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ABSTRACT

Empirical evidence suggests that excess bond returns are forecastable by financial indicators such as forward spreads and yield spreads, a violation of the expectations hypothesis based on constant risk premia. But existing evidence does not tie the forecastable variation in excess bond returns to underlying macroeconomic fundamentals, as would be expected if the forecastability were attributable to time variation in risk premia. We use the methodology of dynamic factor analysis for large datasets to investigate possible empirical linkages between forecastable variation in excess bond returns and macroeconomic fundamentals. We find that several common factors estimated from a large dataset on U.S. economic activity have important forecasting power for future excess returns on U.S. government bonds. Following Cochrane and Piazzesi (2005), we also construct single predictor state variables by forming linear combinations of either five or six estimated common factors. The single state variables forecast excess bond returns at maturities from two to five years, and do so virtually as well as an unrestricted regression model that includes each common factor as a separate predictor variable. The linear combinations we form are driven by both "real" and "inflation" macro factors, in addition to financial factors, and contain important information about one year ahead excess bond returns that is not captured by forward spreads, yield spreads, or the principal components of the yield covariance matrix.

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1 Introduction

Recent empirical research has uncovered significant forecastable variation in the excess returns of U.S. government bonds. Cochrane and Piazzesi (2005), building off of earlier work by Fama and Bliss (1987) and Campbell and Shiller (1991), find that a linear combination of five forward spreads explains between 30 and 35 percent of the variation in next year's excess returns on bonds with maturities ranging from two to five years. Fama and Bliss (1987) report that n-year excess bond returns are forecastable by the spread between the n-year forward rate and the one-year yield. Campbell and Shiller (1991) find that excess bond returns are forecastable by Treasury yield spreads.

Forecastable variation in excess bond returns is a violation of the expectations hypothesis, which presumes that risk premia are constant. As a consequence, forecastability of excess bond returns is often interpreted as evidence of time-varying risk premia, implicitly driven by rational variation in risk or risk-aversion. But economic theories that deliver such rational variation almost always posit that risk premia vary with macroeconomic variables. For example, Campbell and Cochrane (1999) posit that risk premia vary with a slow-moving habit driven by shocks to aggregate consumption. Brandt and Wang (2003) argue that risk premia are driven by shocks to inflation, as well as shocks to aggregate consumption. The empirical evidence cited above, by contrast, finds that risk premia fluctuate not with macroeconomic variables such as aggregate consumption or inflation, but rather with pure financial indicators such as forward spreads and yield spreads. At the same time, common variation in excess returns that is entirely unrelated to aggregate quantities is sometimes interpreted as evidence of irrational investor sentiment rather than rational variation in risk premia (e.g., Campbell, Polk, and Voulteenaho (2005)).

These considerations suggest that if rational variation in risk premia exists, it should be evident from forecasting regressions of excess bond returns on macroeconomic fundamentals. As yet, however, there is little evidence that macroeconomic variables forecast bond returns. Unfortunately, there are several reasons why a judicious, theory-guided empirical investigation using a few macroeconomic series may fail to uncover the predictable dynamics of financial market returns. First, some driving variables may be latent and impossible to summarize with a few observable series. The Campbell-Cochrane habit may fall into this category. Second, macro variables are more likely than financial series to be imperfectly measured and less likely to correspond to the precise economic concepts provided by theoretical models. As one example, aggregate consumption is often measured as nondurables and services expenditure, but this measure omits an important component of theoretical consumption, namely the service flow from the stock of durables. Third, the models themselves are imperfect descriptions of reality and may restrict attention to a small set of variables that fail to span the information sets of financial market participants.

This paper considers one way around these difficulties using the methodology of dynamic factor analysis for large datasets. Recent research on dynamic factor analysis finds that the information in a large number of economic time series can be effectively summarized by a relatively small number of estimated factors, affording the opportunity to exploit a much richer information base than what has been possible in prior empirical study of bond risk premia. In this methodology, "a large number" can mean hundreds or, perhaps, even more than one thousand economic time series. By summarizing the information from a large number of series in a few estimated factors, we eliminate the arbitrary reliance on a small number of imperfectly measured indicators to proxy for macroeconomic fundamentals, and make feasible the use of a vast set of economic variables that are more likely to span the unobservable information sets of financial market participants. We use this methodology to investigate possible empirical linkages between predictable variation in excess bond returns and macroeconomic fundamentals.

Our results indicate bond premia are indeed forecastable by macroeconomic fundamentals, as well as by financial indicators. To implement the dynamic factor analysis methodology, we estimate common factors from a monthly panel of 132 measures of economic activity using the method of principal components. We find that several estimated common factors have important forecasting power for future excess returns on U.S. government bonds. Following Cochrane and Piazzesi (2005), we also construct single predictor state variables from these factors by forming linear combinations of the either five or six estimated common factors (denoted $F5_t$ and $F6_t$, respectively). We find that such state variables forecast excess bond returns at all maturities (two to five years), and do so virtually as well as a regression model that includes each common factor in the linear combination as a separate predictor variable.

The estimated factors have their strongest predictive power for two-year bonds, explaining up to 26 percent of the one year ahead variation in their excess returns. But they also display strong forecasting power for excess returns on three-, four-, and five-year government bonds. The magnitude of the predictability we uncover is less than that found by Cochrane and Piazzesi (their single factor, which we denote CP_t, explains 31 percent of next year's variation in the two-year bond), but is typically more than that found by Fama and Bliss

(1987) and Campbell and Shiller (1991). We also find that our estimated factors have strong out-of-sample forecasting power for excess bond returns of all maturities. The out-of-sample predictive power is stable over time and strongly statistically significant. Finally, the factors continue to exhibit significant predictive power for excess bond returns even when the small sample properties of the data are taken into account.

Of all the estimated factors we study, the single most important in the linear combinations we form is the first common factor from the panel of economic activity. The cubic in this factor also displays predictive power for excess bond returns. This factor is a "real" factor, since it is highly correlated with measures of real output and employment but not highly correlated with prices or financial variables. The third and fourth estimated factors, by contrast, are highly correlated with measures of inflation. Thus, the real and "inflation" factors found in aggregate economic activity are also important factors in the time variation of expected excess bond returns. We discuss the interpretation of the factors further below.

The estimated factors we study are not *pure* macro variables, since the panel of economic indicators from which they are estimated contain financial variables as well as macro variables.[1] This is important because neither theory nor empirical evidence would suggest that macroeconomic variables contain information that is orthogonal to that contained in financial indicators.[2] Thus, the key empirical question we seek to address is not whether macro variables uncover entirely new predictable dynamics not revealed by financial indicators, but rather whether there is any evidence that bond risk premia vary with macroeconomic fundamentals. As it turns out, we find that much of the information contained in the factors that load heavily on the financial variables is already captured by the Cochrane-Piazzesi factor. This is especially true of the second estimated factor, which loads heavily on interest rate spreads. An exception is the eighth factor, which is highly correlated with the stock market. Nevertheless, we find that much of the information contained in our estimated factors is independent of that contained in the Cochrane-Piazzesi factor. As a consequence, when both CP_t and either $F5_t$ or $F6_t$ are included together as predictor variables, the regression model can explain as much as 44 percent of next year's two-year excess bond return. This is an improvement of 13 percent over what is possible using CP_t alone, and an improvement of 18 percent over what is possible using $F5_t$ alone. The results for bonds of other maturities are similar.

[1] Nevertheless, in the interest of brevity, and with slight abuse of terminology, we hereafter refer to the estimated factors from our panel of economic activity simply as "macro factors."

[2] For example, the monetary policy literature emphasizes both empirical and theoretical linkages between bond yields and contemporaneous measures of output and inflation.

The rest of this paper is organized as follows. In the next section we briefly review related literature not discussed above. Section 3 lays out the econometric framework and discusses the use of principal components analysis to estimate common factors. Section 4 explains the empirical implementation and describes the data. We move on in Section 5 to present our empirical findings, including the results of one year ahead predictive regressions for excess bond returns. Two additional analyses are performed as robustness checks: out-of-sample investigations, and small-sample inference. Section 6 concludes.

2 Related Literature

Our use of dynamic factor analysis is an application of statistical procedures developed elsewhere for the case where both the number of economic time series used to construct common factors, N, and the number of time periods, T, are large and converge to infinity (Stock and Watson (2002b); Stock and Watson (2002a); Bai and Ng (2002); Bai and Ng (2005)). Dynamic factor analysis with large N and large T is preceded by a literature studying classical factor analysis for the case where N is relatively small and fixed but $T \to \infty$. See for example, Sargent and Sims (1977); Sargent (1989), and Stock and Watson (1989, 1991). By contrast, Connor and Korajczyk (1986, 1988) pioneered techniques for undertaking dynamic factor analysis when T is fixed and $N \to \infty$.

The presumption of the dynamic factor model is that the covariation among economic time series is captured by a few unobserved common factors. Stock and Watson (2002b) show that consistent estimates of the space spanned by the common factors may be constructed by principal components analysis. Bai and Ng (2005) show that if $\sqrt{T}/N \to 0$, the least squares estimates from factor-augmented forecasting regressions are $\sqrt{T}$ consistent and asymptotically normal, and that pre-estimation of the factors does not affect the consistency of the second-stage parameter estimates or the regression standard errors. A large and growing body of literature has applied dynamic factor analysis in a variety of empirical settings. Stock and Watson (2002b) and Stock and Watson (2004) find that predictions of real economic activity and inflation are greatly improved relative to low-dimensional forecasting regressions when the forecasts are based on the estimated factors of large datasets. An added benefit of this approach is that the use of common factors can provide robustness against the structural instability that plagues low-dimensional forecasting regressions (Stock and Watson (2002a)). The reason is that such instabilities may "average out" in the construction of common factors if the instability is sufficiently dissimilar from one series to the next. Several authors have combined dynamic factor analysis with a vector autoregressive framework to study the macroeconomic effects of policy interventions or patterns of comovement in economic activity (Bernanke and Boivin (2003); Bernanke, Boivin, and Eliasz (2005), Giannone, Reichlin and Sala (2004, 2005); Stock and Watson (2005)). Boivin and Giannoni (2005) use dynamic factor analysis of large datasets to form empirical inputs into dynamic stochastic general equilibrium models. Ludvigson and Ng (2005) use dynamic factor analysis to model the conditional mean and conditional volatility of excess stock market returns.

Our work is also related to research in asset pricing that looks for connections between bond prices and macroeconomic fundamentals. In data spanning the period 1988-2003, Piazzesi and Swanson (2004) find that the growth of nonfarm payroll employment is a strong predictor of excess returns on federal funds futures contracts. Ang and Piazzesi (2003) investigate possible empirical linkages between macroeconomic variables and bond prices in a no-arbitrage factor model of the term structure of interest rates. Building off of earlier work by Duffee (2002) and Dai and Singleton (2002), Ang and Piazzesi study a bond pricing model that allows for time-varying risk premia, consistent with the evidence cited above that excess bond returns are forecastable by forward and yield spreads. But unlike the earlier work, the Ang-Piazzesi pricing kernel is driven by shocks to both observed macro variables and unobserved yield factors; they find empirical support for this model. The investigation of this paper differs in two important respects from that of Ang and Piazzesi. First, we form macro factors from a large set of 132 economic indicators, whereas they study (summary factors from) a small set of macro variables comprised of three inflation measures and four measures of real activity. Second, Ang and Piazzesi focus on yield spread variation and forecasting, whereas we focus on variation in expected excess returns. This latter distinction is important because, as Cochrane and Piazzesi (2005) point out, variables that are relevant for explaining fluctuations in yields may be relatively unimportant for explaining fluctuations in expected excess returns, and vice versa. Of course, yields and excess returns are different transformations of the same underlying bond price data, thus we view our investigation as complimentary to that of Ang and Piazzesi.

3 Econometric Framework

In this section we describe our econometric framework, which involves estimating common factors from a large dataset of economic activity. Such estimation is carried out using principal components analysis, a procedure that has been described and implemented elsewhere for forecasting measures of macroeconomic activity and inflation (e.g., Stock and Watson (2002b), Stock and Watson (2002a), Stock and Watson (2004)). Our notation for excess bond returns and yields closely follows that in Cochrane (2005). We refer the reader to those papers for a detailed description of this procedure; here we only outline how the implementation relates to our application.

The goal of our econometric application is to assess whether forecastable variation in excess bond returns is related to macroeconomic fundamentals. For $t = 1, \ldots T$, let $rx_{t+1}^{(n)}$ denote the continuously compounded (log) excess return on an n-year discount bond in period $t+1$. Excess returns are defined $rx_{t+1}^{(n)} \equiv r_{t+1}^{(n)} - y_t^{(1)}$, where $r_{t+1}^{(n)}$ is the log holding period return from buying an n-year bond at time t and selling it as an $n-1$ year bond at time $t+1$, and $y_t^{(1)}$ is the log yield on the one-year bond. Cochrane and Piazzesi (2005) forecast excess bond returns with a linear combination of $y_t^{(1)}$ and four forward rates, denoted $g_t^{(2)}, g_t^{(3)}, ..., g_t^{(5)}$.[3]

A standard approach to assessing whether excess bond returns are predictable is to select a set of K predetermined conditioning variables at time t, given by the $K \times 1$ vector Z_t, and then estimate

$$rx_{t+1}^{(n)} = \beta' Z_t + \epsilon_{t+1} \tag{1}$$

by least squares. For example, Z_t could include the individual forward rates studied in Fama and Bliss (1987), the single forward factor studied in Cochrane and Piazzesi (2005), or other predictor variables based on a few macroeconomic series. For reasons discussed above, however, such a procedure may be restrictive, especially when investigating potential links between bond premia and macroeconomic fundamentals. In particular, suppose we observe a $T \times N$ panel of macroeconomic data with elements $x_{it}, i = 1, \ldots N,\ t = 1, ..., T$, where the cross-sectional dimension, N, is large, and possibly larger than the number of time periods, T. With standard econometric tools, it is not obvious how a researcher could use the information contained in the panel because, unless we have a way of ordering the importance of the N series in forming conditional expectations (as in an autoregression), there are potentially 2^N possible combinations to consider. Furthermore, letting x_t denote the $N \times 1$ vector of panel observations at time t, estimates from the regression

$$rx_{t+1}^{(n)} = \gamma' x_t + \beta' Z_t + \epsilon_{t+1} \tag{2}$$

quickly run into degrees-of-freedom problems as the dimension of x_t increases, and estimation is not even feasible when $N + K > T$.

[3]Let $p_t^{(n)}$ =log price of n-year discount bond at time t. Then the log yield is $y_t^{(n)} \equiv -(1/n)\, p_t^{(n)}$, and the log holding period return is $r_{t+1}^{(n)_t} \equiv p_{t+1}^{(n-1)} - p_t^{(n)}$. The log forward rate at time t for loans between $t+n-1$ and $t+n$ is $g_t^{(n)} \equiv p_t^{(n-1)} - p_t^{(n)}$.

The approach we consider is to posit that x_{it} has a factor structure taking the form

$$x_{it} = \lambda_i' f_t + e_{it}, \tag{3}$$

where f_t is a $r \times 1$ vector of latent common factors, λ_i is a corresponding $r \times 1$ vector of latent factor loadings, and e_{it} is a vector of idiosyncratic errors.[4] The crucial point here is that $r << N$, so that substantial dimension reduction can be achieved by considering the regression

$$rx_{t+1}^{(n)} = \alpha' F_t + \beta' Z_t + \epsilon_{t+1}, \tag{4}$$

where $F_t \subset f_t$. Equation (1) is nested within the factor-augmented regression, making (4) a convenient framework to assess the importance of x_{it} via F_t, even in the presence of Z_t. But the distinction between F_t and f_t is important, because factors that are pervasive for the panel of data x_{it} need not be important for predicting $rx_{t+1}^{(n)}$.

