap simulation consists of 5,000 replications in which the excess portfolio returns and risk factor realizations are simulated (with replacement from the original sample) independently and without imposing the model's restrictions. Thus, the data generating process is derived under the assumption that the model is not valid. Moreover, the bootstrap accounts for the contemporaneous cross-correlation among the test assets, which leads to their low factor structure (see Lewellen, Nagel, and Shanken (2010) and Nagel (2012)). The full details of the bootstrap algorithm are provided in Appendix B.

Following Lewellen, Nagel, and Shanken (2010) and Kan, Robotti, and Shanken (2013), in order to address the statistical uncertainty associated with the in-sample cross-sectional coefficient of determination, we estimate 90% empirical confidence intervals for the R^2 in the cross-sectional regressions, based on the bootstrap simulation. This confidence interval allows us to infer how likely is it that we obtain the fit found in the original data under the assumption that the model is not true.

The first group of test assets used in the cross-sectional test correspond to the standard 25 size/book-to-market portfolios (SBM25) from Fama and French (1993), in order to test the value premium puzzle. The value premium puzzle stands for the empirical evidence showing that value stocks (stocks with a high book-to-market ratio) have higher average returns than growth stocks (stocks with a low book-to-market) (see Rosenberg, Reid, and Lanstein (1985) and Fama and French (1992), among others). We also use 25 portfolios sorted by both size and long-term past returns (SLTR25) to test the long-term reversal in returns anomaly (De Bondt and Thaler (1985, 1987)). This anomaly corresponds to the evidence showing that stocks with low returns over the long-term past (three to five years) have higher subsequent future returns, while past long-term winners have lower future returns. These spreads in returns are called anomalies since they are not explained by the standard CAPM. In Section 6 below, we test the different multifactor models with an alternative portfolio group—25 portfolios sorted on size and momentum.[8] To compute excess portfolio returns we subtract the one-month T-bill rate from the raw returns. The data on portfolio returns and the T-bill rate are obtained from Kenneth French's webpage. Following Lewellen, Nagel, and Shanken (2010) and Nagel (2012), we add to each group of equity portfolios the excess market return, given that it represents the return on an investable portfolio.

3.1.3 Empirical results

We start by presenting the estimation results for both the baseline CAPM and the FF3 model, which serve as benchmarks for the multifactor models containing the macro factors. The results in Table 2 (Panel A) confirm previous evidence showing that the CAPM cannot price the SBM25 portfolios, as the estimate for the OLS coefficient of determination is negative (-33%). This means that the model has less explanatory power than a simple model that predicts constant expected excess returns within the size-BM portfolios. The FF3 model significantly improves the CAPM in explaining the SBM25 portfolios, with a R^2 estimate of 68%, consistent with previous evidence (e.g., Fama and French (1993, 1996)). However, the model does not pass the $\boldsymbol{\chi}^2$-test (p-value of zero), which should be related with a poor inversion of the covariance matrix of the pricing errors.

In the test with the SLTR25 portfolios (Panel B), the CAPM has basically no explanatory power for the dispersion in average returns, as indicated by the R^2 estimate around zero (-1%). In contrast, the FF3 model explains around 80% of the cross-sectional variation in risk premia within these portfolios, consistent with the results in Fama and French (1996). In both tests (SBM25 and SLTR25), the risk price estimate for the HML factor is highly significant (1% level), thus suggesting that the value factor is the key driving force behind

[8] Hou, Xue, and Zhang (2012) test multifactor models on portfolios sorted by a more comprehensive set of market anomalies beyond the value premium, long-term reversal in returns, and momentum. Our focus in this paper is to check whether the macro models are successful in explaining the more traditional CAPM anomalies.

the model's explanatory power. The bootstrapped 10% confidence intervals for the cross-sectional R^2 are quite wide, thus confirming previous evidence that there is substantial statistical uncertainty associated with the in-sample R^2 in cross-sectional asset pricing tests (see, for example, Lewellen, Nagel, and Shanken (2010), Kan, Robotti, and Shanken (2013), and Maio and Santa-Clara (2013)). However, in the tests with either SBM25 or SLTR25, the sample R^2 associated with the FF3 model is above the upper limit on the respective confidence interval; that is, it is significant at the 10% level.

The results for the two-factor CAPM are displayed in Table 3. We can see that none of the two-factor specifications has explanatory power for the size-BM portfolios, as indicated by the negative R^2 estimates and the clear rejections from the $\boldsymbol{\chi}^2$-test (based on the bootstrap inference, the version with F_1 passes the specification test). In the versions with F_1 and F_2 the risk price estimates for the macro factor are statistically significant, while they are not priced in the other two versions of the model.

The four factors jointly explain a good fraction of the cross-sectional variation in risk premia, as shown by the R^2 close to 60%, which is only slightly below the fit obtained for the FF3 model. However, this point estimate is not significant at the 10% level. Moreover, most risk price estimates from the augmented cross-sectional regression are not statistically significant, with the exception of λ_2. This suggests the existence of multicollinearity among the different factor loadings in the cross-sectional regression.

In the test with the SLTR25 portfolios (Panel B), the fit of the two-factor model increases slightly, but remains at very low levels, as shown by the explanatory ratios quite close to zero (below 10%), and the clear rejections by the specification test. Moreover, the risk price estimates associated with the macro factors are insignificant in all cases, based on both the asymptotic and bootstrap-based inferences. When all the macro factors are included in the cross-sectional regression, the cross-sectional R^2 remains at a relatively modest value (20%), while the model passes the $\boldsymbol{\chi}^2$-test, based on the bootstrapped p-value. The difference in explanatory power of the five-factor macro model for the two sets of equity portfolios suggests that the BM and long-term reversal portfolios, although related, measure to some extent different dimensions of the risk-return tradeoff in the cross-section of stocks.

In sum, the results from Table 3 indicate that the two-factor macro model is not successful in pricing either set of portfolios, and thus, the macro risk factors do not help explaining the value and long-term reversal in returns anomalies. While the four macro factors jointly help to price the size-BM portfolios, it is not clear what is the individual contribution from each of the macro factors.

3.2 Macro factors and the conditional CAPM

3.2.1 A two-factor conditional CAPM

An alternative way to include the macro factors in a multifactor model is by specifying a conditional CAPM in which either the conditional market beta or the conditional market risk price are linear functions of the lagged macro factor.[9] The resulting two-factor conditional CAPM, in unconditional form, is given by

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_{M,j} \beta_{i,M,j}, j = 1, ..., 4, \tag{11}$$

where $\lambda_{M,j}$ and $\beta_{i,M,j}$ denote the risk price and beta associated with the j-th scaled factor, $RM_{t+1}F_{j,t}$, which represents the interaction between the current market factor and the lagged macro variable.[10]

As in the case of the augmented CAPM, we also estimate a version of the conditional

[9] An incomplete list of papers that derive and test the conditional CAPM by assuming a time-varying price of risk/market beta linear in lagged state variable(s) includes Cochrane (1996, 2005), Jagannathan and Wang (1996), Ferson and Harvey (1999), Lettau and Ludvigson (2001), Petkova and Zhang (2005), Maio (2013b), among others.

[10] We follow most of the literature on the conditional CAPM by estimating the unconditional representation of the conditional CAPM. Lewellen and Nagel (2006), Nagel and Singleton (2011), and Ang and Kristensen (2012) use alternative methods to estimate the conditional CAPM.

CAPM including all four scaled factors:

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_{M,1}\beta_{i,M,1} + \lambda_{M,2}\beta_{i,M,2} + \lambda_{M,3}\beta_{i,M,3} + \lambda_{M,4}\beta_{i,M,4}. \qquad (12)$$

In Section 6, we test the conditional CAPM by using four individual macro variables as the conditioning variables. This allows us to control for a possible "look-ahead bias" associated with the estimated macro factors.

3.2.2 Empirical results

The estimation results for the conditional CAPM are displayed in Table 4. In the test with SBM25, the two-factor models based on the output (F_1) and inflation (F_2) factors as conditioning variables explain a reasonable fraction of the cross-sectional dispersion in risk premia, with R^2 estimates above 40%. The R^2 estimate is significant at the 10% level in the version based on F_1, while in the version based on F_2 the sample estimate of 41% is only marginally below the upper limit in the corresponding confidence interval (43%).[11] Moreover, the estimates for the scaled risk prices, $\lambda_{M,1}$ and $\lambda_{M,2}$, are negative and significant at the 1% level (bootstrap-based inference). In contrast, the specifications based on F_3 and F_4 as conditioning variables have no explanatory power for SBM25, as indicated by the negative R^2 estimates. The augmented model including all scaled factors explains almost 70% of the variation in average excess returns, which represents a similar fit to the FF3 model. This point estimate is only marginally below the upper limit on the 10% confidence interval. The scaled factors associated with the first two macro variables are priced in the cross-section of size-BM portfolio returns, within the five-factor model.

In the test with the size-long term reversal portfolios, the two-factor conditional CAPM based on the inflation (F_2) and housing (F_4) factors delivers a relatively modest fit, with R^2 estimates below 30% and that are not statistically significant. On the other hand, the

[11] In related work, Maio (2013b) shows that a scaled factor related to CPI inflation helps to explain the cross-section of returns on size, BM, and momentum portfolios.

versions based on either F_1 or F_3 cannot explain the risk premia among SLTR25, as indicated by the explanatory ratios close to zero (below 10%). In the augmented model, both $\lambda_{M,2}$ and $\lambda_{M,4}$ are significant at the 1% level (based on the empirical p-values), and the model explains about 50% of the cross-sectional variation in risk premia, which lags behind the fit obtained in the test with SBM25. Furthermore, this point estimate is highly insignificant.

In sum, the results from Table 4 indicate that the two-factor conditional CAPM clearly outperforms the two-factor augmented CAPM in pricing the cross-section of average stock returns. Specifically, in the specifications using F_1 or F_2 the model has relevant explanatory power for the size-BM portfolios, while the five-factor specification has a similar fit to the FF3 model. Still, the conditional CAPM with conditioning macro variables lags clearly behind the FF3 model in pricing the SLTR25 portfolios.

4 Macro factors and the Intertemporal CAPM

In this section, we test whether the macro factors are consistent with the Merton (1973) ICAPM by specifying a simple two-factor ICAPM model.

4.1 A two-factor ICAPM

We define the following two-factor ICAPM,

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_j \beta_{i,\Delta F_j}, j = 1, ...4, \tag{13}$$

where λ_j and $\beta_{i,\Delta F_j}$ represent the risk price and beta associated with the innovation on the j-th macro factor, $\Delta F_{j,t+1} = F_{j,t+1} - F_{j,t}$. The key difference relative to the augmented CAPM, analyzed in the previous section, is that the non-market factor represents the innovation rather than the raw value of the macro factor.

As in the previous section, we also estimate an augmented version of the ICAPM that includes all four macro factors:

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_1 \beta_{i,\Delta F_1} + \lambda_2 \beta_{i,\Delta F_2} + \lambda_3 \beta_{i,\Delta F_3} + \lambda_4 \beta_{i,\Delta F_4}. \tag{14}$$

According to Maio and Santa-Clara (2012), if a state variable negatively forecasts expected returns, the risk price associated with the corresponding risk factor in the ICAPM cross-sectional regression should also be negative. The intuition is that if asset i forecasts negative expected market returns (because it is positively correlated with a state variable that forecasts a decline in the expected market return) it pays well when the future market return is lower in average. Hence, this asset provides a hedge against changes in future market returns for a multi-period risk-averse investor, and thus should earn a negative risk premium. This in turn implies a negative risk price for the non-market factor, given the assumption of a positive covariance with the innovation in the state variable.

4.2 Predictive regressions

To test whether each of the macro factors forecast aggregate excess returns, we conduct monthly long-horizon predictive regressions (Keim and Stambaugh (1986), Campbell (1987), Fama and French (1988, 1989)),

$$r^e_{t,t+q} = a_q + b_q F_{j,t} + u_{t,t+q}, j = 1, ..., 4, \tag{15}$$

where $r^e_{t,t+q} \equiv r^e_{t+1} + ... + r^e_{t+q}$ is the continuously compounded excess market return over q periods (from $t+1$ to $t+q$). We use forecasting horizons of 1, 3, 12, 24, 36, 48, and 60 months ahead. The statistical significance of the regression coefficients is assessed by using Newey and West (1987) asymptotic standard errors with q lags, thus accounting for the overlapping in the observations.

The results for the predictive regressions are displayed in Table 5. We can see that the first factor forecasts a decline in the future market return, and this effect is stronger at longer horizons, as indicated by the increasing R^2 estimates. On the other hand, both F_2 and F_3 are positively correlated with future returns, and this effect is stronger and more statistically significant in the case of F_3. The slopes associated with F_4 are negative at short and intermediate horizons (although only at the one-month horizon is there marginal statistical significance), and become positive at long horizons. The R^2 estimates show that none of the macro factors has substantial predictive power for future market returns, with F_1 showing the best overall performance, especially at longer horizons.

4.3 Cross-sectional test

The results for the ICAPM, presented in Table 6, show that none of the two-factor ICAPM specifications has explanatory power for the size-BM portfolios, as indicated by the negative estimates for the cross-sectional R^2. In the augmented model including all four macro factors, the explanatory ratio is only 22%, and none of the risk prices associated with the "hedging" factors is statistically significant.

In the test with SLTR25, the fit of the two-factor ICAPM becomes positive in all four versions, but the values are quite modest. The version based on the output factor (F_1) offers the largest fit with a coefficient of determination of 24%. In the five-factor model, the macro factors jointly explain around 42% of the cross-sectional variation in risk premia, yet this estimate is largely insignificant. Moreover, in both the two-factor specifications and the augmented model the majority of the non-market risk prices are not statistically significant at the 10% level. The exception is the estimate for λ_1 in the two-factor model, which is significant at the 10% level based on the bootstrapped p-value, but the positive estimate is inconsistent with the negative slopes associated with F_1 in the forecasting regressions.

In sum, the results from Table 6 show that the two-factor ICAPM does not outperform the two-factor CAPM in pricing the size-BM portfolios, while it does slightly better in the test with SLTR25 (version based on the first macro factor). On the other hand, the ICAPM clearly underperforms the conditional CAPM in explaining the average returns of the SBM25 portfolios. Moreover, the results in the test with SBM25 show that even a multifactor model with a large number of factors (five) might not be able to price these portfolios.[12]

5 Alternative multifactor models

In this section, we estimate both the conditional CAPM and the ICAPM by using an alternative set of state variables. Specifically, we use four financial variables, which represent valid predictors of the market return in the predictability literature, and thus are frequently employed in empirical applications of either the conditional CAPM or the ICAPM. The goal is to assess whether the multifactor models based on the financial variables outperform the specifications based on the macro factors, analyzed in the previous sections.

The first variable is the FED funds rate (FFR, Maio and Santa-Clara (2013)). The second variable is the slope of the Treasury yield curve or term spread ($TERM$, Ferson and Harvey (1999), Campbell and Vuolteenaho (2004), Petkova and Zhang (2005), Hahn and Lee (2006), and Petkova (2006)). $TERM$ represents the yield spread between the ten-year and the one-year Treasury bonds. The third instrument is the default spread (DEF, Jagannathan and Wang (1996), Ferson and Harvey (1999), Petkova and Zhang (2005), Hahn and Lee (2006), and Petkova (2006)). DEF denotes the yield spread between BAA and AAA corporate bonds from Moody's. The data on FFR and bond yields are obtained from the St. Louis Fed. Finally, we use the log aggregate earnings-to-price ratio (EP, Campbell and Vuolteenaho (2004), Chen and Zhao (2009), and Maio (2013b)). EP is the log ratio of the sum of annual earnings to the price level of the Standard and Poors (S&P) 500 index. The price and earnings data are available from Robert Shiller's website.

The results for the conditional CAPM are presented in Table 7. In the test with SBM25, the two-factor conditional CAPM based on FFR, $TERM$, and DEF have some explanatory

[12] Lewellen, Nagel, and Shanken (2010) argue that any multifactor model with three factors will price SBM25 as well as the FF3 model, as long as those factors are uncorrelated with the residuals in the time-series regressions for the FF3 model. The results in this section suggest that in some cases this orthogonality assumption might not be valid, and thus, not *any* multifactor model with three or more factors will price the size-BM portfolios.

power for the cross-section of average returns, with cross-sectional R^2 varying between 23% (version based on $TERM$) and 43% (FFR). In the last case, the sample R^2 is marginally significant. In all three versions, the risk prices associated with the scaled factor are strongly significant (1% level). In contrast, the two-factor model based on EP cannot explain the size-BM portfolios, as indicated by the negative explanatory ratio (-11%). In the augmented model, the scaled factors jointly explain more than 70% of the cross-sectional dispersion in risk premia, which is statistically significant and marginally above the fit produced by the five-factor conditional model with the macro factors (66%). However, the estimates associated with $\lambda_{M,FFR}$, $\lambda_{M,TERM}$, and $\lambda_{M,DEF}$ are not significant at the 10% level, which suggests the existence of multicollinearity in the augmented cross-sectional regression.

In the test with the size-return reversal portfolios, the specifications based on FFR, $TERM$, and DEF perform relatively well, with explanatory ratios above 40% in all three cases. These point estimates are statistically significant in the version based on FFR, while they are not significant (marginally so) in the other two versions . Furthermore, the risk prices for the corresponding scaled factors are significant at the 1% level, based on the empirical p-values. On the other hand, the version based on EP continues to perform poorly, with a R^2 estimate close to zero (3%). The five-factor conditional model has a similar fit to the test with SBM25 (79%), although none of the scaled risk factors are priced. This fit is above the upper limit on the corresponding confidence interval and is significantly larger than the explanatory ratio of the augmented conditional CAPM with macro factors (49%).

Comparing with the two-factor conditional CAPM based on the macro factors, we see that only the version based on FFR has a similar explanatory power to the models based on the first two macro factors, when the test portfolios are SBM25. However, in the test with SLTR25, most of the financial variables deliver a better fit than the conditional CAPM based on the macro factors.

