Macro Factors in Bond Risk Premia

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Abstract

Are there important cyclical fluctuations in bond market premia and, if so, with what macroeconomic aggregates do these premia vary? 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 "real" and "inflation" factors have important forecasting power for future excess returns on U.S. government bonds, above and beyond the predictive power contained in forward rates and yield spreads. This behavior is ruled out by affine term structure models where the forecastability of bond returns and bond yields is completely summarized by yields or forward rates.

Next we investigate risk premia in yield spreads using a simple bivariate vectorautoregression. In the Greenspan era, term premia are found to have a strong countercyclical component, suggesting that investors must be compensated for risks related to recessions. When the economy is growing, these forces contribute to a flattening of the yield curve, even in periods when the Federal Reserve has been raising interest rates. But because such shocks to the yield spread display no forecasting power for real activity, a flat term structure–when attributable to this component–does not portend a period of slow or negative economic growth. The unusually flat term structure in 2004 and 2005 provides a case in point.

JEL: G10, G12, E0, E4.

1 Introduction

Recent empirical research in financial economics has uncovered significant forecastable variation in the excess returns of U.S. government bonds, a violation of the expectations hypothesis. 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. Cochrane and Piazzesi (2005) 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. These findings imply that risk premia in bond returns and bond yields vary over time and are a quantitatively important source of fluctuations in the bond market.

An unanswered question is whether such movements in bond market risk premia bear any relation to the macroeconomy. Are there important cyclical fluctuations in bond market premia and, if so, with what macroeconomic aggregates do these premia vary? Economic theories that rationalize time-varying risk premia almost always posit that such premia vary with macroeconomic variables. For example, Campbell and Cochrane (1999) posit that risk premia on equity vary with a slow-moving habit driven by shocks to aggregate consumption. Wachter (2006) adapts the Campbell-Cochrane habit model to examine the nominal term structure of interest rates, and shows that bond risk premia (as well as equity premia) should vary with the slow-moving consumption habit. Brandt and Wang (2003) argue that risk premia are driven by shocks to inflation, as well as shocks to aggregate consumption. Such theories imply that rational variation in bond risk premia should be evident from forecasting regressions of excess bond returns on macroeconomic fundamentals.

Despite these theoretical insights, there is little direct evidence of a link between the macroeconomy and bond risk premia. The empirical evidence cited above, for example, finds that excess bond returns are forecastable not by macroeconomic variables such as aggregate consumption or inflation, but rather by pure financial indicators such as forward spreads and yield spreads.

There are several possible reasons why it may be difficult to uncover a direct link between macroeconomic activity and bond market risk premia. First, some macroeconomic 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 dynamic factor analysis to revisit the question of whether there are important macro factors in bond risk premia. We begin with a comprehensive analysis of whether excess bond *returns* are predictable by macroeconomic fundamentals, and then move on to investigate whether risk premia in long-term bond *yields* (sometimes called *term premia*), vary with macroeconomic fundamentals.

Our results indicate bond premia are indeed forecastable by macroeconomic fundamentals, and we find marked countercyclical variation in bond risk premia. 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 magnitude of the forecastability we find associated with macroeconomic activity is economically significant. The estimated factors have their strongest predictive power for two-year bonds, explaining 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. Although this is slightly less than that found by Cochrane and Piazzesi (their single forward-rate factor, which we denote CP_t, explains 31 percent of next year's variation in the two-year bond), it 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 that is stable over time and statistically significant. The factors continue to exhibit significant predictive power for excess bond returns when the small sample properties of the data are taken into account.

Perhaps more significantly, the estimated factors contain substantial information about future bond returns that is not contained in CP_t, a variable that Cochrane and Piazzesi show subsumes the predictive content of forward spreads, yield spreads, and yield factors. For example, when both CP_t and either $F5_t$ or $F6_t$ are included together as predictor variables, each variable is strongly marginally significant and 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.

Of all the estimated factors we study, the single most important in the linear combinations we form is a "real" factor, highly correlated with measures of real output and employment but not highly correlated with prices or financial variables. "Inflation" factors, those highly correlated with measures of the aggregate price-level, also have predictive power for excess bond returns. (We discuss the interpretation of the factors further below.) Moreover, the predictable dynamics we find reveal significant countercyclical variation in bond risk premia: excess bond returns are forecast to be high in recessions, when economic growth is slow or negative, and are forecast to be low in expansions, when the economy is growing quickly.

We emphasize two aspects of these results. First, in contrast to the existing empirical literature, (which has focused on predictive regressions using financial indicators), we find strong predictable variation in excess bond returns that is associated with macroeconomic activity. Second, the estimated factors that load heavily on macroeconomic variables have substantial predictive power for excess bond returns above and beyond that contained in the in forward spreads, yield spreads, or even yield factors estimated as the principal components of the yield covariance matrix. This behavior is ruled out by affine term structure models where the forecastability of bond returns and bond yields is completely summarized by yields or forward rates.

The final part of this paper investigates long-term bond yields using a simple bivariate vectorautoregression for yield spreads and the federal funds rate. The VAR errors are orthgonalized so that the federal funds rate does not respond contemporaneously to the yield spread innovation. We argue that movements in the term structure that are orthogonal to contemporaneous and lagged values of the federal funds rate may be interpreted as movements risk premia on long-term yields. We find that shocks to the yield spread holding fixed the federal funds rate have become an economically important source of variation in the short-run forecast error of the term structure over the last 20 years, but were less important in earlier periods. In the Greenspan era, these shocks are found to have a strong countercyclical component, and are forecastable by the same real factor that we find forecasts excess bond returns. This reinforces the conclusion from our investigation of bond returns that investors must be compensated for risks related to recessions.

When the economy is growing, these forces contribute to a flattening of the yield curve even in periods when the Federal Reserve has been raising interest rates. Conventional wisdom maintains that a flat yield curve portends a slowing of economic activity. But we find that shocks to the yield spread holding fixed the funds rate display no forecasting power for real activity. Accordingly, a flat term structure–when attributable to this component–does not portend a period of slow or negative economic growth. We show that the unusually flat term structure in 2004 and 2005 provides a case in point.

The rest of this paper is organized as follows. In the next section we briefly review related literature not discussed above. We begin with the investigation of risk premia in bond returns. Section 3 lays out the econometric framework and discusses the use of principal components analysis to estimate common factors. Here we present the results of one-year-ahead predictive regressions for excess bond returns. We also discuss an out-of-sample forecasting analysis, and a bootstrap analysis for small-sample inference. Next we explore the potential implications of our findings for the term structure, by studying a simple decomposition of five-year yield spreads. This analysis is conducted in Section 4, using a bivariate vectorautoregression. Section 5 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 2002a, 2002b; Bai and Ng 2002, 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 $N \rightarrow \infty$.

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. 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 (2006) 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 present a multifactor affine bond pricing model that allows for time-varying risk premia, but they allow the pricing kernel to be driven by shocks to both observed macro variables and unobserved yield factors. They find empirical support for this model.[1] The investigation of this paper differs because we

[1]A closely related approach is taken in recent work by Bikbov and Chernov (2005) in which the joint dynamics of yield factors, real activity, and inflation are explicitly modeled as part of an affine term structure model. Others, such as Kozicki and Tinsley (2001) and Kozicki and Tinsley (2005) use affine models to link the term structure to perceptions of monetary policy.

form factors from a large dataset of 132 macroeconomic indicators to conduct a model-free empirical investigation of reduced-form forecasting relations suitable for assessing more generally whether bond premia are forecastable by macroeconomic fundamentals. We view our investigation as complimentary to that of Ang and Piazzesi.

