Macro determinants of U.S. stock market risk premia in bull and bear markets

by Fabian Bätje and Lukas Menkhoff

Abstract

This research uses macro factors to explain four standard U.S. stock market risk premia, i.e. the market excess return (RM-RF), size (SMB), value (HML), and momentum (WML). We find in-sample predictive power of macro factors, in particular at a one-year horizon. Differentiating between bull and bear market states roughly doubles forecast performance compared to neglecting market states. All four stock market risk premia can be explained with R-squares of 10% to 25%. However, macro factors have limited predictive power in a true out-of-sample setting.

JEL-Classification: G10 (general), G12 (asset pricing)

Keywords: stock market, risk premia, factor analysis, market states

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Fabian Bätje, Department of Economics, Leibniz University of Hannover, Königsworther Platz 1, D-30167 Hannover, Germany; e-mail: baetje@gif.uni-hannover.de.
Lukas Menkhoff, Kiel Institute for the World Economy, Hindenburgufer 66, 24105 Kiel, Germany, University of Kiel and Leibniz University of Hannover; e-mail: menkhoff@gif.uni-hannover.de; tel. ++49 (0)431 8814 216.

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1 Introduction

The classical CAPM is often expanded by additionally considering returns to a size portfolio (SMB), to a value portfolio (HML) and to a momentum portfolio as risk factors (Fama and French, 1993, Carhart, 1997). The resulting four risk factors can usefully be seen as risk premia, compensating investors for holding risky assets. Due to the important role of these risk factors and their related risk premia which can be earned, the question arises: are there macroeconomic determinants of these risk premia?

We focus on the macroeconomic aspect because one may argue that in the last instance the riskiness of firms is to a large extent determined by the firms' exposure to macroeconomic risks. Hence, a large number of studies examine links between macroeconomic fundamentals and future stock returns, however, with limited success (see, e.g., Welch and Goyal, 2008). Obviously, the relation between the macroeconomic situation and the stock market is difficult to grasp by relying on standard state variables. One way to address the complexity inherent to this relation is by applying the recently refined factor analysis approach to consider many potentially important predictor variables simultaneously (see, e.g., Stock and Watson, 2002a). In this respect, we follow the benchmark study of Ludvigson and Ng (2009), who use this technique to the U.S. bond market, and implement a similar procedure for standard risk premium measures to the U.S. stock market. According to the best of our knowledge, this factor analysis approach has only recently been applied to predicting the U.S. stock market excess return (Ludvigson and Ng, 2007, Cakmakli and van Dijk, 2010) and has not yet been applied to the three other risk premia.

As another novelty of our research, we investigate the role of macro factors during bull and bear markets, i.e. periods of increasing and decreasing stock prices. This procedure is motivated by the fact that stock market ups and downs are related to business cycle movements (see, e.g., Chauvet and Potter, 2000, Neely et al., 2013); these cycles are characterized by differences in the economic and financial environment. Therefore, it seems interesting to examine the role of macro factors in explaining risk premia separately for bull and bear markets.

We find that distinguishing between bull and bear markets is important for understanding the role of macro determinants in predicting the four risk premia. The distinction between bull and bear markets doubles the explanatory power compared to neglecting these market states in in-sample predictions. As expected, true out-of-sample predictions are more difficult: explanatory power of the macro factors disappears except for the market and momentum premia.

This study proceeds by compiling a dataset for the period 1960:1 – 2012:12 resulting in 636 monthly observations. The selection of potentially meaningful variables is similar to other studies, such as Stock and Watson (2005), and consists of 124 U.S. macroeconomic and financial time-series. These variables stem from various areas. In order to provide an intuition these variables can be put into eight broad categories: (1) income and output, (2) labor market, (3) housing sector, (4) consumption, orders and inventories, (5) bond and interest rates, (6) money and credit, (7) prices, and, finally, (8) stock market information. On the basis of these 124 variables we extract nine factors which explain 54% of total variability of all considered variables. These factors are then used to forecast risk premia in various specifications.

We find remarkable in-sample predictive power of our factors at the *one year* horizon, and also at the two years horizon. However, we find very limited power in predicting the four risk premia *one month* (or three months) ahead which fits into the literature on short horizon predictability, such as Campbell and Thompson (2008) or Welch and Goyal (2008). These findings hold throughout several specifications, however, it does not extend to out-of-sample predictions.

Regarding the four risk premia under investigation, the strength of results varies across these premia. In-sample results are relatively best for the market-premium, still strong (i.e. consistently above 10% R-squared) for the WML-premium, somewhat weaker for the SMB- and HML-premia. Concrete adjusted R-squares of our procedures at the one year horizon are 25.5% (and 11.6% without separating bull and bear markets) for the market excess return, 10.2% (5.5%) for the SMB-premium, 15.7% (1.3%) for the HML-premium and 17.4% (11.7%) for the WML-premium. Interestingly, forecasting power considerably increases in all four cases by taking account of bull and bear markets. These strong results break down in true out-of-sample settings. Here, the only consistent result remaining applies to R-squares of between 17% and 25% for the market-premium, however, only in bull markets; the momentum-premium can be somewhat explained in specific settings.

These investigations contribute to the literature, mainly by covering more premia than just the market premium and by distinguishing into bull and bear markets. A longer explanation of how our research relates to other studies is provided in a separate section on literature (Section 2).

Our paper is structured as follows. Section 2 informs in more detail about related literature and the methods applied, Section 3 describes the underlying data and Section 4 provides interpretation of the macro factors. Empirical results are presented in Section 5 in three steps: first, results for the benchmark case, i.e. in-sample and without market states, second, results for bull and bear markets, and, third, results for various out-of-sample regressions. Section 6 discusses robustness issues, and Section 7 concludes.

2 Literature and methodology

Equity premium prediction is a core field in financial economics. A large bulk of literature focuses on numerous variables as possible predictors for stock market equity prediction but results are quite poor, unstable over time, or vanish if a real-time setting is considered. While the market excess return, the spread between the market return and the risk-free rate, is the primary object in academic research, comparatively little is known about the forecasting performance regarding the remaining stock market portfolio returns considered in the literature, namely the size, value and momentum premium. This paper tries to fill this gap and provides new insights into this field of research. In this section we shortly introduce into related literature and describe the economic framework which has previous been successfully implemented in a wide range of academic research.

Stock risk premia prediction. A major challenge in stock market premium prediction is the decision about the variables being used in forecasting regressions. Regarding this decision, there is a large set of widely used predictive variables covering the short-term interest rate, the credit and the term spread (see, e.g., Ang and Bekaert, 2007, Campbell and Thompson, 2008, Welch and Goyal, 2008), inflation rate (Fama and Schwert, 1977, among others), stock market volatility (investigated by Guo, 2006), the consumption wealth ratio provided by Lettau and Ludvigson (2001), to name just a few. Most of the empirical studies (e.g., Campbell and Shiller, 1988, Lewellen, 2004, Cochrane, 2008) use valuation ratios such as the dividend yield, the price-earnings ratio or the book to market ratio which should serve as proxies for expected business conditions, as mentioned by Campbell and Diebold (2009).

According to the large bulk of possible predictor variables, the primary object of equity premium prediction is the stock market excess return, while little is known about the forecastability of the remaining stock market risk premia. It is well documented that small firms (low market capitalization) as well as value stocks (high book-to-market ratio) tend to have on average higher returns than big firms (high market capitalization) and growth stocks (low book-to-market ratio), respectively.[1] Additionally, portfolios sorted by buying past winners and selling past losers generate a statistically significant premium that is on average highly profitable as found by Jegadeesh and Titman (1993), Rouwenhorst (1998), among others. While it is well known that the analyzed stock market premia yield superior returns, the reasons for this profitability are less obvious and empirical studies often fail to detect predictable components in aggregated returns, especially in an out-of-sample setting.

One possible explanation for these abnormal returns can be based on the assumption of data mining and data-snooping biases. But this explanation seems to be unlikely because of statistically significant evidence in cross-sectional and time dimensions, as found by Fama and French (1998), Jegadeesh and Titman (2001), and debated by van Dijk (2011). Another possible explanation is based on the assumption that behavioral patterns play a dominant role. Under this point of view differences in investors' interpretation of information might explain the high profitability.[2] However, under market efficiency a rational explanation assumes that the stock market risk premia compensate investors for carrying higher risk. Previous studies state that the spread between returns of small and big capitalization stocks (SMB) as well as the spread between value and growth stocks (HML) might be explained by firms' specific distress (see, e.g., Chan and Chen, 1991, Fama and French, 1995). Distressed firms are characterized to a large extent by marginal firms which are less productive, face higher financial leverage and earnings uncertainty and are less likely to survive adverse economic conditions. The problem behind "firm specific distress"-explanations is their missing linkage to systematic risk factors. In aggregated portfolios idiosyncratic components can be diversified away (as mentioned by Cochrane, 2007), which leaves the question unanswered

[1] The profitability of the size and the value premium is documented by Banz (1981), Fama and French (1993, 1995), Lakonishok et al. (1994), among others.
[2] Zarowin (1990) proposes a behavioral explanation for the size effect, Lakonishok et al. (1994), LaPorta (1996) and La Porta et al. (1997) do so for the value premium, and Hong and Stein (1999), Jegadeesh and Titman (2001), among others propose it for the momentum premium.

whether and, if so, which systematic risk factors account for these premia. One might argue that in the last instance well diversified stock market aggregates can only be influenced by general economic state variables which cause changes in investors' opportunity sets, as mentioned by Chen et al. (1986).

Following this argument, Lakonishok et al. (1994) and Griffin and Lemmon (2002) find no evidence that the return differential between value and growth stocks can be explained by economic fundamentals. There is even a controversial debate for the size premium, whether systematic risk factors might explain this return differential, especially after 1980s where the small-firm anomaly seems to have disappeared as mentioned by Horowitz et al. (2000), among others. Implications of this disappearance for a risk based explanation are currently unclear. Finally, a rational explanation for momentum returns is given by Chordia and Shivakumar (2002), who show that momentum returns can be explained by lagged macroeconomic variables but these findings have not been confirmed by Griffin et al. (2003) or Cooper et al. (2004), among others. In general, it is not certain, whether these high profitable stock market return differentials are an equilibrium compensation for higher risk bearing and also accurate risk premia forecasts based on lagged macroeconomic and financial variables are hard to observe (see, e.g., Welch and Goyal, 2008), which supports the early statement by Chen et al. (1986, p.383f.) that "the comovements of asset prices suggest the presence of underlying exogenous influences, but we have not yet determined which economic variables, if any, are responsible."

Distinction between bull and bear market states. Following Fama and French (1989) and Cochrane (1999, 2007), a linkage between the real economy and equity premia is given by an increase in investors' risk aversion during economic downturns which requires a higher risk premium. According to this fact, Rapach et al. (2010), Henkel et al. (2011) and Neely et al. (2013) find evidence that return prediction is much more concentrated during recession periods than during business cycle expansions phases. Under these circumstances two questions arise: understanding the wealth of stock market is a business cycle leading indicator, investors' risk aversion might increase before the real economy shrinks, i.e. in high volatility states and if so, how does the forecasting ability of macroeconomic determinants change during bull and bear market periods.

Related to our approach are the studies by McQueen and Roley (1993), Neely et al. (2013) among others, who identify a time-variation in the relationship between stock market returns and macroeconomic variables according to different states of the economy. We follow Chauvet and Potter (2000) who mentioned that stock market cycles lead business cycles and that the stock market may also be affected by sectoral or shorter-lived real contraction periods which are not accounted for by the NBER dated business cycle. This leads to the assumption that stock market cycles reflect changes in future real economy which might have an impact on the relationship between risk premia and forecasting variables. The assumption mentioned above has been confirmed by Howton and Peterson (1999), showing that the relationship shifts through time and variables perform differently over stock market and economic regimes.

Despite these investigations, comparatively little is known about the asymmetric performance of macroeconomic fundamentals, especially for risk premia additional to the market excess return. Regarding the size premium, Perez-Quiros and Timmermann (2000) analyze the time-series patterns for small and large firms' risk over different states of the economy. Small firms which are to a large extent less collateralized ones should be more strongly affected by tightening credit conditions especially in recession periods than big firms. Therefore, variables linked to credit market conditions might offer an asymmetric relationship to this stock market premium.

A similar behavior has been documented for the value premium. Lettau and Ludvigson (2001) find that value stocks conditioned on the consumption-wealth ratio are riskier than growth stocks in periods where the risk aversion is high. This finding has been confirmed by Petkova and Zhang (2005) who mention that value stocks concern a higher risk than growth stocks especially in bad times, when the expected market risk premium is high.

Momentum asymmetries are hard to observe. Chordia and Shivakumar (2002) and Cooper et al. (2004) find some asymmetries of the premium in different states of the business cycle. They mention that the momentum premium is high in economic expansions but nearly nonexistent in recession phases which might indicates a direct linkage to the business cycle. But these findings have been challenged by Griffin et al. (2003).

Dynamic factor models. In conducting these examinations our empirical investigation is related to economic literature considering a large set of potentially meaningful predictors. In detail, our econometric framework is based on the static approximation of dynamic factor models, proposed by Stock and Watson (2002a,b) and its application to a wide range of academic research. Factor-augmented regression settings are used by Stock and Watson (2002a) and Forni et al. (2003) to reveal the predictive performance of latent common components for output growth and inflation, Ludvigson and Ng (2009) use factor decomposition for risk premium prediction on the bond market and Mönch (2008) considers factor-augmented forecasts for the yield curve. Next to Ludvigson and Ng (2009), our approach bears large resemblance to Ludvigson and Ng (2007), Bai (2010), Cakmakli and Dijk (2010) and Neely et al. (2013) who analyze the forecasting performance of latent common components for stock market excess returns and volatility.

However, our research goes beyond the previous ones in three ways. First, our focus is not restricted to the market excess return. We also conduct factor augmented predictive regressions for three further stock market risk premia. Second, we analyze the factor-augmented forecasts also for bull and bear markets, meaning that the predictive performance might vary according to the current phase of the stock market (e.g. increasing vs. decreasing prices). Third, we investigate the predictive performance of macroeconomic information for a range of horizons, covering monthly, quarterly, yearly and 2-years returns.