As common factors are not observed, we replace f_t by $\widehat{f}_t$, estimates that, when $N, T \to \infty$, span the same space as f_t. (Since f_t and λ_i cannot be separately identified, the factors are only identifiable up to an $r \times r$ matrix.) In practice, f_t are estimated by principal components analysis (PCA).[5] Let the Λ be the $N \times r$ matrix defined as $\Lambda \equiv (\lambda_1', ..., \lambda_N')'$. Intuitively, the estimated time t factors $\widehat{f}_t$ are linear combinations of each element of the $N \times 1$ vector $x_t = (x_{1t}, ..., x_{Nt})'$, where the linear combination is chosen optimally to minimize the sum of squared residuals $x_t - \Lambda f_t$. Throughout the paper, we use "hats" to denote estimated values.

To determine the composition of $\widehat{F}_t$, we form different subsets of $\widehat{f}_t$, and/or functions of $\widehat{f}_t$ (such as $\widehat{f}_{1t}^2$). For each candidate set of factors, $\widehat{F}_t$, we regress $rx_{t+1}^{(n)}$ on $\widehat{F}_t$ and Z_t and evaluate the corresponding BIC and $\bar{R}^2$. Following Stock and Watson (2002b), minimizing the BIC yields the preferred set of factors $\widehat{F}_t$. Z_t contains additional (non-factor) regressors that are thought to be related to future bond returns. For the results reported below, we set

[4] We consider an *approximate* dynamic factor structure, in which the idiosyncratic errors e_{it} are permitted to have a limited amount of cross-sectional correlation. The approximate factor specification limits the contribution of the idiosyncratic covariances to the total variance of x as N gets large:

$$N^{-1} \sum_{i=1}^{N} \sum_{j=1}^{N} |E(e_{it} e_{jt})| \leq M.$$

[5] To be precise, the $T \times r$ matrix $\widehat{f}$ is $\sqrt{T}$ times the r eigenvectors corresponding to the r largest eigenvalues of the $T \times T$ matrix $xx'/(TN)$ in decreasing order. Let Λ be the $N \times r$ matrix of factor loadings $(\lambda_1', ..., \lambda_N')'$. Λ and f are not separately identifiable, so the normalization $f'f/T = I_r$ is imposed, where I_r is the r-dimensional identity matrix. With this normalization, we can additionally obtain $\widehat{\Lambda} = x'\widehat{f}/T$, and $\widehat{\chi}_{it} = \widehat{\lambda}_i' \widehat{f}_t$ denotes the estimated common component in series i at time t. The number of common factors, r, is determined by the panel information criteria developed in Bai and Ng (2002).

Z_t equal to a single variable, the Cochrane-Piazzesi forward factor CP_t, since this variable subsumes the information about bond premia that is contained in the the individual forward spreads used by Fama and Bliss (1987) and yield spreads used by Campbell and Shiller (1991). The final regression model for excess returns is based on Z_t plus this optimal $\widehat{F}_t$. That is,

$$rx_{t+1}^{(n)} = \alpha' \widehat{F}_t + \beta' Z_t + \epsilon_{t+1}. \tag{5}$$

Notice that although we have written (5) so that $\widehat{F}_t$ and Z_t enter as separate regressors, there is no theoretical reason that macro factors should contain information that is entirely orthogonal to the information in financial predictor variables that might be contained in Z_t. Thus, our main empirical question asks whether factors $\widehat{F}_t$ have unconditional predictive power for future returns. This amounts to asking whether the coefficients α from a restricted version of (5) given by

$$rx_{t+1}^{(n)} = \alpha' \widehat{F}_t + \epsilon_{t+1} \tag{6}$$

are different from zero. At the same time, an interesting empirical question is whether the information contained in macro factors $\widehat{F}_t$ overlaps substantially with that contained in financial predictor variables. Therefore we also evaluate regressions of the form (5), in which Z_t includes proven financial predictor variables. This allows us to assess whether $\widehat{F}_t$ has predictive power for excess bond returns, conditional on the information in Z_t. In each case, the null hypothesis is that excess bond returns are unpredictable.

Under the assumption that $N, T \to \infty$ with $\sqrt{T}/N \to 0$, Bai and Ng (2005) showed that (i) $(\widehat{\alpha}, \widehat{\beta})$ obtained from least squares estimation of (5) are $\sqrt{T}$ consistent and asymptotically normal, and the asymptotic variance is such that inference can proceed as though f_t is observed, (ii) the estimated conditional mean, $\widehat{F}_t'\widehat{\alpha} + Z_t'\widehat{\beta}$ is $\min[\sqrt{N}, \sqrt{T}]$ consistent and asymptotically normal, and (iii) the h period forecast error from (5) is dominated in large samples by the variance of the error term, just as if f_t is observed. The importance of a large N must be stressed, however, as without it, the factor space cannot be consistently estimated however large T becomes.

Although our estimates of the predictable dynamics in excess bond returns will clearly depend on the extracted factors and conditioning variables we use, the combination of dynamic factor analysis applied to very large datasets, along with a statistical criterion for choosing parsimonious models of relevant factors and conditioning variables, makes our analysis less dependent than previous applications on only a handful of predetermined conditioning variables. The use of dynamic factor analysis allows us to entertain a much larger set of predictor variables than what has been entertained previously, while the BIC criterion provides a means of choosing among summary factors and conditioning variables by indicating whether these variables have important additional forecasting power for excess bond returns.

4 Empirical Implementation and Data

A detailed description of the data and our sources is given in the Data Appendix. We study monthly data spanning the period 1964:1 to 2003:12, the same sample studied by Cochrane and Piazzesi (2005).

The bond return data are taken from the Fama-Bliss dataset available from the Center for Research in Securities Prices (CRSP), and contain observations on one- through five-year zero coupon U.S. Treasury bond prices. These are used to construct data on excess bond returns, yields and forward rates, as described above. Annual returns are constructed by continuously compounding monthly return observations.

We estimate factors from a balanced panel of 132 monthly economic series, each spanning the period 1964:1 to 2003:12. Following Stock and Watson (2002b, 2004, 2005), the series were selected to represent broad categories of macroeconomic time series: real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventories and inventory sales ratios, orders and unfilled orders, compensation and labor costs, capacity utilization measures, price indexes, interest rates and interest rate spreads, stock market indicators and foreign exchange measures. The complete list of series is given in the Appendix, where a coding system indicates how the data were transformed so as to insure stationarity. All of the raw data in x_t are standardized prior to estimation.

For the specifications in which we include additional predictor variables in Z_t, we report results in which Z_t contains the single variable CP_t. We do so because the Cochrane-Piazzesi factor summarizes virtually all the information in individual yield spreads and forward spread that had been the focus of prior work on predictability in bond returns. We also experimented with including the dividend yield on the Standard and Poor composite stock market index in Z_t, since Fama and French (1989) find that this variable has modest forecasting power for bond returns. We do not report those results, however, since the dividend yield has little forecasting power for future bond returns in our sample and has even less once the macro factors $\widehat{F}_t$ or the Cochrane and Piazzesi factor are included in the forecasting regression.

In estimating the time-t common factors, we face a decision over how much of the time-series dimension of the panel to use. We take two approaches. First, we run in-sample regressions in which the full sample of time-series information is used to estimate the common factors at each date t. This approach can be thought of as providing smoothed estimates of the latent factors, f_t. Smoothed estimates of the latent factors are the most efficient means of summarizing the covariation in the data x because the estimates do not discard information in the sample. Second, we conduct an out-of-sample forecasting investigation in which the predictor factors are reestimated recursively each period using data only up to time t. A description of this procedure is given below.

5 Empirical Results

Table 1 presents summary statistics for our estimated factors $\widehat{f}_t$. The number of factors, r, is determined by the information criteria developed in Bai and Ng (2002). The criteria indicate that the factor structure is well described by eight common factors. The first factor explains the largest fraction of the total variation in the panel of data x, where total variation is measured as the sum of the variances of the individual x_{it}. The second factor explains the largest fraction of variation in x, controlling for the first factor, and so on. The estimated factors are mutually orthogonal by construction. Table 1 reports the fraction of variation in the data explained by factors 1 to i.[6] Table 1 shows that a small number of factors account for a large fraction of the variance in the panel dataset we explore. The first five common factors of the macro dataset account for about 40 percent of the variation in the macroeconomic series.

To get an idea of the persistence of the estimated factors, Table 1 also displays the first-order autoregressive, AR(1), coefficient for each factor. None of the factors have a persistence greater than 0.77, but there is considerable heterogeneity across estimated factors, with coefficients ranging from -0.17, to 0.77.

As mentioned, we formally choose among a range of possible specifications for the forecasting regressions of excess bond returns based on the estimated common factors (and possibly nonlinear functions of those factors such as $\widehat{f}_{1t}^3$) using the BIC criterion. Given the large number of possible specifications, we report only the subset of those specifications analyzed that have the lowest BIC criterion.[7] Results not reported indicate that, when the Cochrane-Piazzesi factor is excluded as a predictor, the six-factor subset $F_t \subset f_t$ given by $F_t = \overrightarrow{F6}_t = \left(\widehat{F}_{1t}, \widehat{F}_{1t}^3, \widehat{F}_{2t}, \widehat{F}_{3t}, \widehat{F}_{4t}, \widehat{F}_{8t}\right)'$ minimizes the BIC criterion across a range of pos-

[6] This is given as the the sum of the first i largest eigenvalues of the matrix xx' divided by the sum of all eigenvalues.

[7] Specifications that include lagged values of the factors beyond the first were also examined, but additional lags were found to contain little information for future returns that was not already contained in the one-period lag specifications.

sible specifications based on the first eight common factors of our panel dataset, as well as nonlinear basis functions of these factors. $\widehat{F}^3_{1t}$, above, denotes the cubic function in the first estimated factor. The estimated factors $\widehat{F}_{5t}$ and $\widehat{F}_{6t}$ exhibit little forecasting power for excess bond returns. When CP_t is included, by contrast, the five-factor subset $F_t \subset f_t$ given by $F_t = \overrightarrow{F5}_t = \left(\widehat{F}_{1t}, \widehat{F}^3_{1t}, \widehat{F}_{3t}, \widehat{F}_{4t}, \widehat{F}_{8t}\right)'$ minimizes the BIC criterion. As we shall see, the second estimated factor $\widehat{F}_{2t}$ is highly correlated with interest rates spreads. As a result, the information it contains about future bond premia is subsumed in CP_t.

The subsets F_t contain five or six factors. To assess whether a single linear combination of these factors forecasts excess bond returns at all maturities, we follow Cochrane and Piazzesi (2005) and form single predictor factors as the fitted values from a regression of average (across maturity) excess returns on the set of six and five factors, respectively. We denote these single factors $F6_t$ and $F5_t$, respectively:

$$\frac{1}{4}\sum_{n=2}^{5} rx^{(n)}_{t+1} = \gamma_0 + \gamma_1\widehat{F}_{1t} + \gamma_2\widehat{F}^3_{1t} + \gamma_3\widehat{F}_{2t} + \gamma_4\widehat{F}_{3t} + \gamma_5\widehat{F}_{4t} + \gamma_6\widehat{F}_{8t} + u_{t+1}, \tag{7}$$

$$F6_t \equiv \widehat{\gamma}'\overrightarrow{F6}_t,$$

$$\frac{1}{4}\sum_{n=2}^{5} rx^{(n)}_{t+1} = \delta_0 + \delta_1\widehat{F}_{1t} + \delta_2\widehat{F}^3_{1t} + \delta_3\widehat{F}_{3t} + \delta_4\widehat{F}_{4t} + \delta_5\widehat{F}_{8t} + v_{t+1}, \tag{8}$$

$$F5_t \equiv \widehat{\delta}'\overrightarrow{F5}_t,$$

where $\widehat{\gamma}$ and $\widehat{\delta}$ denote the 6×1 and 5×1 vectors of estimated coefficients from (7) and (8), respectively. With these factors in hand, we now turn to an empirical investigation of their forecasting properties for excess bond returns.

5.1 In-Sample Analysis

Tables 2a-2d present results from in-sample forecasting regressions of the general form (5), for two-year, three-, four-, and five-year log excess bond returns.[8] In this section, we investigate the two hypotheses discussed above. First we ask whether the estimated factors have unconditional predictive power for excess bond returns; this amounts to estimating the restricted version of (5) given in (6), where β' is restricted to zero. Next we ask whether the estimated factors have predictive power for excess bond returns conditional on Z_t. This amounts to estimating the unrestriced regression (5) with β' freely estimated. The statistical significance of the factors is assessed using asymptotic standard errors. Section 5.3, below, investigates the finite sample properties of the data.

[8]The results reported below for log returns are nearly identical for raw excess returns.

For each regression, the regression coefficients, heteroskedasticity and serial-correlation robust t-statistics, and adjusted R^2 statistic are reported. The asymptotic standard errors use the Newey and West (1987) correction for serial correlation with 18 lags. The correction is needed because the continuously compounded annual return has an MA(12) error structure under the null hypothesis that one-period returns are unpredictable. Because the Newey-West correction down-weights higher order autocorrelations, we follow Cochrane and Piazzesi (2005) and use an 18 lag correction to better insure that the procedure fully corrects for the MA(12) error structure.

We begin with the results in Table 2a, predictive regressions for excess returns on two-year bonds $rx_{t+1}^{(2)}$. As a benchmark, column a reports the results from a specification that includes only the Cochrane-Piazzesi factor CP_t as a predictor variable. This variable, a linear combination of $y_t^{(1)}$ and four forward rates, $g_t^{(2)}, g_t^{(3)}, ..., g_t^{(5)}$, is strongly statistically significant and explains 31 percent of next year's two-year excess bond return. By comparison, column b shows that the six factors contained in the vector $\overrightarrow{F6}_t$ are also strong predictors of the two-year excess return, with t-statistics in excess of five for the first estimated factor $\widehat{F}_{1t}$, but with all factors statistically significant at the 5 percent or better level. Together these factors explain 26 percent of the variation in one year ahead returns. Although the second factor, $\widehat{F}_{2t}$, is strongly statistically significant in column b, column c shows that once CP_t is included in the regression, it loses its marginal predictive power and the adjusted R^2 statistic rises from 26 to 45 percent. This implies that the information contained in $\widehat{F}_{2t}$ is more than captured by CP_t. Because we find similar results for the excess returns on bonds of all maturities, we hereafter omit output from multivariate regressions using $\widehat{F}_{2t}$ and CP_t as a separate predictors in subsequent tables.

Columns d through h display estimates of the marginal predictive power of the estimated factors in $\overrightarrow{F5}_t$ and the single predictor factors $F5_t$ and $F6_t$. The single predictor factors explain virtually the same fraction of future excess returns as do the unrestricted specifications that include each factor as separate predictor variables. For example, both $\overrightarrow{F6}_t$ and $F6_t$ explain 26 percent of next year's excess bond return; both $\overrightarrow{F5}_t$ and $F5_t$ explain 22 percent. Column e shows that the five factors in $\overrightarrow{F5}_t$ are strongly statistically significant even when CP_t is included, implying that these factors contain information about future returns that is not contained in forward spreads. The 45 percent $\overline{R}^2$ from this regression indicates an economically large degree of predictability of future bond returns. About the same degree of predictability is found when the single factor $F5_t$ is included with CP_t ($\overline{R}^2 = 44$ percent).