3 Econometric Framework: Bond Returns

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.

Although any predictability in excess bond returns is a violation of the expectations hypothesis (where risk-premia are presumed constant), the objective of this paper is to assess whether there is palpable forecastable variation in excess bond returns specifically related to macroeconomic fundamentals. In addition, we ask whether macroeconomic variables have predictive power for excess bond returns above and beyond that contained in the in forward spreads, yield spreads, or yield factors estimated as the principal components of the yield covariance matrix. To examine this latter issue, we use the Cochrane and Piazzesi (2005) forward rate factor as a forecasting benchmark. Cochrane and Piazzesi have already shown that, in our sample, the predictive power of forward spreads, yield spreads, and yield factors is subsumed by their single forward-spread factor.

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.[2]

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

[2]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 $g_t^{(n)} \equiv p_t^{(n-1)} - p_t^{(n)}$.

then estimate

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

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), (a linear combination of $y_t^{(1)}$ and four forward rates), or other predictor variables based on a few macroeconomic series. For reasons discussed above, 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

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

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

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

$$x_{it} = \lambda_i' f_t + e_{it}, \quad (3)$$

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.[3] The crucial point here is that $r << N$, so that substantial dimension reduction can be achieved by considering the regression

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

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.

[3] 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:

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

where M is a constant.

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).[4] 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 $\widehat{F}_t$, but we explicitly limit the number of specifications we search over.[5] The vector Z_t contains additional (non-factor) regressors that are thought to be related to future bond returns. The final regression model for excess returns is based on Z_t plus this optimal $\widehat{F}_t$. That is,

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

Although we have written (5) so that $\widehat{F}_t$ and Z_t enter as separate regressors, there is no theoretical reason why factors that load heavily on macro variables should contain information that is entirely orthogonal to that in financial indicators. For this reason we are also interested in whether macro 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 the estimated factors $\widehat{F}_t$ overlaps substantially with that contained

[4] 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).

[5] We first evaluate r univariate regressions of returns on each of the r factors. Then, for only those factors that contribute significantly to minimizing the BIC criterion of the r univariate regressions, we evaluate whether squared and cubed terms help reduce the BIC criterion further. We do not consider other polynomial terms, or polynomial terms of factors not important in the regressions on linear terms.

in financial predictor variables. Therefore we also evaluate multiple regressions of the form (5), in which Z_t includes the Cochrane-Piazzesi factor CP_t as a benchmark. As discussed above, we use this variable as a single summary statistic because it subsumes the information contained in a large number of popular financial indicators known to forecast excess bond returns. Such multiple regressions allow 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 $N, T \rightarrow \infty$ with $\sqrt{T}/N \rightarrow 0$, 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 (i.e., that pre-estimation of the factors does not affect the consistency of the second-stage parameter estimates or the regression standard errors), (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, makes our analysis less dependent than previous applications on 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 by indicating whether these variables have important additional forecasting power for excess bond returns.

3.1 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 sales data, international trade, 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.

Notice that the estimated factors we study will not be *pure* macro variables, since the panel of economic indicators from which they are estimated contain financial variables as well as macro variables. Theoretically speaking, there is no reason why financial and macro variables shouldn't be informative, since the two classes of variables must be endogenously determined by a common set of primitives. The important point, made below, is that several of the estimated factors that are highly correlated with macroeconomic activity (but little correlated with financial indicators) contain economically important predictive power for bond returns that is not contained in financial indicators with known forecasting power for bond returns, e.g., bond yields and forward rates.

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 estimated 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.

3.2 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, (though we restrict our specification search as described above.) We report results only for the 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 possible specifications based on the first eight common factors of our panel dataset, as well as nonlinear functions of these factors. $\widehat{F}_{1t}^3$, above, denotes the cubic function in the first esti-

[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.

mated 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 $F_t = \overrightarrow{F5}_t = \left(\widehat{F}_{1t}, \widehat{F}_{1t}^3, \widehat{F}_{3t}, \widehat{F}_{4t}, \widehat{F}_{8t}\right)'$ 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:

$$\begin{aligned}
\frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)} &= \gamma_0 + \gamma_1 \widehat{F}_{1t} + \gamma_2 \widehat{F}_{1t}^3 + \gamma_3 \widehat{F}_{2t} + \gamma_4 \widehat{F}_{3t} + \gamma_5 \widehat{F}_{4t} + \gamma_6 \widehat{F}_{8t} + u_{t+1}, &(7)\\
F6_t &\equiv \widehat{\gamma}' \overrightarrow{F6}_t,\\
\frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)} &= \delta_0 + \delta_1 \widehat{F}_{1t} + \delta_2 \widehat{F}_{1t}^3 + \delta_3 \widehat{F}_{3t} + \delta_4 \widehat{F}_{4t} + \delta_5 \widehat{F}_{8t} + v_{t+1}, &(8)\\
F5_t &\equiv \widehat{\delta}' \overrightarrow{F5}_t,
\end{aligned}$$

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.

3.2.1 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 unrestricted 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.

For each regression, the regression coefficients, heteroskedasticity and serial-correlation robust t-statistics, and adjusted R^2 statistic are reported. The asymptotic standard errors

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

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. 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.

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. When the information in CP_t and $\widehat{F}_t$ is combined, the magnitude of forecastability exhibited by excess bond returns is remarkable.

Implications for Affine Models The results reported in Tables 2a-2b indicate that good forecasts of excess bond returns can be made with only a few estimated factors, and that the best forecasts are based on combinations of factors that summarize information from a large panel of economic activity 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 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, and therefore 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.) These findings are ruled out by affine term structure models where the forecastability of bond returns and bond yields is completely summarized by yields or forward rates. In affine models, log bond prices are linear functions of the state variables. Thus, if there are K state variables, bond yields can serve as state variables, and will contain any forecasting information that is in the state variables. Since bond returns, forward rates, and yields are all linear functions of one another, affine models imply that any of these variables should contain all the forecastable information about future bond returns and yields.[9] Thus the findings reported above suggest that affine models may fail to describe an important aspect of bond data.

Economic Interpretation of the Factors 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.

Figure 1 shows that 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. 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 (Figure 2), explaining almost 70 percent of the variation in the $Baa-$Fed funds rate spread. The third and fourth factors load most heavily on measures of inflation and price pressure but display little relation to employment and output. Figure 3 and 4 show that 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. We call both $\widehat{F}_{3t}$ and $\widehat{F}_{4t}$ *inflation factors*.

Finally, Figure 5 shows that the eighth estimated factor, $\widehat{F}_{8t}$, loads heavily on measures of the aggregate stock market. It is highly correlated with the log difference in both the composite and industrial Standard and Poor's Index and the Standard and Poor's dividend yield but bears little relation to other variables. We call this factor a *stock market factor*. It should be noted, however, that this factor is not merely proxying for the stock market dividend yield, shown elsewhere to have predictive power for excess bond returns (e.g., Fama and French (1989)). The factor's correlation with the dividend yield is less than 60% in our sample (Figure 5). Moreover, results not reported indicate that–conditional on the dividend

[9] Cochrane (2005), Ch. 19, provides a useful discussion of this issue.

yield–the stock market factor we estimate displays strong marginal predictive power for future excess returns.