According to previously mentioned literature, factor augmented regression settings provide many advantages compared to standard regressions. In particular, it is possible in a factor analytical framework to include several hundred predictor variables, which would be infeasible in standard predictive regressions, because of insufficient degrees of freedom. This limits the loss of information and model uncertainty due to an a priori selection of the most relevant predictors.

To implement factor-augmented regressions, we follow a two step procedure. First, because we assume that the common components are latent, we have to estimate them from the data. According to Stock and Watson (2002b) and Bai and Ng (2002) we suppose that the static factor model admits in the following form:

(1) $$x_{it} = \lambda_i' f_t + e_{it}$$

where x_{it} is the ith observed data at time t, for i = 1,…,N and t = 1,…,T, f_t describes a r×1 vector of common components (with r be the number of factors specified in detail manner in Section 4.1, with the restriction r << N), λ_i is referred to as the r×1vector of factor loadings, giving the weights that the ith variable puts on the factors f_t. e_{it} denotes the corresponding idiosyncratic disturbance term. It is the presumption of factor analytical approaches that a small set of latent common components can be interpreted as major driving forces which largely replicate the comovements in the data. Estimates can be obtained by minimizing the sum of squared residuals according to:

$$V(r) = \min_{\lambda_i, \hat{f}_t} (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \hat{\lambda}_i' \hat{f}_t)^2 \tag{2}$$

We follow Stock and Watson (2002b), and Bai and Ng (2002) and make use of the principal component analysis which yields factor-estimates $\hat{f}_t$ which are $\sqrt{T}$ times the eigenvectors corresponding to the r largest eigenvalues of the T×T matrix XX'/NT. Under some technical assumptions, it can be shown that the estimated factors are consistent when N, T → ∞.

In a second step, we integrate a pre-selected set of factors in the forecast regression. Stock and Watson (2002b) and Bai and Ng (2006) show that assuming N, T → ∞ the usage of factor estimates in the forecast regression does not affect parameter consistency even under heteroskedasticity, serial and/or cross-sectional correlated idiosyncratic errors. The feasible forecast is asymptotically first-order efficient and converges to the optimal infeasible forecast at rate $\sqrt{T}/\min(N, T)$.

3 Data

Like other empirical studies based on factor analyses we compile a large dataset which is used to identify latent common structures of potentially meaningful variables to forecast equity returns. More precisely, our set of potentially important predictors consists of 124 U.S. macroeconomic and financial time-series and is related to information sets used in other studies, such as Stock and Watson (2005) or Ludvigson and Ng (2009). All variables are collected from the "Datastream" database on a monthly frequency and span the sample 1960:1 – 2012:12, for a total of 636 observations. To ensure a widespread representation of business cycle related information we select variables from eight major categories. All variables are described in the Data Appendix and are classified as: (1) income and output, (2) labor market, (3) housing sector, (4) consumption, orders and inventories, (5) bond and interest rates, (6) money and credit, (7) prices and (8) stock market information. Prior to estimation, we check each variable for non-stationarity and use log levels, first differences in levels and/or first and second order log differences to ensure stationary processes. All transformations are reported in the Data Appendix in a coded form. Finally, the variables are standardized to have zero mean and unit variance.

Although the focus of this paper is on macroeconomic related factors to predict stock market premia, we include financial variables in the dataset as suggested by Ludvigson and Ng (2009). This procedure might lead to factors which are not solely determined by macroeconomic information but financial indicators might serve as proxies for expected business conditions as mentioned, for example, by Campbell and Diebold (2009).[3] Moreover, stock market predictor variables have mostly been financial indicators, such as the dividend yield, term spread, interest rates and/or default spreads. Therefore, it seems justified to expand the information set instead of neglecting such information.

For stock market predictability we analyze the U.S. stock market excess return, size, value, and momentum premia. Each portfolio return is collected at monthly frequency from Kenneth French's website.[4] The market excess return is defined as the value-weighted return on all NYSE, AMEX and NASDAQ stocks minus the one-month T-bill rate. SMB and HML are constructed based on 6 weighted portfolios formed on size and book-to-market ratios. SMB is the average return on three small portfolios minus the average return on the three big portfolios while the HML premium is determined by the average return on two value portfolios minus the average return on the two growth portfolios. For further details about portfolio construction see Fama and French (1993). WML denotes the momentum return which is declared as the average return on the two prior high return portfolios minus the average return on the two prior low return portfolios. Descriptive statistics are reported in Table 1.

TABLE 1 ABOUT HERE

As one might see, the profits of these four distinguished stock market portfolio returns are quite different. While each premium generates on average a positive return that is statistically significant, we find large variation in the median values. In detail, the average monthly market excess return is about 0.48 with an annualized Sharpe-ratio of about 0.37. While the value premium provides on average a slightly poorer performance with an average

[3] Campbell and Diebold (2009) mention that financial variables are correlated with expected business conditions, measured by the Livingston real growth expectations, but they also postulate that the relationship is far from perfect.
[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

return of 0.39 the annualized Sharpe-ratio increases to 0.47. The performance of the size premium is comparatively low. The average return is about 0.22 and even the Sharpe-ratio of nearly 0.25 remains markedly below the performance of the other premia. This result is in line with other papers suggesting certain periods of size premium reversals and their disappearance in the 1980s, see e.g. Horowitz et al. (2000). Even more profitable is the momentum premium. The average monthly return is about 0.72 with an annualized Sharpe-ratio in the range of 0.60. Overall, given the high profitability and the unresolved puzzle behind these premia, we examine in various ways whether latent macroeconomic factors have forecasting power.

4 Factor structure and interpretation

In this section, we describe and interpret the latent factor structure. In order to identify an appropriate subset of common components $\hat{F}_t \subset \hat{f}_t$ that is used in forecast regressions we select the panel information criterion (IC_2) proposed by Bai and Ng (2002). Factor analytical frameworks are based on the presumption that each additional common component covers less variability in the data. Therefore, constraining the common components has the advantage that noisy factors (which are sparsely correlated with a lot of variables) can be neglected. More precisely, primarily we select an arbitrary amount of 20 factors. The criterion indicates that for the full sample of 124 variables, IC_2 is minimized with 9 common factors which provide the best trade-off between goodness of fit and over-parameterization. As we illustrate in Table 2, these 9 common factors explain about 54% of total variation of all variables in the dataset. Total variation is defined as the sum of the variances of the standardized individual data series x_i. Due to the fact that the estimated factors are mutually uncorrelated by construction, the marginal R-squares of univariate regressions of the individual variables on each of the nine factors indicate the explanatory power of one specific factor, holding other factors fixed. The largest fraction is picked up by the first factor which explains 17% as can be seen in Table 2. The second and third factors capture an additional contribution of 9% and 7% respectively. The remaining six factors comprise additional variability in the range of 5% to 2%.

TABLE 2 ABOUT HERE

In addition, Table 2 also reports the 1st order autocorrelation coefficient of the estimated factors to specify their persistence. The results indicate that none of the common factors has persistence near the unit root but we also see a large variation across the common components. Most of the factors have highly positive autocorrelation coefficients (maximum persistence is given for the first factor with a coefficient of 0.776) which may contain information about longer-run processes, such as business cycles. In contrast, other factors offer a slightly negative autocorrelation indicating a much faster mean-reverting process, which may contain information about short-term fluctuations around business cycles.

One of the most crucial challenges in factor analysis approaches is to find an appropriate interpretation for the estimated factors. As mentioned by Stock and Watson (2002b), the "true" latent factor structure is identifiable up to a non-singular transformation. This leads to factor identification up to a change of sign. To identify whether the risk premia have a countercyclical component, we transform each common component such that the factors are positively correlated with a favorable business condition, i.e. pro-cyclical behavior, in short rising production, low financial risk, high inflation, expansionary monetary policy and so on. This transformation is based on the correlation structure of the 12-month moving average of the estimated factors $\hat{f}_i$ and IP growth over time; results are given in Table 3.

Table 3 ABOUT HERE

The table shows that the factors $(\hat{f}_1, \hat{f}_2, \hat{f}_6)$ are highly positively correlated with cyclical variation in the real economy. While the correlation of the moving averages of the first factor and industrial production (IP) growth reaches its climax of nearly 90% within a one month delay, the other factors seem to lag behind economic expansion. In contrast, the cyclical behavior of the factors $(\hat{f}_4, \hat{f}_7, \hat{f}_8)$ shows a negative correlation. In particular, the fourth and seventh factor may be leading indicators due to a strengthening correlation with IP growth at increasing leads. The same effect is given for the eights factor but to a smaller extent and the correlation structure is decreasing when IP growth is leading three or more months. Therefore we multiply each common component by -1. The remaining factors $(\hat{f}_3, \hat{f}_5, \hat{f}_9)$ show a more heterogeneous cyclical behavior as the correlation of the moving averages indicates a reversal effect over time. Nevertheless, the moving averages of these factors lead the moving average of future IP growth in an inverse direction (i.e. negative correlation). Therefore we also transform these factors to get a pro-cyclical behavior.

Furthermore one should keep in mind that the common factors are characterized by all variables up to a certain degree. Nevertheless, to get an idea which variables load heavily on each factor, Figure 1 presents the marginal R-squares from a regression of the variables onto the estimated factors labeled in the headings. A high R-square indicates that the analyzed factor replicates the information of the variable to a huge extent.

FIGURE 1 ABOUT HERE

Figure 1 shows that the *first common factor* loads mostly on industrial production indices, employment characteristics as well as leading economic indicators (Purchasing Managers' Index and New Orders' Index). While the factor is positively correlated with industrial production indices and leading economic indicators, the relation to worsening labor market conditions is negative. Therefore, the first factor is labeled as real factor. The *second factor* is highly positively correlated with changes in several price indices. More precisely this factor indicates rising inflation according to an economic expansion. Thus we call the second factor an inflation factor. The interpretation for the factors $(\hat{f}_3, \hat{f}_4, \hat{f}_5)$ can be related to approaches concerning yield curve decomposition, following Dai and Singleton (2000), Ang and Piazzesi (2001), among others. In particular the *third factor* is essentially positively correlated with a steepening of different yield and credit spreads but does not provide any dependence on changes in nominal interest rates. In a nutshell the third factor is named a slope factor. In contrast the *fourth factor* provides a negative dependence on changes in nominal interest rates and a positive correlation to variables from the housing sector. We interpret this factor as the level factor of the yield curve which influences all interest rates with different maturities in the same direction. The *fifth factor* is signed as the curvature factor due to the fact that the spread between medium-term interest rates loads much stronger on this factor than long or short term spreads. All these three factors might serve as proxies which indicate expectations about rising inflation and/or economic growth which is in line with results of Table 3. An appropriate interpretation of the *sixth factor* is not obvious because this factor is correlated with a lot of variables from different categories. However, we find a strong negative dependency between the *seventh factor* and the growth rate of labor cost inflation which tends to grow slower in economic upswings, according to the results of Table 3. Therefore, we label this factor as a labor cost inflation factor. *Factor eight* is positively correlated with the return behavior of the S&P 500 composite index which underlines its leading function as mentioned above. The correlation with the stock market dividend yield, a commonly used predictor variable, is quite high (-0.546) but far from perfect. We label this factor as a stock market factor. Last but not least, the *ninth factor* also offers a suitable economic interpretation as it loads comparatively strong on monetary aggregates, i.e. we observe a negative correlation with an acceleration of monetary growth. This correlation structure can be understood as a tightening monetary policy to restrict spending in the real economy when the economy is growing too quickly. Therefore we name this factor as a monetary policy factor.

5 Empirical results

Our empirical analysis proceeds in three steps. First, we conduct regressions over the whole sample which serves as benchmark (Section 5.1). Second, based on Section 5.1 we evaluate the power of risk premia determinants during bull and bear market states which allows for assessing the benefit from this procedure (Section 5.2). Third, we evaluate the out-of-sample predictive performance (Section 5.3).

5.1 In-sample predictive regressions over the whole sample

In order to examine the importance of the estimated latent components to forecast stock market risk premia we use a conventional framework based on the following factor augmented predictive regression model:

(3) $$r_{t+1} = \alpha + \acute{\beta}\hat{F}_t + \varepsilon_{t+1}$$

where r_{t+1} denotes the continuously compounded portfolio return of the risk premia under analysis from the end of month t to the end of month t+s in dependency on the forecasting horizon s. In consequence of the different persistent behavior of the estimated factors we select a variety of forecasting horizons from the short end (i.e. monthly and quarterly forecasts) to the long end (yearly and two years forecasts). Following Campbell and Shiller (1988), Campbell (2001), Campbell and Thompson (2008) among others, the predictive performance of slow-moving variables which track business cycle movements might increase with the forecasting horizon. Instead of using the entire sample of initially identified common factors, we additionally use the BIC criterion to prohibit a nonessential expansion of the data generating process, indicated by $\hat{F}_t$. In detail, due to the fact that the stock market risk premia might be predictable by various factors, we account for this effect by using an exhaustive search algorithm for model selection. ε_{t+1} describes the corresponding return innovation. Table 4 contains results about the selected macro factors determining the risk premia; estimated slope coefficients and adjusted R-squares of the regressions. To generate statistical inference about the regressions' coefficients we choose two adjustment mechanisms.[5]

TABLE 4 ABOUT HERE

Short term predictability. Table 4 indicates that factor-augmented regressions exhibit some in-sample based forecasting power on stock market risk premia. To maintain the factor interpretation, we restrict the number of full sample factor observations according to the forecasting horizon. Overall, the results on a monthly and quarterly forecasting horizon are rather negligible as adjusted R-squares are between 0.3% and 3.1% for the three risk premia SMB, HML and WML. While the momentum premium offers the largest R-squared at the quarterly horizon, results do not show any statistical significant dependency on the macroeconomic factors which is in contrast to the SMB and HML premia which exhibit significant predictors but small R-squares.