The results for the ICAPM with financial variables are displayed in Table 8. The two-factor ICAPM based on either FFR or $TERM$ explains a significant fraction of the cross-sectional dispersion in risk premia among the two sets of equity portfolios, with explanatory ratios above 50% and significant at the 10% level. In addition, the models pass the χ^2-test (p-values above 5%), and the estimates associated with λ_{FFR} and λ_{TERM} are significant in the tests with either portfolio group. Furthermore, the signs of these two risk prices are consistent with the slopes usually found in the predictive regressions (see, for example, Fama and French (1989) and Campbell and Ammer (1993) for the term spread, and Patelis (1997) and Maio (2013a) for the Fed funds rate).

In contrast, the versions based on DEF and EP do not price either SBM25 or SLTR25, as shown by the negative R^2 estimates, and consistent with the results obtained in Maio and Santa-Clara (2012). The sole exception is the version based on EP (SLTR25 as test portfolios), but the fit is quite low (14%) and the model does not pass the χ^2-test. The augmented ICAPM explains 76% and 68% of the cross-sectional risk premia associated with SBM25 and SLTR25 respectively, which are well above the fit of the corresponding ICAPM with macro factors. In sum, these results indicate that the ICAPM based on FFR and $TERM$, and the five-factor model clearly outperform the ICAPM specifications based on the macro factors.

Overall, the results of this section seem to indicate that risk factors related to asset prices (such as short-term interest rates or bond yield spreads) provide better information in explaining cross-sectional risk premia than "pure" macro factors directly related to real economic activity.

6 Sensitivity analysis

In this section, we present several robustness checks to the main results in the previous two sections. Specifically, we test the models with a GLS cross-sectional regression; estimate the models in covariance representation; estimate a conditional version of the ICAPM; specify an alternative ICAPM specification; add bond returns and industry portfolio returns to the test assets; estimate the models on size-momentum portfolios; use alternative macro factors; and specify the augmented CAPM with factor-mimicking portfolios. The results are presented in the internet appendix.

6.1 GLS cross-sectional regressions

As a robustness check to the OLS cross-sectional regressions discussed in the previous sections, we use a generalized least squares (GLS) cross-sectional regression to estimate factor risk prices associated with the different multifactor models (e.g., Ferson and Harvey (1999), Shanken and Zhou (2007), Lewellen, Nagel, and Shanken (2010)). In a GLS cross-sectional regression, the model is forced to price test assets that represent linear transformations of the original portfolios ("repackaging" portfolios). Specifically, the GLS estimation can allow us to infer whether the model can price a mean-variance efficient combination of the test assets (see Kandel and Stambaugh (1995) and Lewellen, Nagel, and Shanken (2010)). Therefore, this methodology does not allow us to infer the model's explanatory power for the original portfolios (SBM25 or SLTR25). Moreover, since the weights are model-specific we cannot directly compare the fit of two different models (e.g., ICAPM versus the CAPM).

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

$$\boldsymbol{\Sigma}^{-\frac{1}{2}}\overline{\mathbf{r}} = \left(\boldsymbol{\Sigma}^{-\frac{1}{2}}\boldsymbol{\beta}\right)\boldsymbol{\lambda} + \boldsymbol{\alpha}, \tag{16}$$

where $\overline{\mathbf{r}}(N \times 1)$ is a vector of average excess returns; $\boldsymbol{\beta}(N \times K)$ is a matrix of K factor loadings for the N test assets; $\boldsymbol{\lambda}(K \times 1)$ is a vector of risk prices; and $\boldsymbol{\Sigma} \equiv \mathrm{E}(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t')$ denotes the variance-covariance matrix associated with the time-series residuals. The portfolios with lower variance of the residuals in the time-series regressions will receive more weight in the cross-sectional regression.

The joint significance test in equation (9) also applies to the GLS cross-sectional regression, with a different estimate for both the pricing errors and the respective covariance matrix. The cross-sectional GLS coefficient of determination is given by

$$R^2_{GLS} = 1 - \frac{\hat{\boldsymbol{\alpha}}'\boldsymbol{\Sigma}^{-1}\hat{\boldsymbol{\alpha}}}{\overline{\mathbf{r}^*}'\boldsymbol{\Sigma}^{-1}\overline{\mathbf{r}^*}}, \tag{17}$$

where $\overline{\mathbf{r}^*}$ denotes the $N \times 1$ vector of (cross-sectionally) demeaned average excess returns. This metric measures the fraction of the cross-sectional variation in risk premia among the "transformed" portfolios that is explained by a given model.

The results are presented in Tables A.2 to A.5. The GLS R^2 estimates associated with the CAPM are significantly higher than the corresponding OLS explanatory ratios, although still relatively modest (around 20% in both tests). In contrast, the FF3 model is quite successful in explaining the dispersion in risk premia among the "transformed" portfolios of both SBM25 and SLTR25, as indicated by the coefficients of determination at around 100%. However, the model does not pass the $\boldsymbol{\chi}^2$-test based on the asymptotic inference (p-values of zero), which should be related to the ill inversion of the pricing errors' covariance matrix. The 10% confidence intervals for the GLS coefficient of determination from the bootstrap simulation are significantly smaller than the OLS counterparts, confirming the evidence in Lewellen, Nagel, and Shanken (2010). This implies that even the relatively low explanatory ratios associated with the CAPM are now significant at the 10% level.

Regarding the augmented CAPM, in the test with SBM25, and contrary to the OLS cross-sectional regressions, the R^2 estimates associated with the two-factor CAPM specifications are positive in all cases. These estimates vary between 22% (version based on F_1) and 50% (F_3), and all four estimates are statistically significant. Moreover, the risk price estimates for F_2 and F_4 are statistically significant at the 1% level, based on the asymptotic t-ratios. In the augmented regression, the macro factors jointly explain about 94% of the risk premia associated with the repackaged portfolios, which almost matches the fit obtained for the FF3 model. In the test with SLTR25, the fit of the two-factor CAPM is quite small in the versions based on F_1 and F_4, with explanatory ratios around 10%. The versions based on F_2, and especially F_3, deliver a better fit, with R^2 estimates of 32% and 47% (both significant) respectively. However, the "efficient" estimate for λ_3 is not significant at the 10% level. In the augmented GLS regression, the explanatory ratio is only 9%, meaning that the macro factors cannot jointly explain the average returns of the transformed portfolios associated with SLTR25.

In the test with SBM25, the conditional CAPM performs relatively well in pricing the transformed portfolios, with R^2 estimates between 26% (version based on F_1) and 50% (F_2). The sample GLS R^2 is significant in all four versions. The risk price estimates for the scaled factor are negative in all four cases, although only in the versions based on F_2 and F_4 is there statistical significance, based on the robust t-ratios. The five-factor model explains more than 70% of the cross-sectional variation in risk premia. Further, the model is not rejected by the $\boldsymbol{\chi}^2$-test based on the empirical p-value, similarly to the two-factor models. However, none of the risk price estimates associated with the scaled factors in the augmented model are statistically significant, suggesting the presence of multicollinearity in the GLS cross-sectional regression. In the test with SLTR25, the explanatory power of the conditional CAPM is clearly lower than in the test with the size-BM portfolios. As in the OLS case, the versions based on F_2 and F_4 offer the highest fit, with explanatory ratios around 30%, which are significant. However, $\lambda_{M,2}$ is not statistically significant at the 10% level. On the other hand, the augmented model does not explain the efficient combination of the SLTR25 portfolios, as indicated by the slightly negative GLS coefficient of determination (-2%).

The results for the ICAPM in the test with SBM25 show that the performance of the model with GLS cross-sectional regressions is significantly better than in the OLS case. The versions based on F_1 and F_4 produce the best fit, with explanatory ratios above 50% (significant in both cases), while the risk prices for the respective hedging factors are statistically significant at the 10% and 1% levels (based on the robust t-ratios) respectively. However, the positive estimate for λ_1 is inconsistent with the negative slopes associated with F_1 in the predictive regressions for the aggregate equity premium. The joint macro factors explain around 70% of the cross-sectional risk premia, which is similar to the fit obtained for the conditional CAPM, but lags behind the fit of the augmented CAPM and FF3 model. Similarly to the conditional CAPM, none of the risk price estimates associated with the macro factors is significant in the five-factor ICAPM. In the test with SLTR25, the ICAPM performs much worse than in the test with SBM25, as evidenced by the negative coefficients of determination in the versions based on F_1 and F_3. The explanatory ratios are around 20% in the versions based on F_2 and F_4, but the estimates for λ_2 and λ_4 are highly insignificant. Moreover, the five-factor model cannot explain the cross-sectional risk premia for the repackaged portfolios, with a R^2 very close to zero (3%).

Overall, the results of this subsection indicate that, in general, the macro multifactor models do a better job in pricing an efficient combination of the original equity portfolios than the actual original portfolios. This is especially relevant in the cases of the augmented CAPM and ICAPM with SBM25 as testing portfolios.

6.2 Covariance representation

We define and test the expected return-covariance representation for both the augmented CAPM,

$$\begin{aligned} \mathrm{E}(R_{i,t+1} - R_{f,t+1}) &= \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) \\ &+ \gamma_j \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, F_{j,t+1}), j = 1, ..., 4, \end{aligned} \tag{18}$$

and the ICAPM,

$$\begin{aligned} \mathrm{E}(R_{i,t+1} - R_{f,t+1}) &= \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1}) \\ &+ \gamma_j \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, \Delta F_{j,t+1}), j = 1, ..., 4, \end{aligned} \tag{19}$$

where γ is the covariance risk price associated with the market factor, and γ_j denotes the risk price associated with the (innovation in the) macro variable.

Similarly, the conditional CAPM in covariance representation is given by

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \gamma \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1})$$
$$+\gamma_{M,j} \operatorname{Cov}(R_{i,t+1} - R_{f,t+1}, RM_{t+1} F_{j,t}), j = 1, ..., 4, \tag{20}$$

where $\gamma_{M,j}$ denotes the risk price for the scaled factor.

These versions of each of the three multifactor models are equivalent to an expected return-single beta pricing equation. Thus, the fit of each model should be the same as in the version with multiple-regression betas, although the risk prices might have different signs, given possible correlation among the factor loadings. In our case, the macro factors are uncorrelated among themselves by construction, but each of them is possibly correlated with the market factor. The risk prices, and associated t-ratios, associated with the factor covariances (or equivalently, single-regression betas) represent a more correct measure of the marginal contribution of a given risk factor to the overall explanatory power of the model. The reason is that, contrary to the multivariate betas, the covariances (univariate betas) do not change by adding new factors to the pricing equation (see Jagannathan and Wang (1998), Cochrane (2005), Chapter 13, and Kan, Robotti, and Shanken (2013)). Furthermore, both the (conditional) CAPM and ICAPM are originally defined in covariance form (or alternatively, in the pricing kernel representation) since they represent equilibrium models. Specifically, the estimate for the market risk price, γ, provides a direct estimate of the coefficient of relative risk aversion (RRA) for the representative investor.

We estimate the different covariance models by first-stage GMM (Hansen (1982) and Cochrane (2005)). This method uses equally-weighted moments, which is conceptually equivalent to running an OLS cross-sectional regression of average excess returns on factor covariances (right-hand side variables). One advantage of using the GMM procedure is that we do not need to have previous estimates of the individual covariances, since these are implied in the GMM moment conditions. For details on the GMM estimation, see Maio and Santa-Clara (2012) and Maio (2013b).

The estimation results for the covariance representation of the macro models are displayed in Tables A.6 to A.8. As expected, the explanatory ratios are the same as in the corresponding OLS cross-sectional regressions in Sections 3 and 4. Regarding the augmented CAPM, only in one case (γ_2 in the five-factor model tested with SLTR25) is the risk price estimate for the macro factors statistically significant at the 10% level. In all two-factor specifications the macro risk prices are not significant, which means that the macro factors do not add explanatory power in the presence of the market factor.

In the case of the conditional CAPM, the estimates for $\gamma_{M,2}$ have the same sign as the corresponding beta risk prices in the benchmark test. These estimates are significant at the 10% and 5% levels in the estimation with SBM25 and SLTR25 respectively. Thus, the second scaled macro factor has explanatory power beyond that of the market factor. The estimate for $\gamma_{M,4}$ in the five-factor model estimated with SLTR25 is also significant (10% level). Similarly to the benchmark test with multivariate betas (based on the asymptotic p-values), the two-factor conditional CAPM is rejected in most cases by the specification test, the exception being the version based on F_4 in the estimation with SLTR25. The estimates associated with γ represent in most cases plausible values for the RRA parameter, except the version based on F_1, although these estimates are consistently significant only in the version based on F_3.

In what concerns the ICAPM, only in one two-factor model (F_2 in the test with SBM25) is the risk price statistically significant (10% level), but the negative estimate is inconsistent with the positive slopes associated with F_2 in the predictive regressions. Moreover, the estimates for γ_1 in the five-factor model are positive and significant in the estimation with either portfolio set, and thus inconsistent with the negative slopes from the predictive regressions. The estimates associated with γ represent in most cases plausible values, yet in the test with

SBM25 these estimates are not significant at the 10% level for most models.

6.3 Alternative ICAPM specification

In an alternative ICAPM specification, the innovation in each of the macro factors represents the residual from an AR(1) model:

$$F_{j,t+1} \equiv \varepsilon_{j,t+1} = F_{j,t+1} - \psi - \phi F_{j,t}, j = 1, ..., 4. \tag{21}$$

By using this new proxy for $\Delta F_{j,t+1}$, we want to assess whether the results are sensitive to the measurement of the innovation in the macro factors, and also to account for the large persistence of some of the macro factors (see Table 1).

The results (displayed in Table A.9) are not significantly different to the benchmark model based on the first-difference of the macro variables. In the test with SBM25, it turns out that the two-factor ICAPM based on F_1 delivers a positive cross-sectional R^2, but this fit is still very small (8% compared to -10% in the corresponding benchmark case). On the other hand, the five-factor ICAPM produces a higher fit than in the benchmark case (59% compared to 22%), but this point estimate is not statistically significant at the 10% level. In the test with SLTR25, the results tend to be even closer to the benchmark ICAPM based on the first-differences. For example, we obtain a R^2 estimate of 42% for the five-factor model, the same as in the benchmark case.

6.4 A conditional ICAPM

In this section, we test the following three-factor model, which represents a conditional ICAPM:

$$\mathrm{E}(R_{i,t+1} - R_{f,t+1}) = \lambda_M \beta_{i,M} + \lambda_{M,j} \beta_{i,M,j} + \lambda_j \beta_{i,\Delta F_j}, j = 1, ..., 4. \tag{22}$$

Both the two-factor conditional CAPM and the two-factor ICAPM presented in the previous sections are special cases of this model, since both non-market factors depend on the same macro variable. By estimating this model, we can directly compare the relative contribution of the the scaled factor and the "hedging" risk factor in explaining cross-sectional equity risk premia.[13]

The results are shown in Table A.10. In the test with SBM25, the fit of the three-factor model is very similar to the conditional CAPM, since the ICAPM has no explanatory power for these portfolios. On the other hand, in the test with SLTR25 the conditional ICAPM tends to outperform the conditional CAPM, given that the ICAPM has some (small) explanatory power for these portfolios, especially in the version based on F_1. However, in none of the versions of the three-factor model is the R^2 estimate statistically significant, in contrast to the conditional CAPM based on the first macro factor. The reason is that the additional factor in the three-factor model originates confidence intervals for the R^2 that are more positively skewed.

6.5 Adding test assets

6.5.1 Pricing bond returns

We include bond returns in the asset pricing tests to gauge whether the macro models can explain the joint cross-section of stock and bond returns.[14] Moreover, adding bond returns to the set of test assets will help to relax the low factor structure embedded in either SBM25 or SLTR25 (see Lewellen, Nagel, and Shanken (2010)).[15] We add to each equity portfolio group (and the market equity premium) the excess returns on seven Treasury bonds with maturities of 1, 2, 5, 7, 10, 20, and 30 years. The data are available from CRSP. Thus, we have a total of 33 returns to explain in each empirical test. The results are displayed in Tables A.11 to A.14.

[13] Maio and Santa-Clara (2013) test a similar model in the cross-section of stock returns, in which the conditioning/state variable is the Fed funds rate.

[14] Fama and French (1993) and Koijen, Lustig, and Van Nieuwerburgh (2012) also estimate factor models over the joint cross-section of stock and bond returns.

[15] This low factor structure is well illustrated by the fact that the Fama and French (1993) model explains most of the time-series variation in these portfolios (see Fama and French (1996)).

The results show that the explanatory ratios associated with the baseline CAPM are positive for both SBM25 and SLTR25 (31% and 57% respectively). However, these estimates are not statistically significant at the 10% level, although marginally so in the test with SLTR25. Thus, the simple CAPM has some explanatory power for the cross-section of bond risk premia. Regarding the FF3 model, we have a marginally higher fit than in the benchmark tests including only equity risk premia, and the R^2 estimates are significant in the tests with either SBM25 or SLTR25.

The fit of the two-factor augmented CAPM is very close to the baseline CAPM in all cases, showing that the macro factors do not help to price the joint cross-section of stock and bond returns. Only in two cases (F_2 in the test with SBM25 and F_1 in the test with SLTR25) is the macro risk price significant at the 10% level. The joint macro factors explain close to 70% of the cross-sectional equity and bond risk premia, yet the sample R^2 estimates are not statistically significant.

The conditional CAPM based on either F_1 or F_2 clearly outperforms the simple CAPM in pricing the cross-section of stock and bond returns, when the equity portfolios are SBM25, as indicated by the explanatory ratios above 60% (statistically significant in the case of F_1). In the test with SLTR25, the risk prices for the scaled factors based on F_2 and F_4 are statistically significant. However, the global fit is only marginally higher than in the simple CAPM, and the sample explanatory ratios are not significant. The five-factor conditional CAPM explains about 80% of the variation in equity and bond risk premia for either equity portfolio group, yet these estimates are not significant (marginally so in the test with SBM25).