Since the factors are orthogonal by construction, we can characterize their relative importance in $F5_t$ 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 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 because it is a strongly statistically significant once CP_t is included as an additional regressor.) It is also worth noting that $\widehat{F}_{1t}$ and $\widehat{F}_{1t}^{3}$ account for half of the adjusted R-squared statistic reported above.

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 to forecast excess bond returns:

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

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

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

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 lower. Interestingly, 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 arbitrary given the large number of series available, and it is surely the case that different specifications would lead to different results. (The cubic in IP_t, however, is not a statistically important predictor.) This fact serves to illustrate a point: when the information from hundreds of predictors is systematically summarized, the possibility of omitting relevant information is much reduced.

Are Bond Risk Premia Countercyclical? The findings presented so far indicate that excess bond returns are forecastable by macroeconomic aggregates, but they do not tell us whether there is a countercyclical component in risk premia, as predicted by economic theory. To address this question, Figure 6 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 figure shows that the real factor, $\widehat{F}_{1t}$, captures marked cyclical variation in real activity. The correlation between the moving averages of the two series plotted is 92 percent. Both $\widehat{F}_{1t}$ 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 (typically negative) IP growth and low values for $\widehat{F}_{1t}$, while expansions are characterized by strong positive IP growth and high values for $\widehat{F}_{1t}$.

Connecting these findings back to the forecasts of excess bond returns, we see that excess return forecasts are high when $\widehat{F}_{1t}$ is *low* (Table 2). These findings imply that return forecasts have a countercyclical component, consistent with economic theories in which investors must be compensated for bearing risks related to recessions. For example, Campbell and Cochrane (1999) and Wachter (2006) study models in which risk aversion varies over the business cycle and is low in good times when the economy is growing quickly. In these models, risk premia (excess return forecasts) are low in booms but high in recessions, consistent with what we find. The evidence that inflation factors also govern part of the predictable variation in excess bond returns is consistent with economic theories for which risk premia vary with inflation (e.g., Brandt and Wang (2003)), as well as with theories for which inflation and real activity contribute significantly to variation in the price of risk (e.g.,Ang and Piazzesi (2003)).

3.2.2 Out-of-Sample Analysis and Small Sample Inference

We have formed the factors and conducted the regression analysis 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 conduct two model comparisons. First, we compare the out-of-sample forecasting performance of the five-factor model that includes the estimated factors in $\overrightarrow{F5}_t$ to a constant expected returns benchmark where, apart from an MA(12) error term, excess returns are unforecastable as in the expectations hypothesis.[12] Second, we compare the out-of-sample forecasting performance of a specification that includes the same five macro factors plus to the Cochrane-Piazzesi factor, CP_t, to a benchmark model that includes just the Cochrane-Piazzesi factor, CP_t, and a constant. This second specification allows us to assess the incremental predictive power of the macro factors above and beyond the predictive power in CP_t.

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 $\overrightarrow{F5}_t$ or $\overrightarrow{F5}_t$ and CP_t; MSE_r denotes the mean-squared forecasting error of the restricted benchmark (null) model that excludes additional forecasting variables. In the column labeled "MSE_u/MSE_r", a number less than one indicates that the model with the predictor factors $\overrightarrow{F5}_t$ or $\overrightarrow{F5}_t$ and CP_t has lower forecast error than the benchmark model that excludes additional predictor variables.

Results for two forecast samples are reported: 1985:1-2003:2; 1995:1-2003:2. The results for the first forecast sample are reported in Rows 1, 3, 5, and 7 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 1984:12. Next, the forecasting regressions were run over the period t =1964:12,...,1984:12 (dependent variable from

[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)).

[12] Notice that this procedure is conservative, since the out-of-sample performance of the estimated factors could only stronger if, in each recursion, we conducted a BIC specification search to select the subset of factors with the highest predictive power. But a recursive specification search would tell us nothing about the out-of-sample performance of the factors investigated above, so we do not pursue that avenue here.

t =1965:1,...,1984:12, independent variables from t =1964:1,...,1983:12) and the estimated parameters and values of the regressors at t =1984:12 were used to forecast annual compound returns for 1985:12.[13] All parameters and factors are then reestimated from 1964:1 through 1985:1, and forecasts were recomputed for excess returns in 1986:1, 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 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 mean-squared error that is anywhere from 79 to 93 percent of the constant expected returns benchmark mean-squared error, 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, 86, 89, and 93 percent of the constant expected returns benchmark for $rx_{t+1}^{(2)}$, ...,$rx_{t+1}^{(5)}$ respectively. 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, the reduction in mean-square-error over the benchmark is about the same regardless of which forecast period is analyzed.

The results also show that the model including the five factors in $\overrightarrow{F5}_t$ and CP_t improves substantially over a benchmark that includes a constant and CP_t. This reinforces the conclusion form the in-sample analysis, namely that the estimated factors contain information about future returns that is not contained in the CP factor. The models that include the five factors in addition to the CP factor have a mean-squared error that is any where from 81 to 94 percent of that of the benchmark that includes only CP and a constant. The ENC-NEW test statistic always indicates that the improvement in forecast power is strongly statistically significant, at the one percent or better level.

To guard against inadequacy of the asymptotic approximation in finite samples, the Appendix reports the results of a comprehensive bootstrap inference for specifications using four

[13]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.

regression models. The results show that 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.

4 A Decomposition of Yield Spreads

The evidence above suggests that risk premia on bond returns vary significantly with real activity, as captured by $\widehat{F}_{1t}$. Researchers in macroeconomics are often more interested in the behavior of bond *yields* rather than returns. The aim of this section is to investigate whether movements in yield risk premia are also related to real economic activity, in a manner similar to that documented above for return risk premia.

It is not a given that they should be so related. While there is a simple linear relation between returns and yields, there is no simple linear transformation between their risk premium components. To see this, note that the n-period yield can be written as the average of expected future nominal short-rates plus an additional term $\xi_t^{(n)}$, which we refer to as a yield risk-premium:

$$y_t^{(n)} = \frac{1}{N} E_t \left(y_t^{(1)} + y_{t+1}^{(1)} + \cdots + y_{t+N-1}^{(1)} \right) + \xi_t^{(n)}. \tag{9}$$

In the expectations hypothesis, the yield risk premium, $\xi_t^{(n)}$, is assumed constant.

We refer to the yield risk premium $\xi_t^{(n)}$ interchangeably as a *term premium*. The term premium should not be confused with the term spread itself, which is simply the difference in yields between the n-period bond and the one-period bond. Of course, without restrictions of some kind on $\xi_t^{(n)}$, the equation above is just a statement of yields, not a model. But with $\xi_t^{(n)}$ constant, as in the expectations hypothesis, excess bond *returns* (studied above) should be unforecastable. Thus the evidence above implies that risk premia in yields, $\xi_t^{(n)}$, also vary. The precise relation between term premia and risk premia is likely to be complicated and nonlinear, however, because the latter is a function of the *expected* one-period change in the risk premium on yields, $\xi_t^{(n)} - E_t \xi_{t+1}^{(n-1)}$, which in principle varies both with maturity and over time. It therefore remains an open question as to whether term premia are closely related to the same empirical state variables that return risk premia are found to be in linear forecasting regressions.