Results are slightly better for the market excess return. Excess returns in the short run are predictable by financial variables covering the slope and level factor which are significant at the 5% and 1% level, respectively. The predictive performance, measured by the R^2, is in the range of 2.9% for monthly returns and 5.2% on a quarterly basis. In comparison to other predictive regressions, our factor augmented regressions performs quite well. The forecasting performance of commonly used predictor variables as documented in Zhou (2010) is less than

[5] In order to account for problems arising from overlapping observations, small sample biases and persistent predictor variables, we proceed as suggested by Stambaugh (1999). More precisely, following Newey and West (1987) reported t-statistics are based on HAC standard errors computed by the Bartlett kernel estimator and, in addition, we select a nonparametric moving block-bootstrap, following Goncalves and White (2005). The corresponding bandwidth for the kernel based standard errors and for the block-length of the bootstrap procedure is selected in a data-driven manner, according to Andrews' (1991) automatic bandwidth estimator. In detail, the bootstrap procedure resamples the factors and portfolio returns simultaneously in overlapping blocks, where the block-length is selected in a data-driven manner, according to Andrews (1991). The MBB then generates 10,000 artificial time series from resampling blocks randomly with replacement and we estimate our regression based on these artificial data. Reported t-statistics are based on bootstrap standard errors, based on the bootstrap distribution of the estimated coefficients around the original coefficient estimates.

1% for each predictive regression on a monthly forecasting horizon. In summary, the predictive performance is somewhat disappointing with the exception of the market excess return.

Long term predictability. Results are much more promising at longer term horizons which is in line with findings by Campbell (2001), among others, suggesting that the common components capture information over the long-run business cycle frequency. The R-squares are clearly higher than for monthly results, although the absolute R-squared of the HML risk premium regression is still disappointing.

For the *market premium* the results generate statistically significant power for the first and third factor. While the predictive performance for yearly market excess returns measured by the adjusted R-squared increases sharply in comparison to the short term results, the average forecasting performance for two years ahead prediction slightly lags behind the yearly results. Also for the *size premium*, we find that the real factor is significant at the 5% level which explains about 5.5% of next year's portfolio returns. On a two years horizon this effect is barely visible as well as the predictive performance of the fourth factor. Findings for the *value premium* remain comparatively poor as for the short term horizon and even the most relevant predictor variables are strongly varying over the different forecasting horizons. Concerning the *momentum premium* the adjusted R^2 is quite high with values in the range of nearly 12% (yearly returns) and 15% (two years returns). In line with the findings mentioned above we find no statistical significant factor with the exception of the real factor if we consider two years ahead forecasts. This results corresponds to previous outcomes in the literature mentioned that the momentum risk premium is nearly unpredictable by macroeconomic information and might be better explainable by behavioral patterns.

C**yclical behavior of stock market risk premia.** In this step, we focus on the signs of significant macro factors. Due to the fact that each common component was transformed such that it tentatively offers a positive relation with an economic expansion we can analyze the cyclical components in these risk premia. For the market excess return we find a countercyclical as well as a pro-cyclical component. While this premium becomes higher with worsening business conditions measured by IP growth information ($\hat{F}_1$), the factor signs of the third and fourth factor are positive. This is partially in line with previous findings that stock market returns move countercyclical and provide a hedge against higher risk in bad economic conditions but not perfectly. In contrast, the size premium is nearly exclusively predictable by negative factor signs with the exception in the very short run (monthly returns). This risk premium varies over the business cycle in an opposite direction. Whether the HML and WML premia have a pro- or counter-cyclical component is not totally clear, because statistical significance is quite weak and/or the forecasting power is low.

5.2 In-sample predictive regressions during bull and bear markets

The asymmetry we wish to explore in this chapter is related to the time-varying risk premia in different stock market states. According to the theoretical motivation and the empirical evidence that stock market risk premia exhibit a time-varying behavior (see, e.g., Campbell and Cochrane, 1999, among others) we expand the previous analysis to account for this fact. In detail, under the assumption that asset allocations decisions are strongly affected by investors' beliefs about the underlying market state, worsening conditions require higher risk premia to compensate investors for holding stocks. Therefore, also the dependence between risk premia and macroeconomic information might be affected by the overall stock market state.

Implementation. To analyze whether stock market risk premia offer an asymmetric dependency to macroeconomic factors over different market states and to allow for shifts in betas, we run the following regression to account for this non-linearity.

(4) $$r_{t+1} = \alpha + \acute{\beta}_{bear}\hat{F}_t D_{t+1} + \acute{\beta}_{bull}\hat{F}_t(1 - D_{t+1}) + \varepsilon_{t+1}$$

In this setup, D_t is a dummy variable which equals 1 during bear market states at time t and 0 during bull market periods. In order to proxy for changes in stock market conditions (i.e. bullish=low volatility and rising price index, bearish=high volatility and falling price index) we use the non-parametric dating algorithm developed by Bry and Boschan (1971) which has also been used to detect real business cycle turning points (see: Harding and Pagan (2002), Stock and Watson (2010), among others). More precisely we follow Chen (2009) and Nyberg (2013) who assume that a complete cycle must have a duration of at least 15 months and in addition, the time spend in a bull or bear market state must be at least 6 months. For monthly turning point identification we use the cumulative sum of Fama and French's stock market return. Due to the fact that we also consider s-month continuously compounded returns, we have to make use of s-month moving averages of this cumulative sum. Table 5 presents the estimated turning points for monthly U.S. stock market returns.[6]

TABLE 5 ABOUT HERE

The identified turning points in Table 5 are similar to those found in other studies like Chauvet and Potter (2000), Pagan and Sossounov (2003) and Nyberg (2013). We also consider two additional bear market states of shorter duration, the first in 1987 (3 months duration) and the second in 1990 (5 months duration) because of the comparatively strong contraction of 33% and 21% respectively (see also Nyberg, 2013).[7] Overall, the results indicate that the amplitude of bear market states is shorter than for bull market periods. Over the full sample we locate 11 bear markets which correspond to 142 months. To verify our estimates Figure 2 depicts the cumulative sum of Fama and French's stock market return and the located bear market periods.

FIGURE 2 ABOUT HERE

Forecasting results are given in Table 6. To make results easily comparable to those presented above for the non-differentiated sample, we also present results from general to specific. In a nutshell, the forecasting ability of factor augmented predictive regressions largely improves if we allow for nonlinear dependency according to stock market states.

TABLE 6 ABOUT HERE

Short term predictability. For the *market premium* the predictive performance, measured by the adjusted R-squared, rises by nearly 80% for monthly returns and by more than 100% on a quarterly basis (compared to the benchmark case discussed in Section 5.1) if we distinguish between bull and bear market states. We find that monthly market excess returns are predictable by the level and slope factor only in bear market states. Furthermore, the real factor seems to be a good predictor variable and is highly statistical significant at the 1% level in bull market periods. Also for the *size premium* we identify a large increase in the predictive performance of 100% for monthly returns and by more than 50% for quarterly

[6] Obtained turning points based on the s-month moving averages differ from monthly estimates with regard to frequency and amplitude. With increasing forecasting horizon we identify much less bearish market states but the intensity, i.e. the amplitude from a stock markets' peak to the next trough is much larger.
[7] These bear market periods of shorter duration might only have an impact on the short-term predictability but even if we treat them as bull market states the results do not change the fundamental story.

returns. The largest enhancement is obtained for the *value premium*. While the results in Table 4 offer nearly no dependency on macroeconomic factors we have a more than threefold increase in the R-squared and even the relevant factor structure largely differs. Last but not least, the predictive regression for the *momentum premium* is also better than mentioned before. In contrast to the previous findings, this premium has solely a dependency on the estimated factors if the market states in bull periods. While the real factor shows a dependency in both forecasting horizons, the seventh (ninth) seems to be relevant on a monthly (quarterly) basis.

Long term predictability. Also long term return predictability profits enormously from a non-linear forecasting regression. While the variability of yearly *market premium* can be better explained by more than 100% in comparison to the whole sample results, the adjusted R-squared has more than tripled if we consider a 2 years forecasting horizon. Overall, the results signal that the risk premium offers a dependency on the estimated factors in bull as well as bear periods. Yearly returns can be forecasted by the real and stock market factor in bull periods and mainly by the slope and labor cost inflation factor in bear periods. In contrast, two years returns seem to be mostly predictable by the first and third factor in the same market states as mentioned before. Macroeconomic influences for the *size premium* are hard to observe. Although the adjusted R-squared increases for long term results, a statistical significant dependency is only found for the real factor in bear market states. More impressively are the analysis for the *value premium*. While the whole sample factor models as given in Table 4 are nearly uninformative for short and long term predictability, forecasting regressions with distinguished factors according to the market states provide new insights. In contrast to the previous findings the R-squared increases from 1.3% (1.1%) to 15.7% (14.1%) on a yearly (2 years) horizon. While the statistical significance for cumulative two years returns seems to be more stable than for yearly returns, macro factors have an influence in both cases. The yearly value premium can mainly be forecasted by the third (bear market states) and fifth factor (bull market states). The real factor losses significant influence under the nonparametric moving block-bootstrap in bear periods which might illustrates a time dependent instability. Increasing the forecasting horizon fixes this problem. The sixth factor offers a slight dependency to the value premiums in bull market periods, but bear market returns are highly predictable by the first factor and the third to fifth factor in a highly statistical sense. Long term return prediction for the *momentum premium* signals a stable relation to macroeconomic factors over both forecasting horizons. While yearly returns are nearly unpredictable in bull market states, we observe statistical significant dependency to macro factors in bear market periods. The most relevant predictor variables are the first, fourth and sixth factor in this case. Overall, the insignificant relationship to some factors might be explainable by time-varying dependency, which will be analyzed in the robustness section. Forthcoming returns on a two years horizon illustrate a quite similar picture with the exception that the real factor is a significant predictor in bull markets.

C**yclical behavior of stock market risk premia.** Regarding factor signs of significant predictors, we find a similar pattern as for the non-differentiated sample. The market excess return offers primarily a countercyclical dependency in bull market states but a procyclical relationship to macro factors in bear periods. This might explain the fact mentioned above that for the non-differentiated sample pro- as well as countercyclical components could be detected. Also the results for the size premium are in line with the previous findings. The size premium has a clear countercyclical structure with the exception for short term prediction. Here, we even identify a procyclical behavior in bull (monthly) and bear (quarterly) periods but to a much lesser extend as indicated by the adjusted R-squared and the statistical significance. Factor signs for the value and momentum premium are changing over the forecasting horizon and over stock market states. While the value premium has positive factor signs in bull periods for forecasting horizons up to one year, the factor sign reverts for two years regression. In the short run, value returns are negatively influenced by the relevant factors, indicating a short term countercyclical behavior. For long term returns even positive and negative factor signs can be observed. While the factors have mainly a positive beta in bull market states, returns in bear periods have a positive as well as negative dependency to macro factors in bear periods if we focus on long term predictability.

Overall, we learn from the consideration of stock market bull and bear periods that the factor structure is in many respects different during bull and bear periods. Hence, an explicit consideration of the stock market cycle further improves the prediction of the risk premia: the R-squares increase by the order of about 100%.

5.3 Out-of-sample analysis

So far presented results are based on “smoothed” factor estimates (covering the full sample information) which might be strongly influenced by look-ahead biases. This raises the question whether findings can be extended to an out-of-sample setting as it has been shown by Ludvigson and Ng (2007), Cakmakli and van Dijk (2010) and Neely et al. (2013) for the market excess return. We examine in particular whether the out-of-sample forecasting performance is improving if we distinguish between bull and bear market states. In the following we first describe our procedure in some detail and then present results.

Procedure with non-differentiated samples. To conduct the out-of-sample analysis we select a recursive estimation scheme, corresponding to the previous section which fully re-estimates the latent factor structure and the corresponding parameters. To ensure consistent factor estimates we have to make sure that the initial sample period covers a large spectrum of observations, i.e. our out-of-sample forecast is restricted to more recent return movements. In detail, the first forecasting regression covers the sample period from 1960:1 through 1984:12 for the independent variables, i.e. 25 years and covering roughly the first half of our sample. Due to the fact that the estimated factors might change their signs when the sample is expanded and that we have cumulative overlapping returns, the initial period over which the common components are estimated must be expanded by the degree of the forecasting horizon (i.e. 1 observation for monthly returns, 3 observations for quarterly returns, etc.). Estimated parameters and values of the common components at time t+s (where t corresponds to 1984:12 and s signals the forecasting horizon) are used for out-of-sample forecasts of the returns at time t+s+1. Next, we expand the sample by one period, re-estimate the common components and parameters and conduct the out-of-sample forecasts for the returns at time t+s+2.

Procedure with bull and bear markets. The out-of-sample forecasting performance if we distinguish between bull and bear market states is analyzed in two ways. First, we conduct oos forecast under fully known stock market states, estimated by the Bry-Boschan algorithm as mentioned in section 4.3. Additionally we also evaluate the forecasting performance in a full real time setting where we first have to conduct an oos forecast for the bull/bear market probabilities. Because our objective is not focused on accurate turning point prediction, we keep the prediction as simple as possible and use a simple binary response model.[8] In a

[8] We also follow Kauppi and Saikkonen (2008) and Nyberg (2013) and make use of a more dynamic version of binary response models which might enhance the predictive performance. In detail, the process under analysis is given by $\pi_{t+1} = \omega + \alpha\pi_t + \acute{\beta}F_t$. But results are quite similar are not mentioned specifically.

general form, the expectation and probability of being in a bear market state at any given point in time t+1 conditioned on the information at time t can be written as

(5) $$p_{t+1} = E_t(D_{t+1}) = P_t(D_{t+1} = 1) = \Phi(\pi_{t+1})$$

where $\Phi(\cdot)$ is a standard normal cumulative distribution function and π_{t+1} is a process in dependency on employed predictive variables. In detail, under a static probit model π_{t+1} is characterized by

(6) $$\pi_{t+1} = \omega + \acute{\beta} F_t$$

where F_t is a vector of BIC selected common macro factors as mentioned before. Due to the fact that the Bry-Boschan algorithm uses a two sided filter approach, real time turning points prediction by the Bry-Boschan algorithm requires future information which is not available in real time. Therefore, we attend Nyberg's (2013) order in this respect who mentions that a lag of six month is necessary to account for this publication lag which is verified by our findings. Parameters of the probit models are obtained by maximum likelihood estimates using the BHHH method (Berndt et al. (1974)). The monthly log-likelihood is given by

(7) $$f_{t+1}(\omega;\beta) = D_{t+1}\log(\Phi(\pi_{t+1})) + (1 - D_{t+1})\log(1 - \Phi(\pi_{t+1}))$$

Initial parameter estimates covering the sample period 1960:01 through 1984:06 accounting for the publication lag of six months for D_{t+1}. In addition, to classify our stock market states we use a threshold level of 50% to construct strong bear market signals.