The two-factor ICAPM specifications do not significantly outperform the baseline CAPM, as shown by the only marginally higher R^2 estimates. Only in the version based on F_2 is the macro risk price estimate statistically significant at the 10% level. The five-factor ICAPM has a fit of 54% and 70% in the tests with SBM25 and SLTR25 respectively, but these estimates are not significant.

Overall, the results of this subsection show that the conditional CAPM based on the first two macro factors has relevant explanatory power for the joint cross-section of stock and bond returns. These results are not totally surprising in the case of the second factor, since inflation should carry information about bond risk premia.[16]

6.5.2 Pricing industry portfolios

As an alternative exercise, we add industry portfolio returns to the cross-sectional tests. Specifically, we include in the tests with either SBM25 or SLTR25 the returns on ten industry portfolios, available from Kenneth French's webpage. The objective is to relax the factor structure embedded in both SBM25 and SLTR25.

The results presented in Table A.15 show that the baseline CAPM does a marginally better job in pricing the joint equity portfolios as the cross-sectional R^2 estimates increase relative to the test with only SBM25 or SLTR25. Still, the coefficient of determination is negative (test with SBM25) or close to zero (SLTR25). On the other hand, the FF3 model is not as successful in pricing the 35 portfolios as the original 25 portfolios, as the R^2 estimates are now significantly smaller (around 50%). This suggests that the FF3 model cannot explain the cross-sectional variation in risk premia among the industry portfolios.

The results for both the augmented CAPM (in Table A.16) and the ICAPM (A.18) indicate that the explanatory power of the models is either similar or lower than in the benchmark tests excluding the industry portfolios. Specifically, the five-factor augmented CAPM produces explanatory ratios of -7% and 10% in the tests with SBM25 and SLTR25 respectively, compared to 59% and 20% in the benchmark case. Furthermore, the R^2 estimates associated with the five-factor ICAPM are 3% and 24% in the tests with SBM25 and SLTR25 respectively, compared to 22% and 42% in the benchmark tests.

The conditional CAPM (A.17) also underperforms significantly in comparison to the tests containing only 25 portfolios, as indicated by explanatory ratios associated with the five-factor version of 39% (SBM25) and 30% (SLTR25) versus 66% and 49% in the benchmark

[16] Fama and French (1993) and Koijen, Lustig, and Van Nieuwerburgh (2012) use bond yield factors to explain the joint cross-section of stock and bond returns.

case. Overall, the results of this subsection show that the macro factors do not help to price the industry portfolios.

6.6 Alternative equity portfolios

We test our multifactor models with an alternative group of equity portfolios—25 portfolios sorted by size and momentum (SM25), which are available from Kenneth French's website. These portfolios are related to the momentum anomaly in which past short-term winners (stocks with higher returns in the recent past) continue to have subsequent higher returns, while past losers continue to underperform in the near future (Jegadeesh and Titman (1993), and Chan, Jegadeesh, and Lakonishok (1996), among others).

The estimation results are displayed in Tables A.19 to A.22. Neither the CAPM nor FF3 can price the size-momentum portfolios, as indicated by the respective negative and marginally positive coefficients of determination. This confirms previous evidence that the Fama-French model is not able to explain the momentum anomaly (see, for example, Fama and French (1996), Maio and Santa-Clara (2012), and Maio (2013b)). In comparison, the versions of the augmented CAPM based on F_1 and F_4 have some explanatory power for the momentum portfolios, with R^2 estimates of 35% and 49% respectively. Nevertheless, these point estimates are not statistically significant at the 10% level. The specification including all four macro factors explains 62% of the cross-sectional variation in the size-momentum returns, although this estimate is still below the upper limit on the 10% confidence interval.

The conditional CAPM outperforms the augmented CAPM, with explanatory ratios between 48% (version based on F_4) and 81% (F_3), and these point estimates are significant in the versions based on F_1 and F_3. Moreover, the estimates for the scaled risk prices are significant in all four cases. The five-factor conditional CAPM explains 90% of the cross-sectional variation in the returns of SM25, an estimate that is significant at the 10% level, while the scaled factors associated with F_2 and F_3 are statistically significant. The two-factor ICAPM with the largest fit for the SM25 portfolios is the one based on F_3, with a R^2 of 47%, which is still not significant. The five-factor ICAPM explains as much as 76% of the cross-sectional variation in the SM25 portfolios, which outperforms the five-factor augmented CAPM. Still, this estimate is not significant at the 10% level.

Overall, the results of this section show that the conditional CAPM has explanatory power for the size-momentum portfolios, which is in line with the evidence in Maio (2013b) showing that scaled factors can help to price the momentum portfolios. Moreover, in both the conditional CAPM and ICAPM, the version based on F_3 (output and housing factor) outperforms the other versions. This is in line with the evidence in Liu and Zhang (2008) showing that industrial production helps to explain the returns on the momentum portfolios.

6.7 Alternative macro factors

In this section, we estimate the macro multifactor models by using alternative macro variables as risk factors. We use the individual macro variables which are more "representative" of each of the common macro factors estimated in Section 2. Specifically, we conduct univariate regressions of each common factor on all 107 macro variables and then pick the variable which delivers the highest R^2. The motivation for this exercise is three-fold. First, the common macro factors are estimated with error, which can have an impact on the estimated risk prices and associated t-statistics in the cross-sectional test. Second, the common factors summarize the information from several different (and conflicting) macro variables, and thus, choosing a representative variable might provide a more clear interpretation of the results in some cases. Third, using raw macro variables eliminates the "look-ahead" bias associated with the estimated common factors, which is especially relevant in the specification of the conditional-CAPM. For the first factor, we use the variable "Employees on nonfarm payrolls–goods-producing" (series number 29); the second factor is approximated by the series "CPI-U: commodities" (98); for the third factor, we use the variable "Ratio, Manufacturing and trade inventories to sales" (67); and the fourth variable is "Housing starts" (48). A detailed description of the variables is provided in Table A.1.

The results are shown in Tables A.23 to A.25. Regarding the augmented CAPM, the results are not very different from the corresponding benchmark model based on the common macro factors. Only in the version based on the third macro variable, the fit is significantly higher than the benchmark model for both portfolio groups. In the test with SLTR25, the five-factor model produces an explanatory ratio of 67% (versus only 20% in the benchmark model), although this estimate is (marginally) not significant.

The conditional CAPM based on the new macro risk factors outperforms the corresponding benchmark model in the version based on the second macro factor, with R^2 estimates of 55% and 42% in the estimation with SBM25 and SLTR25 respectively, and the first point estimate is significant at the 10% level. However, the five-factor conditional CAPM based on the new macro factors has basically the same explanatory power as the five-factor model based on the original common macro factors. The ICAPM based on the new macro factors performs similarly to the benchmark ICAPM. The main difference occurs in the version based on the third macro factor in the test with SLTR25, with a R^2 of 35%, versus 3% in the benchmark case. The five-factor ICAPM has a similar fit to the corresponding benchmark version.

Overall, the evidence in this section show that the results of the multifactor models based on the new macro variables are very similar to the benchmark models using the common macro factors.

6.8 Using factor-mimicking portfolios

In this subsection, we estimate the augmented CAPM by using factor-mimicking portfolios associated with each of the four macro factors. One reason why the macro models underperform both the FF3 model and the multifactor models based on interest rate and bond yield factors is the large measurement error associated with economic activity indicators. By using factor-mimicking portfolios, we cane ventually mitigate the impact of this measurement error, if such noise is correlated with equity returns.

The factor-mimicking portfolios correspond to the fitted values from the following time-series regressions,

$$F_{j,t} = a_j + \mathbf{b}_j'\mathbf{B}_t + e_{j,t}, j = 1, ..., 4, \tag{23}$$

$$\widehat{F}_{j,t} = \widehat{\mathbf{b}}_j'\mathbf{B}_t \tag{24}$$

where $\mathbf{B}_t$ is the vector of returns on the base portfolios, and $e_{j,t}$ represents the error term. Following Vassalou (2003) and Avramov and Chordia (2006), the base assets are the Fama-French six portfolios sorted by size and book-to-market.

The results are tabulated in Table A.26. In the test with SBM25, the fit of the two-factor CAPM based on the first macro factor becomes positive, but still at a modest level (23%). The most relevant difference relative to the benchmark case (based on the raw macro factors) shows up in the five-factor model, which explains 86% (versus 59% in the corresponding benchmark model) of the cross-sectional variation in the average returns of the size-BM portfolios. This estimate is statistically significant since it lies above the upper limit on the corresponding confidence interval. In the five-factor model, the only risk price that is not significant is for F_1, while the estimates for λ_2, λ_3, and λ_4 are significant at the 1% level.

When the test portfolios are SLTR25, there is substantial improvement in the fit of the two-factor CAPM based on F_1, relative to the corresponding benchmark specification, as indicated by the cross-sectional R^2 of 58% (2% in the benchmark case). The estimate for λ_1 flips sign relative to the benchmark specification and is strongly significant. The two-factor models based on either F_3 or F_4 also outperform the corresponding versions based on the raw macro factors, with explanatory ratios of 23% and 29% respectively. Still, these point estimates are below the upper limits on the corresponding confidence intervals. The five-factor CAPM has basically the same fit as in the test with the size-BM portfolios (87%), which is statistically significant, and well above the fit of the benchmark model (20%). Moreover, the model passes the specification test, based on both the asymptotic and bootstrap-based p-values. The point estimates for λ_2 and λ_3 are significant at the 1% level, while the first and fourth factors are not priced.

Overall, the results in this subsection show that the joint explanatory power of the macro factors, within the augmented CAPM framework, increases when we use factor-mimicking portfolios instead of the original common factors. Nevertheless, in the test with SBM25 the fit of the two-factor CAPM remains modest.[17]

7 Conclusion

This paper evaluates whether macroeconomic variables are valid candidates for risk factors in multifactor asset pricing models, which help to price the cross-section of stock returns. We depart from the existing asset pricing literature in two major aspects. First, we use "pure" macroeconomic variables, which are directly related to economic activity; that is, we exclude variables that are based on asset prices. Second, we use the information from a large panel of macro variables to construct our risk factors, rather than selecting a few macro variables.

We estimate four common macroeconomic factors, using asymptotic principal component analysis, which summarize the information from a panel of 107 macro variables. The first factor is an output factor; the second factor represents an inflation factor; while the third and fourth factors represent output and real estate variables.

We derive and test multifactor models containing the macro factors as additional sources of risk beyond the market factor, which help to price cross-sectional equity risk premia. The test assets are the standard 25 size/book-to-market portfolios, and also 25 portfolios sorted by both size and past long-term returns. First, we test a two-factor model, which contains the beta relative to each macro factor in addition to the market beta (augmented CAPM).

[17]Given that the six size-BM portfolios are highly correlated with SBM25, it is not surprising that using factor-mimicking portfolios in the test with SBM25 does not have a major impact in the model's fit (if we were using SBM25 as base returns, then the two versions of the model would yield the same results in the test with SBM25.)

This model is not successful in pricing either set of equity portfolios. Second, we test a two-factor conditional CAPM in which each of the macro factors appear as conditioning variables that drive a time-varying market price of risk or a time-varying market beta. The results indicate that the two-factor conditional CAPM clearly outperforms the two-factor augmented CAPM in pricing the cross-section of average returns.

We also take to the data a two-factor ICAPM, in which the second factor is the innovation in each of the macro factors. The results show that the two-factor ICAPM does not do better than the two-factor CAPM in pricing the size-BM portfolios, while it outperforms slightly in the test with the size-return reversal portfolios. Overall, the two-factor models containing the macro factors are not very successful in explaining the cross-section of stock returns. Five-factor versions of the macro models (containing all the macro factors) produce higher explanatory power for cross-sectional risk premia. However, it is not always clear which macro factors are driving the model's fit.

Our results show that the multifactor models based on the macro factors perform worse than the Fama and French (1993) three-factor model in pricing both sets of equity portfolios. We also show that alternative conditional CAPM and ICAPM specifications, based on interest rate and bond yield factors, perform better than the multifactor models based on the "economic activity" factors. In sum, these results seem to indicate that risk factors related to asset prices (such as short-term interest rates or bond yield spreads) provide better information in explaining cross-sectional risk premia than "pure" macro factors directly related to real economic activity.

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A Cross-sectional regressions with GMM robust standard errors

The GMM system equivalent to the time series/cross-sectional regressions approach has a set of moment conditions given by

$$g_T(\boldsymbol{\Theta}) = \frac{1}{T}\begin{bmatrix} \sum_{t=1}^{T}(\mathbf{r}_t - R_{f,t}\mathbf{1}_N - \boldsymbol{\delta} - \boldsymbol{\beta}\mathbf{f}_t) \\ \sum_{t=1}^{T}(\mathbf{r}_t - R_{f,t}\mathbf{1}_N - \boldsymbol{\delta} - \boldsymbol{\beta}\mathbf{f}_t) \otimes \mathbf{f}_t \\ \sum_{t=1}^{T}(\mathbf{r}_t - R_{f,t}\mathbf{1}_N - \boldsymbol{\beta}\boldsymbol{\lambda}) \end{bmatrix} = \begin{bmatrix} \mathbf{0}_{(N\times 1)} \\ \mathbf{0}_{(NK\times 1)} \\ \mathbf{0}_{(N\times 1)} \end{bmatrix}, \tag{A.1}$$

where $\mathbf{r}_t(N\times 1)$ is a vector of simple returns; $\mathbf{1}_N(N\times 1)$ is a vector of ones; $\boldsymbol{\delta}(N\times 1)$ is a vector of constants for the time series regressions; $\boldsymbol{\beta}(N\times K)$ is a matrix of K factor loadings for the N test assets; $\mathbf{f}_t(K\times 1)$ is a vector of common factors used to price assets; $\boldsymbol{\lambda}(K\times 1)$ is a vector of beta risk prices; $\otimes$ denotes the Kronecker product; and $\mathbf{0}$ denotes conformable vectors of zeros.

The first two sets of moment conditions identify the factor loadings (including the constants or Jensen alphas), and thus are equivalent to the time-series regressions. These moment conditions are exactly identified with $N+NK$ orthogonality conditions and $N+NK$ parameters to estimate. The third set of moments corresponds to the cross-sectional regression, and identifies the beta risk prices, $\boldsymbol{\lambda}$. Hence, the third set of moments has N moment conditions and K parameters to estimate, leading to $N-K$ overidentifying restrictions, which also corresponds to the number of overidentifying conditions in the entire system.

System (A.1) represents a straightforward generalization of the system presented in Cochrane (2005) (Chapter 12), for the case of $K>1$ risk factors affecting the cross-section of returns.

The vector of parameters to estimate in this GMM system is given by

$$\boldsymbol{\Theta}' = \begin{bmatrix} \boldsymbol{\delta}' & \boldsymbol{\beta}^* & \boldsymbol{\lambda}' \end{bmatrix}, \tag{A.2}$$

where $\boldsymbol{\beta}^* \equiv \text{vec}(\boldsymbol{\beta}')'$, and vec is the operator that enables us to stack the factor loadings for the N assets into a column vector.

The matrix that chooses which moment conditions are set to zero in the GMM first-order condition, $\mathbf{a}g_T(\hat{\boldsymbol{\Theta}}) = 0$, is given by

$$\mathbf{a} = \begin{bmatrix} \mathbf{I}_N \otimes \mathbf{I}_{K+1} & \mathbf{0}_{(N(K+1)\times N)} \\ \mathbf{0}_{(K\times N(K+1))} & \boldsymbol{\beta}' \end{bmatrix}, \tag{A.3}$$

where $\mathbf{I}_m$ denotes an identity matrix of order m.