In this section we first identify movements in the term structure that are plausibly related to the risk-premium component, $\xi_t^{(n)}$, and then ask how movements in $\xi_t^{(n)}$ are related to $\widehat{F}_{1t}$. To accomplish the first objective, we decompose the term structure using a simple bivariate vectorautoregression (VAR) for the yield spread and the federal funds rate. The VAR errors are orthgonalized so that the federal funds rate does not respond contemporaneously to the yield spread innovation. Using this orthogonalization, innovations in the yield spread will be orthogonal to contemporaneous and lagged values of the federal funds rate, FF_t.

It is natural to interpret these orthogonalized innovations as movements in risk premia, $\xi_t^{(n)}$. For example, the expectation term above, a function of future nominal rates, captures movements in expected inflation and expected real interest rates. If the Federal Reserve cares only about inflation and the output gap, it will move the funds rate in response to anticipated changes in these variables, but it will not react to fluctuations in the yield curve that are orthogonal to expected inflation and expected real interest rates, (which affect the output gap). Thus, if the yield curve changes but the federal funds rate does not, that must signify a movement in risk premia. We use this interpretation of Federal Reserve behavior as an identification assumption.

In practice, the Federal Reserve is known to move gradually in response to changes in expected inflation and expected real interest rates. Moreover, the bond market may move in anticipation of policy changes by the Federal Reserve. Nevertheless, the funds rate, as the target of the monetary authority, summarizes a large amount of economic information upon which expectations of future inflation and future real interest rates are based; it is also extremely persistent. Given these facts, we assume that current and lagged values of the federal funds rate (included in the VAR), summarize the market's expectations of future Federal Reserve policy, so that the VAR innovations in the yield spread equation (orthogonalized as described above) capture genuine movements in risk premia.[14] Thus we label the residual in the yield spread equation a "risk premium" component, and present evidence below on this identification assumption. However one labels this component, we argue that it is of interest in its own right, as discussed below. We use the terms "orthogonalized yield spread innovation" and "risk premium component" interchangeably to describe this VAR residual.

Notice that we do not assign any interpretation to the innovations in the federal funds equation. In particular, we do not consider them policy shocks or even exogenous movements

[14] Some researchers have used federal funds futures rates to measure the financial market's expectation of future federal funds rates changes (Krueger and Kuttner (1996), Rudebusch (1998), Brunner (2000), Kuttner (2001), Bernanke and Kuttner (2003)). There are at least two drawbacks with this approach for our application. First, the data from the futures market is more limited, which restricts the sample size. Second, and more important for our application, Piazzesi and Swanson (2004) show that a significant fraction of the variation in feds funds futures reflects movements in risk-premia, not merely movements in expected future funds rates. Since we are interested in the risk premium component of yields, we do not include federal funds futures data in our VAR.

in the funds rate. The aim is to use the bivariate VAR to decompose yields in an interesting way, not to identify policy shocks.

Such a decomposition cannot achieved by estimating a larger VAR (as would be required to identify policy shocks). Under the identifying assumption given above, any movement in the yield spread associated with funds rate changes captures the expectations component in (9). All remaining movements (given by the orthogonalized VAR residuals), must reflect movements in risk-premia $\xi_t^{(n)}$. Including additional variables in the VAR would destroy this identification, since the residuals in the yield spread equation would then be orthogonal not only to the funds rate but also to the additional variables, which, under our identification assumption, reveal movements in risk premia. Since these are precisely the movements we seek to identify as part of the residual, it is important not to remove them by estimating a larger VAR. The essence of our identification assumption is that the federal funds rate itself summarizes a large amount of economic information upon which expectations are based, so it is not necessary to include this information along with the funds rate in the VAR.

The procedure just described decomposes movements in the term structure; it does not provide a complete statistical model of yield changes. It is more common in the term structure literature to measure movements in yield risk premia by imposing multifactor affine models that prohibit arbitrage. The "model" in our decomposition approach boils down to assumptions about Federal Reserve behavior that may admittedly be difficult to assess empirically. On the other hand, the approach allows us to sidestep the counterfactual implication of affine term structure models that bond yields should completely drive out macroeconomic variables as interest rate and return forecasters. This latter consideration is important for our application, since the results above imply that risk premia in returns move with real economic activity unrelated to yields, forward rates and lagged returns.

We focus on the spread between the five-year Treasury bond and the one-year bond using quarterly data, available from the Federal Reserve. We use quarterly data in order to insure that each observation in our sample contains a meeting of the Federal Open Market Committee, at which the Federal Reserve sets interest rates. Table 4 plots variance decompositions from a two-lag, bivariate VAR for the funds rate and the five-year Treasury yield spread, $y_t^{(5)} - y_t^{(1)}$. Below, we denote the orthgonalized VAR *residual* in the yield spread, $ry_t^{(5-1)}$. Several points about the variance decompositions bear noting.

First, in the full sample, yield spread innovations have a negligible affect on the funds rate but an economically significant affect on yields. The innovations explain 34 percent of the one-step-ahead forecast error in the five-year yield spread, and roughly 40 percent of the overall variation in the yield spread. Thus, shocks to the yield curve holding fixed the funds rate account for a large fraction of the variance in the term spread in our sample.

Second, yield spread innovations have become more important over time. We study this decomposition over three subperiods: 1964:Q1-1979:Q2 (pre-Volcker), 1983:Q1-2005:Q4 (recent) and 1987:Q3-2005:Q4 (Greenspan). (We omit the interim years from 1979 to 1983, in which the Federal Reserve was experimenting with a nonborrowed reserve operating procedure.) Comparing the early period to the two latter periods, we see that fraction of forecast error variance in the yield spread that is explained by its own shocks has risen dramatically, especially in the short-run. For example, in the Greenspan period, this component explains the vast majority–82 percent–of the one-step ahead forecast error in the yield spread. The results are similar for the "recent period." Yield spread innovations explain 76 percent of the one-step-ahead forecast error in yields and 35 percent over long horizons. By contrast, in the pre-Volcker period, yield spread innovations explain only 33 percent of one-step-ahead forecast error in yields and 16 percent over long horizons. These findings imply that movements in the term structure that are orthogonal to movements in the funds rate have become a much more economically important source of variation in yields in recent decades.

Third, the differences in variance decompositions across subperiods appear more attributable to differences in the volatility of the orthogonalized forecast errors across subperiods than to differences in the VAR parameter estimates. Indeed, Figure 9 shows that the impulse responses to a one-standard deviation increase in the yield spread are quite similar across subperiods. Moreover, if we fix the VAR parameters at their full sample estimated values, we find a large increase in the standard deviation of the orthogonalized yield spread residual in the recent sample compared to the pre-Volcker sample. This standard deviation is normalized to one in the full sample, but is 0.76 in the pre-Volcker sample and 1.11 in the recent sample. (This can be seen clearly in Figure 10, discussed below.) We conclude that it is reasonable to use the full sample to form a long estimate of the risk premium component of the term structure.