Due to the sample split between bull and bear market periods it might be that we only find an in-sample relation covering bull factors (or bear factors) which leads to a conditional alpha estimate if the out-of-sample forecast is based on bear (bull) periods.

Statistical inference. To assess the out-of-sample forecast performance of latent common components for stock market risk premia prediction we use the historical mean forecasts as a benchmark model. According to Campbell and Thompson (2008), we evaluate the forecasting performance by the out-of-sample R-square which is defined as

(8) $$R^2_{oos} = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2}$$

where $\hat{r}_t$ represents the out-of-sample forecasts from the BIC selected factor-augmented predictive regression and $\bar{r}_t$ signals the forecasts defined by the benchmark model. The evaluation of the out-of-sample predictive performance is identical to in-sample R-squares, which means that a positive R^2_{oos} indicates lower mean-squared predictive errors of the factor augmented regression. In dependence on the previous results where some premia have solely or at least a much stronger relationship to macro factor in specific states, we also measure the predictive performance between realized bull and bear market states.

Results. Results are calculated in three steps: first, the out-of-sample is conducted as described above without distinguishing between market states. Nevertheless, one can calculate the performance of this procedure also within separated bull and bear markets. Second, we repeat the exercise but now we estimate regressions separately for bull and bear markets, i.e. allow for time-varying macro determinants. Critical is the distinction into market states and here we use the Bry-Boschan algorithm which relies on ex post knowledge. In order to also overcome this flaw in a strict out-of-sample analysis we, third, estimate the bull and bear states by a simple probit model. Results for these three steps are presented as Panel A, B and C in Table 7.

TABLE 7 ABOUT HERE

We discuss results from general to specific and would like to highlight four findings: (1) The out-of-sample results confirm earlier studies that the forecasting of stock market risk premia is a difficult task to undertake. Findings for all three dimensions – i.e. across three procedures (Panels), four horizons and four premia – do not show mostly positive R-squares, indicating that there is no general out-of-sample forecasting power in macro determinants, at least not in the way we make use of them. (2) When we compare Panel A with Panel B and simply count sign changes and improvements of positive signs, we find 16 improvements versus 7 deteriorations, confirming the usefulness of a disaggregation into bull and bear markets. (3) When we compare Panel C results, i.e. with estimating market states, to Panel B results where states are known, R-squares become smaller. Best results of these true forecasts are yielded at the three months and one year horizons, compared to one month and 2 years. (4) Finally looking at the four risk premia, out-of-sample forecasting is limited mainly to the market premium during bull markets and to a much smaller extent to the momentum premium.

6 Robustness tests

This section presents several robustness tests, first, regarding the sample length underlying the analysis, second, regarding alternative nonlinearities, i.e. real business expansion and contraction periods, and third, regarding the use of further benchmark predictors.

Sample length. To check our results for robustness, we first analyze the predictive performance of factor augmented regressions over time. As mentioned in the forecasting literature, the predictive performance might be unstable over time and even the relevance of common factors might be time-varying. To take this into account, we estimate in-sample predictive regressions over three different time horizons maintaining the factor interpretation of Section 4.1, i.e. we estimate the common factors over the full sample and just restrict the number of observations according to the different subsamples. The first subsample ranges from 1960:02 through 2006:12 for the risk premia under analysis, where December 2006 is the last monthly observation even for the continuously compounded returns. This sample neglects the recent financial crisis, the biggest financial crisis in recent history. Not surprising, this sample reduction makes our results more comparable to other studies.

In addition, we are following Welch and Goyal (2008) who mention that the dividend yield as one of the most common predictor variable has distinct periods of forecasting performance in-sample as well as out-of-sample. Since the mid 1990s the dividend yield offers a poor performance in predicting the stock market excess return. Therefore, we also analyze factor augmented predictive performance over the sample 1960:02 through 1989:12 and from 1990:01 through 2013:01. We just focus on results under distinguished market states because results largely improve as mentioned before. Results are presented in Appendix A.

The subsample analysis indicates some important results for stock *market premium* prediction which raises questions for further research. Concerning the market excess return in the first subsample, i.e. excluding the recent financial crisis, has a large effect especially for long horizon returns. While the BIC selected factors are time-varying to some extent the main point we want to focus on is the real factor in bear market periods. Previous results reject a significant dependency over the full sample which strongly depends on the last few observations. If we examine the sample split at the beginning of the 1990s the real factor is negatively related to the market excess return at the one year horizon in the first subsample but positively related in the second one which illustrates a breakpoint in the cycle variation of the stock market excess return. Furthermore, relying on the adjusted R-squared the predictive performance improves largely in the subsample 1990:01 through 2013:01 with the exception of yearly returns. Regarding the *size premium* results does not change much in magnitude whether or not the recent financial crisis is considered. But results are quite better in the subsample 1960:02 – 1989:12 especially under short forecasting horizons which might confirm the discussion of a size reversal effect especially after 1980s. Long term risk premia on the other hand yields superior results in both samples with time-varying factors and factor loadings. Short term *value premium* prediction is much more concentrated in the 1990:01 – 2013:01 subsample. In contrast to the sample before 1990 the predictive performance measured by the adjusted R-squared increases by a factor of nearly 4 on a monthly horizon and by a factor of 10 on a quarterly basis. On the other hand long term prediction is largely influenced by the most recent observations since 2007, reducing the adjusted R-squared by 6% and 10% for yearly and two years returns. In addition the subsample analysis offers for some factors a reversal effect in the dependency to the value premium in the different stock market states which might be an explanation for the low predictive performance of comparative studies. Results for the *momentum premium* are quite disappointing compared to the previous results. In detail, excluding observations since the recent financial crisis largely reduces the predictive performance and even the statistical significance of some macroeconomic determinants indicating the importance of rare events, such as the recent financial crisis on this premium. With the exception of momentum returns over a two years forecasting horizon, one might say that momentum returns are nearly unpredictable by macroeconomic variables.

Predictive regressions over real business cycles. In addition to the superior predictive performance if we distinguish between stock market bull and bear periods, we also check our results for real business cycle non-linearity. In detail, based on IP growth we construct a dummy variable which equals 1 if the economy states in a recession period and 0 otherwise. In a nutshell, the results indicate that the predictive performance also benefits strongly under this nonlinear setting but to a lesser extent which goes along with the findings of Chauvet and Potter (2000). They mentioned that stock market cycles lead business cycles and that the stock market may also be affected by sectoral or shorter-lived real contraction periods which are not accounted for by dated real business cycle turning points. Nevertheless, the key massage is nearly the same even under this configuration: the dependency between macro factors and stock market risk premia varies strongly over the stock market and real business cycle. Results are available on request.

Further control variables. So far presented results indicate that factor augmented forecast regressions have some, especially in-sample based, predictive performance. In this section we deal with the additional predictive performance of the factor augmented regression models above commonly used predictor variables. In detail, we expand our analysis by alternative benchmark models, using the dividend yield, further valuation ratios, net equity expansion, among others as additional predictors. In a nutshell, results indicate that the inclusion of macro determinants rather improves the predictive performance furthermore. Results are available on request.

7 Conclusions

The identification of common risk factors and respective risk premia in stock returns by Fama and French (1993) marks an important progress during the 1990s. Quite naturally, this has raised questions about their determination: what helps to forecast such premia? Theories point at macroeconomic determinants but empirical studies have had problems to convincingly show such relations.

We contribute to this literature by applying the recently developed factor analysis approach to the full set of standard U.S. stock market risk premia, i.e. the market excess return, size, value and momentum. To the best of our knowledge, other studies either focus on a subset of these premia, in particular on the market excess return, or they use different approaches. We by and large follow the procedures of Ludvigson and Ng (2009) and use a universe of 124 U.S. macroeconomic and financial time-series in order to determine factors that help to predict premia over the whole sample. Going beyond this literature, we examine the determinants of stock market risk premia depending on bull and bear market states.

We find that in-sample prediction exercises provide insights at a somewhat longer horizon, in particular at the one-year horizon (also at the two-years horizons) but hardly anything useful at a one- or three-month horizon. This difference with respect to the time horizon is fully compatible with available literature. We also find that the sample split in bull and bear markets improves explanatory power to a great extent: all four risk premia, i.e. the market premium, the size premium, the value premium and the momentum premium can be forecasted with R-squares of 10% and more, by macroeconomic variables. However, if we proceed from the in-sample to a true out-of-sample prediction, forecasting power of macro determinants is dramatically smaller. Basically, forecasting is limited to the market premium in bull markets and – with very limited power – to the momentum premium.

Whereas these findings show the power of the factor analysis approach in revealing relations between macroeconomic variables and stock market risk premia, the structure of findings raises new questions: Why are premia related to macroeconomic forces in some empirical settings but not in others? Why are there different signs of macro determinants for different risk premia? Can we understand the recent crisis in effect as a rare risk event or should it be seen as an irregular episode? This provides motivation for further research.

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Table 1: Descriptive statistics of monthly U.S. stock market risk premia

This Table shows descriptive statistics for monthly US market excess return (RM-RF), size (SMB), value (HML) as well as momentum (WML) premium for the sample size 1960:2 – 2013:1. The first six rows report performance characteristics of the underlying portfolio returns while the remaining four rows contain additional distributional information and the one-sided t-test (H_0: mean=0). Corresponding t-statistics are given in parenthesis and stars refer to significance level of 10% (*), 5% (**) and 1% (***).

	RM-RF	**SMB**	**HML**	**WML**
Mean	0.478	0.217	0.387	0.724
Std. Deviation	4.484	3.066	2.843	4.206
Annualized Sharpe-ratio	0.369	0.245	0.472	0.597
Max	16.10	22.00	13.84	18.39
Min	-23.24	-16.39	-12.60	-34.74
Share of neg. returns	0.417	0.487	0.429	0.360
Median	0.845	0.070	0.395	0.830
Skewness	-0.508	0.558	-0.010	-1.428
Kurtosis	4.802	8.662	5.556	14.189
H0: mean=0	2.689***	1.783**	3.437***	4.343***

Table 2: Descriptive statistics for estimated factors $(\hat{f}_{it})$

The following results present the relative importance of the common factors $\hat{f}_i$ (i =1,…,9) measured as the proportion of total variance in the data explained by the factors 1 to i, given by R_i^2. $\rho(\hat{f}_i)$ is the first order autocorrelation coefficient with corresponding t-statistics given in parenthesis and stars refer to significance level of 10% (*), 5% (**) and 1% (***).

$\hat{f}_i$	R_i^2	ΣR_i^2	$\rho(\hat{f}_i)$
1	0.173	0.173	0.776*** (31.148)
2	0.092	0.266	-0.191*** (4.885)
3	0.071	0.336	0.772*** (30.641)
4	0.051	0.388	0.636*** (20.767)
5	0.042	0.430	0.505*** (14.708)
6	0.036	0.465	0.401*** (11.020)
7	0.028	0.494	-0.354*** (9.511)
8	0.025	0.519	-0.046 (1.168)
9	0.022	0.541	-0.173*** (4.384)

Table 3: Correlation between the 12-month moving average of the estimated factors ($\hat{f}_{it}$) and IP_t growth over time

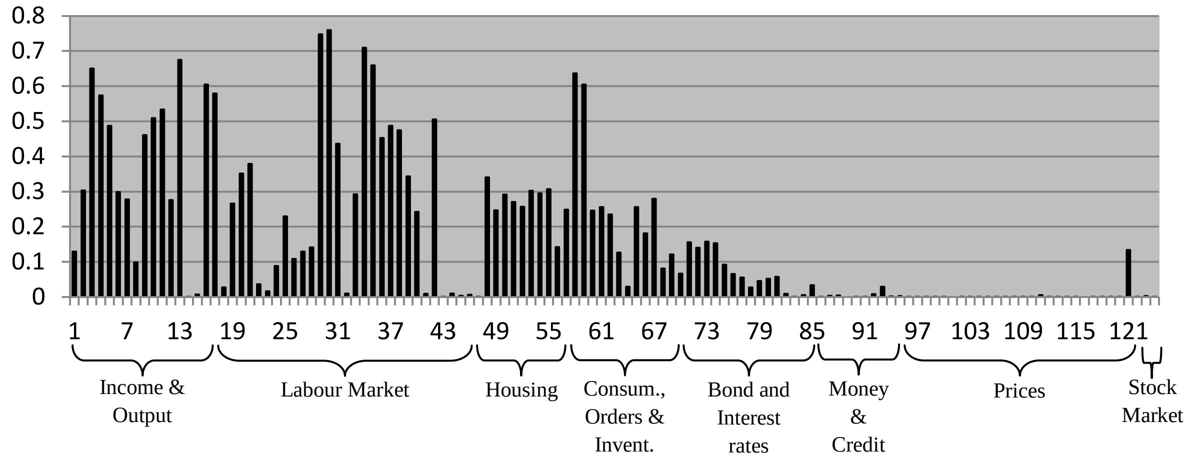
The following table describes the correlation between the 12-month moving average of the estimated factors and IP growth to determine whether the macro factors have a pro-or countercyclical behavior. In addition to the contemporaneous dependency the table also displays different lead/lag relationships. Corresponding t-statistics given in parenthesis and stars refer to significance level of 10% (*), 5% (**) and 1% (***).