The matrix of sensitivities of the moment conditions to the parameters is given by

$$\mathbf{d} \equiv \frac{\partial g_T(\boldsymbol{\Theta})}{\partial \boldsymbol{\Theta}'} = -\begin{bmatrix} \mathbf{I}_N & \mathbf{I}_N \otimes \left(\frac{1}{T}\sum_{t=1}^T \mathbf{f}_t'\right) & \mathbf{0}_{(N\times K)} \\ \mathbf{I}_N \otimes \left(\frac{1}{T}\sum_{t=1}^T \mathbf{f}_t\right) & \mathbf{I}_N \otimes \left(\frac{1}{T}\sum_{t=1}^T \mathbf{f}_t\mathbf{f}_t'\right) & \mathbf{0}_{(NK\times K)} \\ \mathbf{0}_{(N\times N)} & \mathbf{I}_N \otimes \boldsymbol{\lambda} & \boldsymbol{\beta} \end{bmatrix}. \tag{A.4}$$

The variance-covariance matrix of the moments, $\mathbf{S}$, has the form

$$\begin{aligned} \mathbf{S} &= \sum_{j=-\infty}^{\infty} \mathrm{E}\left(\begin{bmatrix} \mathbf{r}_t - R_{f,t}\mathbf{1}_N - \boldsymbol{\delta} - \boldsymbol{\beta}\mathbf{f}_t \\ (\mathbf{r}_t - R_{f,t}\mathbf{1}_N - \boldsymbol{\delta} - \boldsymbol{\beta}\mathbf{f}_t)\otimes \mathbf{f}_t \\ \mathbf{r}_t - R_{f,t}\mathbf{1}_N - \boldsymbol{\beta}\boldsymbol{\lambda} \end{bmatrix}\begin{bmatrix} \mathbf{r}_{t-j} - R_{f,t-j}\mathbf{1}_N - \boldsymbol{\delta} - \boldsymbol{\beta}\mathbf{f}_{t-j} \\ (\mathbf{r}_{t-j} - R_{f,t-j}\mathbf{1}_N - \boldsymbol{\delta} - \boldsymbol{\beta}\mathbf{f}_{t-j})\otimes \mathbf{f}_{t-j} \\ \mathbf{r}_{t-j} - R_{f,t-j}\mathbf{1}_N - \boldsymbol{\beta}\boldsymbol{\lambda} \end{bmatrix}'\right) \\ &= \sum_{j=-\infty}^{\infty} \mathrm{E}\left(\begin{bmatrix} \boldsymbol{\epsilon}_t \\ \boldsymbol{\epsilon}_t \otimes \mathbf{f}_t \\ \boldsymbol{\beta}(\mathbf{f}_t - \mathrm{E}(\mathbf{f}_t)) + \boldsymbol{\epsilon}_t \end{bmatrix}\begin{bmatrix} \boldsymbol{\epsilon}_{t-j} \\ \boldsymbol{\epsilon}_{t-j} \otimes \mathbf{f}_{t-j} \\ \boldsymbol{\beta}(\mathbf{f}_{t-j} - \mathrm{E}(\mathbf{f}_t)) + \boldsymbol{\epsilon}_{t-j} \end{bmatrix}'\right), \end{aligned} \tag{A.5}$$

where $\boldsymbol{\epsilon}_t \equiv \mathbf{r}_t - R_{f,t}\mathbf{1}_N - \boldsymbol{\delta} - \boldsymbol{\beta}\mathbf{f}_t$ represents the vector of time-series residuals. In the last equality, we impose the null that the asset pricing model relation is true, $\mathrm{E}\left(\mathbf{r}_t - R_{f,t}\mathbf{1}_N\right) =$

$\boldsymbol{\beta\lambda}$:

$$\begin{aligned}\mathbf{r}_t - R_{f,t}\mathbf{1}_N - \boldsymbol{\beta\lambda} &= \mathbf{r}_t - R_{f,t}\mathbf{1}_N - \mathrm{E}\left(\mathbf{r}_t - R_{f,t}\mathbf{1}_N\right) \\ &= \mathbf{r}_t - R_{f,t}\mathbf{1}_N - \boldsymbol{\delta} - \boldsymbol{\beta}\,\mathrm{E}(\mathbf{f}_t) = \boldsymbol{\beta}(\mathbf{f}_t - \mathrm{E}(\mathbf{f}_t)) + \boldsymbol{\epsilon}_t. \end{aligned} \tag{A.6}$$

By using the general GMM formula for the variance-covariance matrix of the parameter estimates,

$$\mathrm{Var}(\hat{\boldsymbol{\Theta}}) = \frac{1}{T}(\mathbf{ad})^{-1}\mathbf{a}\hat{\mathbf{S}}\mathbf{a}'(\mathbf{ad})^{-1\prime}, \tag{A.7}$$

the last K elements of the main diagonal give the variances of the estimated factor risk prices, used to calculate the t-statistics.

In addition, if we use the formula for the variance-covariance matrix of the GMM moment conditions (errors),

$$\mathrm{Var}(g_T(\hat{\boldsymbol{\Theta}})) = \frac{1}{T}\left(\mathbf{I}_{N(K+2)} - \mathbf{d}(\mathbf{ad})^{-1}\mathbf{a}\right)\hat{\mathbf{S}}\left(\mathbf{I}_{N(K+2)} - \mathbf{d}(\mathbf{ad})^{-1}\mathbf{a}\right)', \tag{A.8}$$

we obtain the covariance matrix of the cross-sectional pricing errors ($\hat{\boldsymbol{\alpha}}$) from the bottom-right ($N \times N$) block of $\mathrm{Var}(g_T(\hat{\boldsymbol{\Theta}}))$, which is used to conduct the test that the pricing errors are jointly equal to zero:

$$\hat{\boldsymbol{\alpha}}'\,\mathrm{Var}(\hat{\boldsymbol{\alpha}})^{-1}\hat{\boldsymbol{\alpha}} \sim \boldsymbol{\chi}^2(N-K). \tag{A.9}$$

The Shanken (1992) standard errors can be derived as a special case of the GMM "robust" standard errors derived above, as noted by Cochrane (2005) (Chapter 12). If we assume that $\boldsymbol{\epsilon}_t$ is jointly i.i.d.; $\boldsymbol{\epsilon}_t$ and $\mathbf{f}_t$ are independent; and finally $\mathbf{f}_t$ has no serial correlation, then the spectral density matrix $\mathbf{S}$ in (A.5) specializes to

$$\mathbf{S} = \mathrm{E}\left(\begin{bmatrix} \boldsymbol{\epsilon}_t \\ \boldsymbol{\epsilon}_t \otimes \mathbf{f}_t \\ \boldsymbol{\beta}(\mathbf{f}_t - \mathrm{E}(\mathbf{f}_t)) + \boldsymbol{\epsilon}_t \end{bmatrix} \begin{bmatrix} \boldsymbol{\epsilon}_t \\ \boldsymbol{\epsilon}_t \otimes \mathbf{f}_t \\ \boldsymbol{\beta}(\mathbf{f}_t - \mathrm{E}(\mathbf{f}_t)) + \boldsymbol{\epsilon}_t \end{bmatrix}'\right)$$
$$= \begin{bmatrix} \boldsymbol{\Sigma} & \boldsymbol{\Sigma} \otimes \mathrm{E}(\mathbf{f}_t') & \boldsymbol{\Sigma} \\ \boldsymbol{\Sigma} \otimes \mathrm{E}(\mathbf{f}_t) & \boldsymbol{\Sigma} \otimes \mathrm{E}(\mathbf{f}_t\mathbf{f}_t') & \boldsymbol{\Sigma} \otimes \mathrm{E}(\mathbf{f}_t) \\ \boldsymbol{\Sigma} & \boldsymbol{\Sigma} \otimes \mathrm{E}(\mathbf{f}_t') & \boldsymbol{\beta}\boldsymbol{\Sigma}_f\boldsymbol{\beta}' + \boldsymbol{\Sigma} \end{bmatrix}, \tag{A.10}$$

where $\boldsymbol{\Sigma}_f \equiv \mathrm{E}\left[(\mathbf{f}_t - \mathrm{E}(\mathbf{f}_t))(\mathbf{f}_t - \mathrm{E}(\mathbf{f}_t))'\right]$ represents the variance-covariance matrix associated with the factors, and $\boldsymbol{\Sigma} \equiv \mathrm{E}(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t')$ denotes the variance-covariance matrix associated with the residuals from the time-series regressions. By replacing (A.10) in (A.7) we obtain the Shanken variances for the estimated factor risk premia:

$$\mathrm{Var}(\hat{\boldsymbol{\lambda}}) = \frac{1}{T}\left[(\boldsymbol{\beta}'\boldsymbol{\beta})^{-1}\boldsymbol{\beta}'\boldsymbol{\Sigma}\boldsymbol{\beta}\,(\boldsymbol{\beta}'\boldsymbol{\beta})^{-1}\left(1 + \boldsymbol{\lambda}'\boldsymbol{\Sigma}_f^{-1}\boldsymbol{\lambda}\right) + \boldsymbol{\Sigma}_f\right]. \tag{A.11}$$

Similarly, the Shanken variances for pricing errors are given by

$$\mathrm{Var}(\hat{\boldsymbol{\alpha}}) = \frac{1}{T}\left(\mathbf{I}_N - \boldsymbol{\beta}\,(\boldsymbol{\beta}'\boldsymbol{\beta})^{-1}\boldsymbol{\beta}'\right)\boldsymbol{\Sigma}\left(\mathbf{I}_N - \boldsymbol{\beta}\,(\boldsymbol{\beta}'\boldsymbol{\beta})^{-1}\boldsymbol{\beta}'\right)\left(1 + \boldsymbol{\lambda}'\boldsymbol{\Sigma}_f^{-1}\boldsymbol{\lambda}\right). \tag{A.12}$$

B Bootstrap simulation

For illustration purposes consider the case of the two-factor augmented CAPM estimated with OLS. The bootstrap algorithm associated with the cross-sectional regression consists of the following steps:

1. For each empirical test, we estimate the time-series regressions to obtain the factor

loadings,

$$R_{i,t+1} - R_{f,t+1} = \delta_i + \beta_{i,M} RM_{t+1} + \beta_{i,j} F_{j,t+1} + \varepsilon_{i,t}, j = 1, ..., 4,$$

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

$$\overline{R_i - R_f} = \lambda_M \beta_{i,M} + \lambda_j \beta_{i,j} + \alpha_i, j = 1, ..., 4.$$

We compute and save both the t-statistics associated with the risk price estimates and also the $\boldsymbol{\chi}^2$ statistic, both based on Shanken (1992) standard errors, $\left[t(\widehat{\lambda}_M), t(\widehat{\lambda}_j), \boldsymbol{\chi}^2\right]$.

2. In each replication $b = 1, ..., 5000$, we construct a pseudo-sample of excess returns for each testing asset (of size T) by drawing with replacement:

$$\{(R_{i,t+1} - R_{f,t+1})^b, t = s_1^b, s_2^b, ..., s_T^b\}, i = 1, ..., N,$$

where the time indices $s_1^b, s_2^b, ..., s_T^b$ are created randomly from the original time sequence $1, ..., T$. Notice that all excess returns have the same time sequence in order to preserve the contemporaneous cross-correlation between asset returns.

3. For each replication $b = 1, ..., 5000$, we construct an independent pseudo-sample of the risk factors:

$$\{RM_{t+1}^b, F_{j,t+1}^b, t = r_1^b, r_2^b, ..., r_T^b\},$$

where the time sequence $(r_1^b, r_2^b, ..., r_T^b)$ is independent from $s_1^b, s_2^b, ..., s_T^b$. The time sequence is the same for all factors to preserve their cross-correlations.

4. In each replication, we estimate the augmented CAPM by the two-step procedure, but

using the artificial data rather than the original data:

$$(R_{i,t+1} - R_{f,t+1})^b = \delta_i^b + \beta_{i,M}^b RM_{t+1}^b + \beta_{i,j}^b F_{j,t+1}^b + \varepsilon_{i,t}^b, j = 1, ..., 4,$$

$$\overline{(R_i - R_f)^b} = \lambda_M^b \beta_{i,M}^b + \lambda_j^b \beta_{i,j}^b + \alpha_i^b, j = 1, ..., 4.$$

We compute and save both the t-statistics for the factor risk prices and the $\boldsymbol{\chi}^2$ statistic, $\left[t(\widehat{\lambda}_M^b), t(\widehat{\lambda}_j^b), \boldsymbol{\chi}^{2,b}\right]$, leading to an empirical distribution of the statistics. We also compute the cross-sectional OLS R^2 for each pseudo sample, $R^{2,b}$.

5. The empirical p-value associated with the risk price for factor j (for a two-sided test) is computed as

$$p(\widehat{\lambda}_j) = \begin{cases} \left[\#\left\{t(\widehat{\lambda}_j^b) \geq t(\widehat{\lambda}_j)\right\} + \#\left\{t(\widehat{\lambda}_j^b) < -t(\widehat{\lambda}_j)\right\}\right]/5000, if\ \widehat{\lambda}_j \geq 0 \\ \left[\#\left\{t(\widehat{\lambda}_j^b) \leq t(\widehat{\lambda}_j)\right\} + \#\left\{t(\widehat{\lambda}_j^b) > -t(\widehat{\lambda}_j)\right\}\right]/5000, if\ \widehat{\lambda}_j < 0 \end{cases},$$

and similarly for the other factor risk prices. In the above expression, $\#\left\{t(\widehat{\lambda}_j^b) \geq t(\widehat{\lambda}_j)\right\}$ denotes the number of replications in which the pseudo t-stats are greater than or equal to the t-ratio from the original sample.

The p-value for the $\boldsymbol{\chi}^2$ statistic is computed as

$$p(\chi^2) = \#\left\{\chi^{2,b} \geq \chi^2\right\}/5000.$$

Finally, we order the pseudo values of the cross-sectional coefficient of determination, $R^{2,b}$, and compute a 90% confidence interval by using the 5% and 95% percentiles of the bootstrapped distribution.

Table 1: Summary statistics for the macroeconomic factors

Panel A reports the summary statistics for the factors estimated using asymptotic principal component analysis on the macroeconomic panel of 107 variables. The sample is from 1964:01 to 2010:09. F_1 to F_4 are the four statistically significant factors of the macroeconomic panel. The Row $\phi(1)$ designates the first-order autocorrelation coefficients of the factors. The numbers in parentheses are the heteroskedasticity-adjusted robust $t-$statistics. The Row *Proportion* reports the proportion of the variance explained by the factors. Panel B reports the highest r-squares per category from simple univariate regressions of the four factors against each of the 107 macroeconomic variables belonging to the seven broad categories (output and income; employment and labor force; housing; manufacturing, inventories and sales; money and credit; exchange rates; and prices).

	F_1	F_2	F_3	F_4
Panel A: Summary Statistics				
$\phi(1)$	0.710	-0.200	0.381	0.003
	(14.364)	(-2.140)	(6.447)	(0.046)
Proportion	0.182	0.081	0.064	0.039
Panel B: Highest r-squares per category				
Output and income	0.752	0.043	0.206	0.196
Employment and labor force	0.800	0.008	0.241	0.178
Housing	0.013	0.033	0.352	0.327
Manufacturing, inventories and sales	0.628	0.006	0.413	0.029
Money and credit	0.008	0.104	0.046	0.024
Exchange rates	0.002	0.061	0.006	0.157
Prices	0.125	0.827	0.254	0.157

Table 2: Factor risk premia for CAPM and FF3 model

This table reports the estimation results for the CAPM and the three-factor Fama-French (FF3) model. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M, λ_{SMB}, and λ_{HML} denote the beta risk price estimates for the market, size, and value factors respectively. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_{SMB}	λ_{HML}	χ^2	R^2
			Panel A (SBM25)		
1	0.60***			91.34	−0.33
	(**2.96**)			(0.00)	(−3.33, 0.25)
2	0.41**	0.24*	0.47***	74.84	0.68
	(<u>2.09</u>)	(*1.74*)	(**3.63**)	(0.00)	(−1.86, 0.58)
			Panel B (SLTR25)		
1	0.66***			70.86	−0.01
	(**3.21**)			(0.00)	(−4.30, 0.26)
2	0.44**	0.10	0.71***	44.10	0.79
	(<u>2.22</u>)	(0.60)	(**3.33**)	(0.01)	(−2.39, 0.56)

Table 3: Factor risk premia for augmented CAPM

This table reports the estimation results for the augmented CAPM. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
			Panel A (SBM25)				
1	0.65***	129.77**				**39.12**	−0.04
	(**2.86**)	(*1.85*)				(0.03)	(−2.69, 0.43)
2	0.56***		83.21			59.15	−0.14
	(**2.63**)		(*1.66*)			(0.00)	(−2.61, 0.44)
3	0.58***			17.97		88.58	−0.32
	(**2.92**)			(0.47)		(0.00)	(−2.66, 0.42)
4	0.59***				44.31	67.93	−0.32
	(**2.89**)				(1.19)	(0.00)	(−2.69, 0.43)
5	0.33	148.64	211.83*	153.74	−13.14	**7.50**	0.59
	(1.52)	(1.00)	(1.50)	(1.22)	(−0.14)	(1.00)	(−0.54, 0.71)
			Panel B (SLTR25)				
1	0.62***	−41.15				50.66	0.02
	(**2.97**)	(−1.21)				(0.00)	(−3.41, 0.44)
2	0.65***		16.85			64.61	0.01
	(**3.11**)		(0.67)			(0.00)	(−3.41, 0.44)
3	0.59***			42.08		61.30	0.09
	(**3.01**)			(1.18)		(0.00)	(−3.62, 0.44)
4	0.66***				−11.81	67.53	−0.01
	(**3.23**)				(−0.54)	(0.00)	(−3.57, 0.44)
5	0.52***	32.98	66.81**	78.91	0.29	**32.80**	0.20
	(**2.58**)	(0.71)	(<u>2.18</u>)	(1.45)	(0.01)	(0.05)	(−0.83, 0.71)

Table 4: Factor risk premia for conditional CAPM

This table reports the estimation results for the conditional CAPM. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_{M,1}, \lambda_{M,2}, \lambda_{M,3}, \lambda_{M,4}$ denote the risk prices associated with the scaled risk factors in which the conditioning variables are the lagged macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	$\lambda_{M,1}$	$\lambda_{M,2}$	$\lambda_{M,3}$	$\lambda_{M,4}$	χ^2	R^2
				Panel A (SBM25)			
1	0.54***	−6.40***				**55.74**	0.45
	($\underline{2.09}$)	($\underline{-2.49}$)				(0.00)	(−2.72, 0.43)
2	0.46**		−7.50***			**47.98**	0.41
	($\underline{2.12}$)		($\underline{-2.24}$)			(0.00)	(−2.66, 0.43)
3	0.60***			−0.07		91.27	−0.33
	(**3.03**)			(−0.04)		(0.00)	(−2.65, 0.44)
4	0.66***				3.29*	55.29	−0.15
	(**3.17**)				(1.55)	(0.00)	(−2.60, 0.43)
5	0.46***	−5.48***	−4.37***	0.37	−1.52	41.17	0.66
	($\underline{2.17}$)	($\underline{-2.52}$)	(−1.55)	(0.14)	(−0.66)	(0.01)	(−0.55, 0.71)
				Panel B (SLTR25)			
1	0.51***	−2.38				58.44	0.09
	(**2.86**)	(−1.22)				(0.00)	(−3.37, 0.43)
2	0.60***		−4.88***			**39.99**	0.28
	(**2.93**)		($\underline{-2.42}$)			(0.02)	(−3.38, 0.44)
3	0.65***			−0.26		70.75	−0.01
	(**3.24**)			(−0.20)		(0.00)	(−3.39, 0.43)
4	0.59***				−5.61***	**27.45**	0.22
	($\underline{2.36}$)				(−1.60)	(0.28)	(−3.37, 0.45)
5	0.57***	−2.49	−3.84***	2.78	−4.24***	**18.73**	0.49
	($\underline{2.42}$)	(−0.68)	(−1.58)	(0.93)	(*−1.78*)	(0.60)	(−0.82, 0.70)

Table 5: Long-horizon regressions for the excess market return

This table reports the results for single long-horizon regressions for the monthly continuously compounded excess return on the value-weighted market index, at horizons of 1, 3, 12, 24, 36, 48, and 60 months ahead. The forecasting variables are the macro factors, F_1, F_2, F_3, F_4. The original sample is 1964:01–2010:09. For each regression, line 1 reports the slope estimates, and line 2 reports Newey-West t-ratios (in parentheses) computed with q lags. Italic, underlined, and bold t-statistics denote statistical significance at the 10%, 5%, and 1% levels respectively. R^2(%) denotes the coefficient of determination (in %).