We have assumed that that VAR innovations in the yield spread, which hold fixed the funds rate, capture movements in term premia rather than movements in expected inflation and expected real interest rates. We have also assumed that current and lagged values of the funds rate summarize the market's expectation of future Federal Reserve policy moves. If either of these identification assumptions were incorrect, we would expect the funds rate to respond subsequently to innovations in the yield spread. The left panels of Figures 9 provide no evidence that this is the case. The impact reaction is zero by construction, since the shock to yields does not contemporaneously affect the funds rate (by the orthogonalization assumption). But the responses in *future* periods are outcomes of the analysis. These responses show that yield spread innovations have an economically small and statistically insignificant impact on the federal funds rate over any future horizon. In three distinct subperiods, the impulse response of the funds rate to a yield spread innovation is almost flat, suggesting that our identification assumption is reasonable. By contrast, the response of yield spread itself to such a shock strongly positive and persistent, dying out after about 15 quarters.

We now turn to the question of whether the term premium component of the yield spread we identify is related to real economic activity, as measured by the real factor $\widehat{F}_{1t}$. Table 5 displays the results of univariate forecasting regressions of the orthogonalized innovations in the yield spread onto the lagged factor $\widehat{F}_{1t}$, where we have estimated both the forecast error for the yield spread and $\widehat{F}_{1t}$ over the same sample used to estimate return risk premia above. Results for other factor are not reported since we find little relation between the risk premium component in yields and the other factors. The table shows that $\widehat{F}_{1t}$ is unrelated to the orthogonal component of future yields in the early subperiods, but is a strong predictor in the Greenspan period. This factor alone explains 11 percent of the variation in $ry_t^{(5-1)}$ one quarter ahead in the Greenspan period. Since $\widehat{F}_{1t}$ is positively correlated with measures of output and employment, these findings are qualitatively similar to those presented above for bond returns: they suggest that investors must be compensated for risks related to recessions or, conversely, that investors require lower risk premia in good times when the economy has been expanding.

The point estimate in the regression reported in Table 5 suggests that the affect of $\widehat{F}_{1t}$ on risk premia in yields in the Greenspan period is economically large. A one-standard deviation increase in $\widehat{F}_{1t}$ leads to a decline of 0.48 in the orthogonalized yield spread. This implies a decline of greater than two standard deviations in the risk premium component of the term spread. Given the large fraction of variation in the short-term forecast error of yield spreads that is explained by this component in recent decades, these findings imply that much of the variation in yield spreads associated with real activity in the Greenspan era was entirely unrelated to Federal Reserve Policy. When the economy is growing, as in recent data, these forces contribute to a flattening of the yield curve even in periods when the Federal Reserve has been raising interest rates.

4.1 Is the Term Premium Related to Future Real Activity?

It is well known that the term spreads as a whole forecast real activity, particularly output growth (Stock and Watson (1989), Chen (1991), Estrella and Hardouvelis (1991)). A conventional interpretation of these results is that a flat yield curve portends a slowing of economic activity. Table 6, top panel, confirms these findings in our sample: the term spread as a whole, $y_t^{(5)} - y_t^{(1)}$, is a strong predictor of the real factor $\widehat{F}_{1t+1}$, explaining eight percent of its one-quarter-ahead variation. Moreover, the estimated coefficient has the anticipated sign: high yield spreads forecast positive economic activity, and vice versa.

Table 6 suggests that this forecasting power comes entirely from the expectations component of long term yields, rather than the term premium. We disaggregate the total yield spread into its orthogonalized residual, or term premium, component $ry_t^{(5-1)}$, and the remaining component explained by the VAR. We denote this expectations component $ey_{t+1}^{(5-1)}$. The components $ry_t^{(5-1)}$ and $ey_{t+1}^{(5-1)}$ are orthogonal and sum to $y_t^{(5)} - y_t^{(1)}$. Note that $ey_{t+1}^{(5-1)}$ contains movements in the yield spread that are related to current and lagged values of the funds rate, as well as to lagged values of the yield spread.

The second panel of Table 6 shows that $ry_t^{(5-1)}$ has no predictive power for future real activity. The coefficient in the regression is zero, as is the R^2. The third panel of Table 6 shows that, historically, the only component of the yield spread that has forecast real activity is the expectations component, $ey_{t+1}^{(5-1)}$. This component is a strongly statistically significant predictor of real activity, while the risk premium component $ry_t^{(5-1)}$ has no marginal predictive power. Thus, while the yield spread as a whole forecasts real activity, as is well known, the risk premium component we identify is completely uninformative about future real activity. The findings imply that real activity responds differently to movements in the term structure that are unrelated to the federal funds rate than it does to other movements in the term structure.

The risk premium component $ry_t^{(5-1)}$ also has no predictive power in the Greenspan period (bottom panel of Table 6), although, in this shorter sample, neither does the explained component $ey_{t+1}^{(5-1)}$. Yield spreads as a whole display little forecasting power for real activity over this period, consistent with previous findings of (Stock and Watson (2003)).

These findings may be related to the behavior of the yield curve in recent quarters. The economy has grown robustly in recent data. The results above suggest that show that such growth has a negative affect on the term premium. Figure 10 displays a time series plot of our estimated term premium component $ry_t^{(5-1)}$, the orthogonalized shock to the yield spread equation from the bivariate VAR. From the far right-hand-side of the figure it is clear that, since 2004:Q2, this component of yields has been entirely responsible for the flat yield curve observed in recent data. In particular, in every quarter from 2004:Q3 to 2005:Q4, this component was negative and in some periods strongly so. In 2004:Q3, for example, this component stood at -1.33 percent per annum. But since the total yield spread was positive in each of these quarters, (ranging from 1.02 to 0.10 percent per annum), these results imply that the expectations component of the yield spread, $ey_{t+1}^{(5-1)}$, was even more strongly positive over this period. Indeed, the average value of $ey_{t+1}^{(5-1)}$ over the last five quarters exceeds the full-sample mean of the yield spread itself. Since it is this component and only this component of the term structure that has historically forecast real activity, the findings provide no evidence that the flat yield curve in recent data is currently signaling slow or negative economic growth. If anything, recent data imply that the term structure is currently signaling positive economic growth.

The behavior of the term structure in recent data appears to have been perceived, at least in part, as a surprise by the Federal Reserve, precisely because important movements in long-term yields seem to have been unrelated to Federal Reserve policy.[15] The findings here imply that such movements in long-term yields have become more important in recent decades, and now comprise a significant fraction of yield spread forecast error. These findings also lend some support to the judgements of Federal Reserve policymakers, which suggested that a significant portion of the decline in yield spreads recently appears to have resulted from a fall in risk premia (Greenspan (2005)). For the Greenspan era, our results suggest that term premia fall when the economy has been growing.