	IP growth										
	lags						leads				
	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5
$\hat{f}_{t1}$	0.804	0.847	0.877	0.894	0.896	0.880	0.837	0.780	0.710	0.631	0.546
	(33.631)***	(39.621)***	(45.451)***	(49.728)***	(50.263)***	(46.267)***	(38.171)***	(31.018)***	(25.075)***	(20.224)***	(16.192)***
$\hat{f}_{2t}$	0.207	0.204	0.212	0.220	0.205	0.185	0.180	0.162	0.142	0.112	0.078
	(5.271)***	(5.190)***	(5.400)***	(5.626)***	(5.226)***	(4.689)***	(4.571)***	(4.097)***	(3.563)***	(2.808)***	(1.948)*
$\hat{f}_{3t}$	0.231	0.165	0.094	0.019	-0.059	-0.137	-0.204	-0.265	-0.319	-0.365	-0.401
	(5.898)***	(4.167)***	(2.361)**	(0.478)	(1.484)	(3.460)***	(5.185)***	(6.845)***	(8.372)***	(9.740)***	(10.883)***
$\hat{f}_{4t}$	-0.079	-0.092	-0.106	-0.123	-0.144	-0.169	-0.205	-0.244	-0.281	-0.311	-0.333
	(1.975)**	(2.303)**	(2.656)***	(3.088)***	(3.619)***	(4.284)***	(5.214)***	(6.271)***	(7.278)***	(8.129)***	(8.783)***
$\hat{f}_{5t}$	0.151	0.135	0.110	0.079	0.043	0.003	-0.045	-0.088	-0.127	-0.163	-0.198
	(3.801)***	(3.390)***	(2.768)***	(1.970)**	(1.062)	(0.086)	(1.126)	(2.207)**	(3.177)***	(4.120)***	(5.020)***
$\hat{f}_{6t}$	0.512	0.515	0.505	0.483	0.448	0.402	0.370	0.335	0.302	0.267	0.234
	(14.816)***	(14.949)***	(14.573)***	(13.743)***	(12.481)***	(10.950)***	(9.941)***	(8.866)***	(7.880)***	(6.899)***	(5.988)***
$\hat{f}_{7t}$	-0.140	-0.159	-0.180	-0.193	-0.203	-0.208	-0.229	-0.259	-0.278	-0.290	-0.299
	(3.507)***	(4.012)***	(4.562)***	(4.902)***	(5.162)***	(5.302)***	(5.871)***	(6.689)***	(7.218)***	(7.534)***	(7.802)***
$\hat{f}_{8t}$	-0.024	-0.045	-0.067	-0.092	-0.111	-0.122	-0.141	-0.144	-0.128	-0.103	-0.076
	(0.597)	(1.122)	(1.669)*	(2.300)**	(2.794)***	(3.063)***	(3.555)***	(3.633)***	(3.193)***	(2.566)**	(1.885)*
$\hat{f}_{9t}$	-0.236	-0.233	-0.226	-0.206	-0.180	-0.148	-0.106	-0.069	-0.029	0.014	0.055
	(6.031)***	(5.972)***	(5.780)***	(5.234)***	(4.562)***	(3.731)***	(2.665)***	(1.715)*	(0.731)	(0.352)	(1.370)

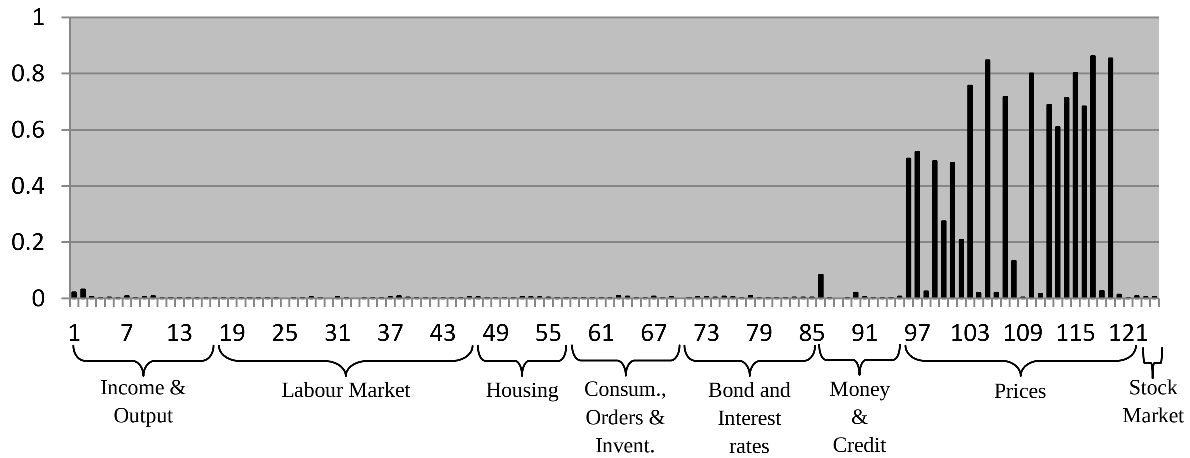
Figure 1: Marginal R-squares for the corresponding in-sample factors

The barplot displays the marginal R-squares that are referred to a univariate regression of all 124 variables on the relevant in-sample factors. The x-axis is coded corresponding to the coding of the variables in the data Appendix.