The results in Tables 2b-2d for excess returns on three-, four-, and five-year bonds are similar to those reported in Table 2a for two-year bonds. In particular, (i) the single factors $F5_t$ and $F6_t$ predict future bond returns just as well than the unrestricted regressions that include each factor as separate predictor variables, (ii) the first estimated factor continues to display strongly statistically significant predictive power for bonds of all maturities, and (iii) the specifications explain an economically large fraction of the variation in future returns. There are, however, a few notable differences from Table 2a. The coefficients on the third and fourth common factors are more imprecisely estimated in unrestricted regressions of $rx_{t+1}^{(3)}$, $rx_{t+1}^{(5)}$, and $rx_{t+1}^{(5)}$ on $\overrightarrow{F5}_t$, as evident from the lower t-statistics. But notice that, in every case, the third factor retains the strong predictive power it exhibited for $rx_{t+1}^{(2)}$ once CP_t is included as an additional predictor (column c of Tables 2b-2d). Moreover, the single factors $F5_t$ and $F6_t$ remain strongly statistically significant predictors of excess returns on bonds of all maturities and continue to deliver high $\overline{R}^2$. $F6_t$ alone explains 24, 23, and 21 percent of next years excess return on the three-, four-, and five-year bond, respectively; $F5_t$ explains 19, 17, and 14 percent of next years excess returns on these bonds, and $F5_t$ and CP_t together explain 44, 45, and 42 percent of next years excess returns.

In summary, the results reported in Tables 2a-2b indicate that good forecasts of excess bond returns can be made with only a few macro factors, and that the best forecasts are based on combinations of macro factors and the Cochrane-Piazzesi factor CP_t. It is reassuring that some of estimated factors ($\widehat{F}_{2t}$ in particular, and to a lesser extent $\widehat{F}_{3t}$) are found to contain information that is common to that the Cochrane-Piazzesi factor, suggesting that CP_t summarizes a large body of information about economic and financial activity. The Cochrane-Piazzesi factor CP_t contains more *overall* information about future bond returns than what is contained in the estimated macro factors. This is evident from a comparison of $\overline{R}^2$ statistics. The crucial point, however, is that measures of real activity and inflation in the aggregate economy contain economically meaningful information about future bond returns that is not contained in CP_t. This implies not only that returns are significantly more forecastable than what is indicated by CP_t alone, but also that specifications using pure financial variables omit pertinent information about future bond returns associated with macroeconomic fundamentals. As a consequence, when the information in CP_t and the macro factors is combined, the magnitude of forecastability exhibited by excess bond returns is remarkable.

What economic interpretation can we give to the predictor factors? Because the factors are only identifiable up to a $r \times r$ matrix, a detailed interpretation of the individual factors would be inappropriate. Nonetheless, it is useful to briefly characterize the factors as they relate to the underlying variables in our panel dataset. Figures 1 through 5 show the marginal R^2 for our estimates of F_{1t}, F_{2t}, F_{3t}, F_{4t}, and F_{8t}. The marginal R^2 is the R^2 statistic from regressions of each of the 132 individual series in our panel dataset onto each estimated factor, one at a time, using the full sample of data. The figures display the R^2 statistics as bar charts, with one figure for each factor. The individual series that make up the panel dataset are grouped by broad category and labeled using the numbered ordering given in the Data Appendix.

The first factor loads heavily on measures of employment and production (employees on nonfarm payrolls and manufacturing output, for example), but also on measures of capacity utilization and new manufacturing orders. It displays little correlation with prices or financial variables, however, hence we call this factor a *real factor*. The second factor, which has a correlation with CP_t of -45%, loads heavily on several interest rate spreads, explaining almost 70 percent of the variation in the $Baa-$Fed funds rate spread, for example. The third and fourth factors load most heavily on measures of inflation and price pressure but display little relation to employment and output. They are highly correlated with both commodity prices and consumer prices, while $\widehat{F}_{4t}$ is also highly correlated with the level of nominal interest rates (for example by the five-year government bond yield). Nominal interest rates may contain information about inflationary expectations that is not contained in measures of the price level. Notice however, that the highest marginal R^2 in the regression of $\widehat{F}_{4t}$ on inflation variables is less than half of that from regressions of $\widehat{F}_{3t}$ on inflation measures; thus the latter is the economically more important factor related to inflation. Nevertheless, we call both $\widehat{F}_{3t}$ and $\widehat{F}_{4t}$ *inflation factors*. The eighth factor loads heavily on measures of the aggregate stock market: the log difference in both the composite and industrial Standard and Poor's Index and the Standard and Poor's dividend yield. It bears little relation to other variables. We call this factor a *stock market factor*.[9]

Since the factors are orthogonal by construction, we can characterize their relative importance in the linear combinations $F5_t$ and $F6_t$ by investigating the absolute value of the coefficients on each factor in the regressions (7) and (8). (Since the factors are identifiable up to an $r \times r$ matrix, the signs of the coefficients have no particular interpretation.) Because the factors are orthogonal, it is sufficient for this characterization to investigate just the

[9] This factor is not simply picking up information contained in the stock market dividend yield (Fama and French (1989)). Results not reported indicate that the dividend yield on Standard & Poor composite index has only a small amount of predictive power for excess bond returns in our sample; moreover, conditional on the dividend yield, the stock market factor we estimate has strong marginal predictive power.

coefficients from the regression on all six factors contained in $\overrightarrow{F6}_t$, as in (7).[10] Using data from 1964:1-2003:12, we find the following regression results (t-statistics in parentheses):

$$\frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)} = \underset{(2.96)}{1.03} - \underset{(-5.12)}{1.72} \cdot \widehat{F}_{1t} + \underset{(2.97)}{0.13} \cdot \widehat{F}_{1t}^3 - \underset{(-3.90)}{1.01} \cdot \widehat{F}_{2t} + \underset{(1.18)}{0.18} \cdot \widehat{F}_{3t} - \underset{(-2.40)}{0.56} \cdot \widehat{F}_{4t} + \underset{(4.56)}{0.78} \cdot \widehat{F}_{8t} + u_{t+1},$$

$$\overline{R}^2 = 0.224.$$

The real factor, $\widehat{F}_{1t}$, has the largest coefficient in absolute value, implying that it is the single most important factor in the linear combinations we form. The interest rate factor $\widehat{F}_{2t}$ is second most important, and the stock market factor $\widehat{F}_{8t}$ third most. The inflation factors $\widehat{F}_{3t}$ and $\widehat{F}_{4t}$ are relatively less important but still contribute more than the cubic in the real factor. ($\widehat{F}_{3t}$ is not marginally significant in these regressions because its coefficient is imprecisely estimated in forecasts of three-, four-, and five-year excess bond returns when only factors are included as predictors. The variable is nonetheless an important predictor of future bond returns at all maturities because it is a strongly statistically significant once CP_t is included as an additional regressor.)

In most empirical applications involving macro variables, researchers choose a few time series thought to be representative of aggregate activity. In monthly data, the usual suspects tend to be a measure of industrial production, consumer and commodity inflation, and unemployment. The next regression shows what happens if individual series of this type are used instead of factors to forecast excess bond returns:

$$\frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)} = \underset{(2.88)}{6.06} - \underset{(-0.74)}{28.01} \cdot IP_t + \underset{(0.02)}{0.56} \cdot CPI - \underset{(-2.55)}{0.09} \cdot CMPI_t - \underset{(-0.79)}{11.80} \cdot PPI_t + \underset{(0.99)}{1.36} \cdot UN_t + u_{t+1},$$

$$\overline{R}^2 = 0.113.$$

IP_t is the log difference in the industrial production index, CPI_t is the log difference in the consumer price index, $CMPI_t$ is the log difference in the NAPM commodity price index; PPI_t is the log difference in the producer price index, and UN_t is the unemployment rate for the total population over 16 years of age. Unlike the factors, many of the usual suspect macro series have little marginal predictive power for excess bond returns, and the $\overline{R}^2$ statistic is significantly lower. This occurs even though, for example, IP_t and $\widehat{F}_{1t}$ have a simple correlation of 83 percent in our sample. Of course, the choice of predictors above is somewhat

[10]Strictly speaking, $\widehat{F}_{1t}^3$ is not orthogonal, but in practice is found to be nearly so.

arbitrary given the large number of series available. This fact serves to illustrate a point: not only does the factor approach employed above free the researcher from arbitrary decisions about which of many macro series should be used to represent aggregate activity, but it is also likely to provide a superior means capturing time-variation in excess bond returns.

Is the forecastable variation in excess bond returns we uncover related to macroeconomic risks in the way predicted by theory? The real factor, $\widehat{F}_{1t}$, captures marked cyclical variation in real activity. This is illustrated in Figure 6, which plots the 12 month moving average of both $\widehat{F}_{1t}$ and IP_t over time, along with shaded bars indicating dates designated by the National Bureau of Economic Research (NBER) as recession periods. The correlation between the moving averages of these two series is 92 percent. The figure shows that both the first factor and IP growth reach peaks in the mid-to-late stages of economic expansions, and take on their lowest values at the end of recessions. Thus recessions are characterized by low and typically negative IP growth, while expansions are characterized by strong positive growth. Connecting these findings back to forecasts of excess bond returns, the results in Tables 2a-2d show that excess return forecasts are high when $\widehat{F}_{1t}$ is *low,* implying that return forecasts have a countercyclical component. They are high at the bottom of recessions and low at the height of economic expansions. Such findings are consistent with economic theories that imply investors must be compensated for bearing risks related to recessions. For example, Campbell and Cochrane (1999) study a model in which risk aversion varies over the business cycle and is low in good times when consumption growth is high. This implies that risk premia are also low when the economy is growing quickly, or that excess return forecasts are low in booms, consistent with what we find. By linking the forecastability of excess returns to real economic activity, the findings here provide direct evidence that risk premia are connected to macroeconomic risks in the direction predicted by economic theory.

The evidence that inflation factors govern part of the predictable variation in excess bond returns also provides independent empirical support for the general theoretical framework proposed by Brandt and Wang (2003). Brandt and Wang estimate a consumption-based asset-pricing model in which aggregate risk-aversion varies with news about inflation, as well as with news about real quantities. Since in their model risk-aversion varies with these news variables, risk premia do as well. Thus excess bond returns in that framework should be forecastable by measures of inflation, consistent with what we find. Our evidence is also consistent with findings in Ang and Piazzesi (2003) that inflation and real activity contribute significantly to variation in the price of risk in term structure models where risk premia are allowed to vary over time with macroeconomic variables.

We emphasize an additional aspect of the results above: the macro factors we study contain information for future bond premia that is not contained in forward spreads, yield spreads, or even yield factors estimated as the principal components of the yield covariance matrix. (The first three principal components of the yield covariance matrix are the "level," "slope," and "curvature," yield factors studied in term structure models in finance.) This can be understood by noting that the macro factors we study contain independent information that is not in CP_t, the linear combination of forward rates and $y_t^{(1)}$. But Cochrane and Piazzesi have already shown in our sample that the information in individual yield spreads and the three yield factors is subsumed by that in CP_t. It follows the macro factors in $\overrightarrow{F5}_t$, or $\overrightarrow{F6}_t$, or their corresponding linear combinations $\widehat{F}5_t$, and $\widehat{F}6_t$, contain information above and beyond that already contained in forward spreads, yield spreads, and yield factors. Since yield factors explain the vast majority of variation in yields, this evidence reinforces the conclusion of Cochrane and Piazzesi, namely that information that is unimportant for explaining bond yields can be paramount for explaining expected excess returns on bonds. Our next two subsections present additional results that pertain to the robustness of these forecasting relations: out-of-sample analysis and small-sample inference.

5.2 Out-of-Sample Analysis

The regression analysis described above, as well as the formation of the factors, is conducted using the full sample of data. In this section we report results on the out-of-sample forecasting performance of the regression models studied in the previous section.[11] This procedure involves fully recursive factor estimation and parameter estimation using data only through time t for forecasting at time $t+1$. We compare the out-of-sample forecasting performance of the five-factor model that includes the macro factors in $\overrightarrow{F5}_t$, to a constant expected returns benchmark where, aside from an MA(12) error term, excess returns are unforecastable, as in the expectations hypothesis. The results for $\overrightarrow{F6}_t$ lead to the same out-of-sample performance, if not stronger, than what is reported for $\overrightarrow{F5}_t$ below, thus we omit those results to conserve space. In addition, we do not include CP_t as an additional predictor variable for these results, since the out-of-sample performance of CP_t has already been established in Cochrane and Piazzesi (2005) and we wish to focus on the out-of-sample performance of the new factors

[11] An important caveat with out-of-sample statistical tests is that they lack power relative to in-sample regression forecasts (Inoue and Kilian (2004)). With this caveat in mind, we proceed using tests known to have the best size and power properties among those available (Clark and McCracken (2001)), but the reader should be aware that the predictor variables we study may contain more forecasting power than what is indicated by the out-of-sample statistical tests reported here.

introduced here. Of course, rejections of the no-predictability null would be even stronger if CP_t were included.

Table 3 reports results from one year ahead out-of-sample forecast comparisons of log excess bond returns, $rx_{t+1}^{(n)}$, $n = 2, .., 5$. For each forecast, MSE_u denotes the mean-squared forecasting error of the unrestricted model including predictor factors $\overrightarrow{F5}_t$; MSE_r denotes the mean-squared forecasting error of the restricted benchmark (null) model that excludes these additional forecasting variables. In the column labeled "MSE_u/MSE_r", a number less than one indicates that the model with the additional macro factors has lower forecast error than the benchmark constant expected returns model.

Results for three forecast samples are reported: 1975:1-2003:2; 1985:1-2003:2; 1995:1-2003:2. The results for the first forecast sample are reported in Rows 1, 4, 7 and 10 for $rx_{t+1}^{(2)}$, ...,$rx_{t+1}^{(5)}$ respectively. Here the parameters and factors were estimated recursively, with the initial estimation period using only data available from 1964:12 through 1974:12. Next, the forecasting regressions were run over the period t =1964:12,...,1974:12 (dependent variable from t =1965:1,...,1974:12, independent variable from t =1964:1,...,1973:12) and the estimated parameters and values of the regressors at t =1974:1 were used to forecast returns at 1975:1.[12] All parameters and factors are then reestimated from 1964:1 through 1975:1, and forecasts were recomputed for excess returns in 1975:2, and so on, until the final out-of-sample forecast is made for returns in 2003:12. The same procedure is used to compute results reported in the other rows, where the initial estimation period is either t =1964:1,...,1985:1 or t =1964:1,...,1995:1. The column labeled "Test Statistic" in Table 3 reports the ENC-NEW test statistic of Clark and McCracken (2001) for the null hypothesis that the benchmark model encompasses the unrestricted model with additional predictors. The alternative is that the unrestricted model contains information that could be used to improve the benchmark model's forecast. "95% Asympt. CV" gives the 95th percentile of the asymptotic distribution of the ENC-NEW test statistic.

The results show that the model including the five factors in $\overrightarrow{F5}_t$ improves substantially over the constant expected returns benchmark, for excess bond returns of every maturity. The models have a forecast error variance that is any where from 84 to 93 percent of the constant expected returns benchmark, depending on the excess return being forecast and the forecast period. For the period 1995:1-2003:12 the model has a forecast error variance that is only 84, 85, 89, and 92 percent of the constant expected returns benchmark for

[12] Note that the regressors must be lagged 12 months to account for the 12-period overlap induced from continuously compounding monthly returns to obtain annual returns.

$rx_{t+1}^{(2)}$, ...,$rx_{t+1}^{(5)}$ respectively. No matter what subperiod the model is evaluated over, and no matter what return is being forecast, the ENC-NEW test statistic always indicates that the improvement in forecast power is strongly statistically significant, at the one percent or better level. Moreover, these results show that relative forecast improvement afforded by the estimated factors is stable over time: the reduction in mean-square-error over the benchmark is about the same regardless of which forecast period is analyzed.