5 Conclusion

We contribute to the literature on bond return forecastability by showing that 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 emphasize two aspects of our findings. First, in contrast to the existing empirical

[15] For example, Chairman Alan Greenspan noted that "The drop in long-term rates is especially surprising given the increase in the federal funds rate over the same period. Such a pattern is clearly without precedent in our recent experience" (Greenspan (2005)).

literature, (which has focused on predictive regressions using financial indicators), we find strong predictable variation in excess bond returns that is associated with macroeconomic activity. Second, specifications using pure financial variables omit pertinent information about future bond returns associated with macroeconomic fundamentals. The factors we estimate have substantial predictive power independent of that in the Cochrane-Piazzesi forward factor, and therefore 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 our estimated factors is combined with that in the Cochrane-Piazzesi forward factor, we find remarkably large violations of the expectations hypothesis. These findings suggest that affine term structure models–which imply that bond yields or their linear transformations should summarize the predictive content in bond returns and yields–may be missing a quantitatively important aspect of bond data.

The predictive power of the estimated factors not just statistically significant, it is economically important, with 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 variables are factors based on real activity that are highly correlated with measures of output and employment, but two inflation factors and a stock market factor also contain information about future bond returns.

We then investigate the behavior of the term structure. Using a bivariate VAR for the yield spread and the federal funds rate, we show that shocks to the yield spread holding fixed the federal funds rate (interpreted as movements in risk premia) have become an economically important source variation in the forecast error of the term structure over the last 20 years. In the Greenspan era, these shocks are found to have a strong countercyclical component, and are forecastable by a "real" factor highly correlated with measures of output and employment growth. This suggests that investors must be compensated for risks related to recessions or, conversely, that investors require lower risk premia in good economic times. When the economy is growing, these forces contribute to a flattening of the yield curve even in periods when–as recently–the Federal Reserve has been raising interest rates.

Movements in the risk premium component of the yield curve display no forecasting power for real activity, however. Thus, real activity has historically responded differently to movements in the term structure that are orthogonal to the federal funds rate than it does to other movements.

The results for the post-Greenspan period also suggest that the behavior of the term structure may depend on whether Federal Reserve policy moves coincide with positive or negative economic growth. On the one hand, if an increase in interest rates is accompanied by an increase in economic activity (as recently), the policy movement is likely to coincide with a decline in risk premia, which works to flatten yield curve. Such a movement should partially offset any increase in the yield spread that arises from an increase in expected inflation. On the other hand, if an increase in interest rates is accompanied by an decline in economic activity, (perhaps partly as a result of the rate increase), the policy movement may coincide with an increase in risk premia, which works to steepen yield curve. In this event, the change in risk premia should reinforce any increase in the yield spread that arises from an increase in expected inflation.

The overall results support the hypothesis that bond risk premia 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), Brandt and Wang (2003) and Wachter (2006). At the same time, the analysis here leaves a number of 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 macro factors that are highly correlated with measures of real activity and inflation remains unanswered. These questions and more pose interesting research challenges for the future.

Appendix: 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, provided $\sqrt{T}/N$ goes to zero as the sample increases, the $\widehat{F}_t$ can be treated as observed regressors, and the usual t-statistics are valid (Bai and Ng (2005)). 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 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 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 estimated factors $\widehat{F}_t$ are presumed to contain additional predictive power for excess returns above and beyond that implied by the moving average error structure.

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 resampled (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 A1-A4 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.

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: $rx^{(4)}_{t+1} = \beta_0 + \beta_1' \widehat{F}_t + \beta_2 CP_t + \epsilon_{t+1}$,						
Regressor	(a)	(b)	(c)	(d)	(e)	(f)
$\widehat{F}_{1t}$		**-2.05**	**-1.51**			
(t-stat)		(-4.49)	(-4.20)			
$\widehat{F}^3_{1t}$		**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	1985:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.794	50.07*	3.28
2	1995:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.838	21.83*	2.01
3	1985:1-2003:12	$\overrightarrow{F5}_t + CP$ v.s. $const + CP$	0.810	45.77*	3.28
4	1995:1-2003:12	$\overrightarrow{F5}_t + CP$ v.s. $const + CP$	0.884	14.04*	2.01
		$rx_{t+1}^{(3)}$			
5	1985:1-2003:2	$\overrightarrow{F5}_t$ v.s. $const$	0.839	35.17*	3.28
6	1995:1-2003:2	$\overrightarrow{F5}_t$ v.s. $const$	0.858	16.75*	2.01
7	1985:1-2003:2	$\overrightarrow{F5}_t + CP$ v.s. $const + CP$	0.858	29.77*	3.28
8	1995:1-2003:2	$\overrightarrow{F5}_t + CP$ v.s. $const + CP$	0.894	10.70*	2.01
		$rx_{t+1}^{(4)}$			
9	1985:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.874	26.28*	3.28
10	1995:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.888	14.05*	2.01
11	1985:1-2003:12	$\overrightarrow{F5}_t + CP$ v.s. $const + CP$	0.891	21.86*	3.28
12	1995:1-2003:12	$\overrightarrow{F5}_t + CP$ v.s. $const + CP$	0.913	9.00*	2.01
		$rx_{t+1}^{(5)}$			
13	1985:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.905	20.20*	3.28
14	1995:1-2003:12	$\overrightarrow{F5}_t$ v.s. $const$	0.925	10.30*	2.01
15	1985:1-2003:12	$\overrightarrow{F5}_t + CP$ v.s. $const + CP$	0.926	15.18*	3.28
16	1995:1-2003:12	$\overrightarrow{F5}_t + CP$ v.s. $const + CP$	0.941	6.39*	2.01

*Significant at the one percent or better level.

Notes: See next page.

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 $\left(\widehat{F}_{1t}, \widehat{F}_{1t}^3, \widehat{F}_{3t}, \widehat{F}_{4t}, \widehat{F}_{8t}\right)'$. Rows denoted "$\overrightarrow{F5}_t$ v.s. $const$" report forecast comparisons of an unrestricted model, which includes the variables in $\overrightarrow{F5}_t$ as predictors, with a restricted, constant expected returns benchmark ($const$). Rows denoted "$\overrightarrow{F5}_t + CP$ v.s. $const + CP$" report forecast comparisons of an unrestricted model, which includes the variables in $\overrightarrow{F5}_t$ and CP as predictors, with a restricted benchmark model that includes a constant and CP. MSE_u is the mean-squared forecasting error of the unrestricted model; MSE_r is the mean-squared forecasting error of the restricted benchmark model that excludes additional forecasting variables. In the column labeled "MSE_u/MSE_r", a number less than one indicates that the unrestricted model has lower forecast error than the restricted benchmark 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 1984:12. The forecasting regressions are run for t =1964:1,...,1984:12 (dependent variables from 1964:1-1983:12, independent variable from 1965:1-1984:12), and the values of the regressors at t =1984:12 are used to forecast annual returns for 1975:1-1975:12. All parameters and factors are then reestimated from 1964:1 through 1985:1, and forecasts are recomputed for returns in 1985:2-1986:1, 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 second row, where the initial estimation period is 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 4: Variance Decomposition of Funds Rate and Five-Year Yield Spread