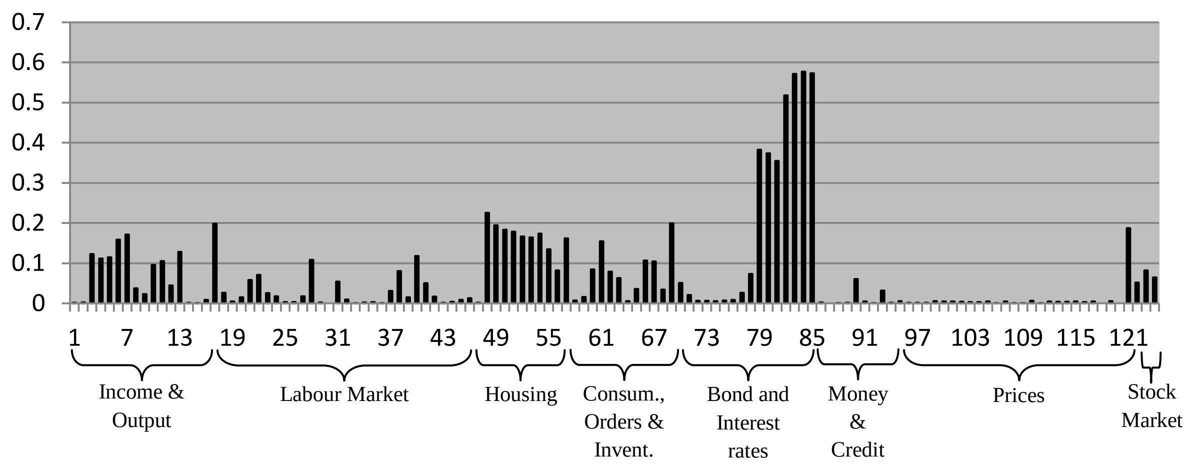
Marginal R-squares for $\hat{f}_1$



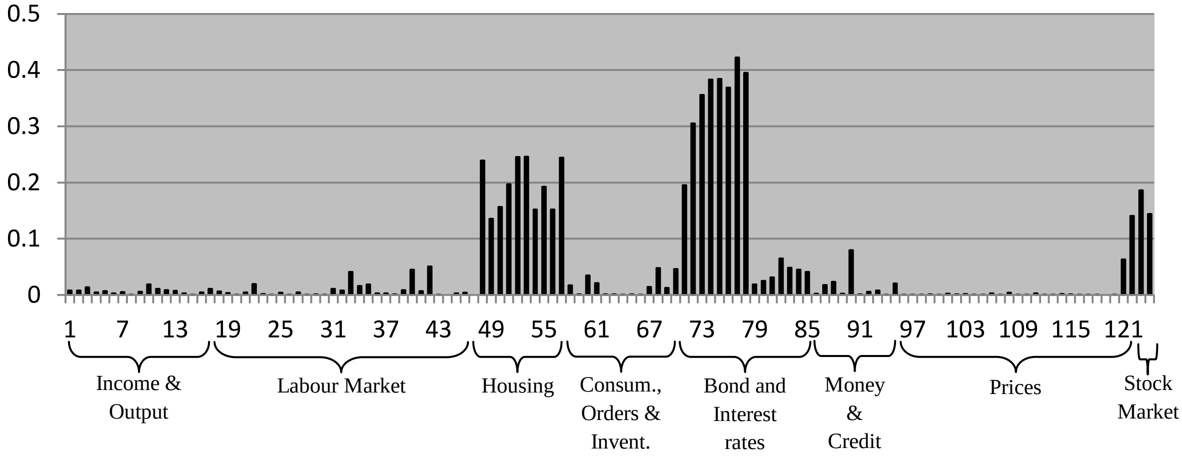
Marginal R-squares for $\hat{f}_2$



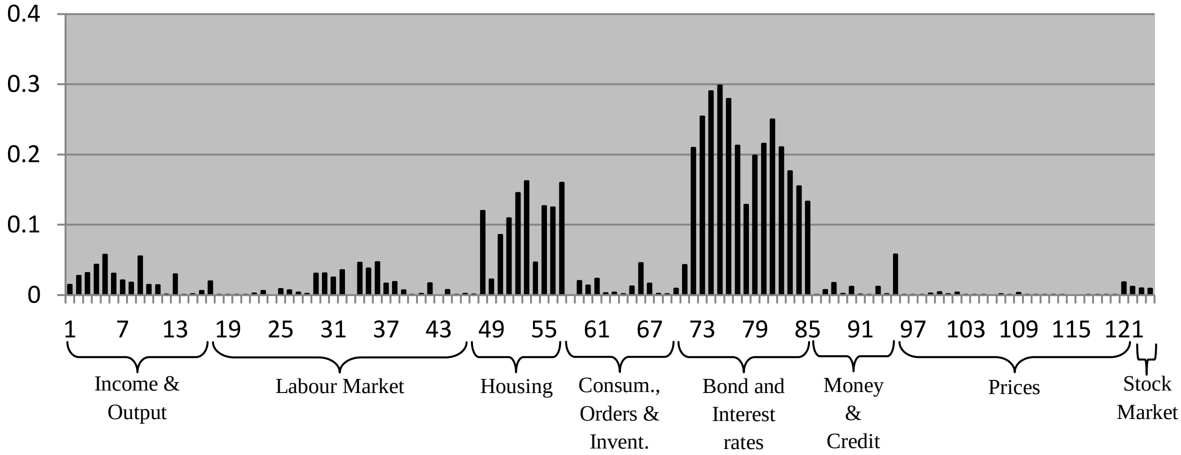
Marginal R-squares for $\hat{f}_3$



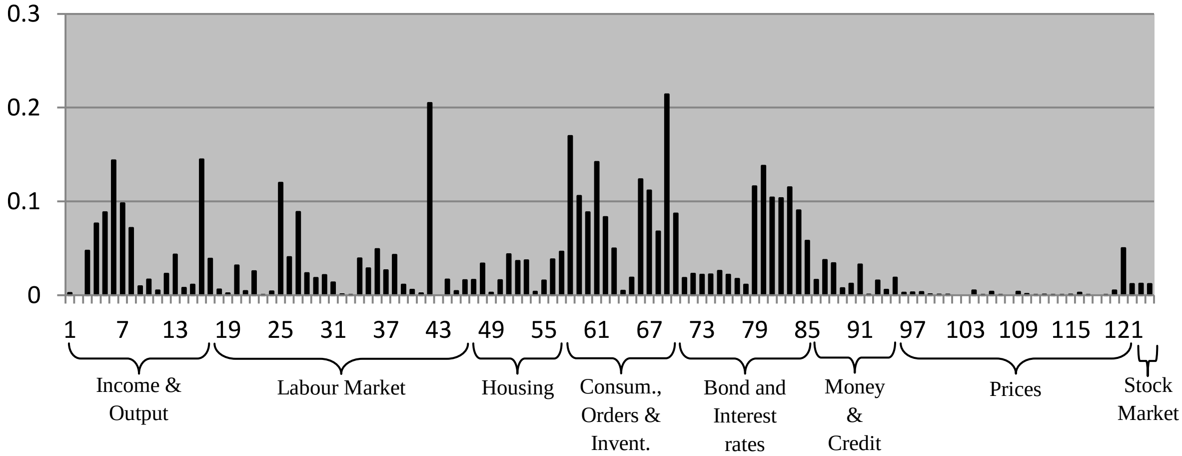
Marginal R-squares for $\hat{f}_4$



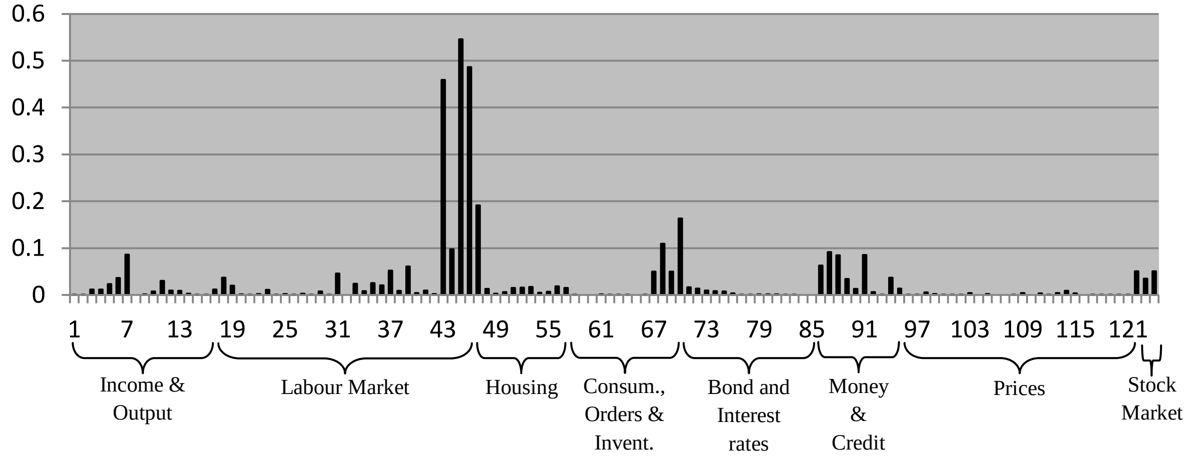
Marginal R-squares for $\hat{f}_5$



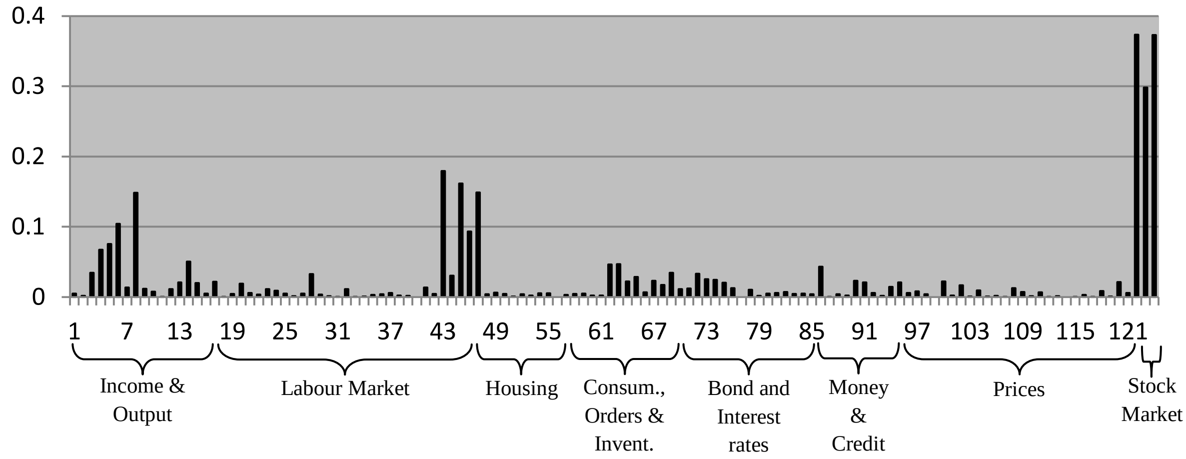
Marginal R-squares for $\hat{f}_6$



Marginal R-squares for $\hat{f}_7$



Marginal R-squares for $\hat{f}_8$



Marginal R-squares for $\hat{f}_9$

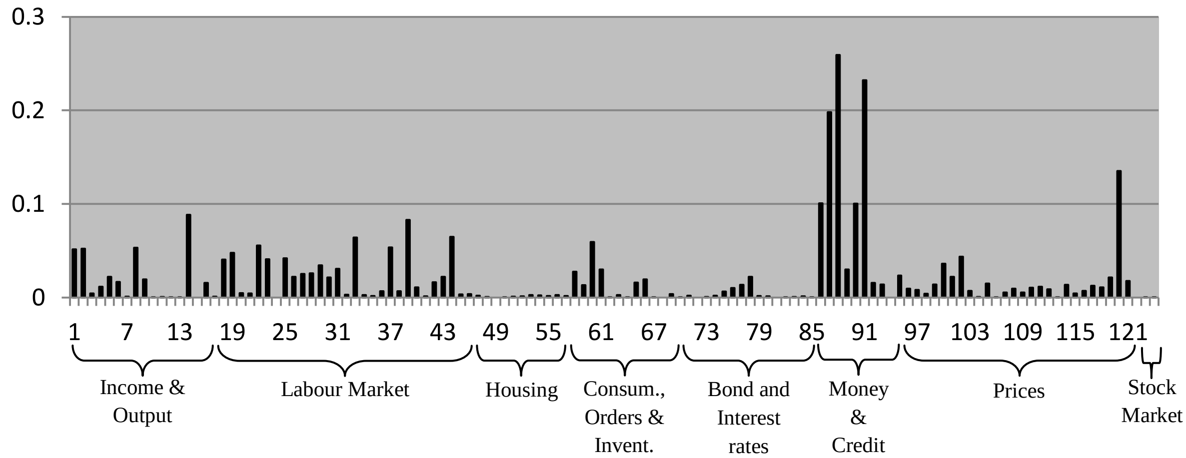


Table 4: Summarized results from in-sample predictive models

The table presents results from OLS forecasting regressions of continuously compounded stock market risk premia on lagged macroeconomic factors. Dependent variables are named in the headings, where RM-RF is the U.S. stock market excess return, SMB is the size premium, HML represents the value premium and WML stands for the momentum premium. The forecasting horizon ranges from 1 month up to 2 years. Relevant predictor variables $\hat{F}_i$ of the estimated common components are identified by the the Bai and NG as well as the BIC criterion. We report the estimated coefficients and the corresponding t-statistics (in absolute values) in parenthesis adjusted by Newey-West HAC estimates (.) and by moving block-bootstrap standard errors [.]. Stars refer to significance level of 10% (*), 5% (**) and 1% (***).

	RM-RF				**SMB**			
	1 month	3 month	1 year	2 years	1 month	3 month	1 year	2 years
$\hat{F}_1$		-0.955 (1.388) [1.342]	-4.041 (2.915)*** [2.755]***	-5.144 (2.531)** [2.404]**		-0.837 (2.355)** [2.252]**	-2.753 (2.500)** [2.400]**	-3.128 (1.825)* [1.776]*
$\hat{F}_2$								
$\hat{F}_3$	0.553 (2.857)*** [2.824]***	1.387 (3.079)*** [2.935]***	3.947 (2.787)*** [2.604]***	4.725 (3.018)*** [2.762]***				
$\hat{F}_4$	0.580 (3.119)*** [3.082]***	0.921 (2.315)** [2.251]**			0.207 (1.926)* [1.898]*			-3.243 (1.984)** [1.817]*
$\hat{F}_5$								-1.903 (1.089) [1.029]
$\hat{F}_6$								
$\hat{F}_7$								
$\hat{F}_8$								
$\hat{F}_9$								
(adj.) R^2	0.029	0.052	0.116	0.098	0.003	0.021	0.055	0.066

Table 4: continued

	HML				WML			
	1 month	3 month	1 year	2 years	1 month	3 month	1 year	2 years
$\hat{F}_1$			1.398 (1.713)* [1.625]		0.486 (1.606) [1.614]	1.328 (1.438) [1.444]	4.069 (1.614) [1.554]	6.986 (2.630)*** [2.446]**
$\hat{F}_2$								
$\hat{F}_3$							-1.788 (1.618) [1.280]	-1.851 (1.014) [0.822]
$\hat{F}_4$							1.766 (1.550) [1.277]	2.296 (1.260) [1.058]
$\hat{F}_5$							-1.890 (1.368) [1.373]	
$\hat{F}_6$				-1.912 (1.944)* [1.891]*				
$\hat{F}_7$								
$\hat{F}_8$	0.229 (1.688)* [1.694]*	0.522 (1.882)* [1.892]*						
$\hat{F}_9$								
(adj.) R^2	0.005	0.008	0.013	0.011	0.012	0.031	0.117	0.153

Table 5: Turning points of the U.S. stock market

This Table shows the peak and through turning month of the cumulative sum of Fama/French market return determined by the Bry-Boschan (1971) method. The sample period is from 1960:02 to 2013:01. The columns Bull (Bear) duration represents the time spent in a bull (bear) market, starting after a through (peak) and ending at the next peak (through), measured in months. The corresponding cumulative change is given in the columns labeled by Change in %.

Peak	Through	Bull duration (month)	Bull Change in %	Bear duration (month)	Bear Change in %
1961:12	1962:06	---	---	6	-26.47
1966:01	1966:09	43	53.96	8	-19.29
1968:11	1970:06	26	40.30	19	-48.57
1972:12	1974:09	30	47.48	21	-72.11
1976:12	1978:02	27	56.95	14	-15.18
1981:05	1982:07	39	39.59	14	-31.44
1983:06	1984:05	11	48.22	11	-19.31
1987:08	1987:11	39	68.03	3	-33.60
1990:05	1990:10	30	35.95	5	-21.19
2000:08	2002:09	118	150.1	25	-62.78
2007:10	2009:02	61	66.33	16	-68.16

Figure 2: U.S. stock market performance in bull and bear market states

This figure shows the cumulative sum of Fama/French´s stock market return and the bull and bear market states determined by the Bry-Boschan (1971) method. Shaded Areas represents the U.S. bear market phases.

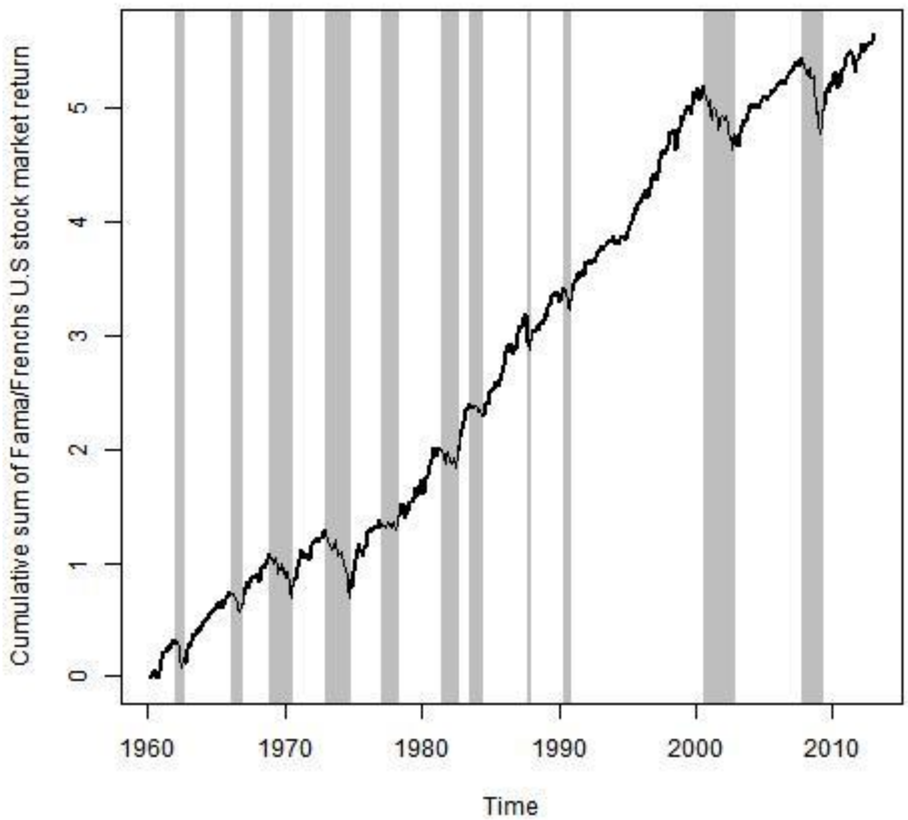


Table 6: Summarized results from in-sample predictive models during bull and bear market states

The table presents results from OLS forecasting regressions of continuously compounded stock market risk premia on lagged macroeconmic factors during financial market cycles. Bull and bear stock market periods are determined by the Bry-Boschans' (1971) method. Dependent variables are named in the headings, where RM-RF is the U.S. stock market excess return, SMB is the size premium, HML represents the value premium and WML stands for the momentum premium. The forecasting horizon ranges from 1 month up to 2 years. Relevant predictor variables $\hat{F}_i$ of the estimated common components are identified by the the Bai and NG as well as the BIC criterion. We report the estimated coefficients and the corresponding t-statistics (in absolute values) in parenthesis adjusted by Newey-West HAC estimates (.) and by moving block-bootstrap standard errors [.]. Stars refer to significance level of 10% (*), 5% (**) and 1% (***).

	RM-RF								**SMB**							
	1 month		3 month		1 year		2 years		1 month		3 month		1 year		2 years	
	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear
$\hat{F}_1$	-0.673 (3.101)*** [2.979]***		-1.919 (3.673)*** [3.402]***	1.503 (0.780) [0.729]	-4.388 (5.270)*** [4.703]***		-3.923 (2.778)*** [2.751]***	-7.195 (0.966) [0.395]			-0.956 (2.797)*** [2.629]***		-1.711 (1.633) [1.556]	-7.656 (3.914)*** [3.570]***		-13.979 (4.267)*** [3.454]***
$\hat{F}_2$																
$\hat{F}_3$		1.030 (2.197)** [2.096]**		4.213 (4.432)*** [3.412]***		13.942 (4.288)*** [3.503]***	2.190 (1.665)* [1.543]	31.263 (3.699)*** [1.784]*				1.377 (2.213)** [2.044]**		2.506 (1.468) [1.269]		
$\hat{F}_4$		1.058 (2.154)** [2.036]**						-15.450 (1.797)* [1.113]							-2.699 (1.898)* [1.743]*	
$\hat{F}_5$								-6.352 (1.225) [0.867]							-2.142 (1.278) [1.206]	
$\hat{F}_6$								9.699 (1.342) [0.823]								
$\hat{F}_7$						6.556 (2.239)** [2.100]**		8.042 (1.748)* [1.609]								
$\hat{F}_8$					-1.593 (3.830)*** [3.675]***				0.331 (1.709)* [1.701]*							
$\hat{F}_9$						-3.803 (1.946)* [1.699]*										
(adj.) R^2	0.052		0.110		0.255		0.304		0.006		0.033		0.102		0.103	

Table 6: continued

	HML								WML							
	1 month		3 month		1 year		2 years		1 month		3 month		1 year		2 years	
	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear
$\hat{F}_1$						3.980 (2.262)** [1.644]		8.106 (3.282)*** [2.222]**	0.934 (2.125)** [2.118]**		2.056 (1.917)* [1.838]*		3.854 (1.622) [1.548]	6.488 (2.340)** [1.699]*	5.836 (2.719)*** [2.554]**	13.387 (2.311)** [1.172]
$\hat{F}_2$																
$\hat{F}_3$		-0.705 (2.197)** [1.963]**		-1.475 (2.183)** [1.894]*	2.601 (2.062)** [1.865]*	-7.611 (3.647)*** [2.883]***		-10.484 (3.193)*** [2.028]**			-0.966 (1.358) [1.276]		-2.618 (1.556) [1.364]		-1.806 (0.943) [0.828]	
$\hat{F}_4$						4.684 (1.675)* [1.297]		11.056 (3.407)*** [2.568]**						7.108 (3.314)*** [2.358]**		15.793 (2.773)*** [1.794]*
$\hat{F}_5$			0.746 (2.713)*** [2.618]***		1.961 (2.410)** [2.241]**			7.354 (3.303)*** [2.487]**			-0.962 (1.408) [1.381]		-2.705 (1.763)* [1.768]*		-2.170 (1.516) [1.417]	9.613 (2.359)** [1.751]*
$\hat{F}_6$		-0.548 (2.722)*** [2.548]**		-1.324 (2.280)** [2.147]**		-3.374 (2.823)*** [1.952]*	-2.218 (2.159)** [2.103]**							-5.031 (2.387)** [1.862]*		-9.439 (2.706)*** [1.984]**
$\hat{F}_7$									0.672 (3.337)*** [3.242]***							
$\hat{F}_8$													1.657 (1.336) [1.372]		1.873 (1.770)* [1.805]*	
$\hat{F}_9$											-1.094 (2.229)** [2.162]**					
(adj.) R^2	0.024		0.042		0.157		0.141		0.044		0.081		0.174		0.280	

Table 7: Summarized results from out-of-sample predictive models

This table shows results from out-of-sample regressions over different forecasting horizons. Panel A reports results without distinguishing between market states, panel B reports results ex-post knowledge of bull and bear markets, estimated by the Bry-Boschan algorithm and panel C displays results under a strict out-of-sample analysis where we estimate market state probabilities by a simple probit model. We evaluate the predictive performance by the out-of-sample R-square defined as $R^2_{oos} = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2}$.