	$q = 1$	$q = 3$	$q = 12$	$q = 24$	$q = 36$	$q = 48$	$q = 60$
				Panel A (F_1)			
b_q	−0.000	−0.006	−0.032	−0.032	−0.037	−0.043	−0.075
	(−0.16)	(−0.81)	(−2.17)	(−1.21)	(−1.62)	(−2.43)	(−**3.99**)
R^2(%)	0.01	0.53	3.61	1.82	1.89	2.26	5.57
				Panel B (F_2)			
b_q	0.003	−0.001	0.004	0.010	0.003	0.003	0.016
	(1.11)	(−0.19)	(0.84)	(1.96)	(0.48)	(0.62)	(2.34)
R^2(%)	0.34	0.01	0.05	0.15	0.00	0.00	0.18
				Panel C (F_3)			
b_q	0.006	0.015	0.031	0.015	0.014	0.037	0.049
	(**3.35**)	(**3.10**)	(1.99)	(1.00)	(1.17)	(2.31)	(**2.86**)
R^2(%)	1.96	3.21	3.32	0.43	0.32	1.80	2.59
				Panel D (F_4)			
b_q	−0.003	−0.006	−0.004	−0.007	0.001	0.014	0.025
	(*−1.70*)	(−1.43)	(−0.47)	(−0.79)	(0.07)	(1.59)	(2.26)
R^2(%)	0.48	0.44	0.05	0.09	0.00	0.24	0.63

Table 6: Factor risk premia for ICAPM

This table reports the estimation results for the Intertemporal CAPM (ICAPM). The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the innovation in each of the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
				Panel A (SBM25)			
1	0.47***	123.12				**30.34**	−0.10
	($\underline{2.31}$)	(1.43)				(0.17)	(−2.64, 0.43)
2	0.62***		−209.49			**41.73**	−0.15
	(**2.77**)		(−1.64)			(0.01)	(−2.69, 0.45)
3	0.64***			−130.02		**47.50**	−0.14
	(**3.09**)			(*−1.73*)		(0.00)	(−2.73, 0.43)
4	0.59***				23.16	84.83	−0.33
	(**2.95**)				(0.27)	(0.00)	(−2.69, 0.44)
5	0.51***	90.58	9.03	10.13	8.59	**24.48**	0.22
	($\underline{2.42}$)	(1.54)	(0.07)	(0.13)	(0.08)	(0.27)	(−0.57, 0.72)
				Panel B (SLTR25)			
1	0.54***	80.85*				**41.09**	0.24
	(**2.68**)	(1.53)				(0.02)	(−3.35, 0.44)
2	0.66***		−89.79			52.26	0.07
	(**3.16**)		(−1.25)			(0.00)	(−3.34, 0.44)
3	0.68***			−47.08		58.06	0.03
	(**3.41**)			(−1.13)		(0.00)	(−3.48, 0.44)
4	0.59***				122.20	49.69	0.09
	(**2.90**)				(1.38)	(0.00)	(−3.52, 0.43)
5	0.57***	54.02	0.16	−8.36	21.60	**28.99**	0.42
	(**2.86**)	(1.29)	(0.00)	(−0.16)	(0.29)	(0.11)	(−0.77, 0.71)

Table 7: Factor risk premia for conditional CAPM: alternative conditioning variables

This table reports the estimation results for the conditional CAPM with alternative conditioning variables. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor. $\lambda_{M,FFR}$, $\lambda_{M,TERM}$, $\lambda_{M,DEF}$, and $\lambda_{M,EP}$ denote the risk prices associated with the scaled risk factors in which the conditioning variables are the Fed funds rate (FFR), term spread ($TERM$), default spread (DEF), and earnings yield (EP) respectively. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	$\lambda_{M,FFR}$	$\lambda_{M,TERM}$	$\lambda_{M,DEF}$	$\lambda_{M,EP}$	χ^2	R^2
			Panel A (SBM25)				
1	0.52^{***}	-0.13^{***}				63.92	0.43
	($\underline{2.40}$)	($\mathbf{-3.29}$)				(0.00)	$(-2.68, 0.43)$
2	0.58^{***}		0.03^{***}			75.88	0.23
	(**2.72**)		(**2.79**)			(0.00)	$(-2.60, 0.44)$
3	0.57^{***}			0.02^{***}		57.28	0.33
	(**2.62**)			(**2.98**)		(0.00)	$(-2.62, 0.44)$
4	0.63^{***}				-2.16^{***}	67.20	−0.11
	(**2.84**)				($\underline{-2.14}$)	(0.00)	$(-2.65, 0.43)$
5	0.37^{**}	−0.01	0.00	−0.00	1.65^{***}	37.80	0.74
	(*1.77*)	(−0.22)	(0.13)	(−0.23)	(*1.90*)	(0.01)	$(-0.58, 0.72)$
			Panel B (SLTR25)				
1	0.59^{***}	-0.09^{***}				50.59	0.46
	(**2.85**)	($\underline{-2.54}$)				(0.00)	$(-3.54, 0.44)$
2	0.62^{***}		0.03^{***}			39.08	0.42
	(**2.95**)		(**3.08**)			(0.03)	$(-3.50, 0.44)$
3	0.53^{***}			0.02^{***}		**40.00**	0.41
	($\underline{2.46}$)			($\underline{2.21}$)		(0.02)	$(-3.39, 0.43)$
4	0.67^{***}				−0.61	62.44	0.03
	(**3.18**)				(−0.92)	(0.00)	$(-3.44, 0.43)$
5	0.44^{**}	−0.04	0.01	0.00	0.62	**24.44**	0.79
	($\underline{2.20}$)	(−0.96)	(0.51)	(0.03)	(1.25)	(0.27)	$(-0.83, 0.70)$

Table 8: Factor risk premia for ICAPM: alternative state variables

This table reports the estimation results for the Intertemporal CAPM (ICAPM) with alternative state variables. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor. λ_{FFR}, λ_{TERM}, λ_{DEF}, and λ_{EP} denote the risk prices associated with the innovation in the Fed funds rate (FFR), term spread ($TERM$), default spread (DEF), and earnings yield (EP) respectively. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_{FFR}	λ_{TERM}	λ_{DEF}	λ_{EP}	χ^2	R^2
			Panel A (SBM25)				
1	0.50***	−0.76***				**39.10**	0.66
	($\underline{2.31}$)	(**−2.80**)				(0.03)	(−2.75, 0.43)
2	0.50**		0.52***			**26.51**	0.67
	($\underline{2.18}$)		($\underline{2.28}$)			(0.33)	(−2.60, 0.45)
3	0.60***			−0.01		90.13	−0.33
	(**3.00**)			(−0.15)		(0.00)	(−2.64, 0.45)
4	0.62***				0.20	90.56	−0.33
	(**3.11**)				(0.12)	(0.00)	(−2.65, 0.43)
5	0.46***	−0.82***	0.31**	−0.04	−1.05	*33.39*	0.76
	($\underline{2.31}$)	(**−2.71**)	(**1.75**)	(−0.74)	(−0.49)	(0.04)	(−0.53, 0.71)
			Panel B (SLTR25)				
1	0.53***	−0.65***				**32.43**	0.54
	($\underline{2.53}$)	($\underline{-2.43}$)				(0.12)	(−3.49, 0.44)
2	0.51***		0.35***			**24.96**	0.62
	($\underline{2.46}$)		($\underline{2.09}$)			(0.41)	(−3.48, 0.44)
3	0.66***			−0.00		68.96	−0.01
	(**3.23**)			(−0.02)		(0.00)	(−3.40, 0.42)
4	0.55***				−2.96	53.05	0.14
	(**2.81**)				(−1.44)	(0.00)	(−3.33, 0.44)
5	0.49***	−0.69***	0.32***	−0.01	−0.77	**27.07**	0.68
	($\underline{2.46}$)	($\underline{-2.15}$)	(*1.86*)	(−0.32)	(−0.31)	(0.17)	(−0.80, 0.71)

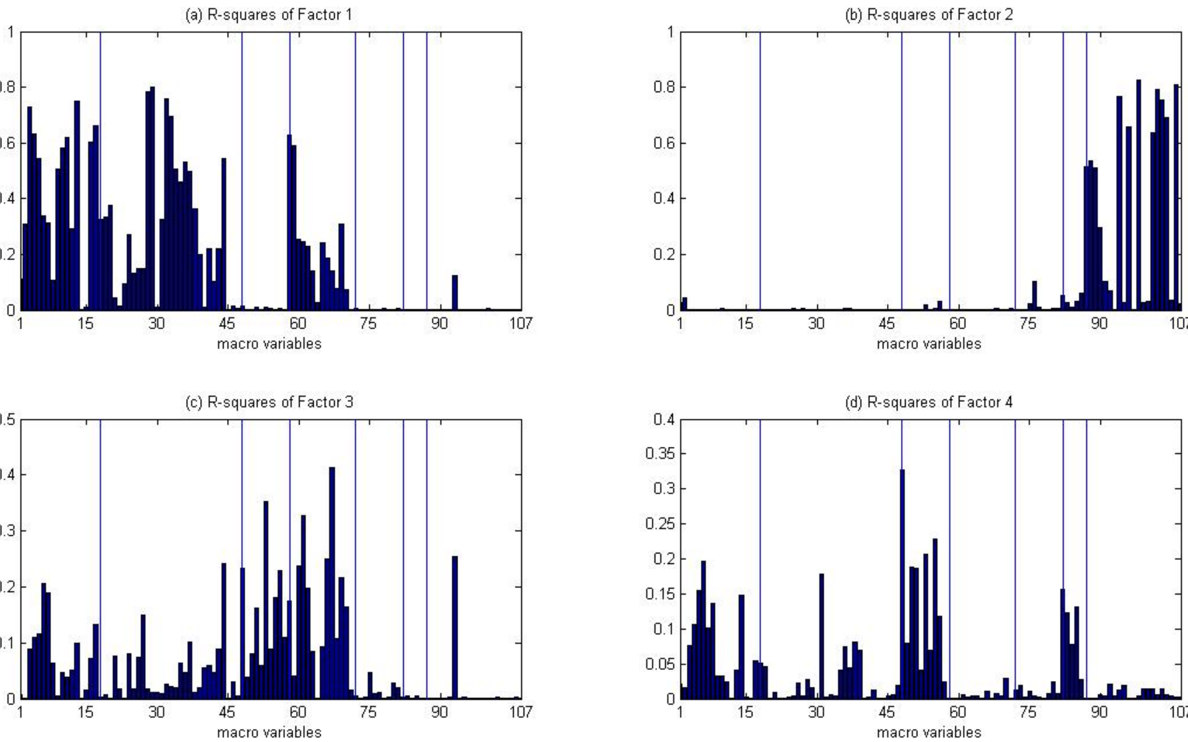
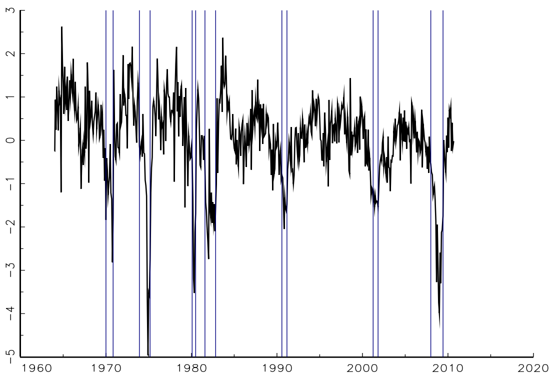
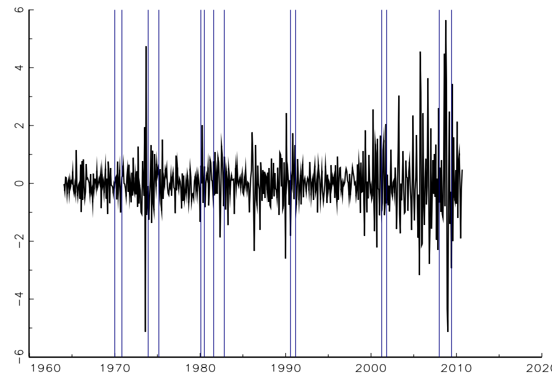


Figure 1: R-squares of macro factors

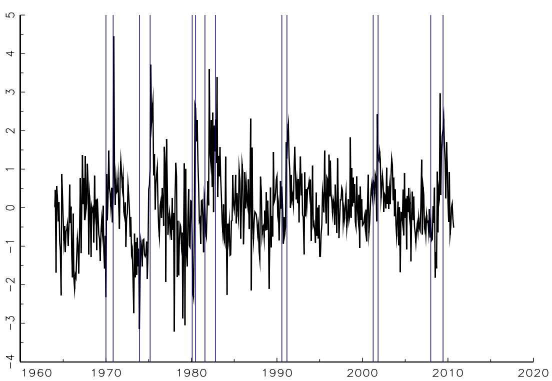
This figure reports the r-squares from simple univariate regressions of the four statistically significant factors against each of the 107 macroeconomic variables. The broad categories are output and income (series 1 to 17); employment and labor force (18–47); housing (48–57); manufacturing, inventories and sales (58–71); money and credit (72–81); exchange rates (82–86); and prices (87–107). The sample period is 1964:01–2010:09.



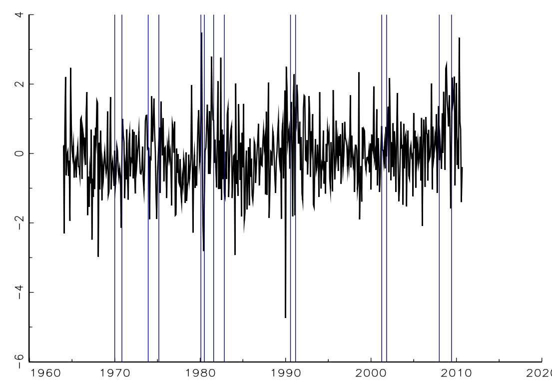
Panel A (F_1)



Panel B (F_2)



Panel C (F_3)



Panel D (F_4)

Figure 2: Macro factors

This figure plots the time-series for the macro factors, F_1, F_2, F_3, F_4. The sample period is 1964:01–2010:09. The vertical lines indicate the NBER recession periods.

C Internet appendix

Table A.1: Macroeconomic variables

This appendix lists the 107 macroeconomic variables along with the mnemonic labels, a brief description of the series and the transformations applied to the series. The broad categories are output and income (series 1 to 17); employment and labor force (18–47); housing (48–57); manufacturing, inventories and sales (58–71); money and credit (72–81); exchange rates (82–86); and prices(87–107). In the *transf* column, we report the transformations for the variables where 1 denotes using levels, 2 denotes taking first-differences, 3 denotes taking second-differences, 4 denotes taking logs, 5 denotes taking log-differences and 6 denotes taking second-log-differences. All the series are from Global Insights Basic Economics database unless specified as TCB (The Conference Board) or AC (Author calculation). The sample is 1964:01–2010:09.