Figure 6 gives a graphical impression of the predictive power of the estimated factors by plotting the forecasted value of the two-year excess bond return along with the actual value over the period 1975:1-2003:12. Naturally the fitted value is less volatile than actual value, but the figure shows that the estimated factors do a remarkable job of forecasting the increases in excess returns in the mid 1980s to early 1990s, the declines over 1982-1985 and 1992-1995, and the flat period from 1995-2000. The period 1984-1987 is one in which the model is noticeably off: it misses the dramatic surge in actual excess returns over this period, instead predicting that they fluctuate around zero. Results not reported indicate that the plots for bonds of other maturities are similar.

In summary, the results indicate that the real, inflation, and stock market factors we study have stable out-of-sample forecasting power for excess bond returns of all maturities that is both strongly statistically significant and economically large in magnitude.

5.3 Small Sample Inference

According to the asymptotic theory for PCA estimation discussed in Section 2, heteroskedasticity and autocorrelation consistent standard errors that are asymptotically $N(0,1)$ can be used to obtain robust t-statistics for the in-sample regressions studied in Section 5.1. Moreover, because the factors are estimated "superconsistently," the t-statistics do not need to be adjusted for the preestimation of the factors. To guard against inadequacy of the asymptotic approximation in finite samples, in this section consider bootstrap inference for specifications using four regression models: (i) a model using just the estimated factors in $\overrightarrow{F5}_t$ as predictor variables, (ii) a model using the estimated factors in $\overrightarrow{F5}_t$ and CP_t, (iii) a model using just the single linear combination of five estimated factors, $F5_t$, and (iv) a model using $F5_t$ and CP_t. Small sample inference is especially important when the right-hand-side variables are highly persistent (e.g., Bekaert, Hodrick, and Marshall (1997); Stambaugh (1999); Ferson, Sarkissian, and Simin (2003)) but, as Table 1 demonstrates, none of the factors from our preferred specifications are highly persistent. Nevertheless, we proceed with a bootstrap analysis as a robustness check, by generating bootstrap samples of the exogenous predictors

Z_t (here just CP_t), as well as of the estimated factors $\widehat{F}_t$.

Bootstrap samples of $rx_{t+1}^{(n)}$ are obtained in two ways, first by imposing the null hypothesis of no predictability, and second, under the alternative that excess returns are forecastable by the factors and conditioning variables studied above. The use of monthly bond price data to construct continuously compounded annual returns induces an MA(12) error structure in the annual log returns. Thus under the null hypothesis that the expectations hypothesis is true, annual compound returns are forecastable up to an MA(12) error structure, but are not forecastable by other predictor variables or additional moving average terms. Bootstrap sampling that captures the serial dependence of the data is straightforward when, as in this case, there is a parametric model (e.g., an ARMA model) for the dependence under the null hypothesis (Horowitz (2003)). In this event, the bootstrap may be accomplished by drawing random samples from the empirical distribution of the residuals of a $\sqrt{T}$ consistent, asymptotically normal estimator of the parametric ARMA model, in our application a twelfth-order moving average process. We use this approach to form bootstrap samples of excess returns under the null. Under the alternative, excess returns still have the MA(12) error structure induced by the use of overlapping data, but additional macro factors are presumed to contain predictive power for excess returns.

We take into account the pre-estimation of the factors by re-sampling the $T \times N$ panel of data, x_{it}. This creates bootstrapped samples of the factors themselves. For each i, least squares estimation of $\widehat{e}_{it} = \rho_i \widehat{e}_{it-1} + v_{it}$ yields estimates $\widehat{\rho}_i$ of the persistence of the idiosyncratic errors and of the residuals $\widehat{v}_{it}$, $t = 2, \ldots T$, where recall that $\widehat{e}_{it} = x_{it} - \widehat{\lambda}_i' \widehat{f}_t$. Then $\widehat{v}_{it}$ is re-sampled (while preserving the cross-section correlation structure) to yield bootstrap samples of the idiosyncratic errors $\widehat{e}_{it}$. Bootstrap samples are denoted $\widetilde{e}_{it}$. In turn, bootstrap values of x_{it} are constructed by adding the bootstrap estimates of the idiosyncratic errors, $\widetilde{e}_{it}$, to $\widehat{\lambda}_i' \widehat{f}_t$. Estimation by the method of principal components on the bootstrapped data then yields a new set of estimated factors. The linear combination $F5_t$ is reestimated in each bootstrap simulation. Together with bootstrap samples of Z_t (also based on an AR(1) model), this delivers a set of bootstrap regressors. Each regression using the bootstrapped data gives new estimates of the regression coefficients in (2) and new $\bar{R}^2$ statistics. This is repeated B times. Bootstrap confidence intervals for the parameter estimates and $\bar{R}^2$ statistics are calculated from $B = 10,000$ replications. The results are reported in Tables 4a-4d for two-, three-, four- and five-year excess bond returns, respectively.

Tables 4a-4d indicate that the results based on bootstrap inference are broadly consistent with those based on asymptotic inference in Tables 2a-2d. Confidence intervals from data generated under the alternative are reported in the columns headed "bootstrap." Confidence intervals from data generated under the null are reported in the columns headed "Bootstrap under the null." The coefficients on the exogenous predictors and estimated factors are all well outside the 95% confidence interval under the no-predictability null. Moreover, the coefficients on factors that are statistically different from zero in Table 2a-2d have confidence intervals under the alternative that exclude zero, indicating statistical significance at the 5 percent level. The exceptions to this are the two inflation factors, which display confidence intervals under the alternative that contain zero for some specifications (as in the asymptotic analysis). However, even these coefficients are too large to be explained under the null of no predictability, and the single linear combination of factors, $F5_t$, is always strongly statistically significant regardless of which excess return is being forecast.

We also compute the small sample distribution of the R^2 statistics. For two-year bond returns, the five-factor model $\overrightarrow{F5}_t$ generates an adjusted R-squared statistic of 22% in historical data; by contrast, using bootstrapped data, the 95% bootstrapped confidence interval for this statistic under the no-predictability null ranges from 1.4% to 1.9%. Similarly, the five factors and CP_t deliver an adjusted R-squared statistic of 45% in historical data; by contrast, using bootstrapped data, the 95% bootstrapped confidence interval for this statistic under the no-predictability null ranges from just 2.3% to 4.3%. The results are similar for bonds of other maturities. In short, the magnitude of predictability found in historical data is too large to be accounted for by sampling error in samples of the size we currently have. The statistical relation of the factors to future returns is evident, even accounting for the small sample distribution of standard test statistics.

6 Conclusion

We contribute to the literature on bond return forecastability by showing that measures of macroeconomic fundamentals have important predictive power for excess returns on U.S. government bonds. To do so, we use dynamic factor analysis to summarize the information from a large number of macroeconomic series. The approach allows us to eliminate the arbitrary reliance on a small number of imperfectly measured indicators to proxy for macroeconomic fundamentals, and makes feasible the use of a vast set of economic variables that are more likely to span the unobservable information sets of financial market participants.

We find that the predictive power of the estimated factors is economically important, with macro factors explaining between 21-26 percent of one year ahead excess bond returns. The factors also exhibit stable and strongly statistically significant out-of-sample forecasting power for future returns. The main predictor variable is a real factor that is highly correlated with measures of output and employment, but two inflation factors and a stock market factor also contain information about future bond returns. The macro factors have predictive power that is independent of that in the Cochrane-Piazzesi forward factor, indicating that the information they contain about future excess returns is independent of that in the forward rates, yields, and yield factors of bonds with maturities from one to five years. When the information contained in the macro factors is combined with that in the Cochrane-Piazzesi forward factor, we find remarkably large violations of the expectations hypothesis.

The results support the hypothesis that expected excess returns vary with aggregate quantities and prices, consistent with theoretical notions that risk premia move with preferences and technologies themselves driven by macroeconomic fundamentals. For example, the real and inflation factors we study may be reasonable proxies for the consumption and inflations shocks that enter models of time-varying risk premia like those of Campbell and Cochrane (1999) and Brandt and Wang (2003). At the same time, the analysis here leaves a number of crucial questions for future work. For one, we cannot rule out the possibility that the evidence we uncover is driven, not by rational variation in risk premia, but instead by behavioral biases. Moreover, the statistical evidence we offer falls far short of estimating a yet-to-be developed general equilibrium model that marries the dynamics of macro variables and bond risk premia. Finally, the question of why forward rates and yields appear to contain information about future bond returns that is largely independent of that in broad-based macro factors remains unanswered. These questions and more pose interesting research challenges for the future.

Data Appendix

Table A.1 lists the short name of each series, its mnemonic (the series label used in the source database), the transformation applied to the series, and a brief data description. All series are from the Global Insights Basic Economics Database, unless the source is listed (in parentheses) as TCB (The Conference Board's Indicators Database) or AC (author's calculation based on Global Insights or TCB data). In the transformation column, ln denotes logarithm, Δln and Δ^2ln denote the first and second difference of the logarithm, lv denotes the level of the series, and Δlv denotes the first difference of the series.

Table A.1 Data sources, transformations, and definitions

Series Number	Short name	Mnemonic	Tran	Description
1	PI	a0m052	Δln	Personal Income (AR, Bil. Chain 2000 $) (TCB)
2	PI less transfers	a0m051	Δln	Personal Income Less Transfer Payments (AR, Bil. Chain 2000 $) (TCB)
3	Consumption	a0m224_r	Δln	Real Consumption (AC) a0m224/gmdc (a0m224 is from TCB)
4	M&T sales	a0m057	Δln	Manufacturing And Trade Sales (Mil. Chain 1996 $) (TCB)
5	Retail sales	a0m059	Δln	Sales Of Retail Stores (Mil. Chain 2000 $) (TCB)
6	IP: total	ips10	Δln	Industrial Production Index - Total Index
7	IP: products	ips11	Δln	Industrial Production Index - Products, Total
8	IP: final prod	ips299	Δln	Industrial Production Index - Final Products
9	IP: cons gds	ips12	Δln	Industrial Production Index - Consumer Goods
10	IP: cons dble	ips13	Δln	Industrial Production Index - Durable Consumer Goods
11	IP: cons nondble	ips18	Δln	Industrial Production Index - Nondurable Consumer Goods
12	IP: bus eqpt	ips25	Δln	Industrial Production Index - Business Equipment
13	IP: matls	ips32	Δln	Industrial Production Index - Materials
14	IP: dble matls	ips34	Δln	Industrial Production Index - Durable Goods Materials
15	IP: nondble matls	ips38	Δln	Industrial Production Index - Nondurable Goods Materials
16	IP: mfg	ips43	Δln	Industrial Production Index - Manufacturing (Sic)
17	IP: res util	ips307	Δln	Industrial Production Index - Residential Utilities
18	IP: fuels	ips306	Δln	Industrial Production Index - Fuels
19	NAPM prodn	pmp	lv	Napm Production Index (Percent)
20	Cap util	a0m082	Δlv	Capacity Utilization (Mfg) (TCB)
21	Help wanted indx	lhel	Δlv	Index Of Help-Wanted Advertising In Newspapers (1967=100;Sa)
22	Help wanted/emp	lhelx	Δlv	Employment: Ratio; Help-Wanted Ads:No. Unemployed Clf
23	Emp CPS total	lhem	Δln	Civilian Labor Force: Employed, Total (Thous.,Sa)
24	Emp CPS nonag	lhnag	Δln	Civilian Labor Force: Employed, Nonagric.Industries (Thous.,Sa)
25	U: all	lhur	Δlv	Unemployment Rate: All Workers, 16 Years & Over (%,Sa)
26	U: mean duration	lhu680	Δlv	Unemploy.By Duration: Average(Mean)Duration In Weeks (Sa)
27	U < 5 wks	lhu5	Δln	Unemploy.By Duration: Persons Unempl.Less Than 5 Wks (Thous.,Sa)
28	U 5-14 wks	lhu14	Δln	Unemploy.By Duration: Persons Unempl.5 To 14 Wks (Thous.,Sa)
29	U 15+ wks	lhu15	Δln	Unemploy.By Duration: Persons Unempl.15 Wks + (Thous.,Sa)
30	U 15-26 wks	lhu26	Δln	Unemploy.By Duration: Persons Unempl.15 To 26 Wks (Thous.,Sa)
31	U 27+ wks	lhu27	Δln	Unemploy.By Duration: Persons Unempl.27 Wks + (Thous,Sa)
32	UI claims	a0m005	Δln	Average Weekly Initial Claims, Unemploy. Insurance (Thous.) (TCB)
33	Emp: total	ces002	Δln	Employees On Nonfarm Payrolls: Total Private
34	Emp: gds prod	ces003	Δln	Employees On Nonfarm Payrolls - Goods-Producing
35	Emp: mining	ces006	Δln	Employees On Nonfarm Payrolls - Mining
36	Emp: const	ces011	Δln	Employees On Nonfarm Payrolls - Construction
37	Emp: mfg	ces015	Δln	Employees On Nonfarm Payrolls - Manufacturing
38	Emp: dble gds	ces017	Δln	Employees On Nonfarm Payrolls - Durable Goods
39	Emp: nondbles	ces033	Δln	Employees On Nonfarm Payrolls - Nondurable Goods
40	Emp: services	ces046	Δln	Employees On Nonfarm Payrolls - Service-Providing