	FF_{t+h}		$y^{(5)}_{t+h} - y^{(1)}_{t+h}$	
Horizon h	FF shock	Yield spread shock	FF shock	Yield spread shock
1954:Q3-2005:Q4				
1	1.000	0.000	0.663	0.337
2	0.997	0.003	0.656	0.344
3	0.996	0.004	0.647	0.353
4	0.995	0.005	0.637	0.363
∞	0.997	0.003	0.594	0.406
1954:Q3-1979:Q2 (pre-Volcker)				
1	1.000	0.000	0.671	0.329
2	1.000	0.000	0.780	0.220
3	0.998	0.002	0.818	0.182
4	0.995	0.005	0.833	0.167
∞	0.907	0.093	0.836	0.164
1983:Q1-2005:Q4 (recent)				
1	1.000	0.000	0.237	0.763
2	0.993	0.007	0.407	0.593
3	0. 984	0.016	0.516	0.484
4	0.975	0.025	0.597	0.421
∞	0.906	0.094	0.649	0.351
1987:Q3-2005:Q4 (Greenspan)				
1	1.000	0.000	0.183	0.817
2	0.994	0.006	0.462	0.538
3	0.999	0.001	0.636	0.364
4	0.998	0.002	0.730	0.270
∞	0.938	0.062	0.830	0.170

Notes: The table reports the fraction of the variance in the h step-ahead forecast error of the variable listed at the head of each column that is attributable to innovations in the federal funds rate equation, "FF shock," and to innovations in the yield spread equation. The decompositon is calculated from a second order bivariate VAR for FF_t and $y^{(5)}_{t+1} - y^{(1)}_{t+1}$. The residuals are orthogonalized by a Cholesky decomposition of the VAR errors with FF_t ordered first.

Table 5: Forecasts of Orthgonalized Yield Spread

Model: $ry_{t+1}^{(5-1)} = \gamma_0 + \gamma \widehat{F}_{1,t} + \varepsilon_{t+1}$		
γ_0	γ	R^2
(t-stat)	(t-stat)	—
1964:Q1-2003:Q4		
0.014	0.015	0.000
(0.18)	(0.14)	—
1964:Q1-1979:Q2 (pre-Volcker)		
-0.096	-0.030	0.001
(−1.24)	(−0.48)	—
1979:Q3-2003:Q4 (post-Volcker)		
0.078	0.106	0.007
(0.63)	(0.65)	—
1987:Q3-2003:Q4 (Greenspan)		
0.004642	**-0.529**	0.11
(0.04)	(−3.21)	—

Notes: $ry_{t+1}^{(5-1)}$ is the orthogonalized yield spread between the five-year Treasury bond and the one-year bond, calculated from a second order bivariate VAR for FF_t and $y_{t+1}^{(5)} - y_{t+1}^{(1)}$. The residuals are orthogonalized by a Cholesky decomposition of the VAR errors with FF_t ordered first. $ry_{t+1}^{(5-1)}$ denotes the orthogonalized residuals in the yield equation. $\widehat{F}_{1,t}$ denotes the first common factor from the dataset on aggregate activity. Newey and West (1987) corrected t-statistics have lag orderthree quarters and are reported in parentheses. Coefficients that are statistically significant at the 5% or better level are highlighted in bold.

Table 6: Forecasts of Real Factor with Five-Year Yield Spread Components

Model: $\widehat{F}_{1,t+1} = \gamma_0 + \gamma \left(y_t^{(5)} - y_t^{(1)} \right) + \varepsilon_{t+1}$			
γ_0 (t-stat)	γ (t-stat)		$\overline{R}^2$ —
-0.194	**0.310**		0.08
(-1.20)	(2.30)		—

Model: $\widehat{F}_{1,t+1} = \gamma_0 + \gamma \left(ry_t^{(5-1)} \right) + \varepsilon_{t+1}$			
γ_0 (t-stat)	γ (t-stat)		$\overline{R}^2$
-0.011	-0.007		-0.01
(-0.09)	(-0.02)		

Model: $\widehat{F}_{1,t+1} = \gamma_0 + \gamma_1 \left(ey_t^{(5-1)} \right) + \gamma_2 \left(ry_t^{(5-1)} \right) + \varepsilon_{t+1}$			
γ_0 (t-stat)	γ_1 (t-stat)	γ_2 (t-stat)	$\overline{R}^2$ —
-0.223	**0.339**	-0.006	0.08
(-1.41)	(2.60)	(-0.02)	—

1987:Q3-2003:Q4 (Greenspan)			
Model: $\widehat{F}_{1,t+1} = \gamma_0 + \gamma_1 \left(ey_t^{(5-1)} \right) + \gamma_2 \left(ry_t^{(5-1)} \right) + \varepsilon_{t+1}$			
γ_0 (t-stat)	γ_1 (t-stat)	γ_2 (t-stat)	$\overline{R}^2$ —
-0.231	0.11	0.07	-0.02
(-1.11)	(0.78)	(0.20)	—

Notes: $\widehat{F}_{1,t}$ denotes the first common factor from the dataset on aggregate activity. The explanatory variables include $y_t^{(5)} - y_t^{(1)}$, the spread between the five-year Treasury bond and the one-year bond. This yield spread is decomposed into two components using a second order bivariate VAR for FF_t and $y_{t+1}^{(5)} - y_{t+1}^{(1)}$. The component denoted $ry_{t+1}^{(5-1)}$ is the orthogonalized innovation in the yield spread equation calculated from the VAR, where the VAR errors are orthgonalized so that the federal funds rate does not respond contemporaneously to the yield spread innovation.. The component denoted $ey_{t+1}^{(5-1)}$ is the remaining component of the yield spread, that component "explained" by current and lagged values of the funds rate and lagged values of the yield spread. Newey and West (1987) corrected t-statistics with lag order three quarters and are reported in parentheses. Coefficients that are statistically significant at the 5% or better level are highlighted in bold. Except for the third panel, the data are quarterly and span the period 1964:Q1-2003:Q4.

Table A1: Small Sample Inference, $rx_{t+1}^{(2)}$

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

		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)
$\widehat{F}_{1t}^3$	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: $rx_{t+1}^{(2)} = \beta_0 + \beta_1' \overrightarrow{F5}_t + \beta_2 CP_t + \epsilon_{t+1}$

		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)
$\widehat{F}_{1t}^3$	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: $rx_{t+1}^{(2)} = \beta_0 + \beta_1' F5_t + \epsilon_{t+1}$

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

		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 A2: 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 A1.

Table A3: 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 A1.

Table A4: 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: $rx_{t+1}^{(5)} = \beta_0 + \beta_1' F5_t + \epsilon_{t+1}$