Series no.	Name	Mnemonic	Description	transf
1	PI	ypr	Personal Income (AR, Bil. Chain 2000 $)	5
2	PI less transfers	a0m051	Personal Income less Transfer Payments (AR, Bil. Chain 2000 $)	5
3	IP: total	ips10	Industrial Production Index - Total Index	5
4	IP:products	ips11	Industrial Production Index - Products, Total	5
5	IP:final prod	ips299	Industrial Production Index - Final Products	5
6	IP:consgds	ips12	Industrial Production Index - Consumer Goods	5
7	IP: cons dble	ips13	Industrial Production Index - Durable Consumer	5
8	IP: cons nondble	ips18	Industrial Production Index - Nondurable Consumer	5
9	IP: bus eqpt	ips25	Industrial Production Index - Business Equipment	5
10	IP: matls	ips32	Industrial Production Index - Materials	5
11	IP: dble matls	ips34	Industrial Production Index - Durable Goods	5
12	IP: nondble	ips38	Industrial Production Index - Nondurable Goods	5
13	IP: mfg	ips43	Industrial Production Index - Manufacturing	5
14	IP: res util	ips307	Industrial Production Index - Residential Utilities	5
15	IP: fuels	ips306	Industrial Production Index - Fuels	5
16	NAPM prodn	pmp	Napm Production Index (Percent)	1
17	Cap util	utl11	Capacity Utilization (SIC-Mfg)	2
18	Emp CPS total	lhem	Civilian Labor Force: Employed, Total (Thous.,Sa)	5
19	Emp CPS nonag	lhnag	Civilian Labor Force: Employed, Nonagric.Industries (Thous.,Sa)	5
20	U: all	lhur	Unemployment Rate: All Workers, 16 Years	2
21	U: mean duration	lhu680	Unemploy.By Duration: Average(Mean)Duration In Weeks (Sa)	2

Series no.	Name	Mnemonic	Description	transf
22	U ¡ 5 wks	lhu5	Unemploy.By Duration: Persons Unempl.Less Than 5 Wks (Thous.,Sa)	5
23	U 5-14 wks	lhu14	Unemploy.By Duration: Persons Unempl.5 To 14 Wks (Thous.,Sa)	5
24	U 15+ wks	lhu15	Unemploy.By Duration: Persons Unempl.15 Wks + (Thous.,Sa)	5
25	U 15-26 wks	lhu26	Unemploy.By Duration: Persons Unempl.15 To 26 Wks (Thous.,Sa)	5
26	U 27+ wks	lhu27	Unemploy.By Duration: Persons Unempl.27 Wks + (Thous,Sa)	5
27	UI claims	luinc	Average Weekly Initial Claims, Unemploy. Insurance (Thous. Sa)	5
28	Emp: total	ces002	Employees On Nonfarm Payrolls: Total Private	5
29	Emp: gds prod	ces003	Employees On Nonfarm Payrolls - Goods-Producing	5
30	Emp: mining	ces006	Employees On Nonfarm Payrolls - Mining	5
31	Emp: const	ces011	Employees On Nonfarm Payrolls - Construction	5
32	Emp: mfg	ces015	Employees On Nonfarm Payrolls - Manufacturing	5
33	Emp: dble gds	ces017	Employees On Nonfarm Payrolls - Durable Goods	5
34	Emp: nond-bles	ces033	Employees On Nonfarm Payrolls - Nondurable Goods	5
35	Emp: ser-vices	ces046	Employees On Nonfarm Payrolls - Service-Providing	5
36	Emp: TTU	ces048	Employees On Nonfarm Payrolls - Trade, Transportation, & Utilities	5
37	Emp: whole-sale	ces049	Employees On Nonfarm Payrolls - Wholesale Trade.	5
38	Emp: retail	ces053	Employees On Nonfarm Payrolls - Retail Trade	5
39	Emp: FIRE	ces088	Employees On Nonfarm Payrolls - Financial Activities	5
40	Emp: Govt	ces140	Employees On Nonfarm Payrolls - Government	5
41	Avg hrs	ces151	Avg Weekly Hrs of Prod or Nonsup Workers On Private Nonfarm Payrolls - Goods-Producing	1
42	Overtime:	ces155	Avg Weekly Hrs of Prod or Nonsup Workers On Private Nonfarm Payrolls - Mfg Overtime Hours	2
43	Avg hrs: mfg	a0m001	Average Weekly Hours, Mfg. (Hours)	1
44	NAPM empl	pmemp	Napm Employment Index (Percent)	1
45	AHE: goods	ces275	Avg Hourly Earnings of Prod or Nonsup Workers On Private Nonfarm Payrolls - Goods-Producing	6

Series no.	Name	Mnemonic	Description	transf
46	AHE: const	ces277	Avg Hourly Earnings of Prod or Nonsup Workers On Private Nonfarm Payrolls - Construction	6
47	AHE: mfg	ces278	Avg Hourly Earnings of Prod or Nonsup Workers On Private Nonfarm Payrolls - Manufacturing	6
48	Starts: nonfarm	hsfr	Housing Starts:Nonfarm(1947-58);Total Farm & Nonfarm(1959-)(Thous.,Saar)	5
49	Starts: NE	hsne	Housing Starts:Northeast (Thous.U.)S.A.	5
50	Starts: MW	hsmw	Housing Starts:Midwest(Thous.U.)S.A.	5
51	Starts: South	hssou	Housing Starts:South (Thous.U.)S.A.	5
52	Starts: West	hswst	Housing Starts:West (Thous.U.)S.A.	5
53	BP: total	hsbr	Housing Authorized: Total New Priv Housing Units (Thous.,Saar)	5
54	BP: NE	hsbne	Houses Authorized By Build. Permits:Northeast(Thou.U.)S.A	5
55	BP: MW	hsbmw	Houses Authorized By Build. Permits:Midwest(Thou.U.)S.A.	5
56	BP: South	hsbsou	Houses Authorized By Build. Permits:South(Thou.U.)S.A.	5
57	BP: West	hsbwst	Houses Authorized By Build. Permits:West(Thou.U.)S.A.	5
58	PMI	pmi	Purchasing Managers Index (Sa)	1
59	NAPM new ordrs	pmno	Napm New Orders Index (Percent)	1
60	NAPM vendor del	pmdel	Napm Vendor Deliveries Index (Percent)	1
61	NAPM Invent	pmnv	Napm Inventories Index (Percent)	1
62	Orders: cons gds	a1m008	Mfrs New Orders, Consumer Goods & Materials (Mil. Chain 1982 $) (TCB)	5
63	Orders: dble gds	a0m007	Mfrs New Orders, Durable Goods Industries (Bil. Chain 2000 $) (TCB)	5
64	Orders: cap gds	a0m027	Mfrs New Orders, Nondefense Capital Goods (Mil. Chain 1996 $) (TCB)	5
65	Unf orders: dble	a1m092	Mfrs Unfilled Orders, Durable Goods Indus. (Bil. Chain 2000 $) (TCB)	5
66	M&T invent	a0m070	Manufacturing & Trade Inventories (Bil. Chain 2005 $) (TCB)	5
67	M&T invent/sales	a0m077	Ratio, Mfg. & Trade Inventories To Sales (Based On Chain 2005 $) (TCB)	2

Series no.	Name	Mnemonic	Description	transf
68	Consumption	cons-r	Real Personal Consumption Expenditures (AC) (Bil. $) pi031 / gmdc	5
69	M&Tsales	mtq	Manufacturing & Trade Sales (Mil. Chain 1996 $)	5
70	Retail sales	a0m059	Sales Of Retail Stores (Mil. Chain 2000 $) (TCB)	5
71	Consumer expect	hhsntn	U. Of Mich. Index Of Consumer Expectations(Bcd-83)	2
72	M1	fm1	Money Stock: M1(Curr,Trav.Cks,Dem Dep,Other Ckable Dep)(Bil. $,Sa)	6
73	M2	fm2	Money Stock:M2(M1+Onite Rps,Euro$,G/P&B/D & Mmmfs&Sav&Sm Time Dep(Bil. $,Sa)	6
74	Currency	fmscu	Money Stock: Currency held by the public (Bil $,Sa)	6
75	M2 (real)	fm2-r	Money Supply: Real M2, fm2 / gmdc (AC)	5
76	MB	fmfba	Monetary Base, Adj For Reserve Requirement Changes(Mil. $,Sa)	6
77	Reserves tot	fmrra	Depository Inst Reserves:Total, Adj For Reserve Req Chgs(Mil. $,Sa)	6
78	C&I loans	fclnbw	Commercial & Industrial Loans Outstanding + Non-Fin Comm. Paper (Mil. $, SA) (Bci)	6
79	C&I loans	fclbmc	Wkly Rp Lg Coml Banks:Net Change Coml & Indus Loans(Bil$,Saar)	1
80	Cons credit	ccinrv	Consumer Credit Outstanding - Nonrevolving(G19)	6
81	Inst cred/PI	crdpi	Ratio, Consumer Installment Credit To Personal Income (Pct.) (TCB)	2
82	Eff ex rate: US	exrus	United States;Effective Exchange Rate (Merm)(Index No.)	5
83	Ex rate: Switz	exrsw	Foreign Exchange Rate: Switzerland (Swiss Franc Per U.S.$)	5
84	Ex rate: Japan	exrjan	Foreign Exchange Rate: Japan (Yen Per U.S.$)	5
85	Ex rate: UK	exruk	Foreign Exchange Rate: United Kingdom (Cents Per Pound)	5
86	EX rate: Canada	exrcan	Foreign Exchange Rate: Canada (Canadian $Per U.S.$)	5
87	PPI: fin gds	pwfsa	Producer Price Index: Finished Goods (82=100,Sa)	6
88	PPI: cons gds	pwfcsa	Producer Price Index: Finished Consumer Goods (82=100,Sa)	6
89	PPI: int materials	pwimsa	Producer Price Index: Intermed Mat.Supplies & Components(82=100,Sa)	6
90	PPI: crude materials	pwcmsa	Producer Price Index: Crude Materials (82=100,Sa)	6

Series no.	Name	Mnemonic	Description	transf
91	Spot market price	psccom	Spot market price index: bls & crb: all commodities(1967=100)	6
92	PPI: nonferrous materials	pw102	Producer Price Index: Nonferrous Materials (1982=100, Nsa)	6
93	NAPM com price	pmcp	Napm Commodity Prices Index (Percent)	1
94	CPI-U: all	punew	Cpi-U: All Items (82-84=100,Sa)	6
95	CPI-U: apparel	pu83	Cpi-U: Apparel & Upkeep (82-84=100,Sa)	6
96	CPI-U:transp	pu84	Cpi-U: Transportation (82-84=100,Sa)	6
97	CPI-U: medical	pu85	Cpi-U: Medical Care (82-84=100,Sa)	6
98	CPI-U: comm.	puc	Cpi-U: Commodities (82-84=100,Sa)	6
99	CPI-U:dbles	pucd	Cpi-U: Durables (82-84=100,Sa)	6
100	CPI-U:services	pus	Cpi-U: Services (82-84=100,Sa)	6
101	CPI-U:exfood	puxf	Cpi-U: All Items Less Food (82-84=100,Sa)	6
102	CPI-U:exshelter	puxhs	Cpi-U: All Items Less Shelter (82-84=100,Sa)	6
103	CPI-U:exmed	puxm	Cpi-U: All Items Less Midical Care (82-84=100,Sa)	6
104	PCEdefl	gmdc	Pce, Impl Pr Defl:Pce (2005=100, Sa) (BEA)	6
105	PCEdefl: dlbes	gmdcd	Pce, Impl Pr Defl:Pce; Durables (2005=100, Sa) (BEA)	6
106	PCEdefl: nondble	gmdcn	Pce, Impl Pr Defl:Pce; Nondurables (2005=100, Sa) (BEA)	6
107	PCEdefl: service	gmdcs	Pce, Impl Pr Defl:Pce; Services (2005=100, Sa) (BEA)	6

Table A.2: Factor risk premia for CAPM and FF3 model: GLS

This table reports the estimation results for the CAPM and the three-factor Fama-French (FF3) model. The estimation procedure is the time-series/cross-sectional regressions approach, with a GLS cross-sectional regression in the second step. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M, λ_{SMB}, and λ_{HML} denote the beta risk price estimates for the market, size, and value factors respectively. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional GLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_{SMB}	λ_{HML}	χ^2	R^2
			Panel A (SBM25)		
1	0.42			**92.55**	0.22
	(<u>2.17</u>)			(0.00)	$(-0.03, 0.14)$
2	0.42	0.27	0.41**	**75.03**	1.00
	(<u>2.17</u>)	(<u>2.00</u>)	(**3.26**)	(0.00)	$(-0.03, 0.28)$
			Panel B (SLTR25)		
1	0.42			**70.40**	0.19
	(<u>2.17</u>)			(0.00)	$(-0.02, 0.16)$
2	0.42	0.26	0.58**	**79.98**	1.00
	(<u>2.17</u>)	(*1.75*)	(**3.13**)	(0.00)	$(-0.01, 0.29)$

Table A.3: Factor risk premia for augmented CAPM: GLS

This table reports the estimation results for the augmented CAPM. The estimation procedure is the time-series/cross-sectional regressions approach, with a GLS cross-sectional regression in the second step. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional GLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
				Panel A (SBM25)			
1	0.42	1.78				**123.41**	0.22
	(<u>2.17</u>)	(0.10)				(0.00)	$(-0.04, 0.21)$
2	0.42		59.68**			**102.10**	0.47
	(<u>2.17</u>)		(**3.05**)			(0.00)	$(-0.03, 0.22)$
3	0.42			31.51		**88.38**	0.50
	(<u>2.17</u>)			(1.35)		(0.00)	$(-0.03, 0.21)$
4	0.42				69.71**	**61.30**	0.32
	(<u>2.17</u>)				(**3.24**)	(0.00)	$(-0.03, 0.21)$
5	0.42	30.54	63.47	82.73	56.76	**29.55**	0.94
	(<u>2.17</u>)	(0.05)	(0.44)	(0.10)	(0.06)	(0.10)	$(-0.01, 0.37)$
				Panel B (SLTR25)			
1	0.42	14.85				**76.66**	0.09
	(<u>2.17</u>)	(0.85)				(0.00)	$(-0.02, 0.23)$
2	0.42		27.64			**71.79**	0.32
	(<u>2.17</u>)		(*1.93*)			(0.00)	$(-0.02, 0.23)$
3	0.42			32.19		**84.87**	0.47
	(<u>2.17</u>)			(1.63)		(0.00)	$(-0.02, 0.23)$
4	0.42				−39.03	**85.41**	0.10
	(<u>2.17</u>)				(<u>−2.11</u>)	(0.00)	$(-0.02, 0.22)$
5	0.42	5.30	23.90	−10.69	−30.47	**57.85**	0.09
	(<u>2.17</u>)	(0.02)	(0.03)	(−0.41)	(−0.22)	(0.00)	$(0.01, 0.39)$

Table A.4: Factor risk premia for conditional CAPM: GLS

This table reports the estimation results for the conditional CAPM. The estimation procedure is the time-series/cross-sectional regressions approach, with a GLS cross-sectional regression in the second step. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_{M,1}, \lambda_{M,2}, \lambda_{M,3}, \lambda_{M,4}$ denote the risk prices associated with the scaled risk factors in which the conditioning variables are the lagged macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional GLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	$\lambda_{M,1}$	$\lambda_{M,2}$	$\lambda_{M,3}$	$\lambda_{M,4}$	χ^2	R^2
Panel A (SBM25)							
1	0.42	−0.65				**117.76**	0.26
	(<u>2.17</u>)	(−0.92)				(0.00)	(−0.04, 0.21)
2	0.42		−2.05			**82.98**	0.50
	(<u>2.17</u>)		(<u>−2.31</u>)			(0.00)	(−0.03, 0.21)
3	0.42			−0.51		**95.47**	0.30
	(<u>2.17</u>)			(−0.75)		(0.00)	(−0.04, 0.21)
4	0.42				−2.02	**117.69**	0.44
	(<u>2.17</u>)				(<u>−2.23</u>)	(0.00)	(−0.04, 0.21)
5	0.42	−1.92	−2.16	0.66	−2.48	**63.93**	0.73
	(<u>2.17</u>)	(−0.06)	(−0.23)	(0.01)	(−0.05)	(0.00)	(−0.01, 0.37)
Panel B (SLTR25)							
1	0.42	1.57				**57.20**	−0.16
	(<u>2.17</u>)	(<u>2.15</u>)				(0.00)	(−0.02, 0.23)
2	0.42		−1.03			**69.40**	0.27
	(<u>2.17</u>)		(−1.18)			(0.00)	(−0.02, 0.24)
3	0.42			0.53		**71.40**	0.10
	(<u>2.17</u>)			(0.80)		(0.00)	(−0.02, 0.23)
4	0.42				−1.74	**65.85**	0.33
	(<u>2.17</u>)				(<u>−2.16</u>)	(0.00)	(−0.02, 0.23)
5	0.42	1.54	−1.11	0.51	−0.92	**50.16**	−0.02
	(<u>2.17</u>)	(0.04)	(−0.01)	(0.00)	(−0.05)	(0.00)	(0.01, 0.39)

Table A.5: Factor risk premia for ICAPM: GLS

This table reports the estimation results for the Intertemporal CAPM (ICAPM). The estimation procedure is the time-series/cross-sectional regressions approach, with a GLS cross-sectional regression in the second step. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the innovation in each of the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional GLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
				Panel A (SBM25)			
1	0.42	44.01				**197.92**	0.53
	(2.17)	(*1.91*)				(0.00)	$(-0.04, 0.21)$
2	0.42		28.96			**119.74**	0.24
	(2.17)		(0.84)			(0.00)	$(-0.03, 0.22)$
3	0.42			−39.24		**86.35**	0.14
	(2.17)			(−1.39)		(0.00)	$(-0.03, 0.21)$
4	0.42				85.17*	**100.10**	0.59
	(2.17)				(**2.78**)	(0.00)	$(-0.04, 0.21)$
5	0.42	29.11	−8.16	−16.03	77.26	**49.25**	0.71
	(2.17)	(0.04)	(−0.00)	(−0.06)	(0.03)	(0.00)	$(-0.02, 0.37)$
				Panel B (SLTR25)			
1	0.42	−23.19				**71.74**	−0.05
	(2.17)	(−1.47)				(0.00)	$(-0.02, 0.24)$
2	0.42		25.10			**68.81**	0.20
	(2.17)		(0.95)			(0.00)	$(-0.03, 0.27)$
3	0.42			−75.08*		**52.74**	−0.06
	(2.17)			(−**2.94**)		(0.00)	$(-0.02, 0.23)$
4	0.42				21.56	**71.09**	0.26
	(2.17)				(0.77)	(0.00)	$(-0.02, 0.22)$
5	0.42	−26.02	18.96	−71.78**	5.20	**53.32**	0.03
	(2.17)	(−0.40)	(0.05)	(−0.09)	(0.00)	(0.00)	$(0.01, 0.39)$

Table A.6: Factor risk premia for augmented CAPM: estimation by GMM

This table reports the estimation and evaluation results for the augmented CAPM. The estimation procedure is first-stage GMM with equally weighted errors. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). γ denotes the (covariance) risk price estimate for the market factor, while $\gamma_1, \gamma_2, \gamma_3, \gamma_4$ denote the risk prices associated with the macro factors. The first line associated with each row presents the covariance risk price estimates, and the second line reports the asymptotic GMM robust t-statistics (in parentheses). The column labeled R^2 denotes the cross-sectional OLS R^2. The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line), and associated asymptotic p-values (in parentheses) for the test on the joint significance of the pricing errors. The sample is 1964:02–2010:09. Italic, underlined, and bold numbers denote statistical significance at the 10%, 5%, and 1% levels respectively.