	1 month			3 months			1 year			2 years		
	Full sample	Bull states	Bear states	Full sample	Bull states	Bear states	Full sample	Bull states	Bear states	Full sample	Bull states	Bear states
Panel A: (non-distinguishing between bull and bear market states)												
RM-RF	-0.006	0.010	-0.034	-0.067	0.050	-0.197	-0.093	0.172	-0.321	0.014	0.116	-0.064
SMB	-0.011	-0.011	-0.012	0.007	0.013	-0.021	-0.036	-0.016	-0.182	-0.567	-0.553	-0.623
HML	-0.010	-0.010	-0.010	-0.016	-0.026	0.006	-0.005	0.004	-0.017	-0.043	-0.052	-0.025
WML	-0.032	0.001	-0.114	-0.002	0.004	-0.028	0.008	-0.001	0.031	0.089	0.101	0.071
Panel B: (bull/bear market states by Bry-Boschan algorithm)												
RM-RF	-0.047	-0.004	-0.120	-0.066	0.108	-0.259	-0.802	0.247	-1.706	-0.377	0.236	-0.851
SMB	-0.020	-0.025	0.003	-0.010	-0.016	0.018	-0.145	-0.182	0.123	-0.549	-0.686	-0.014
HML	-0.015	-0.000	-0.049	-0.022	0.000	-0.071	-0.210	-0.150	-0.298	-0.229	-0.253	-0.184
WML	0.021	0.029	0.001	0.024	0.035	-0.017	-0.010	0.009	-0.061	0.111	0.122	0.096
Panel C: (predicted bull/bear market states by probit models)												
RM-RF	-0.072	-0.032	-0.140	-0.053	0.108	-0.230	-0.102	0.185	-0.350	-0.085	0.017	-0.165
SMB	-0.019	-0.019	-0.020	-0.025	-0.016	-0.071	-0.167	-0.170	-0.146	-0.683	-0.723	-0.525
HML	0.003	-0.001	0.013	0.004	-0.007	0.028	-0.210	-0.201	-0.222	-0.247	-0.316	-0.121
WML	-0.031	-0.017	-0.067	0.015	0.013	0.020	0.006	0.006	0.006	0.083	0.095	0.067

Data Appendix

This appendix lists the broad categories and the data description as well as the transformation code to ensure stationarity. All variables are collected from the "Datastream" database on a monthly frequency. The required transformation is coded as lv (level data), ln (log level data), Δlv (first differences in levels), Δln (first differences in log levels) and Δ^2ln denotes the second differences in log levels. The data are available from 1960:1-2012:12.

Group 1: Output

No.	Tran.	Description
1	Δln	Personal Income (AR, Bil. Chain 2005$), SA (TCB)
2	Δln	Personal Income Less Transfer (AR, Bil. Chain 2005$), SA (TCB)
3	Δln	Industrial Production Index – Total Index, SA
4	Δln	Industrial Production Index – Products, Total, SA
5	Δln	Industrial Production Index – Final Products, SA
6	Δln	Industrial Production Index – Consumer Goods, SA
7	Δln	Industrial Production Index – Durable Consumer Goods, SA
8	Δln	Industrial Production Index – Nondurable Consumer Goods, SA
9	Δln	Industrial Production Index – Business Equipments, SA
10	Δln	Industrial Production Index – Materials, SA
11	Δln	Industrial Production Index – Durable Goods Materials, SA
12	Δln	Industrial Production Index – Nondurable Goods Materials, SA
13	Δln	Industrial Production Index – Manufacturing (SIC), SA
14	Δln	Industrial Production Index – Residential Utilities, SA
15	Δln	Industrial Production Index – Fuels, SA
16	lv	ISM Manufacturers Survey: Production Index (%), SA
17	Δlv	Capacity Utilization: Manufacturing (SIC), SA

Group 2: Labor market

No.	Tran.	Description
18	Δln	Civilian Labor Force (Thous.) (TCB), SA
19	Δln	Civilian Employment (Thous.) (TCB), SA
20	Δlv	Civilian Unemployment Rate (TCB), SA
21	Δlv	Average Weekly Insured Unemployment Rate (TCB), SA
22	Δlv	Average Duration of Unemployment: Average in Weeks, SA
23	Δln	Unemploy. By Duration: Persons Unempl. Less Than 5 Wks (Thous), SA
24	Δln	Unemploy. By Duration: Persons Unempl. 5 to 14 Wks (Thous), SA
25	Δln	Unemploy. By Duration: Persons Unempl. 15 Wks + (Thous), SA
26	Δln	Unemploy. By Duration: Persons Unempl. 15 to 26 Wks (Thous), SA
27	Δln	Unemploy. By Duration: Persons Unempl. 27 Wks + (Thous), SA
28	Δln	Average Weekly Initial Claims, Unempl. Insurance (Thous.) (TCB), SA
29	Δln	Employees On Nonfarm Payrolls – Total Private (Thous.), SA
30	Δln	Employees On Nonfarm Payrolls – Goods-Producing (Thous.), SA
31	Δln	Employees On Nonfarm Payrolls – Service-Providing (Thous.), SA
32	Δln	Employees On Nonfarm Payrolls – Mining (Thous.), SA
33	Δln	Employees On Nonfarm Payrolls – Construction (Thous.), SA

34	Δln	Employees On Nonfarm Payrolls – Manufacturing (Thous.), SA
35	Δln	Employees On Nonfarm Payrolls – Durable Goods (Thous.), SA
36	Δln	Employees On Nonfarm Payrolls – Nondurable Goods (Thous.), SA
37	Δln	Employees On Nonfarm Payrolls – Trade, Trans. and Util. (Thous.), SA
38	Δln	Employees On Nonfarm Payrolls – Wholesale Trade (Thous.), SA
39	Δln	Employees On Nonfarm Payrolls – Retail Trade (Thous.), SA
40	Δln	Employees On Nonfarm Payrolls – Financial Activities (Thous.), SA
41	Δln	Employees On Nonfarm Payrolls – Government (Thous.), SA
42	lv	ISM Manufacturers Survey: Employment Index, SA
43	Δ^2ln	Avg Hrly Earnings of Prod Workers on Priv Nonf Payr (Goods-Prod), SA
44	Δ^2ln	Avg Hrly Earnings of Prod Workers on Priv Nonf Payr (Const), SA
45	Δ^2ln	Avg Hrly Earnings of Prod Workers on Priv Nonf Payr (Mfg), SA
46	Δ^2ln	Avg Hrly Earnings of Prod Workers on Priv Nonf Payr (Dur. Goods), SA
47	Δ^2ln	Avg Hrly Earnings of Prod Workers on Priv Nonf Payr (Nondur. Goods), SA

Group 3: Housing sector

No.	Tran.	Description
48	ln	Housing Starts: Total (Thous.U.) AR, SA
49	ln	Housing Starts: Northeast (Thous.U.) AR, SA
50	ln	Housing Starts: Midwest (Thous.U.) AR, SA
51	ln	Housing Starts: South (Thous.U.) AR, SA
52	ln	Housing Starts: West (Thous.U.) AR, SA
53	ln	Housing Authorized: Total New Priv. Housing Units (Thous.U.) AR, SA
54	ln	Houses Authorized By Build. Permits: Northeast (Thous. U.) AR, SA
55	ln	Houses Authorized By Build. Permits: Midwest (Thous. U.) AR, SA
56	ln	Houses Authorized By Build. Permits: South (Thous. U.) AR, SA
57	ln	Houses Authorized By Build. Permits: West (Thous. U.) AR, SA

Group 4: Consumption, orders, and inventories

No.	Tran.	Description
58	lv	ISM Purchasing Manager Index, SA
59	lv	ISM Manufacturers Survey: New Orders Index, SA
60	lv	ISM Manufacturers Survey: Supplier Delivery Index, SA
61	lv	ISM Manufacturers Survey: Inventories Index, SA
62	Δln	Mfrs´ New Orders, Consumer Goods and Materials (Bil. $) (TCB), SA
63	Δln	Mfrs´ New Orders, Durable Goods Indus. (Bil. Chain 2000$) (TCB), SA
64	Δln	Mfrs´ New Orders, Nondefense Capital Goods (Mil. Chain 1982$) (TCB), SA
65	Δln	Mfrs´ Unfilled Orders, Durable Goods Indus. (Bil. Chain 2000$) (TCB), SA
66	Δln	Manufacturing & Trade Inventories (Bil. Chain 2005$) (TCB), SA
67	Δln	Manufacturing and Trade Sales (Mil. Chain 2005$) (TCB), SA
68	Δln	Real Personal Consumption Expenditures (Bil. $), SA
69	Δlv	Ratio, Mfg. and Trade Invent. To Sales (Based on Chain 2005$) (TCB)
70	Δln	Sales of Retail Stores (Mil. Chain 2000$) (TCB)

Group 5: Bond and interest rates

No.	Tran.	Description
71	Δlv	Interest Rate: Federal Funds (Effective) (% Per Annum), Not SA
72	Δlv	Interest Rate: U.S. Treasury Bills, Sec Mkt, 3-Months (% Per Annum)
73	Δlv	Interest Rate: U.S. Treasury Bills, Sec Mkt, 6-Months (% Per Annum)
74	Δlv	Interest Rate: U.S. Treasury Const Maturities., 1-Yr (% Per Annum)
75	Δlv	Interest Rate: U.S. Treasury Const Maturities., 5-Yr (% Per Annum)
76	Δlv	Interest Rate: U.S. Treasury Const Maturities., 10-Yr (% Per Annum)
77	Δlv	Bond Yield: Moody´s Aaa Corporate (% Per Annum)
78	Δlv	Bond Yield: Moody´s Baa Corporate (% Per Annum)
79	lv	T-Bill, Sec Mkt., 3 Months – Fed Funds Rate (72-71)
80	lv	T-Bill, Sec Mkt., 6 Months – Fed Funds Rate (73-71)
81	lv	T-Bill, Const Mat., 1 Year – Fed Funds Rate (74-71)
82	lv	T-Bill, Const Mat., 5 Year – Fed Funds Rate (75-71)
83	lv	T-Bill, Const Mat., 10 Year – Fed Funds Rate (76-71)
84	lv	Bond Yield, Moody´s Aaa– Fed Funds Rate (77-71)
85	lv	Bond Yield, Moody´s Baa– Fed Funds Rate (78-71)

Group 6: Money and credit

No.	Tran.	Description
86	Δ^2ln	Monetary Base, Adj. For Chgs. In Res. Req. (Mil.$), SA
87	Δ^2ln	Money Supply: M1 (Curr,Trav.Cks,Dem Dep, Other Ck´able Dep) (Bil.$), SA
88	Δ^2ln	Money Supply: M2 (M1+O´nite Rps, Euro$, G/P&B/D & …) (Bil.$), SA
89	Δ^2ln	Money Stock: Currency In Circulation (Bil.$), SA
90	Δln	Money Supply: Real M2 (85÷128)
91	Δ^2ln	Depository Inst Reserves: Total, Adj For Chgs. In Res. Req. (Mil.$), SA
92	Δ^2ln	Commercial and Indus Loans Outstanding + NonFin Comm. Paper (Mil. $), SA
93	lv	Commercial and Indus Loans: Net Changes (Bil. $), SA
94	Δ^2ln	Consumer Installment Credit Outstanding: Nonrevolving (Bil. $), SA
95	Δlv	Ratio, Consumer Installment Credit To Personal Income (%) (TCB), SA

Group 7: Prices

No.	Tran.	Description
96	Δ^2ln	Producer Price Index: Finished Goods (82=100,), SA
97	Δ^2ln	Producer Price Index: Finished Consumer Goods (82=100), SA
98	Δ^2ln	Producer Price Index: Capital Equipment (82=100), SA
99	Δ^2ln	Producer Price Index: Intermed Mat. Supplies&Components (82=100), SA
100	Δ^2ln	Producer Price Index: Crude Materials (82=100), SA
101	Δ^2ln	Producer Price Index: Intermed Mat. Less Food & Feeds (82=100), SA
102	Δ^2ln	Producer Price Index: Crude Mat. Less Agric. Products (82=100), SA
103	Δ^2ln	CPI-U: All Items (82-84=100), SA
104	Δ^2ln	CPI-U: Apparel & Unkeep (82-84=100), SA
105	Δ^2ln	CPI-U: Commodities (82-84=100), SA

106	Δ^2ln	CPI-U: Durables (82-84=100) SA
107	Δ^2ln	CPI-U: Energy (82-84=100) SA
108	Δ^2ln	CPI-U: Food (82-84=100) SA
109	Δ^2ln	CPI-U: Medical Care (82-84=100), SA
110	Δ^2ln	CPI-U: Nondurables (82-84=100) SA
111	Δ^2ln	CPI-U: Services (82-84=100), SA
112	Δ^2ln	CPI-U: Transportation (82-84=100), SA
113	Δ^2ln	CPI-U: All Items Less Food (82-84=100), SA
114	Δ^2ln	CPI-U: All Items Less Medical Care (82-84=100), SA
115	Δ^2ln	CPI-U: All Items Less Shelter (82-84=100), SA
116	Δ^2ln	PCE-Index: Total (2005=100) (BEA), SA
117	Δ^2ln	PCE-Index: Goods (2005=100) (BEA), SA
118	Δ^2ln	PCE-Index: Durables (2005=100) (BEA), SA
119	Δ^2ln	PCE-Index: Nondurable Goods (2005=100) (BEA), SA
120	Δ^2ln	PCE-Index: Services (2005=100) (BEA), SA
121	lv	ISM Manufacturers Survey: Prices Paid Index, SA

Group 8: Stock market

No.	Tran.	Description
122	Δln	S&P´s 500 Common Stock Price Index: Composite (1941-43 = 10) (TCB)
123	Δlv	S&P´s 500 Composite Common Stock: Dividend Yield (% Per Ann.)
124	Δln	S&P´s 500 Composite Common Stock: Price-Earnings Ratio (% Per Ann.)