41	Emp: TTU	ces048	Δln	Employees On Nonfarm Payrolls - Trade, Transportation, And Utilities
42	Emp: wholesale	ces049	Δln	Employees On Nonfarm Payrolls - Wholesale Trade
43	Emp: retail	ces053	Δln	Employees On Nonfarm Payrolls - Retail Trade
44	Emp: FIRE	ces088	Δln	Employees On Nonfarm Payrolls - Financial Activities
45	Emp: Govt	ces140	Δln	Employees On Nonfarm Payrolls - Government
46	Emp-hrs nonag	a0m048	Δln	Employee Hours In Nonag. Establishments (AR, Bil. Hours) (TCB)
47	Avg hrs	ces151	lv	Avg Weekly Hrs of Prod or Nonsup Workers On Private Nonfarm Payrolls - Goods-Producing
48	Overtime: mfg	ces155	Δlv	Avg Weekly Hrs of Prod or Nonsup Workers On Private Nonfarm Payrolls - Mfg Overtime Hours
49	Avg hrs: mfg	aom001	lv	Average Weekly Hours, Mfg. (Hours) (TCB)
50	NAPM empl	pmemp	lv	Napm Employment Index (Percent)
51	Starts: nonfarm	hsfr	ln	Housing Starts:Nonfarm(1947-58);Total Farm&Nonfarm(1959-)(Thous.,Saar)
52	Starts: NE	hsne	ln	Housing Starts:Northeast (Thous.U.)S.A.
53	Starts: MW	hsmw	ln	Housing Starts:Midwest(Thous.U.)S.A.
54	Starts: South	hssou	ln	Housing Starts:South (Thous.U.)S.A.
55	Starts: West	hswst	ln	Housing Starts:West (Thous.U.)S.A.
56	BP: total	hsbr	ln	Housing Authorized: Total New Priv Housing Units (Thous.,Saar)
57	BP: NE	hsbne*	ln	Houses Authorized By Build. Permits:Northeast(Thou.U.)S.A
58	BP: MW	hsbmw*	ln	Houses Authorized By Build. Permits:Midwest(Thou.U.)S.A.
58	BP: South	hsbsou*	ln	Houses Authorized By Build. Permits:South(Thou.U.)S.A.
60	BP: West	hsbwst*	ln	Houses Authorized By Build. Permits:West(Thou.U.)S.A.
61	PMI	pmi	lv	Purchasing Managers' Index (Sa)
62	NAPM new ordrs	pmno	lv	Napm New Orders Index (Percent)
63	NAPM vendor del	pmdel	lv	Napm Vendor Deliveries Index (Percent)
64	NAPM Invent	pmnv	lv	Napm Inventories Index (Percent)
65	Orders: cons gds	a0m008	Δln	Mfrs' New Orders, Consumer Goods And Materials (Bil. Chain 1982 $) (TCB)
66	Orders: dble gds	a0m007	Δln	Mfrs' New Orders, Durable Goods Industries (Bil. Chain 2000 $) (TCB)
67	Orders: cap gds	a0m027	Δln	Mfrs' New Orders, Nondefense Capital Goods (Mil. Chain 1982 $) (TCB)
68	Unf orders: dble	a1m092	Δln	Mfrs' Unfilled Orders, Durable Goods Indus. (Bil. Chain 2000 $) (TCB)
69	M&T invent	a0m070	Δln	Manufacturing And Trade Inventories (Bil. Chain 2000 $) (TCB)
70	M&T invent/sales	a0m077	Δlv	Ratio, Mfg. And Trade Inventories To Sales (Based On Chain 2000 $) (TCB)
71	M1	fm1	Δ^2ln	Money Stock: M1(Curr,Trav.Cks,Dem Dep,Other Ck'able Dep)(Bil$,Sa)
72	M2	fm2	Δ^2ln	Money Stock:M2(M1+O'nite Rps,Euro$,G/P&B/D Mmmfs&Sav&Sm Time Dep(Bil$,Sa)
73	M3	fm3	Δ^2ln	Money Stock: M3(M2+Lg Time Dep,Term Rp's&Inst Only Mmmfs)(Bil$,Sa)
74	M2 (real)	fm2dq	Δln	Money Supply - M2 In 1996 Dollars (Bci)
75	MB	fmfba	Δ^2ln	Monetary Base, Adj For Reserve Requirement Changes(Mil$,Sa)
76	Reserves tot	fmrra	Δ^2ln	Depository Inst Reserves:Total, Adj For Reserve Req Chgs(Mil$,Sa)
77	Reserves nonbor	fmrnba	Δ^2ln	Depository Inst Reserves:Nonborrowed,Adj Res Req Chgs(Mil$,Sa)
78	C&I loans	fclnq	Δ^2ln	Commercial & Industrial Loans Oustanding In 1996 Dollars (Bci)
79	ΔC&I loans	fclbmc	lv	Wkly Rp Lg Com'l Banks:Net Change Com'l & Indus Loans(Bil$,Saar)
80	Cons credit	ccinrv	Δ^2ln	Consumer Credit Outstanding - Nonrevolving(G19)
81	Inst cred/PI	a0m095	Δlv	Ratio, Consumer Installment Credit To Personal Income (Pct.) (TCB)
82	S&P 500	fspcom	Δln	S&P's Common Stock Price Index: Composite (1941-43=10)
83	S&P: indust	fspin	Δln	S&P's Common Stock Price Index: Industrials (1941-43=10)
84	S&P div yield	fsdxp	Δlv	S&P's Composite Common Stock: Dividend Yield (% Per Annum)
85	S&P PE ratio	fspxe	Δln	S&P's Composite Common Stock: Price-Earnings Ratio (%,Nsa)
86	Fed Funds	fyff	Δlv	Interest Rate: Federal Funds (Effective) (% Per Annum,Nsa)
87	Comm paper	cp90	Δlv	Cmmercial Paper Rate (AC)
88	3 mo T-bill	fygm3	Δlv	Interest Rate: U.S.Treasury Bills,Sec Mkt,3-Mo.(% Per Ann,Nsa)
89	6 mo T-bill	fygm6	Δlv	Interest Rate: U.S.Treasury Bills,Sec Mkt,6-Mo.(% Per Ann,Nsa)
90	1 yr T-bond	fygt1	Δlv	Interest Rate: U.S.Treasury Const Maturities,1-Yr.(% Per Ann,Nsa)
91	5 yr T-bond	fygt5	Δlv	Interest Rate: U.S.Treasury Const Maturities,5-Yr.(% Per Ann,Nsa)
92	10 yr T-bond	fygt10	Δlv	Interest Rate: U.S.Treasury Const Maturities,10-Yr.(% Per Ann,Nsa)
93	Aaa bond	fyaaac	Δlv	Bond Yield: Moody's Aaa Corporate (% Per Annum)
94	Baa bond	fybaac	Δlv	Bond Yield: Moody's Baa Corporate (% Per Annum)
95	CP-FF spread	scp90	lv	cp90-fyff (AC)
96	3 mo-FF spread	sfygm3	lv	fygm3-fyff (AC)
97	6 mo-FF spread	sfygm6	lv	fygm6-fyff (AC)
98	1 yr-FF spread	sfygt1	lv	fygt1-fyff (AC)
99	5 yr-FF spread	sfygt5	lv	fygt5-fyff (AC)
100	10 yr-FF spread	sfygt10	lv	fygt10-fyff (AC)
101	Aaa-FF spread	sfyaaac	lv	fyaaac-fyff (AC)
102	Baa-FF spread	sfybaac	lv	fybaac-fyff (AC)
103	Ex rate: avg	exrus	Δln	United States;Effective Exchange Rate(Merm)(Index No.)

104	Ex rate: Switz	exrsw	Δln	Foreign Exchange Rate: Switzerland (Swiss Franc Per U.S.$)
105	Ex rate: Japan	exrjan	Δln	Foreign Exchange Rate: Japan (Yen Per U.S.$)
106	Ex rate: UK	exruk	Δln	Foreign Exchange Rate: United Kingdom (Cents Per Pound)
107	EX rate: Canada	exrcan	Δln	Foreign Exchange Rate: Canada (Canadian $ Per U.S.$)
108	PPI: fin gds	pwfsa	Δ^2ln	Producer Price Index: Finished Goods (82=100,Sa)
109	PPI: cons gds	pwfcsa	Δ^2ln	Producer Price Index: Finished Consumer Goods (82=100,Sa)
110	PPI: int mat'ls	pwimsa	Δ^2ln	Producer Price Index:I ntermed Mat.Supplies & Components(82=100,Sa)
111	PPI: crude mat'ls	pwcmsa	Δ^2ln	Producer Price Index: Crude Materials (82=100,Sa)
112	Spot market price	psccom	Δ^2ln	Spot market price index: bls & crb: all commodities(1967=100)
113	Sens mat'ls price	psm99q	Δ^2ln	Index Of Sensitive Materials Prices (1990=100)(Bci-99a)
114	NAPM com price	pmcp	lv	Napm Commodity Prices Index (Percent)
115	CPI-U: all	punew	Δ^2ln	Cpi-U: All Items (82-84=100,Sa)
116	CPI-U: apparel	pu83	Δ^2ln	Cpi-U: Apparel & Upkeep (82-84=100,Sa)
117	CPI-U: transp	pu84	Δ^2ln	Cpi-U: Transportation (82-84=100,Sa)
118	CPI-U: medical	pu85	Δ^2ln	Cpi-U: Medical Care (82-84=100,Sa)
119	CPI-U: comm.	puc	Δ^2ln	Cpi-U: Commodities (82-84=100,Sa)
120	CPI-U: dbles	pucd	Δ^2ln	Cpi-U: Durables (82-84=100,Sa)
121	CPI-U: services	pus	Δ^2ln	Cpi-U: Services (82-84=100,Sa)
122	CPI-U: ex food	puxf	Δ^2ln	Cpi-U: All Items Less Food (82-84=100,Sa)
123	CPI-U: ex shelter	puxhs	Δ^2ln	Cpi-U: All Items Less Shelter (82-84=100,Sa)
124	CPI-U: ex med	puxm	Δ^2ln	Cpi-U: All Items Less Midical Care (82-84=100,Sa)
125	PCE defl	gmdc	Δ^2ln	Pce, Impl Pr Defl:Pce (1987=100)
126	PCE defl: dlbes	gmdcd	Δ^2ln	Pce, Impl Pr Defl:Pce; Durables (1987=100)
127	PCE defl: nondble	gmdcn	Δ^2ln	Pce, Impl Pr Defl:Pce; Nondurables (1996=100)
128	PCE defl: service	gmdcs	Δ^2ln	Pce, Impl Pr Defl:Pce; Services (1987=100)
129	AHE: goods	ces275	Δ^2ln	Avg Hourly Earnings of Prod or Nonsup Workers On Private Nonfarm Payrolls - Goods-Producing
130	AHE: const	ces277	Δ^2ln	Avg Hourly Earnings of Prod or Nonsup Workers On Private Nonfarm Payrolls - Construction
131	AHE: mfg	ces278	Δ^2ln	Avg Hourly Earnings of Prod or Nonsup Workers On Private Nonfarm Payrolls - Manufacturing
132	Consumer expect	hhsntn	Δlv	U. Of Mich. Index Of Consumer Expectations(Bcd-83)

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Table 1: Summary Statistics for $\widehat{f}_{it}$

i	AR1($\widehat{f}_{it}$)	R_i^2
1	0.767	0.177
2	0.764	0.249
3	-0.172	0.304
4	0.289	0.359
5	0.341	0.403
6	-0.0132	0.439
7	0.320	0.471
8	0.233	0.497

For $i = 1, \ldots 8$, $\widehat{f}_{it}$ is estimated by the method of principal components using a panel of data with 132 indicators of economic activity from t=1964:1-2003:12 (480 time series observations). The data are transformed (taking logs and differenced where appropriate) and standardized prior to estimation. AR1($\widehat{f}_{it}$), is the first-order autocorrelation coefficients for factors i. The relative importance of the common component, R_i^2, is calculated as the fraction of total variance in the data explained by factors 1 to i.

Table 2a: Regressions of Monthly Excess Bond Returns on Lagged Factors

Model: $rx_{t+1}^{(2)} = \beta_0 + \beta_1'\widehat{F}_t + \beta_2 CP_t + \epsilon_{t+1}$,								
Regressor	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
$\widehat{F}_{1t}$		**-0.93**	**-0.74**	**-0.93**	**-0.75**			
(t-stat)		(-5.19)	(-4.48)	(-4.96)	(-4.71)			
$\widehat{F}_{1t}^3$		**0.06**	**0.05**	**0.06**	**0.05**			
(t-stat)		(2.78)	(2.70)	(2.87)	(2.71)			
$\widehat{F}_{2t}$		**-0.40**	0.08					
(t-stat)		(-3.10)	(0.71)					
$\widehat{F}_{3t}$		**0.18**	**0.24**	0.18	**0.24**			
(t-stat)		(2.24)	(3.84)	(1.87)	(3.85)			
$\widehat{F}_{4t}$		**-0.33**	**-0.24**	**-0.33**	**-0.25**			
(t-stat)		(-2.94)	(-2.51)	(-2.65)	(-2.61)			
$\widehat{F}_{8t}$		**0.35**	**0.24**	**0.35**	**0.24**			
(t-stat)		(4.35)	(2.70)	(3.83)	(2.89)			
CP_t	**0.45**		**0.41**		**0.40**			**0.39**
(t-stat)	(8.90)		(5.22)		(5.89)			(6.0)
$F5_t$						**0.54**		**0.43**
(t-stat)						(5.52)		(5.78)
$F6_t$							**0.50**	
(t-stat)							(6.78)	
$\overline{R}^2$	0.31	0.26	0.45	0.22	0.45	0.22	0.26	0.44

Notes: The table reports estimates from OLS regressions of excess bond returns on the lagged variables named in column 1. The dependent variable $rx_{t+1}^{(n)}$ is the excess log return on the n-year Treasury bond. $\widehat{F}_t$ denotes a set of regressors including $F5_t, F6_t$, and $\widehat{F}_{it}$. These denote factors estimated by the method of principal components using a panel of data with 132 individual series over the period 1964:1-2003:12. $F5_t$, is the single factor constructed as a linear combination of the five estimated factors $\widehat{F}_{1t}$, $\widehat{F}_{1t}^3$, $\widehat{F}_{3t}$, $\widehat{F}_{4t}$, and $\widehat{F}_{8t}$. $F6_t$, is the single factor constructed as a linear combination of the six estimated factors $\widehat{F}_{1t}$, $\widehat{F}_{2t}$, $\widehat{F}_{1t}^3$, $\widehat{F}_{3t}$, $\widehat{F}_{4t}$, and $\widehat{F}_{8t}$. CP_t is the Cochrane and Piazzesi (2005) factor that is a linear combination of five forward spreads. Newey and West (1987) corrected t-statistics have lag order 18 months and are reported in parentheses. Coefficients that are statistically significant at the 5% or better level are highlighted in bold. A constant is always included in the regression even though its estimate is not reported in the Table. The sample spans the period 1964:1 to 2003:12.

Table 2b: Regressions of Monthly Excess Bond Returns on Lagged Factors

Model: $rx_{t+1}^{(3)} = \beta_0 + \beta_1' \widehat{F}_t + \beta_2 CP_t + \epsilon_{t+1}$,						
Regressor	(a)	(b)	(c)	(d)	(e)	(f)
$\widehat{F}_{1t}$		**-1.59**	**-1.22**			
(t-stat)		(-4.68)	(-4.39)			
$\widehat{F}_{1t}^3$		**0.11**	**0.10**			
(t-stat)		(3.12)	(2.96)			
$\widehat{F}_{3t}$		0.19	**0.30**			
(t-stat)		(1.05)	(2.78)			
$\widehat{F}_{4t}$		**-0.53**	**-0.36**			
(t-stat)		(-2.23)	(-2.12)			
$\widehat{F}_{8t}$		**0.64**	**0.44**			
(t-stat)		(3.73)	(2.74)			
CP_t	**0.85**		**0.76**			**0.75**
(t-stat)	(8.52)		(6.13)			(6.16)
$F5_t$				**0.91**		**0.69**
(t-stat)				(5.28)		(5.55)
$F6_t$					**0.89**	
(t-stat)					(6.57)	
$\overline{R}^2$	0.34	0.18	0.44	0.19	0.24	0.44

Notes: See Table 2a.

Table 2c: Regressions of Monthly Excess Bond Returns on Lagged Factors

Model: $rx_{t+1}^{(4)} = \beta_0 + \beta_1' \widehat{F}_t + \beta_2 CP_t + \epsilon_{t+1}$,						
Regressor	(a)	(b)	(c)	(d)	(e)	(f)
$\widehat{F}_{1t}$		**-2.05**	**-1.51**			
(t-stat)		(-4.49)	(-4.20)			
$\widehat{F}_{1t}^3$		**0.16**	**0.14**			
(t-stat)		(3.20)	(3.08)			
$\widehat{F}_{3t}$		0.18	**0.35**			
(t-stat)		(0.68)	(2.22)			
$\widehat{F}_{4t}$		-0.63	-0.37			
(t-stat)		(-1.77)	(-1.50)			
$\widehat{F}_{8t}$		**0.95**	**0.64**			
(t-stat)		(3.75)	(2.83)			
CP_t	**1.24**		**1.13**			**1.11**
(t-stat)	(8.58)		(6.40)			(6.30)
$F5_t$				**1.19**		**0.87**
(t-stat)				(5.08)		(5.39)
$F6_t$					**1.20**	
(t-stat)					(6.57)	
$\overline{R}^2$	0.37	0.16	0.45	0.17	0.23	0.45

Notes: See Table 2a.