	γ	γ_1	γ_2	γ_3	γ_4	χ^2	R^2
				Panel A (SBM25)			
1	2.91					94.70	−0.33
	(**2.74**)					(0.00)	
2	3.31	1.30				34.55	−0.04
	(1.42)	(1.58)				(0.08)	
3	2.49		0.83			59.42	−0.14
	(*1.66*)		(1.45)			(0.00)	
4	2.37			0.17		92.27	−0.32
	(*1.72*)			(0.44)		(0.00)	
5	4.07				0.46	75.46	−0.32
	(**3.27**)				(1.33)	(0.00)	
6	−3.04	1.48	2.12	1.55	−0.15	7.59	0.59
	(−0.60)	(0.90)	(1.31)	(1.05)	(−0.16)	(1.00)	
				Panel B (SLTR25)			
1	3.18					62.65	−0.01
	(**3.00**)					(0.00)	
2	2.94	−0.41				65.24	0.02
	(**2.65**)	(−1.39)				(0.00)	
3	3.08		0.17			61.72	0.01
	(**2.85**)		(0.69)			(0.00)	
4	1.84			0.41		55.94	0.09
	(1.31)			(1.16)		(0.00)	
5	2.93				−0.10	59.24	−0.01
	(<u>2.41</u>)				(−0.44)	(0.00)	
6	0.43	0.33	0.67	0.79	0.01	26.39	0.20
	(0.22)	(0.58)	(*1.70*)	(1.17)	(0.01)	(0.19)	

Table A.7: Factor risk premia for conditional CAPM: estimation by GMM

This table reports the estimation and evaluation results for the conditional CAPM. The estimation procedure is first-stage GMM with equally weighted errors. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). γ denotes the (covariance) risk price estimate for the market factor, while $\gamma_{M,1}, \gamma_{M,2}, \gamma_{M,3}, \gamma_{M,4}$ denote the risk prices associated with the scaled risk factors in which the conditioning variables are the lagged macro factors. The first line associated with each row presents the covariance risk price estimates, and the second line reports the asymptotic GMM robust t-statistics (in parentheses). The column labeled R^2 denotes the cross-sectional OLS R^2. The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line), and associated asymptotic p-values (in parentheses) for the test on the joint significance of the pricing errors. The sample is 1964:02–2010:09. Italic, underlined, and bold numbers denote statistical significance at the 10%, 5%, and 1% levels respectively.

	γ	$\gamma_{M,1}$	$\gamma_{M,2}$	$\gamma_{M,3}$	$\gamma_{M,4}$	χ^2	R^2
			Panel A (SBM25)				
1	−4.84	−17.11				46.10	0.45
	(−1.40)	(−1.59)				(0.00)	
2	3.56		−24.30			46.66	0.41
	(1.21)		(*−1.83*)			(0.00)	
3	2.89			−0.24		93.89	−0.33
	(**2.81**)			(−0.03)		(0.00)	
4	2.64				16.17	64.25	−0.15
	(1.45)				(1.61)	(0.00)	
5	−2.85	−14.15	−13.80	3.03	−7.16	38.17	0.66
	(−1.03)	(−1.63)	(−1.35)	(0.26)	(−0.52)	(0.01)	
			Panel B (SLTR25)				
1	0.31	−5.90				48.05	0.09
	(0.15)	(−1.19)				(0.00)	
2	3.79		−15.87			37.11	0.28
	(*1.73*)		(<u>−2.09</u>)			(0.04)	
3	3.12			−1.01		61.13	−0.01
	(**2.96**)			(−0.18)		(0.00)	
4	3.77				−27.82	22.78	0.22
	(1.11)				(−1.64)	(0.53)	
5	1.97	−5.84	−12.73	12.63	−21.24	16.65	0.49
	(0.42)	(−0.55)	(−1.43)	(0.95)	(*−1.76*)	(0.73)	

Table A.8: Factor risk premia for ICAPM: estimation by GMM

This table reports the estimation and evaluation results for the Intertemporal CAPM (ICAPM). The estimation procedure is first-stage GMM with equally weighted errors. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). γ denotes the (covariance) risk price estimate for the market factor, while $\gamma_1, \gamma_2, \gamma_3, \gamma_4$ denote the risk prices associated with the innovation in each of the macro factors. The first line associated with each row presents the covariance risk price estimates, and the second line reports the asymptotic GMM robust t-statistics (in parentheses). The column labeled R^2 denotes the cross-sectional OLS R^2. The column labeled χ^2 presents the χ^2 statistic (first line), and associated asymptotic p-values (in parentheses) for the test on the joint significance of the pricing errors. The sample is 1964:02–2010:09. Italic, underlined, and bold numbers denote statistical significance at the 10%, 5%, and 1% levels respectively.

	γ	γ_1	γ_2	γ_3	γ_4	χ^2	R^2
				Panel A (SBM25)			
1	1.54	2.12				26.53	−0.10
	(0.82)	(1.35)				(0.33)	
2	2.05		−0.87			39.59	−0.15
	(1.03)		(*−1.79*)			(0.02)	
3	2.49			−1.05		48.58	−0.14
	(1.39)			(−1.51)		(0.00)	
4	2.95				0.12	87.40	−0.33
	(**2.71**)				(0.30)	(0.00)	
5	0.35	2.95	−0.04	−1.31	−0.26	24.21	0.22
	(0.17)	(<u>2.38</u>)	(−0.07)	(−1.49)	(−0.42)	(0.28)	
				Panel B (SLTR25)			
1	2.13	1.39				30.84	0.24
	(1.50)	(1.54)				(0.16)	
2	2.81		−0.37			52.25	0.07
	(<u>2.16</u>)		(−1.47)			(0.00)	
3	3.07			−0.38		47.61	0.03
	(<u>2.47</u>)			(−1.09)		(0.00)	
4	3.50				0.62	44.86	0.09
	(**2.59**)				(1.43)	(0.01)	
5	1.36	1.93	−0.04	−0.97	−0.10	27.18	0.42
	(0.91)	(<u>2.43</u>)	(−0.15)	(*−1.85*)	(−0.26)	(0.16)	

Table A.9: Factor risk premia for ICAPM: innovations from AR(1)

This table reports the estimation results for the Intertemporal CAPM (ICAPM) in which the innovations in the macro factors are constructed from an AR(1) process. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the innovation in each of the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
				Panel A (SBM25)			
1	0.51**	146.46*				**23.79**	0.08
	(<u>2.21</u>)	(*1.74*)				(0.47)	$(-2.68, 0.43)$
2	0.55***		91.17*			**56.29**	-0.03
	(<u>2.57</u>)		(*1.92*)			(0.00)	$(-2.77, 0.43)$
3	0.61***			-9.16		90.13	-0.33
	(**3.09**)			(-0.21)		(0.00)	$(-2.69, 0.41)$
4	0.59***				44.41	67.92	-0.32
	(**2.89**)				(1.20)	(0.00)	$(-2.63, 0.44)$
5	0.34*	180.17	151.49	171.12	-10.52	**8.32**	0.59
	(1.60)	(1.36)	(1.63)	(1.30)	(-0.13)	(0.99)	$(-0.52, 0.71)$
				Panel B (SLTR25)			
1	0.60***	93.76				**33.57**	0.20
	(**2.82**)	(1.40)				(0.09)	$(-3.52, 0.45)$
2	0.64***		25.70			61.79	0.03
	(**3.06**)		(1.12)			(0.00)	$(-3.40, 0.44)$
3	0.62***			28.30		62.33	0.03
	(**3.13**)			(0.76)		(0.00)	$(-3.48, 0.44)$
4	0.66***				-11.33	67.62	-0.01
	(**3.23**)				(-0.51)	(0.00)	$(-3.38, 0.44)$
5	0.52***	153.29	72.70	105.23	4.02	**12.18**	0.42
	(<u>2.48</u>)	(1.46)	(1.25)	(1.07)	(0.06)	(0.93)	$(-0.76, 0.71)$

Table A.10: Factor risk premia for (C)ICAPM

This table reports the estimation results for the three-factor conditional ICAPM. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor; $\lambda_{M,z}$ denotes the risk price associated with the scaled factor; and λ_z represents the risk price associated with the innovation in each of the macro factors, F_1, F_2, F_3, F_4. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	$\lambda_{M,z}$	λ_z	χ^2	R^2
			Panel A (SBM25)		
F_1	0.49***	−6.10***	54.60	**42.57**	0.49
	(<u>2.28</u>)	(<u>−2.45</u>)	(0.57)	(0.01)	(−1.79, 0.57)
F_2	0.48**	−7.09***	−109.78	**45.52**	0.45
	(<u>2.17</u>)	(<u>−2.24</u>)	(−0.80)	(0.00)	(−1.85, 0.56)
F_3	0.53***	−5.46	−260.62	**15.22**	0.10
	(<u>2.39</u>)	(−1.06)	(−1.41)	(0.89)	(−1.84, 0.56)
F_4	0.59***	4.12*	120.98	**36.03**	−0.07
	(**2.79**)	(1.61)	(1.09)	(0.04)	(−1.79, 0.57)
			Panel B (SLTR25)		
F_1	0.54***	0.13	92.93*	**30.88**	0.25
	(**2.71**)	(0.05)	(1.63)	(0.13)	(−2.26, 0.57)
F_2	0.61***	−5.20***	−107.92	**32.75**	0.38
	(**2.92**)	(<u>−2.01</u>)	(−1.15)	(0.09)	(−2.36, 0.57)
F_3	0.65***	−2.33	−115.63**	**32.10**	0.10
	(**3.12**)	(−1.23)	(<u>−2.32</u>)	(0.10)	(−2.22, 0.56)
F_4	0.52***	−5.75**	128.19	**24.60**	0.31
	(<u>2.40</u>)	(−1.46)	(0.72)	(0.37)	(−2.29, 0.58)

Table A.11: Factor risk premia for CAPM and FF3 model: bond returns

This table reports the estimation results for the CAPM and the three-factor Fama-French (FF3) model. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return, equity portfolios, and seven Treasury bonds. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M, λ_{SMB}, and λ_{HML} denote the beta risk price estimates for the market, size, and value factors respectively. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_{SMB}	λ_{HML}	χ^2	R^2
			Panel A (SBM25)		
1	0.60***			**108.47**	0.31
	(**2.97**)			(0.00)	$(-0.85, 0.49)$
2	0.42**	0.22	0.47***	93.47	0.80
	(<u>2.16</u>)	(1.58)	(**3.62**)	(0.00)	$(-0.40, 0.74)$
			Panel B (SLTR25)		
1	0.66***			94.54	0.57
	(**3.22**)			(0.00)	$(-1.01, 0.60)$
2	0.44***	0.06	0.76***	73.00	0.89
	(<u>2.25</u>)	(0.36)	(**3.48**)	(0.00)	$(-0.41, 0.79)$

Table A.12: Factor risk premia for augmented CAPM: bond returns

This table reports the estimation results for the augmented CAPM. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return, equity portfolios, and seven Treasury bonds. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
				Panel A (SBM25)			
1	0.61***	6.09				106.94	0.31
	(**2.98**)	(0.28)				(0.00)	$(-0.69, 0.66)$
2	0.57***		63.78*			85.11	0.40
	(**2.73**)		(*1.69*)			(0.00)	$(-0.70, 0.66)$
3	0.60***			6.51		105.53	0.31
	(**3.01**)			(0.17)		(0.00)	$(-0.69, 0.65)$
4	0.59***				51.73	83.90	0.31
	(**2.87**)				(1.25)	(0.00)	$(-0.67, 0.66)$
5	0.35*	87.34	197.25**	134.82	−31.02	**17.08**	0.68
	(1.52)	(1.09)	(1.45)	(1.25)	(−0.36)	(0.95)	$(0.04, 0.83)$
				Panel B (SLTR25)			
1	0.62***	−40.70*				70.79	0.61
	(**2.90**)	(−1.38)				(0.00)	$(-0.79, 0.72)$
2	0.64***		28.35			83.22	0.59
	(**3.08**)		(1.14)			(0.00)	$(-0.76, 0.72)$
3	0.62***			29.26		91.40	0.60
	(**3.12**)			(0.83)		(0.00)	$(-0.78, 0.72)$
4	0.66***				−2.29	86.95	0.57
	(**3.23**)				(−0.10)	(0.00)	$(-0.76, 0.72)$
5	0.52***	−14.20	48.78**	61.69	−17.78	51.08	0.67
	(**2.61**)	(−0.49)	(<u>2.11</u>)	(1.35)	(−0.55)	(0.00)	$(0.09, 0.86)$

Table A.13: Factor risk premia for conditional CAPM: bond returns

This table reports the estimation results for the conditional CAPM. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return, equity portfolios, and seven Treasury bonds. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_{M,1}, \lambda_{M,2}, \lambda_{M,3}, \lambda_{M,4}$ denote the risk prices associated with the scaled risk factors in which the conditioning variables are the lagged macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	$\lambda_{M,1}$	$\lambda_{M,2}$	$\lambda_{M,3}$	$\lambda_{M,4}$	χ^2	R^2
				Panel A (SBM25)			
1	0.55***	−6.28***				**62.92**	0.68
	($\underline{2.12}$)	($\underline{-2.48}$)				(0.00)	(−0.69, 0.66)
2	0.50***		−5.14***			**86.20**	0.61
	($\underline{2.34}$)		(**−3.06**)			(0.00)	(−0.69, 0.67)
3	0.59***			−0.61		108.37	0.31
	(**2.98**)			(−0.36)		(0.00)	(−0.69, 0.67)
4	0.67***				3.44*	**64.18**	0.40
	(**3.18**)				(1.59)	(0.00)	(−0.73, 0.66)
5	0.47***	−6.09***	−3.64***	0.88	−2.21	**47.82**	0.81
	($\underline{2.08}$)	(−1.44)	(−1.58)	(0.32)	(−0.55)	(0.01)	(0.06, 0.83)
				Panel B (SLTR25)			
1	0.60***	−2.22				85.79	0.61
	(**2.90**)	(−1.15)				(0.00)	(−0.77, 0.73)
2	0.62***		−3.39***			75.89	0.69
	(**3.00**)		($\underline{-2.23}$)			(0.00)	(−0.76, 0.72)
3	0.65***			−0.65		93.65	0.58
	(**3.19**)			(−0.53)		(0.00)	(−0.79, 0.72)
4	0.60***				−4.76**	**48.75**	0.65
	($\underline{2.51}$)				(−1.42)	(0.02)	(−0.78, 0.73)
5	0.57***	−2.41	−3.54**	2.63	−4.32**	**35.02**	0.78
	($\underline{2.42}$)	(−0.63)	(−1.31)	(0.85)	(−1.49)	(0.17)	(0.08, 0.86)

Table A.14: Factor risk premia for ICAPM: bond returns

This table reports the estimation results for the Intertemporal CAPM (ICAPM). The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return, equity portfolios, and seven Treasury bonds. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the innovation in each of the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
			Panel A (SBM25)				
1	0.56***	41.28				85.04	0.34
	(**2.79**)	(0.89)				(0.00)	(−0.68, 0.65)
2	0.62***		−222.92**			**53.07**	0.42
	(**2.75**)		(*−1.88*)			(0.01)	(−0.71, 0.66)
3	0.63***			−89.99		**75.21**	0.36
	(**3.11**)			(−1.56)		(0.00)	(−0.67, 0.66)
4	0.64***				−46.19	102.56	0.31
	(**3.14**)				(−0.81)	(0.00)	(−0.70, 0.66)
5	0.63***	48.09	−137.09	15.71	−102.65	**36.27**	0.54
	(**2.86**)	(0.87)	(−1.00)	(0.19)	(−1.01)	(0.14)	(0.07, 0.84)
			Panel B (SLTR25)				
1	0.60***	39.46				81.77	0.61
	(**3.01**)	(1.04)				(0.00)	(−0.78, 0.72)
2	0.67***		−109.39*			69.69	0.62
	(**3.14**)		(−1.64)			(0.00)	(−0.74, 0.72)
3	0.67***			−17.74		93.79	0.58
	(**3.33**)			(−0.50)		(0.00)	(−0.79, 0.72)
4	0.67***				−15.38	90.61	0.57
	(**3.29**)				(−0.29)	(0.00)	(−0.79, 0.72)
5	0.66***	27.98	−69.16	−9.84	−100.39	**46.57**	0.70
	(**3.22**)	(0.67)	(−1.09)	(−0.17)	(−1.39)	(0.02)	(0.09, 0.86)

Table A.15: Factor risk premia for CAPM and FF3 model: industry portfolios

This table reports the estimation results for the CAPM and the three-factor Fama-French (FF3) model. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return, 10 industry portfolios, and other equity portfolios. The other equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M, λ_{SMB}, and λ_{HML} denote the beta risk price estimates for the market, size, and value factors respectively. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_{SMB}	λ_{HML}	χ^2	R^2
	Panel A (SBM25)				
1	0.58***			**124.36**	−0.24
	(**2.91**)			(0.00)	(−2.91, 0.12)
2	0.46***	0.21	0.35***	109.53	0.46
	(<u>2.35</u>)	(1.50)	(**2.70**)	(0.00)	(−2.01, 0.35)
	Panel B (SLTR25)				
1	0.62***			**93.78**	0.05
	(**3.11**)			(0.00)	(−3.46, 0.16)
2	0.49***	0.23	0.29**	79.64	0.50
	(<u>2.51</u>)	(1.53)	(*1.88*)	(0.00)	(−2.30, 0.42)

Table A.16: Factor risk premia for augmented CAPM: industry portfolios

This table reports the estimation results for the augmented CAPM. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return, 10 industry portfolios, and other equity portfolios. The other equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
				Panel A (SBM25)			
1	0.60***	37.65*				116.15	−0.18
	(**2.99**)	(*1.67*)				(0.00)	(−2.48, 0.24)
2	0.57***		23.53			123.42	−0.21
	(**2.83**)		(1.00)			(0.00)	(−2.61, 0.24)
3	0.58***			3.41		122.49	−0.24
	(**2.96**)			(0.12)		(0.00)	(−2.65, 0.23)
4	0.58***				10.38	118.04	−0.24
	(**2.89**)				(0.34)	(0.00)	(−2.52, 0.24)
5	0.56***	68.74**	51.24	24.88	−14.10	78.81	−0.07
	(**2.81**)	(*1.73*)	(1.46)	(0.73)	(−0.42)	(0.00)	(−0.99, 0.53)
				Panel B (SLTR25)			
1	0.60***	−25.86				82.60	0.07
	(**2.97**)	(−1.24)				(0.00)	(−2.94, 0.29)
2	0.62***		−0.41			93.72	0.05
	(**3.10**)		(−0.02)			(0.00)	(−2.94, 0.29)
3	0.60***			20.83		86.11	0.08
	(**3.05**)			(0.76)		(0.00)	(−2.98, 0.30)
4	0.62***				−5.86	89.94	0.05
	(**3.12**)				(−0.22)	(0.00)	(−2.96, 0.28)
5	0.59***	−27.54	−10.23	12.97	−6.53	73.25	0.10
	(**3.02**)	(−1.17)	(−0.53)	(0.37)	(−0.23)	(0.00)	(−1.04, 0.57)