Appendix A: Subsample results from in-sample predictive models during bull and bear market states

The table presents results from OLS forecasting regressions of continuously compounded stock market risk premia on full sample estimated macroeconmic factors over different subsamples and during financial market cycles. Bull and bear stock market periods are determined by the Bry-Boschans' (1971) method. Dependent variables are named in the headings, where RM-RF is the U.S. stock market excess return, SMB is the size premium, HML represents the value premium and WML stands for the momentum premium. The forecasting horizon ranges from 1 month up to 2 years. Relevant predictor variables $\hat{F}_i$ of the estimated common components are identified by the BIC criterion. We report the estimated coefficients and the corresponding t-statistics (in absolute values) in parenthesis adjusted by Newey-West HAC estimates (.) and by moving block-bootstrap standard errors [.]. Stars refer to significance level of 10% (*), 5% (**) and 1% (***).

RM-RF																
	1960:2-2006:12								**1960:2-1989:12**							
	monthly		quarterly		yearly		2 years		monthly		quarterly		yearly		2 years	
	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear
$\hat{F}_1$			-1.574 (2.809)*** [2.525]**		-3.894 (4.612)*** [4.269]***	-13.524 (4.018)*** [2.248]**	-2.396 (1.795)* [1.755]*	-17.049 (4.675)*** [1.036]		-1.179 (2.091)** [1.911]*	-1.740 (3.322)*** [3.018]***	-2.673 (1.447) [1.269]	-4.547 (5.566)*** [5.197]***	-17.155 (6.279)*** [5.123]***	-2.826 (1.862)* [1.784]*	-32.141 (13.037)*** [5.802]***
$\hat{F}_2$	-0.691 (3.321)*** [3.137]***								-1.506 (3.252)*** [3.191]***							
$\hat{F}_3$		1.669 (3.944)*** [3.916]***		4.324 (4.108)*** [3.547]***		16.697 (4.958)*** [3.548]***		28.219 (4.074)*** [1.639]				4.198 (4.702)*** [3.738]***		11.837 (5.788)*** [4.803]***		7.913 (1.894)* [0.626]
$\hat{F}_4$						-7.270 (2.184)** [1.258]		-27.335 (5.274)*** [2.754]***		1.967 (4.067)*** [3.564]***						
$\hat{F}_5$						-3.475 (1.104) [0.729]		-11.627 (3.927)*** [2.089]**		1.060 (2.741)*** [2.368]**		2.390 (3.741)*** [2.664]***		5.205 (5.240)*** [2.582]***		
$\hat{F}_6$						9.201 (2.389)** [1.708]*		12.766 (3.317)*** [1.528]								
$\hat{F}_7$						4.558 (2.730)*** [2.150]**										
$\hat{F}_8$	-0.615 (2.643)*** [2.610]***				-1.916 (4.101)*** [3.943]***	3.352 (2.055)** [1.451]	-2.240 (2.993)*** [2.860]***		-0.689 (2.441)** [2.387]**				-2.009 (3.569)*** [3.459]***		-2.790 (3.382)*** [3.114]***	
$\hat{F}_9$																
(adj.) R^2	0.059		0.106		0.375		0.438		0.128		0.236		0.588		0.468	

Appendix A: continued

	RM-RF								SMB							
	1990:1-2013:1								1960:2-2006:12							
	monthly		quarterly		yearly		2 years		monthly		quarterly		yearly		2 years	
	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear
$\hat{F}_1$	-1.171 (3.126)*** [2.851]***	2.583 (6.330)*** [3.689]***	-2.450 (3.539)*** [2.955]***	7.022 (4.585)*** [3.457]***	-4.410 (3.418)*** [2.620]***	16.573 (3.003)*** [1.793]*	-3.872 (1.741)* [1.252]				-0.940 (2.554)** [2.389]**		-1.647 (1.347) [1.259]	-9.589 (4.916)*** [4.265]***		-15.851 (4.154)*** [3.066]***
$\hat{F}_2$								-7.260 (2.546)** [2.057]**								
$\hat{F}_3$						8.550 (1.173) [0.841]	4.214 (2.116)** [1.689]*	71.240 (7.006)*** [4.549]***				1.422 (2.220)** [2.059]**				
$\hat{F}_4$								18.460 (1.650) [1.173]							-3.517 (2.029)** [1.971]**	
$\hat{F}_5$											-0.863 (2.238)** [2.152]**				-2.891 (1.521) [1.460]	
$\hat{F}_6$								26.051 (3.577)*** [2.400]**							2.389 (1.339) [1.364]	
$\hat{F}_7$		1.074 (2.644)*** [1.677]*				13.784 (3.717)*** [3.053]***		17.266 (4.043)*** [2.709]***								
$\hat{F}_8$								-8.584 (3.240)*** [2.048]**								
$\hat{F}_9$						-9.632 (3.845)*** [2.810]***			-0.373 (2.251)** [2.181]**							
(adj.) R^2	0.161		0.240		0.355		0.493		0.006		0.043		0.102		0.121	

Appendix A: continued

	SMB															
	1960:2-1989:12								**1990:1-2013:01**							
	monthly		quarterly		yearly		2 years		monthly		quarterly		yearly		2 years	
	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear
$\hat{F}_1$			-0.884 (2.289)** [2.144]**		-1.545 (1.394) [1.266]	-10.595 (4.560)*** [3.487]***		-15.963 (3.573)*** [2.110]**			-1.202 (2.395)** [1.980]**		-3.456 (2.193)** [1.674]*	-7.543 (2.828)*** [1.989]**	-6.493 (4.028)*** [2.887]***	-5.934 (1.075) [0.844]
$\hat{F}_2$																
$\hat{F}_3$				1.688 (2.391)** [2.165]**		4.982 (2.076)** [1.648]*							3.330 (2.077)** [1.809]*			
$\hat{F}_4$					-2.957 (2.684)*** [2.527]**	-3.639 (1.532) [0.971]	-5.492 (3.543)*** [3.389]***	-12.850 (2.662)*** [1.763]*					2.458 (1.962)* [1.750]*			
$\hat{F}_5$	-0.570 (3.163)*** [3.066]***		-1.182 (2.733)*** [2.487]**		-3.502 (3.368)*** [3.187]***		-5.383 (3.192)*** [3.101]***						3.321 (2.218)** [1.874]*		3.119 (1.960)* [1.724]*	7.229 (1.534) [1.304]
$\hat{F}_6$					1.579 (1.879)* [1.830]*		4.523 (2.700)*** [2.694]***									
$\hat{F}_7$																-7.704 (2.447)** [1.964]**
$\hat{F}_8$									0.491 (1.276) [1.262]							
$\hat{F}_9$	-0.574 (3.117)*** [3.000]***															
(adj.) R^2	0.039		0.084		0.255		0.287		0.009		0.018		0.203		0.245	

Appendix A: continued

	HML															
	1960:2-2006:12								**1960:2-1989:12**							
	monthly		quarterly		yearly		2 years		monthly		quarterly		yearly		2 years	
	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear
$\hat{F}_1$						3.598 (1.845)* [1.260]	-4.567 (4.074)*** [3.701]***	8.381 (3.900)*** [1.127]						3.584 (1.695)* [1.269]	-4.517 (4.170)*** [3.732]***	12.151 (8.110)*** [2.688]***
$\hat{F}_2$																
$\hat{F}_3$		-0.518 (1.671)* [1.545]		-1.232 (1.813)* [1.515]	5.526 (4.551)*** [4.346]***	-7.099 (3.891)*** [2.955]***	5.928 (3.446)*** [3.330]***	-11.454 (3.185)*** [1.309]				-1.123 (1.647) [1.370]	5.223 (3.886)*** [3.846]***	-4.467 (3.655)*** [2.864]***	6.178 (3.751)*** [3.593]***	
$\hat{F}_4$					-1.418 (1.793)* [1.700]*	4.244 (1.800)* [1.273]	-3.354 (3.153)*** [2.860]***	11.515 (4.102)*** [1.866]*		-0.706 (2.707)*** [2.511]**			-1.339 (1.797)* [1.649]*		-3.764 (3.860)*** [3.500]***	
$\hat{F}_5$								7.259 (2.868)*** [1.665]*							-1.582 (1.839)* [1.612]	4.524 (1.449) [0.969]
$\hat{F}_6$					2.693 (2.639)*** [2.568]**	-3.607 (3.625)*** [2.464]**							2.136 (2.131)** [2.124]**			
$\hat{F}_7$																
$\hat{F}_8$																
$\hat{F}_9$																
Adj. R^2	0.008		0.012		0.218		0.245		0.025		0.018		0.293		0.359	

Appendix A: continued

	HML								WML							
	1990:1-2013:01								1960:2-2006:12							
	monthly		quarterly		yearly		2 years		monthly		quarterly		yearly		2 years	
	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear
$\hat{F}_1$						5.274 (0.995) [0.431]		10.222 (0.970) [0.432]							2.903 (2.436)** [2.336]**	
$\hat{F}_2$				1.525 (3.798)*** [2.118]**		4.694 (2.670)*** [1.683]*		5.720 (2.590)** [1.862]*								
$\hat{F}_3$		-3.655 (3.309)*** [2.801]***	1.242 (1.969)** [1.799]*	-5.931 (1.917)* [1.541]	5.315 (2.519)** [2.315]**	-24.238 (2.987)*** [1.769]*	5.169 (1.354) [1.165]	-32.000 (2.038)** [1.541]								
$\hat{F}_4$					3.339 (2.468)** [2.145]**	13.479 (3.642)*** [1.476]	5.105 (2.800)*** [1.891]*							3.747 (1.928)* [1.715]*		10.493 (3.609)*** [2.829]***
$\hat{F}_5$		1.147 (2.013)** [1.809]*	1.970 (3.381)*** [3.169]***		4.548 (3.206)*** [2.768]***	8.524 (2.529)** [1.212]	5.982 (2.034)** [1.721]*	10.704 (2.827)*** [1.669]*					-1.487 (1.457) [1.425]			5.187 (1.765)* [1.404]
$\hat{F}_6$		-1.265 (3.697)*** [2.494]**		-4.242 (4.804)*** [2.522]**								-1.118 (1.804)* [1.744]*				
$\hat{F}_7$									0.567 (3.793)*** [3.682]***							
$\hat{F}_8$																
$\hat{F}_9$						2.326 (3.087)*** [1.387]										
(adj.) R^2	0.096		0.174		0.276		0.175		0.014		0.006		0.027		0.069	

Appendix A: continued

	WML															
	1960:2-1989:12								1990:1-2013:01							
	monthly		quarterly		yearly		2 years		monthly		quarterly		yearly		2 years	
	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear	Bull	Bear
$\hat{F}_1$						5.004 (2.449)** [1.942]*	2.742 (2.158)** [2.096]**		2.554 (2.410)** [2.301]**		5.347 (3.453)*** [2.595]***		11.320 (3.810)*** [2.640]***	10.864 (2.557)** [0.481]	10.851 (4.453)*** [3.223]***	30.651 (5.450)*** [3.416]***
$\hat{F}_2$	1.004 (2.774)*** [2.737]***															
$\hat{F}_3$											-1.765 (2.121)** [1.772]*			-9.569 (1.192) [0.300]		
$\hat{F}_4$								15.318 (5.156)*** [2.099]**								30.129 (4.601)*** [3.428]***
$\hat{F}_5$											-3.106 (3.055)*** [2.518]**		-4.289 (2.137)** [1.774]*		-7.924 (4.449)*** [3.749]***	17.438 (3.666)*** [2.718]***
$\hat{F}_6$														-16.672 (5.219)*** [0.363]	-4.164 (2.392)** [1.907]*	
$\hat{F}_7$	0.526 (3.330)*** [3.256]***								1.070 (1.923)* [1.919]*					-8.406 (3.674)*** [0.517]		
$\hat{F}_8$													3.829 (2.518)** [2.131]**		3.784 (2.939)*** [2.615]***	
$\hat{F}_9$			-0.761 (1.635) [1.582]												-2.737 (3.397)*** [2.883]***	
(adj.) R^2	0.038		0.005		0.034		0.115		0.105		0.244		0.424		0.544	