Table 2d: Regressions of Monthly Excess Bond Returns on Lagged Factors

Model: $rx_{t+1}^{(5)} = \beta_0 + \beta_1' \widehat{F}_t + \beta_2 CP_t + \epsilon_{t+1}$,						
Regressor	(a)	(b)	(c)	(d)	(e)	(f)
$\widehat{F}_{1t}$		**-2.27**	**-1.63**			
(t-stat)		(-4.10)	(-3.86)			
$\widehat{F}_{1t}^3$		**0.18**	**0.15**			
(t-stat)		(3.06)	(2.95)			
$\widehat{F}_{3t}$		0.18	**0.38**			
(t-stat)		(0.55)	(1.92)			
$\widehat{F}_{4t}$		-0.78	-0.48			
(t-stat)		(-1.80)	(-1.54)			
$\widehat{F}_{8t}$		**1.13**	**0.76**			
(t-stat)		(3.68)	(2.76)			
CP_t	**1.46**		**1.34**			**1.32**
(t-stat)	(7.90)		(6.00)			(5.87)
$F5_t$				**1.36**		**0.98**
(t-stat)				(4.80)		(5.08)
$F6_t$					**1.41**	
(t-stat)					(6.47)	
$\overline{R}^2$	0.34	0.14	0.41	0.14	0.21	0.42

Notes: See Table 2a.

Table 3: Out-of-Sample Predictive Power of Macro Factors

Row	Forecast Sample	Comparison	MSE_u/MSE_r	Test Statistic	95% Asympt. CV
			$rx_{t+1}^{(2)}$		
1	1975:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.848	64.87*	7.98
2	1985:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.882	33.15*	4.70
3	1995:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.838	25.29*	3.15
			$rx_{t+1}^{(3)}$		
4	1975:1-2003:2	$\overrightarrow{F5}_t$ v.s. $const$	0.879	47.24*	7.98
5	1985:1-2003:2	$\overrightarrow{F5}_t$ v.s. $const$	0.889	27.51*	4.70
6	1995:1-2003:2	$\overrightarrow{F5}_t$ v.s. $const$	0.854	19.86*	3.15
			$rx_{t+1}^{(4)}$		
7	1975:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.905	36.32*	7.98
8	1985:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.909	22.03*	4.70
9	1995:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.889	16.48*	3.15
			$rx_{t+1}^{(5)}$		
10	1975:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.926	29.53*	7.98
11	1985:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.931	17.33*	4.70
12	1995:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.924	12.07*	3.15

*Significant at the one percent or better level.

Notes: The table reports results from one-year-ahead out-of-sample forecast comparisons of n-period log excess bond returns, $rx_{t+1}^{(n)}$. $\overrightarrow{F5}_t$ denotes the vector of factors $\left(\widehat{F}_{1t}, \widehat{F}_{1t}^3, \widehat{F}_{3t}, \widehat{F}_{4t}, \widehat{F}_{8t}\right)'$. Each row reports forecast comparisons of an unrestricted model, which includes $\overrightarrow{F5}_t$ as predictors, with a restricted, constant expected returns benchmark ($const$). MSE_u is the mean-squared forecasting error of the unrestricted model; MSE_r is the mean-squared forecasting error of the restricted model that excludes additional forecasting variables. In the column labeled "MSE_u/MSE_r", a number less than one indicates that theunrestricted model has lower forecast error than the benchmark constant expected returns model. The first row of each panel displays results in which the parameters and factors were estimated recursively, using an initial sample of data from 1964:1 through 1974:12. The forecasting regressions are run for t =1964:1,...,1974:12, and the values of the regressors at t =1974:1 are used to forecast annual returns in 1975:1. (The predictor variables are lagged 12 months since the annual returns created by continuously compounding monthly returns over the 12 months in the year.) All parameters and factors are then reestimated from 1964:1 through 1975:1, and forecasts are recomputed for returns in 1975:2, and so on, until the final out-of-sample forecast is made for returns in 2003:12. The same procedure is used to compute results reported in the other rows, where the initial estimation period is either t =1964:1,...,1984:12 or t =1964:1,...,1994:12. The column labeled "Test Statistic" reports the ENC-NEW test statistic of Clark and McCracken (2001) for the null hypothesis that the benchmark model encompasses the unrestricted model with additional predictors. The alternative is that the unrestricted model contains information that could be used to improve the benchmark model's forecast. "95% Asympt. CV" gives the 95th percentile of the asymptotic distribution of the test statistic.

Table 4a: Small Sample Inference, $rx^{(2)}_{t+1}$

Model: $rx^{(2)}_{t+1} = \beta_0 + \beta_1' \overrightarrow{F5}_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
$\widehat{F}_{1t}$	-0.935	(-1.389 -0.474)	(-1.333 -0.538)	(-0.022 -0.020)	(-0.022 -0.020)
$\widehat{F}^3_{1t}$	0.062	(0.023 0.102)	(0.031 0.094)	(0.001 0.001)	(0.001 0.001)
$\widehat{F}_{3t}$	0.177	(-0.043 0.413)	(-0.009 0.371)	(-0.003 0.003)	(-0.003 0.003)
$\widehat{F}_{4t}$	-0.334	(-0.533 -0.137)	(-0.494 -0.182)	(-0.004 0.003)	(-0.003 0.002)
$\widehat{F}_{8t}$	0.352	(0.141 0.542)	(0.184 0.511)	(-0.007 0.008)	(-0.007 0.007)
R^2	0.225	(0.123 0.400)	(0.139 0.381)	(0.014 0.019)	(0.015 0.018)
$\bar{R}^2$	0.217	(0.113 0.393)	(0.130 0.375)	(0.004 0.008)	(0.004 0.008)

Model: $rx^{(2)}_{t+1} = \beta_0 + \beta_1' \overrightarrow{F5}_t + \beta_2 CP_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
$\widehat{F}_{1t}$	-0.745	(-1.141 -0.325)	(-1.075 -0.401)	(-0.025 -0.016)	(-0.024 -0.017)
$\widehat{F}^3_{1t}$	0.055	(0.020 0.091)	(0.026 0.083)	(0.000 0.001)	(0.000 0.001)
$\widehat{F}_{3t}$	0.237	(0.010 0.459)	(0.046 0.412)	(-0.004 0.004)	(-0.003 0.003)
$\widehat{F}_{4t}$	-0.247	(-0.450 -0.055)	(-0.389 -0.099)	(-0.005 0.003)	(-0.004 0.002)
$\widehat{F}_{8t}$	0.244	(0.065 0.424)	(0.095 0.394)	(-0.007 0.008)	(-0.006 0.007)
CP_t	0.395	(0.262 0.519)	(0.283 0.498)	(0.004 0.012)	(0.005 0.011)
R^2	0.455	(0.245 0.548)	(0.268 0.524)	(0.022 0.047)	(0.023 0.043)
$\bar{R}^2$	0.448	(0.235 0.542)	(0.258 0.518)	(0.009 0.034)	(0.010 0.031)

Model: $rx^{(2)}_{t+1} = \beta_0 + \beta_1' F5_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
$F5_t$	0.539	(0.304 0.758)	(0.356 0.729)	(0.008 0.011)	(0.008 0.011)
R^2	0.221	(0.084 0.384)	(0.111 0.368)	(0.008 0.015)	(0.009 0.014)
$\bar{R}^2$	0.219	(0.082 0.383)	(0.109 0.367)	(0.006 0.013)	(0.007 0.012)

Model: $rx^{(2)}_{t+1} = \beta_0 + \beta_1' F5_t + \beta_2 CP_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
$F5_t$	0.427	(0.216 0.626)	(0.252 0.601)	(0.007 0.012)	(0.007 0.012)
CP_t	0.389	(0.255 0.516)	(0.273 0.493)	(0.004 0.011)	(0.005 0.011)
R^2	0.447	(0.215 0.530)	(0.240 0.506)	(0.017 0.041)	(0.019 0.038)
$\bar{R}^2$	0.444	(0.211 0.528)	(0.237 0.504)	(0.013 0.037)	(0.014 0.034)

Notes: See next page.

Notes: Let x_{it} denote the regressor variables used to predict $rx_{t+1}^{(n)}$. Let $z_{it}, i = 1, \ldots N, t = 1, \ldots T$ be standardized data from which the factors are extracted. The vector of factors, $\overrightarrow{F5}_t = \left(\widehat{F}_{1t}, \widehat{F}_{1t}^3, \widehat{F}_{2t}, \widehat{F}_{3t}, \widehat{F}_{4t}, \widehat{F}_{8t}\right)'$; $F5_t$ is the single linear combination of these factors formed by regressing the average (across maturity) of excess bond returns on $\overrightarrow{F5}_t$. $\overrightarrow{F5}_t \subset f_t$, where f_t is a $r \times 1$ vector of latent common factors. Denote $\overrightarrow{F5}_t = F_t$. By definition, $z_{it} = \lambda_i' F_t + u_{it}$. Let $\hat{\lambda}_i$ and $\widehat{F}_t$ be the principal components estimators of λ_i and F_t, and let $\hat{u}_{it}$ be the estimated idiosyncratic errors. For each $i = 1, \ldots N$, we estimate an AR(1) model $\hat{u}_{it} = \rho_i \hat{u}_{it-1} + w_{it}$. Let $\tilde{u}_{1,\cdot} = u_{1,\cdot}$. For $t = 2, \ldots T$, let $\tilde{u}_{it} = \hat{\rho}_i \tilde{u}_{it-1} + \tilde{w}_{it}$, where $\tilde{w}_{i,t}$ is sampled (with replacement) from $\hat{w}_{\cdot,t}, t = 2, \ldots T$. Then $\tilde{z}_{it} = \hat{\lambda}_i' \widehat{F}_t + \tilde{u}_{it}$. Estimation by principal components on the data $\tilde{z}$ yields $\widetilde{F}_t$. The remaining regressor, CP_t, is obtained by first estimating an AR(1), and then resampling the residuals of the autoregression. Denote the dependent variable $rx_{t+1}^{(n)}$ as $\tilde{y}$. Unrestricted samples $\tilde{y}_t$ are generated as $\tilde{y} = \tilde{X}\hat{\beta} + \tilde{e}$, where $\hat{\beta}$ are the least squares estimates reported in column 2, and $\tilde{e}$ are resampled from least squares MA(12) residuals, and $\tilde{X}$ is a set of bootstrapped regressors with $\hat{F}_t$ replaced by $\tilde{F}_t$. Samples under the null are generated as $\tilde{y} = \bar{y} + \tilde{e}^0$, where $\tilde{e}^0$ is resampled form the residuals of least squares estimated MA(12) process.

Table 4b: Small Sample Inference, $rx_{t+1}^{(3)}$

Model: $rx_{t+1}^{(3)} = \beta_0 + \beta_1' \overrightarrow{F5}_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	99% CI	95% CI	99% CI
$\widehat{F}_{1t}$	-1.589	(-2.547 -0.713)	(-2.356 -0.882)	(-0.022 -0.020)	(-0.022 -0.020)
$\widehat{F}_{1t}^3$	0.114	(0.045 0.185)	(0.058 0.173)	(0.001 0.001)	(0.001 0.001)
$\widehat{F}_{3t}$	0.185	(-0.251 0.679)	(-0.175 0.560)	(-0.004 0.003)	(-0.003 0.002)
$\widehat{F}_{4t}$	-0.530	(-0.933 -0.127)	(-0.849 -0.210)	(-0.004 0.003)	(-0.003 0.002)
$\widehat{F}_{8t}$	0.645	(0.259 1.029)	(0.319 0.969)	(-0.008 0.008)	(-0.006 0.008)
R^2	0.189	(0.089 0.377)	(0.103 0.342)	(0.014 0.019)	(0.015 0.018)
$\bar{R}^2$	0.180	(0.079 0.370)	(0.093 0.335)	(0.004 0.008)	(0.004 0.008)

Model: $rx_{t+1}^{(3)} = \beta_0 + \beta_1' \overrightarrow{F5}_t + \beta_2 CP_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
$\widehat{F}_{1t}$	-1.223	(-2.015 -0.431)	(-1.875 -0.545)	(-0.033 -0.021)	(-0.032 -0.022)
$\widehat{F}_{1t}^3$	0.100	(0.035 0.162)	(0.045 0.152)	(0.000 0.002)	(0.001 0.001)
$\widehat{F}_{3t}$	0.300	(-0.132 0.753)	(-0.047 0.667)	(-0.004 0.004)	(-0.004 0.003)
$\widehat{F}_{4t}$	-0.361	(-0.702 0.018)	(-0.632 -0.058)	(-0.005 0.003)	(-0.004 0.002)
$\widehat{F}_{8t}$	0.436	(0.113 0.774)	(0.155 0.718)	(-0.008 0.010)	(-0.007 0.008)
CP_t	0.764	(0.525 0.982)	(0.556 0.941)	(0.005 0.015)	(0.006 0.014)
R^2	0.446	(0.227 0.539)	(0.249 0.522)	(0.021 0.042)	(0.022 0.040)
$\bar{R}^2$	0.439	(0.217 0.533)	(0.239 0.516)	(0.008 0.030)	(0.009 0.028)

Model: $rx_{t+1}^{(3)} = \beta_0 + \beta_1' F5_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
$F5_t$	0.911	(0.473 1.376)	(0.560 1.285)	(0.008 0.011)	(0.008 0.011)
R^2	0.189	(0.055 0.367)	(0.076 0.335)	(0.009 0.015)	(0.009 0.014)
$\bar{R}^2$	0.187	(0.053 0.366)	(0.074 0.334)	(0.006 0.013)	(0.007 0.012)

Model: $rx_{t+1}^{(3)} = \beta_0 + \beta_1' F5_t + \beta_2 CP_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
$F5_t$	0.694	(0.278 1.087)	(0.338 1.026)	(0.007 0.012)	(0.007 0.012)
CP_t	0.754	(0.504 0.971)	(0.546 0.938)	(0.004 0.011)	(0.005 0.010)
R^2	0.442	(0.203 0.521)	(0.226 0.495)	(0.017 0.040)	(0.018 0.037)
$\bar{R}^2$	0.440	(0.199 0.519)	(0.223 0.493)	(0.013 0.035)	(0.014 0.033)

Notes: See Table 4a.