Table A.17: Factor risk premia for conditional CAPM: industry portfolios

This table reports the estimation results for the conditional CAPM. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return, 10 industry portfolios, and other equity portfolios. The other equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_{M,1}, \lambda_{M,2}, \lambda_{M,3}, \lambda_{M,4}$ denote the risk prices associated with the scaled risk factors in which the conditioning variables are the lagged macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	$\lambda_{M,1}$	$\lambda_{M,2}$	$\lambda_{M,3}$	$\lambda_{M,4}$	χ^2	R^2
			Panel A (SBM25)				
1	0.55***	−2.99***				113.44	−0.02
	(**2.60**)	($\underline{-1.99}$)				(0.00)	(−2.62, 0.24)
2	0.49***		−5.35***			**86.40**	0.31
	($\underline{2.43}$)		($\underline{-2.48}$)			(0.00)	(−2.49, 0.23)
3	0.55***			−1.79*		124.45	−0.17
	(**2.77**)			(*−1.70*)		(0.00)	(−2.59, 0.23)
4	0.61***				2.16*	98.99	−0.12
	(**3.09**)				(1.59)	(0.00)	(−2.63, 0.23)
5	0.51***	−1.69	−4.54***	−0.24	1.08	95.12	0.39
	(**2.58**)	(−1.28)	(**−2.66**)	(−0.18)	(0.62)	(0.00)	(−0.95, 0.53)
			Panel B (SLTR25)				
1	0.61***	−0.88				83.14	0.06
	(**3.06**)	(−0.66)				(0.00)	(−3.00, 0.30)
2	0.59***		−3.61***			**74.32**	0.28
	(**2.95**)		($\underline{-2.39}$)			(0.00)	(−2.98, 0.29)
3	0.59***			−1.96**		88.15	0.16
	(**2.93**)			($\underline{-1.96}$)		(0.00)	(−2.92, 0.30)
4	0.61***				−0.76	94.07	0.06
	(**3.06**)				(−0.64)	(0.00)	(−2.89, 0.30)
5	0.57***	−0.37	−3.23***	−0.65	−1.04	65.69	0.30
	(**2.89**)	(−0.25)	($\underline{-2.05}$)	(−0.56)	(−0.87)	(0.00)	(−1.11, 0.57)

Table A.18: Factor risk premia for ICAPM: industry portfolios

This table reports the estimation results for the Intertemporal CAPM (ICAPM). The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return, 10 industry portfolios, and other equity portfolios. The other equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the innovation in each of the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled χ^2 presents the χ^2 statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold χ^2 indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
				Panel A (SBM25)			
1	0.57***	15.64				118.41	−0.23
	(**2.88**)	(0.54)				(0.00)	(−2.53, 0.23)
2	0.59***		−122.88**			**80.99**	−0.13
	(**2.90**)		(<u>−1.96</u>)			(0.00)	(−2.59, 0.22)
3	0.60***			−91.43		**92.78**	−0.11
	(**3.04**)			(*−1.67*)		(0.00)	(−2.64, 0.22)
4	0.60***				−26.80	122.27	−0.24
	(**3.04**)				(−0.45)	(0.00)	(−2.59, 0.23)
5	0.60***	27.20	−74.41	−2.95	−71.15	**67.10**	0.03
	(**2.99**)	(0.76)	(−0.79)	(−0.06)	(−1.08)	(0.00)	(−1.00, 0.53)
				Panel B (SLTR25)			
1	0.59***	26.36				79.35	0.09
	(**3.00**)	(0.87)				(0.00)	(−3.00, 0.29)
2	0.63***		−75.61			74.88	0.11
	(**3.10**)		(−1.55)			(0.00)	(−2.95, 0.29)
3	0.63***			−28.84		82.99	0.06
	(**3.22**)			(−0.75)		(0.00)	(−2.99, 0.29)
4	0.62***				7.46	93.35	0.05
	(**3.14**)				(0.14)	(0.00)	(−2.94, 0.29)
5	0.62***	29.15	−41.82	4.01	−67.42	**53.24**	0.24
	(**3.10**)	(0.83)	(−0.70)	(0.08)	(−1.22)	(0.01)	(−1.12, 0.58)

Table A.19: Factor risk premia for CAPM and FF3 model: alternative portfolios

This table reports the estimation results for the CAPM and the three-factor Fama-French (FF3) model. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and momentum. λ_M, λ_{SMB}, and λ_{HML} denote the beta risk price estimates for the market, size, and value factors respectively. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_{SMB}	λ_{HML}	χ^2	R^2
1	0.53^{***}			**101.65**	-0.16
	(**2.58**)			(0.00)	$(-1.67, 0.47)$
2	0.48^{***}	0.47^{***}	-0.67^{***}	90.84	0.05
	($\underline{2.47}$)	(**3.10**)	($\underline{-2.17}$)	(0.00)	$(-0.79, 0.72)$

Table A.20: Factor risk premia for augmented CAPM: alternative portfolios

This table reports the estimation results for the augmented CAPM. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and momentum. λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
1	0.71^{***}	185.98^{**}				**29.15**	0.35
	(**2.96**)	($\underline{2.16}$)				(0.21)	$(-1.32, 0.61)$
2	0.53^{***}		-25.78			93.57	-0.15
	(**2.59**)		(-0.75)			(0.00)	$(-1.34, 0.62)$
3	0.62^{***}			-47.69		109.14	-0.10
	(**3.09**)			(-1.35)		(0.00)	$(-1.34, 0.60)$
4	0.60^{***}				-201.02^{**}	**28.42**	0.49
	($\underline{2.51}$)				($\underline{-2.14}$)	(0.24)	$(-1.32, 0.61)$
5	0.58^{***}	130.69^{***}	110.78^{*}	59.16	-166.64	**16.46**	0.62
	(**2.59**)	($\underline{2.11}$)	(*1.72*)	(0.85)	(-1.50)	(0.74)	$(-0.09, 0.83)$

Table A.21: Factor risk premia for conditional CAPM: alternative portfolios

This table reports the estimation results for the conditional CAPM. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and momentum. λ_M denotes the risk price estimate for the market factor, while $\lambda_{M,1}, \lambda_{M,2}, \lambda_{M,3}, \lambda_{M,4}$ denote the risk prices associated with the scaled risk factors in which the conditioning variables are the lagged macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	$\lambda_{M,1}$	$\lambda_{M,2}$	$\lambda_{M,3}$	$\lambda_{M,4}$	χ^2	R^2
1	0.67^{***}	3.04^{***}				67.98	0.62
	(**3.42**)	(**3.52**)				(0.00)	$(-1.32, 0.60)$
2	0.48^{**}		-11.23^{***}			**22.66**	0.52
	(*1.68*)		(*−1.67*)			(0.54)	$(-1.23, 0.60)$
3	0.39			-8.94^{***}		**20.55**	0.81
	(1.40)			(**−2.66**)		(0.67)	$(-1.36, 0.61)$
4	0.50^{**}				-7.52^{***}	**29.40**	0.48
	(*1.74*)				(*−1.66*)	(0.21)	$(-1.37, 0.61)$
5	0.49^{***}	0.33	-3.25^{**}	-4.12^{***}	-1.56	30.05	0.90
	(<u>2.39</u>)	(0.21)	(*−1.68*)	(<u>−2.21</u>)	(−0.59)	(0.09)	$(-0.09, 0.82)$

Table A.22: Factor risk premia for ICAPM: alternative portfolios

This table reports the estimation results for the Intertemporal CAPM (ICAPM). The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and momentum. λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the innovation in each of the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
1	0.67***	−110.74				**47.11**	0.04
	(**3.30**)	(−1.53)				(0.00)	(−1.30, 0.61)
2	0.55***		280.01*			**25.54**	0.10
	(<u>2.27</u>)		(*1.70*)			(0.38)	(−1.33, 0.60)
3	0.66***			−184.97**		**41.71**	0.47
	(**3.07**)			(−**2.59**)		(0.01)	(−1.33, 0.61)
4	0.34				454.79	**10.79**	0.24
	(1.37)				(*1.69*)	(0.99)	(−1.29, 0.61)
5	0.48**	−52.74	89.03	−168.26	437.38**	**7.90**	0.76
	(<u>2.18</u>)	(−0.48)	(0.52)	(−1.05)	(*1.75*)	(1.00)	(−0.08, 0.82)

Table A.23: Factor risk premia for augmented CAPM: alternative macro factors

This table reports the estimation results for the augmented CAPM using alternative macro risk factors. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively. For a description of the factors, see Section 6.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
				Panel A (SBM25)			
1	0.64***	117.38**				**41.54**	−0.00
	(**2.92**)	(*1.79*)				(0.01)	(−2.65, 0.42)
2	0.57***		−81.83			62.39	−0.17
	(**2.70**)		(*−1.66*)			(0.00)	(−2.67, 0.45)
3	0.39**			−101.66***		**55.74**	0.15
	(1.98)			(−2.42)		(0.00)	(−2.59, 0.44)
4	0.61***				−4.53	85.28	−0.33
	(**3.07**)				(−0.12)	(0.00)	(−2.69, 0.42)
5	0.35*	74.02	−72.55*	−140.77***	−12.28	**23.19**	0.60
	(*1.73*)	(1.04)	(−1.48)	(−2.47)	(−0.21)	(0.33)	(−0.59, 0.71)
				Panel B (SLTR25)			
1	0.67***	16.25				72.68	−0.00
	(**3.39**)	(0.43)				(0.00)	(−3.33, 0.43)
2	0.65***		−11.89			67.14	−0.00
	(**3.12**)		(−0.42)			(0.00)	(−3.35, 0.43)
3	0.49***			−76.02**		48.23	0.37
	(2.48)			(−1.98)		(0.00)	(−3.42, 0.42)
4	0.63***				42.00	65.07	0.05
	(**3.13**)				(0.95)	(0.00)	(−3.33, 0.43)
5	0.45**	139.05**	−42.78	−162.23**	−35.18	**11.68**	0.67
	(2.10)	(*1.86*)	(−0.89)	(*−1.73*)	(−0.46)	(0.95)	(−0.83, 0.71)

Table A.24: Factor risk premia for conditional CAPM: alternative macro factors

This table reports the estimation results for the conditional CAPM using alternative macro risk factors. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_{M,1}, \lambda_{M,2}, \lambda_{M,3}, \lambda_{M,4}$ denote the risk prices associated with the scaled risk factors in which the conditioning variables are the lagged macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively. For a description of the factors, see Section 6.

	λ_M	$\lambda_{M,1}$	$\lambda_{M,2}$	$\lambda_{M,3}$	$\lambda_{M,4}$	χ^2	R^2
				Panel A (SBM25)			
1	0.58***	−5.05***				62.98	0.42
	($\underline{2.33}$)	(**−2.79**)				(0.00)	(−2.65, 0.42)
2	0.48**		6.75***			**54.43**	0.55
	($\underline{2.20}$)		($\underline{2.24}$)			(0.00)	(−2.72, 0.44)
3	0.49***			7.38***		**32.81**	0.02
	(*1.95*)			(1.44)		(0.11)	(−2.70, 0.45)
4	0.48***				−5.30***	**52.85**	0.09
	($\underline{2.20}$)				($\underline{-2.24}$)	(0.00)	(−2.64, 0.44)
5	0.48***	−2.92	4.93***	2.61	−1.49	51.21	0.63
	($\underline{2.36}$)	(−1.35)	(*1.93*)	(1.10)	(−0.56)	(0.00)	(−0.59, 0.72)
				Panel B (SLTR25)			
1	0.59***	−3.15*				51.27	0.13
	(**2.79**)	(−1.18)				(0.00)	(−3.42, 0.44)
2	0.58***		5.58***			**33.30**	0.42
	(**2.73**)		($\underline{2.53}$)			(0.10)	(−3.55, 0.44)
3	0.63***			1.04		71.12	0.01
	(**3.05**)			(0.80)		(0.00)	(−3.47, 0.43)
4	0.64***				−0.57	65.15	0.00
	(**3.22**)				(−0.38)	(0.00)	(−3.30, 0.42)
5	0.55***	−2.63	5.49***	−0.58	−1.06	**26.40**	0.49
	(**2.69**)	(−1.41)	($\underline{2.22}$)	(−0.28)	(−0.49)	(0.19)	(−0.82, 0.71)

Table A.25: Factor risk premia for ICAPM: alternative macro factors

This table reports the estimation results for the Intertemporal CAPM (ICAPM) using alternative macro risk factors. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the innovation in each of the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. The sample is 1964:02–2010:09. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively. For a description of the factors, see Section 6.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
				Panel A (SBM25)			
1	0.63***	100.76				**51.05**	−0.15
	(**2.87**)	(1.13)				(0.00)	(−2.77, 0.43)
2	0.61***		90.86			76.40	−0.29
	(**2.95**)		(0.96)			(0.00)	(−2.72, 0.42)
3	0.44**			−201.43***		**45.66**	−0.02
	(2.09)			(−2.31)		(0.00)	(−2.58, 0.44)
4	0.64***				−96.46	74.02	−0.25
	(**3.17**)				(−1.13)	(0.00)	(−2.68, 0.42)
5	0.52***	102.53	173.58	−199.12**	−51.46	**24.14**	0.27
	(2.35)	(0.88)	(1.22)	(*−1.75*)	(−0.52)	(0.29)	(−0.58, 0.72)
				Panel B (SLTR25)			
1	0.66***	65.48**				56.79	0.12
	(**3.06**)	(*1.87*)				(0.00)	(−3.43, 0.44)
2	0.68***		83.70			56.65	0.04
	(**3.23**)		(1.32)			(0.00)	(−3.35, 0.43)
3	0.48***			−159.03***		**41.65**	0.35
	(2.37)			(*−1.95*)		(0.01)	(−3.47, 0.42)
4	0.66***				−1.41	66.81	−0.01
	(**3.28**)				(−0.02)	(0.00)	(−3.35, 0.43)
5	0.52***	31.86	104.18	−153.53**	−51.95	**29.64**	0.46
	(**2.58**)	(0.92)	(1.40)	(*−1.82*)	(−0.67)	(0.10)	(−0.76, 0.70)

Table A.26: Factor risk premia for augmented CAPM: factor-mimicking portfolios

This table reports the estimation results for the augmented CAPM with factor-mimicking portfolios. The estimation procedure is the time-series/cross-sectional regressions approach. The test assets are the market return and equity portfolios. The equity portfolios are 25 portfolios sorted by size and book-to-market (SBM25, Panel A) and 25 portfolios sorted by size and past long-term returns (SLTR25, Panel B). λ_M denotes the risk price estimate for the market factor, while $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ denote the risk prices associated with the macro factors. Below the risk price estimates (in %) are displayed t-statistics based on GMM standard errors (in parentheses). The column labeled $\boldsymbol{\chi}^2$ presents the $\boldsymbol{\chi}^2$ statistic (first line) and associated p-values (in parentheses) for the test on the joint significance of the pricing errors. The column labeled R^2 denotes the cross-sectional OLS R^2 (first line) and an associated 90% confidence interval (in parentheses) from a bootstrap simulation. Italic, underlined, and bold t-ratios denote statistical significance at the 10%, 5%, and 1% levels respectively. A bold $\boldsymbol{\chi}^2$ indicates that the model is not rejected (based on the bootstrap simulation) at the 5% level. ***, **, and * denote statistical significance of the risk prices (based on the bootstrap simulation) at the 1%, 5%, and 10% levels respectively.

	λ_M	λ_1	λ_2	λ_3	λ_4	χ^2	R^2
				Panel A (SBM25)			
1	0.56***	1.93***				80.36	0.23
	(**2.72**)	(**3.01**)				(0.00)	$(-2.69, 0.43)$
2	0.67***		1.77***			71.16	0.06
	(**3.30**)		(**3.32**)			(0.00)	$(-2.76, 0.42)$
3	0.59***			1.50**		87.25	−0.33
	(**2.98**)			(2.09)		(0.00)	$(-2.62, 0.43)$
4	0.55***				−3.31***	93.07	−0.13
	(**2.72**)				(**−3.57**)	(0.00)	$(-2.62, 0.45)$
5	0.46***	0.15	2.38***	2.49***	−1.94***	51.51	0.86
	(2.34)	(0.28)	(**4.94**)	(**3.57**)	(**−2.98**)	(0.00)	$(-0.53, 0.72)$
				Panel B (SLTR25)			
1	0.52***	4.13***				50.94	0.58
	(2.55)	(**2.91**)				(0.00)	$(-3.48, 0.43)$
2	0.67***		0.87			57.58	0.01
	(**3.32**)		(1.12)			(0.00)	$(-3.52, 0.44)$
3	0.55***			2.45***		61.70	0.23
	(**2.80**)			(**3.04**)		(0.00)	$(-3.52, 0.45)$
4	0.57***				−4.59***	66.27	0.29
	(**2.85**)				(−2.49)	(0.00)	$(-3.45, 0.44)$
5	0.45***	0.33	3.72***	3.08***	−0.92	**27.36**	0.87
	(2.29)	(0.35)	(**4.22**)	(**2.87**)	(−0.60)	(0.16)	$(-0.82, 0.71)$