Table 4c: Small Sample Inference, $rx^{(4)}_{t+1}$

Model: $rx^{(4)}_{t+1} = \beta_0 + \beta_1' \overrightarrow{F5}_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	99% CI	95% CI	99% CI
$\widehat{F}_{1t}$	-2.046	(-3.281 -0.917)	(-3.155 -1.090)	(-0.022 -0.020)	(-0.022 -0.020)
$\widehat{F}^3_{1t}$	0.157	(0.062 0.261)	(0.078 0.240)	(0.001 0.001)	(0.001 0.001)
$\widehat{F}_{3t}$	0.183	(-0.442 0.826)	(-0.293 0.721)	(-0.003 0.003)	(-0.003 0.002)
$\widehat{F}_{4t}$	-0.625	(-1.165 -0.086)	(-1.076 -0.180)	(-0.004 0.003)	(-0.003 0.002)
$\widehat{F}_{8t}$	0.948	(0.433 1.462)	(0.506 1.389)	(-0.007 0.008)	(-0.006 0.007)
R^2	0.167	(0.084 0.357)	(0.098 0.331)	(0.015 0.019)	(0.015 0.018)
$\bar{R}^2$	0.158	(0.074 0.350)	(0.088 0.324)	(0.004 0.008)	(0.004 0.008)

Model: $rx^{(4)}_{t+1} = \beta_0 + \beta_1' \overrightarrow{F5}_t + \beta_2 CP_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
$\widehat{F}_{1t}$	-1.506	(-2.518 -0.440)	(-2.338 -0.640)	(-0.045 -0.029)	(-0.042 -0.030)
$\widehat{F}^3_{1t}$	0.136	(0.052 0.222)	(0.064 0.208)	(0.001 0.002)	(0.001 0.002)
$\widehat{F}_{3t}$	0.353	(-0.215 0.923)	(-0.104 0.805)	(-0.007 0.005)	(-0.006 0.004)
$\widehat{F}_{4t}$	-0.375	(-0.849 0.131)	(-0.754 0.002)	(-0.006 0.004)	(-0.005 0.003)
$\widehat{F}_{8t}$	0.640	(0.166 1.105)	(0.244 1.027)	(-0.008 0.010)	(-0.007 0.008)
CP_t	1.128	(0.789 1.447)	(0.846 1.386)	(0.008 0.019)	(0.008 0.018)
R^2	0.459	(0.254 0.560)	(0.278 0.537)	(0.021 0.041)	(0.022 0.039)
$\bar{R}^2$	0.452	(0.244 0.554)	(0.269 0.530)	(0.008 0.029)	(0.009 0.027)

Model: $rx^{(4)}_{t+1} = \beta_0 + \beta_1' F5_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
$F5_t$	1.188	(0.660 1.784)	(0.735 1.713)	(0.008 0.011)	(0.008 0.011)
R^2	0.167	(0.053 0.343)	(0.071 0.316)	(0.008 0.015)	(0.009 0.014)
$\bar{R}^2$	0.165	(0.051 0.342)	(0.069 0.315)	(0.006 0.013)	(0.007 0.012)

Model: $rx^{(4)}_{t+1} = \beta_0 + \beta_1' F5_t + \beta_2 CP_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
c	0.033	(-1.321 1.274)	(-0.163 0.623)	(0.466 0.479)	(0.467 0.478)
$F5_t$	1.188	(0.660 1.784)	(-1.075 -0.401)	(-0.025 -0.016)	(-0.024 -0.017)
CP_t	0.395	(0.262 0.519)	(0.283 0.498)	(0.004 0.012)	(0.005 0.011)
R^2	0.455	(0.245 0.548)	(0.268 0.524)	(0.022 0.047)	(0.023 0.043)
$\bar{R}^2$	0.448	(0.235 0.542)	(0.258 0.518)	(0.009 0.034)	(0.010 0.031)

Notes: See Table 4a.

Table 4d: Small Sample Inference, $rx_{t+1}^{(5)}$

Model: $rx_{t+1}^{(5)} = \beta_0 + \beta_1' \overrightarrow{F5}_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	99% CI	95% CI	99% CI
$\widehat{F}_{1t}$	-2.271	(-3.822 -0.735)	(-3.513 -1.023)	(-0.022 -0.020)	(-0.022 -0.020)
$\widehat{F}_{1t}^3$	0.179	(0.056 0.295)	(0.078 0.280)	(0.001 0.001)	(0.001 0.001)
$\widehat{F}_{3t}$	0.182	(-0.612 0.929)	(-0.444 0.790)	(-0.003 0.003)	(-0.003 0.002)
$\widehat{F}_{4t}$	-0.782	(-1.445 -0.125)	(-1.329 -0.269)	(-0.004 0.003)	(-0.003 0.002)
$\widehat{F}_{8t}$	1.129	(0.481 1.841)	(0.598 1.700)	(-0.008 0.008)	(-0.007 0.007)
R^2	0.147	(0.069 0.315)	(0.078 0.294)	(0.014 0.019)	(0.015 0.019)
$\bar{R}^2$	0.138	(0.059 0.308)	(0.068 0.286)	(0.004 0.008)	(0.004 0.008)

Model: $rx_{t+1}^{(5)} = \beta_0 + \beta_1' \overrightarrow{F5}_t + \beta_2 CP_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
$\widehat{F}_{1t}$	-1.629	(-2.914 -0.185)	(-2.638 -0.368)	(-0.049 -0.032)	(-0.047 -0.033)
$\widehat{F}_{1t}^3$	0.154	(0.040 0.264)	(0.057 0.247)	(0.001 0.002)	(0.001 0.002)
$\widehat{F}_{3t}$	0.384	(-0.404 1.112)	(-0.236 0.978)	(-0.007 0.005)	(-0.006 0.004)
$\widehat{F}_{4t}$	-0.485	(-1.116 0.133)	(-1.025 0.017)	(-0.007 0.005)	(-0.006 0.004)
$\widehat{F}_{8t}$	0.764	(0.145 1.351)	(0.242 1.282)	(-0.010 0.012)	(-0.009 0.010)
CP_t	1.341	(0.922 1.711)	(0.993 1.645)	(0.009 0.022)	(0.009 0.021)
R^2	0.421	(0.213 0.514)	(0.242 0.492)	(0.020 0.040)	(0.021 0.038)
$\bar{R}^2$	0.414	(0.203 0.508)	(0.232 0.485)	(0.007 0.028)	(0.008 0.026)

Model: $rx_{t+1}^{(5)} = \beta_0 + \beta_1' F5_t + \epsilon_{t+1}$

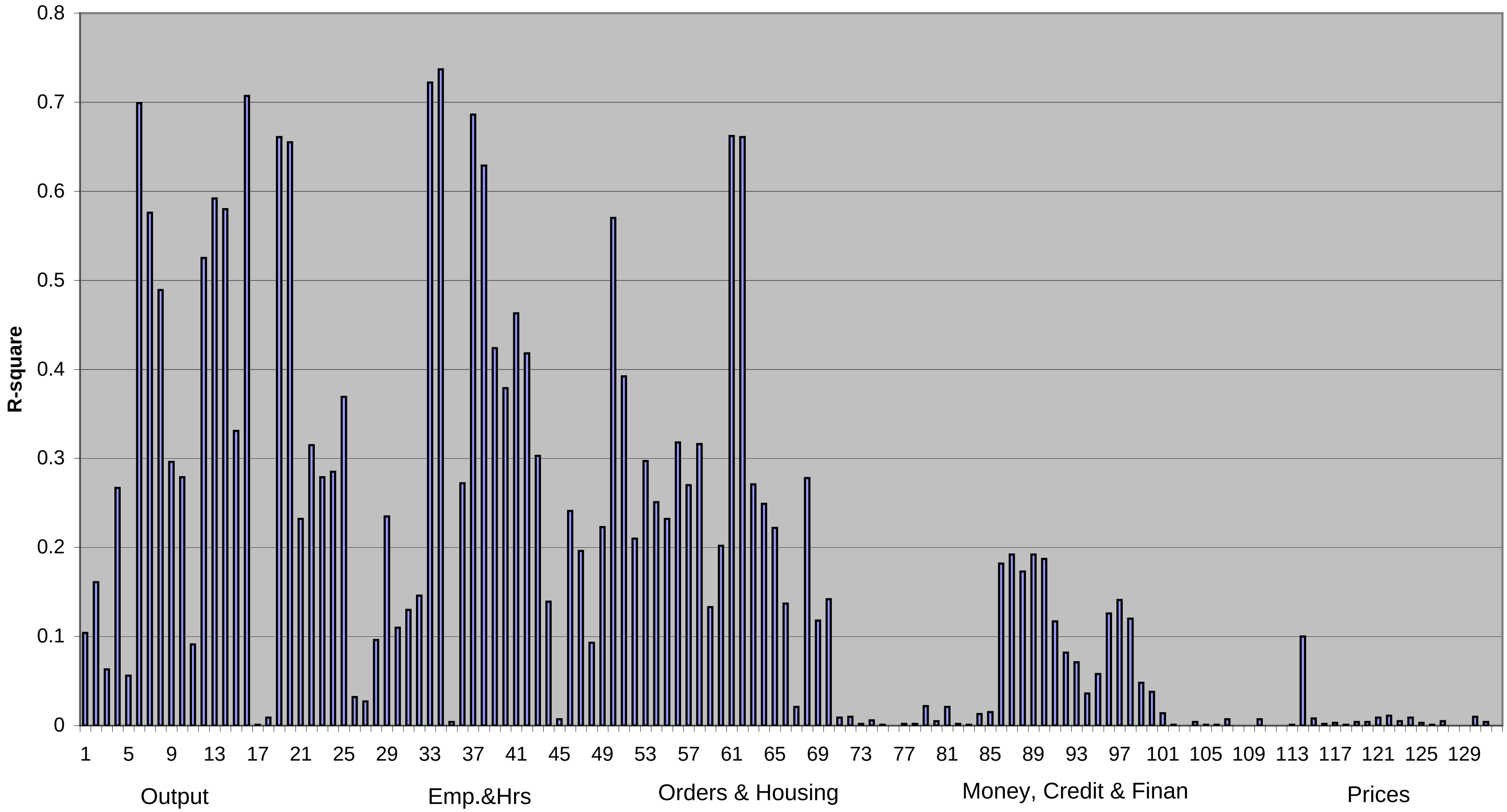
		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
c	-0.145	(-1.940 1.457)	(-1.725 1.238)	(0.470 0.473)	(0.470 0.472)
$F5_t$	1.362	(0.596 2.087)	(0.756 2.001)	(0.008 0.011)	(0.008 0.011)
R^2	0.146	(0.027 0.303)	(0.046 0.287)	(0.008 0.015)	(0.009 0.014)
$\bar{R}^2$	0.145	(0.025 0.301)	(0.044 0.286)	(0.006 0.013)	(0.007 0.012)

Model: $rx_{t+1}^{(5)} = \beta_0 + \beta_1' F5_t + \beta_2 CP_t + \epsilon_{t+1}$

		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
$F5_t$	-0.745	(-1.141 -0.325)	(-1.075 -0.401)	(-0.025 -0.016)	(-0.024 -0.017)
CP_t	0.395	(0.262 0.519)	(0.283 0.498)	(0.004 0.012)	(0.005 0.011)
R^2	0.455	(0.245 0.548)	(0.268 0.524)	(0.022 0.047)	(0.023 0.043)
$\bar{R}^2$	0.448	(0.235 0.542)	(0.258 0.518)	(0.009 0.034)	(0.010 0.031)

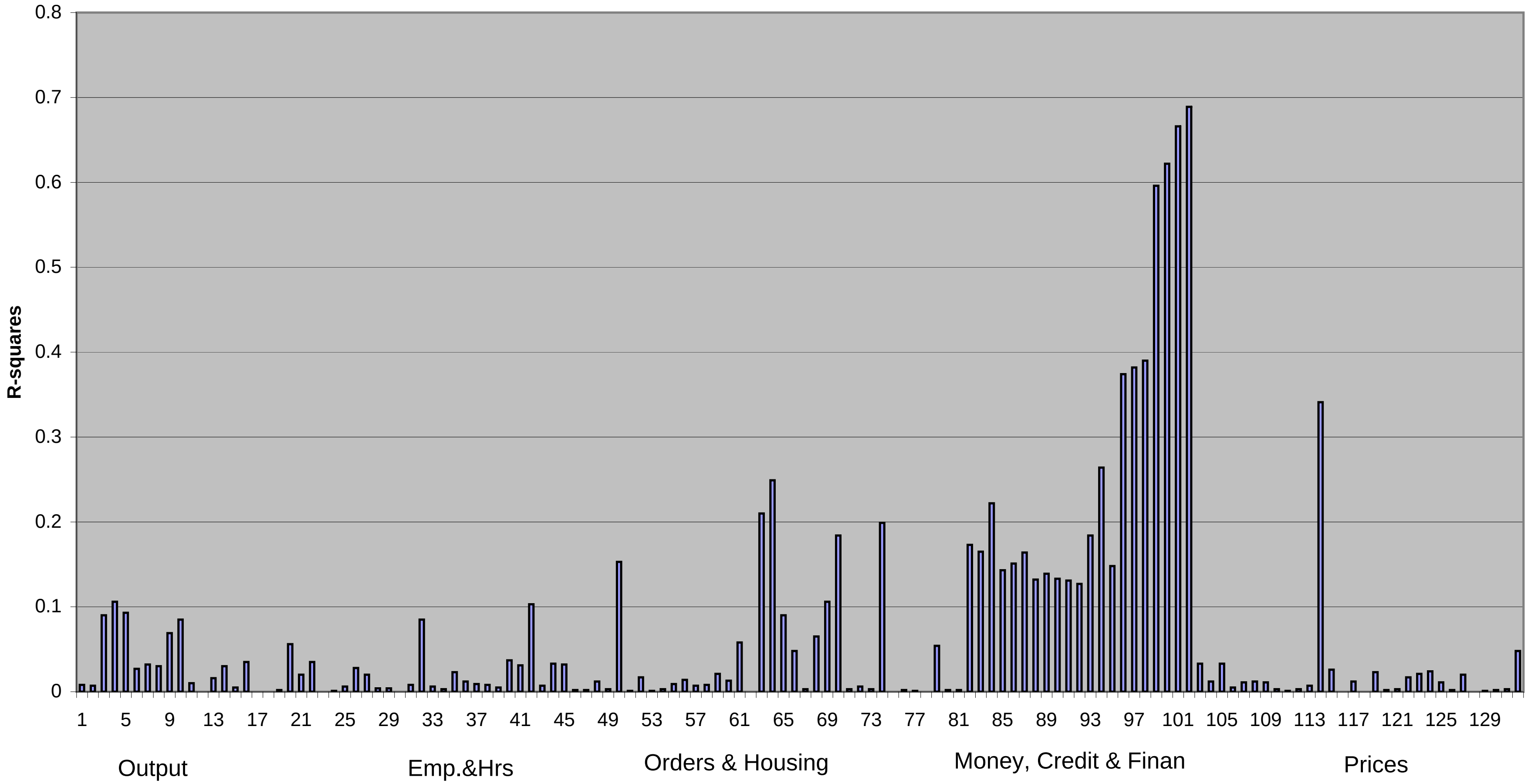
Notes: See Table 4a.

Figure1: Marginal R-squares for F_1



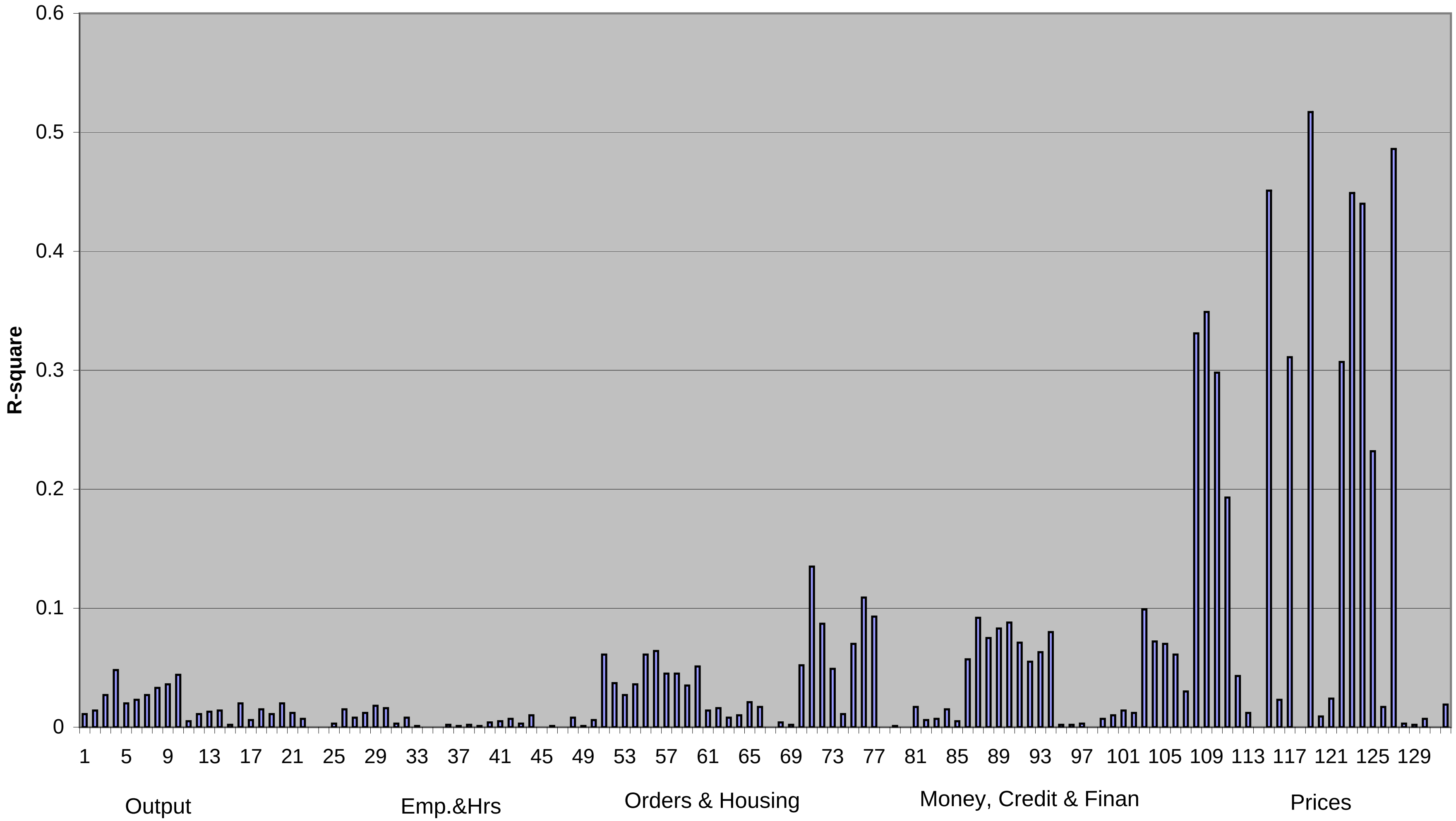
Notes: Chart shows the R-square from regressing the series number given on the x-axis onto F_1. See the appendix for a description of the numbered series. The factors are estimated using data from 1964:1-2003:12.

Figure 2: Marginal R-squares for F_2



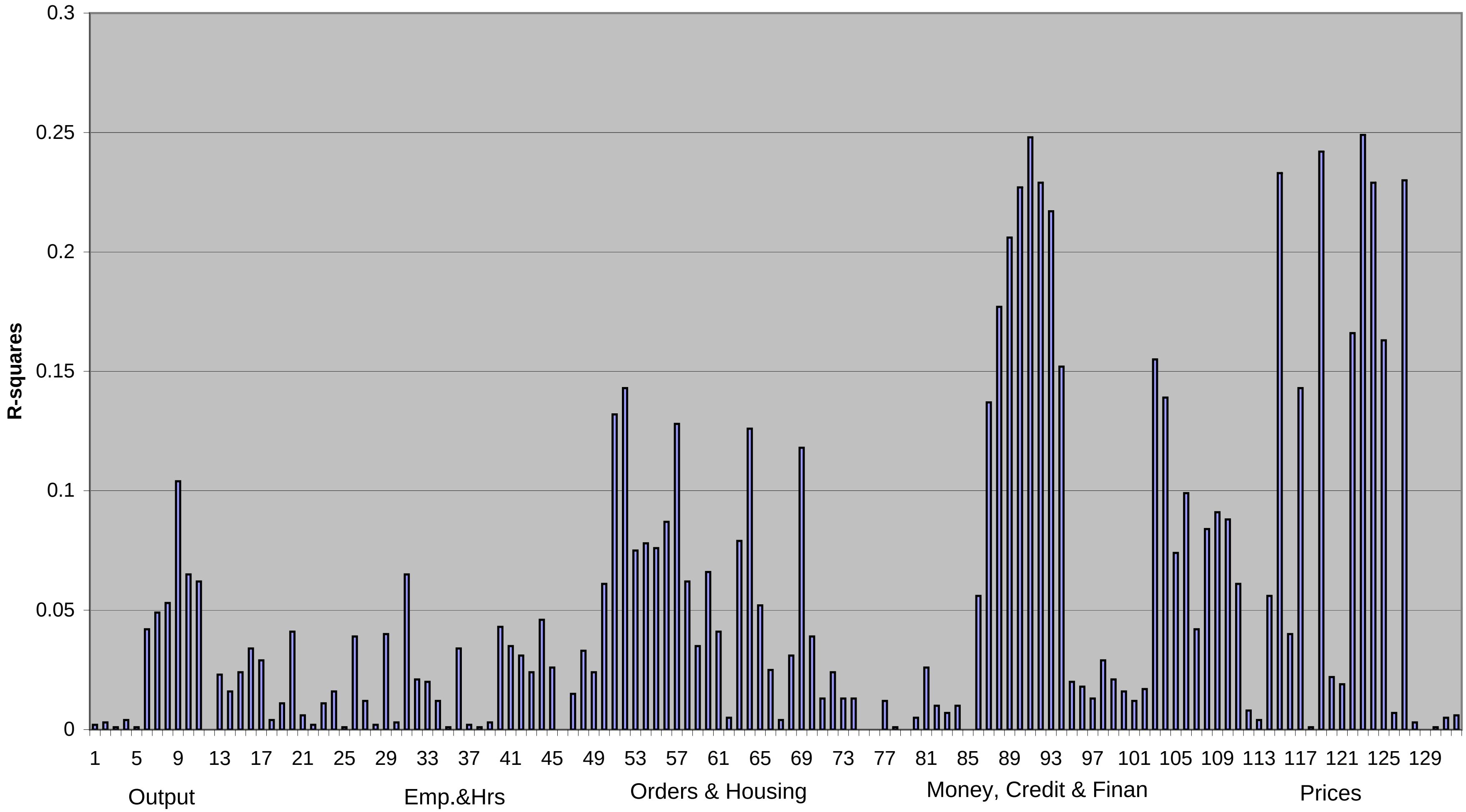
Notes: See Figure 1.

Figure 3: Marginal R-squares for F_3



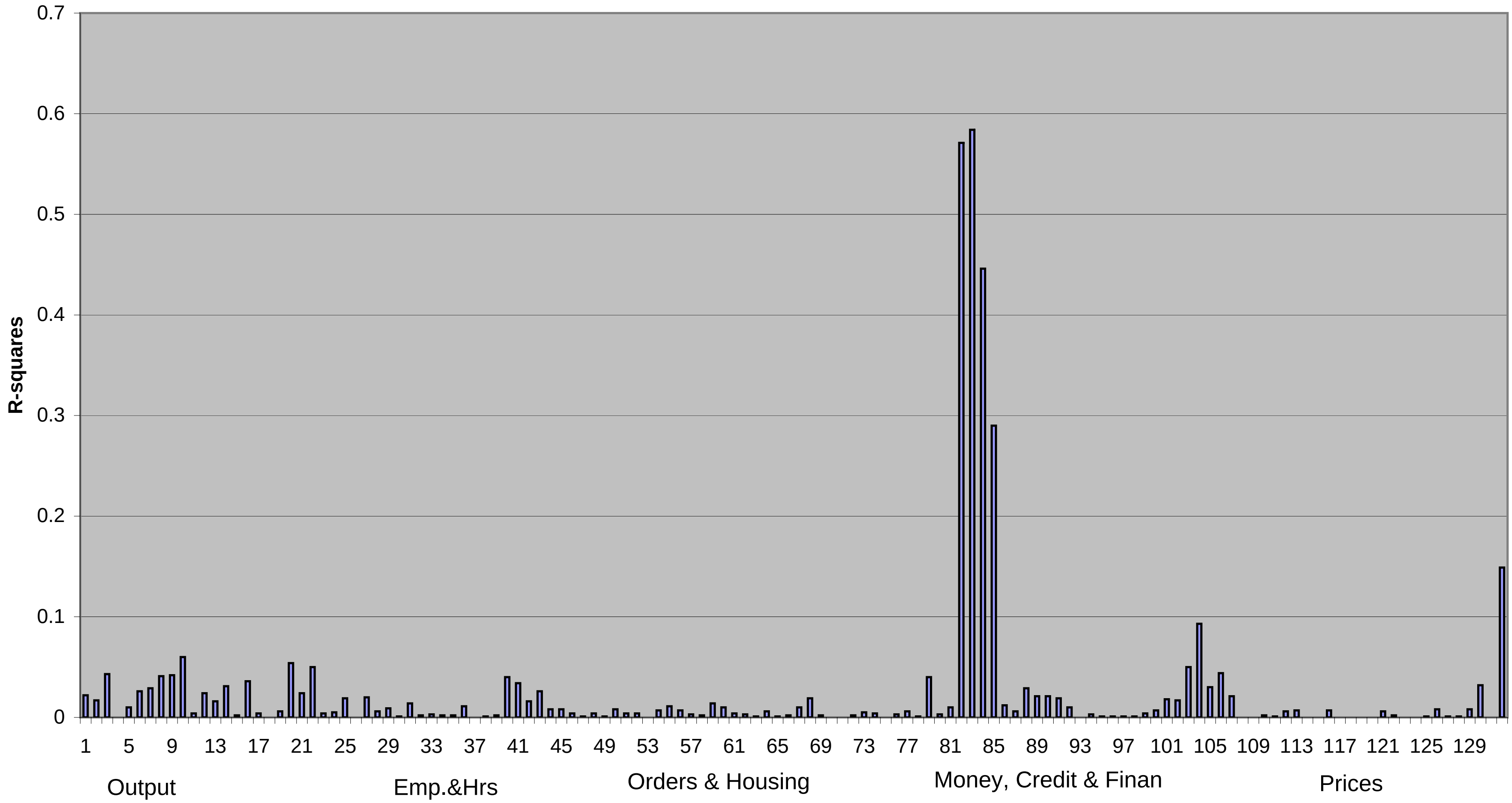
Notes: See Figure 1.

Figure 4: Marginal R-squares for F_4



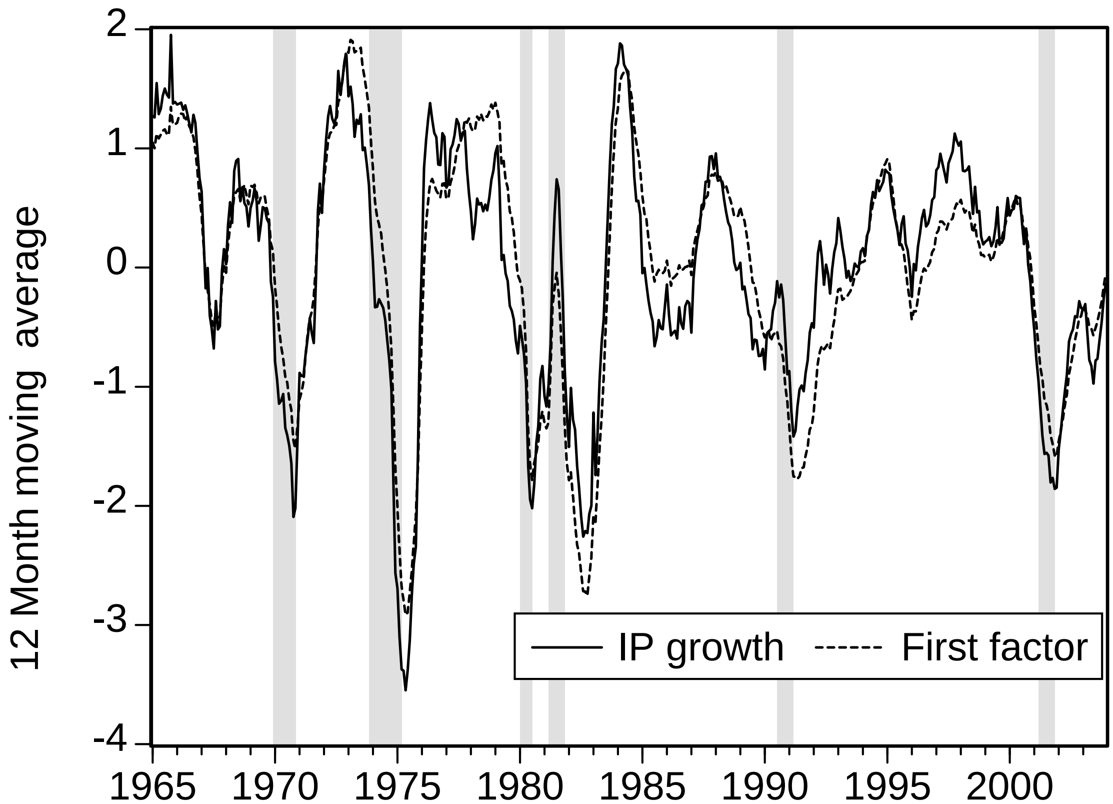
Notes: See Figure 1.

Figure 5: Marginal R-squares for F_8



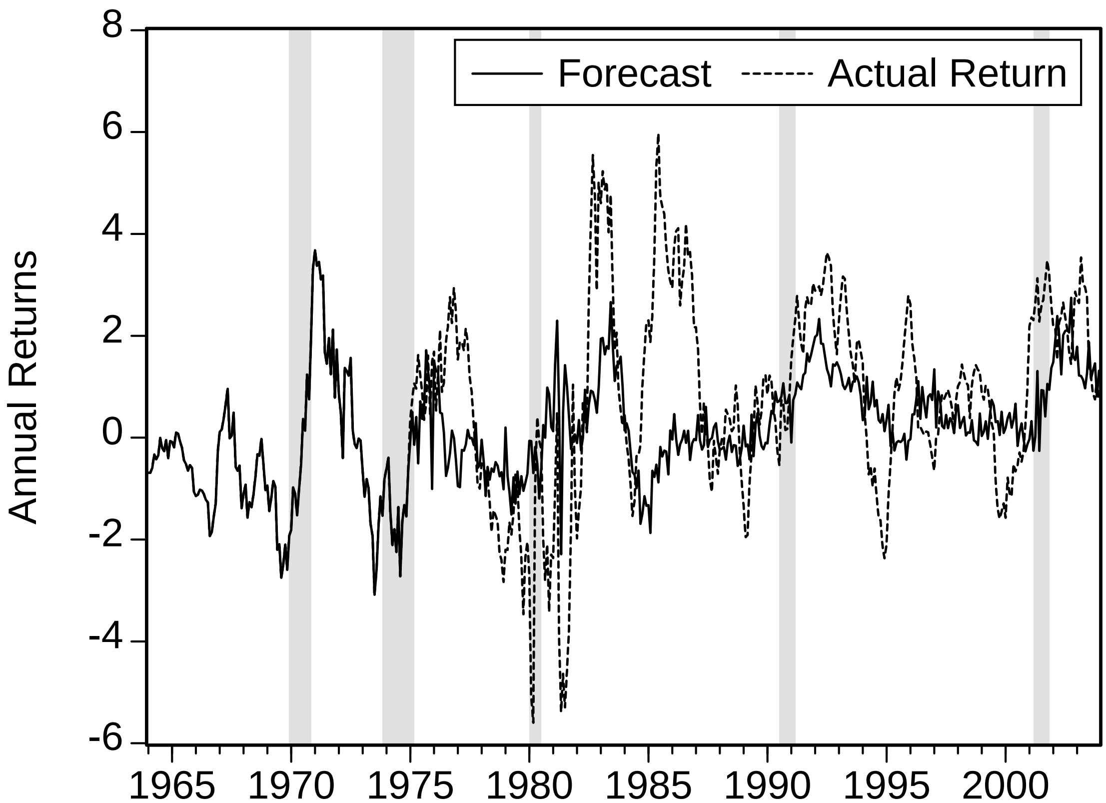
Notes: See Figure 1.

Figure 6: First factor and IP growth



Note: Standardized units are reported. Shadings denote months designated as recessions by the NBER

Figure 7: Out-of-Sample Forecasts of 2-yr Bond Returns



Note: Shading denotes months designated as recessions by the NBER.