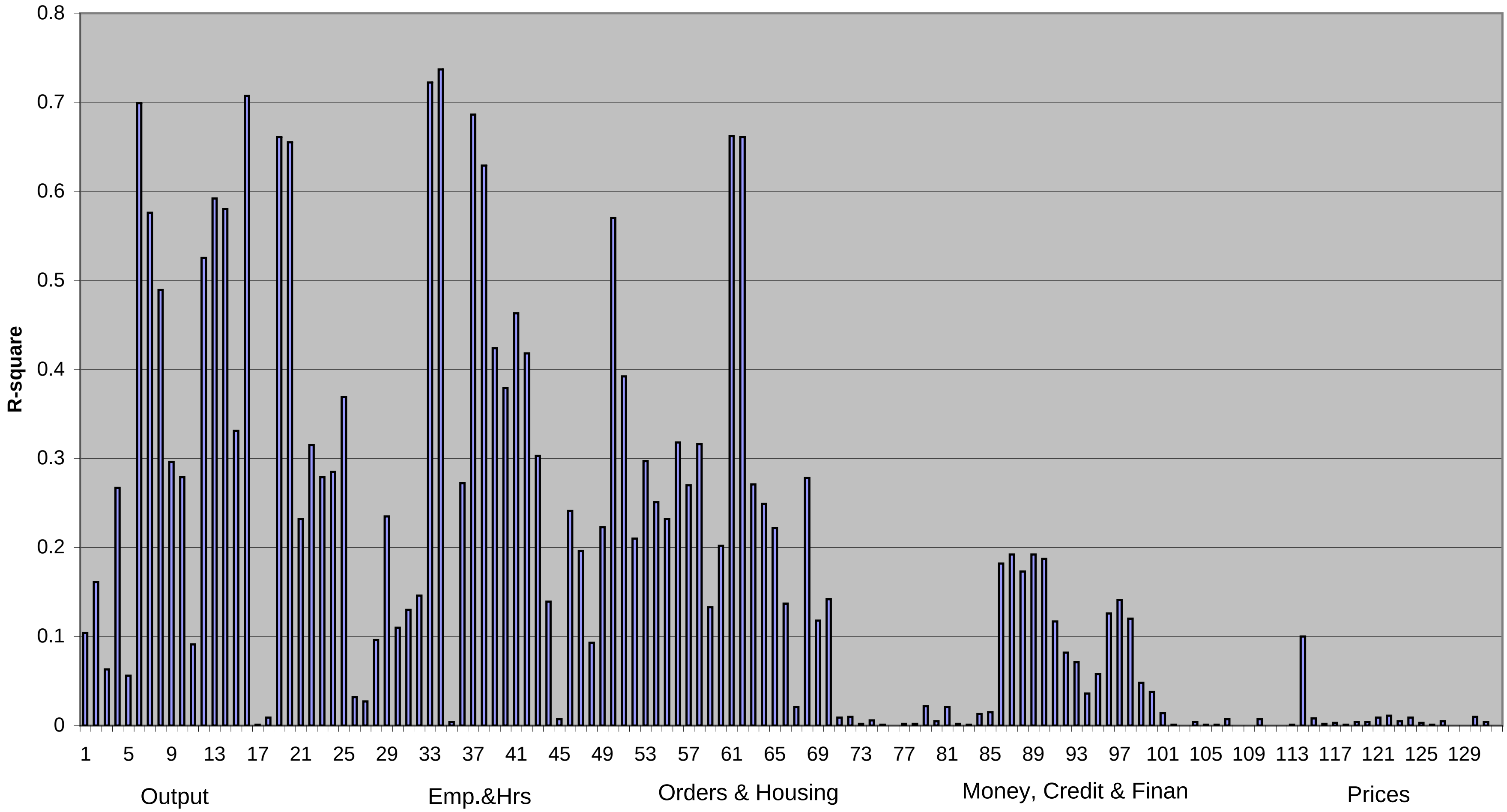
		Bootstrap		Bootstrap under the null	
x_t	$\hat{\beta}$	95% CI	90% CI	95% CI	90% CI
c	-0.145	(-1.940 1.457)	(-1.725 1.238)	(0.470 0.473)	(0.470 0.472)
$F5_t$	1.362	(0.596 2.087)	(0.756 2.001)	(0.008 0.011)	(0.008 0.011)
R^2	0.146	(0.027 0.303)	(0.046 0.287)	(0.008 0.015)	(0.009 0.014)
$\bar{R}^2$	0.145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

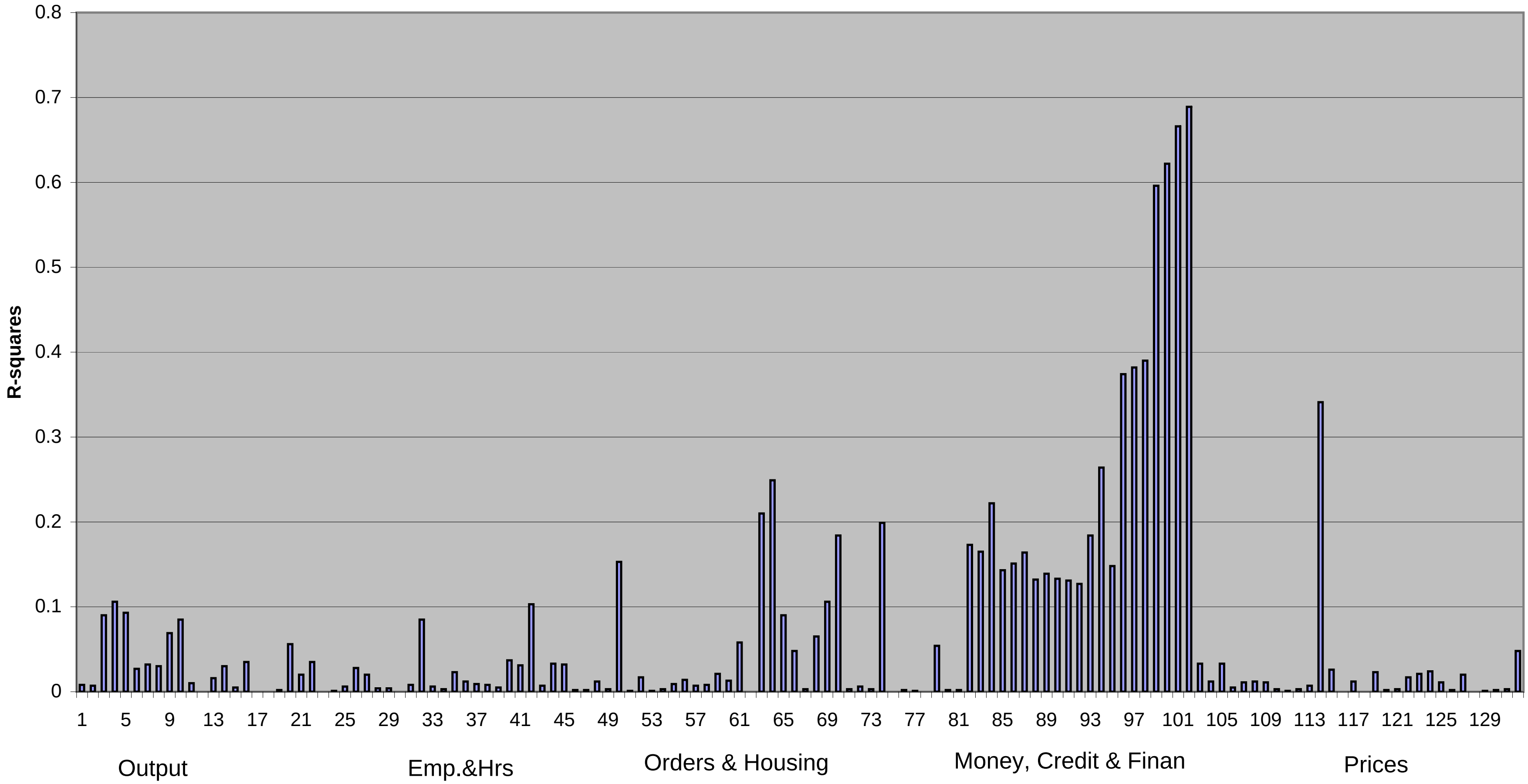
Notes: See Table A1.

Figure1: Marginal R-squares for F_1



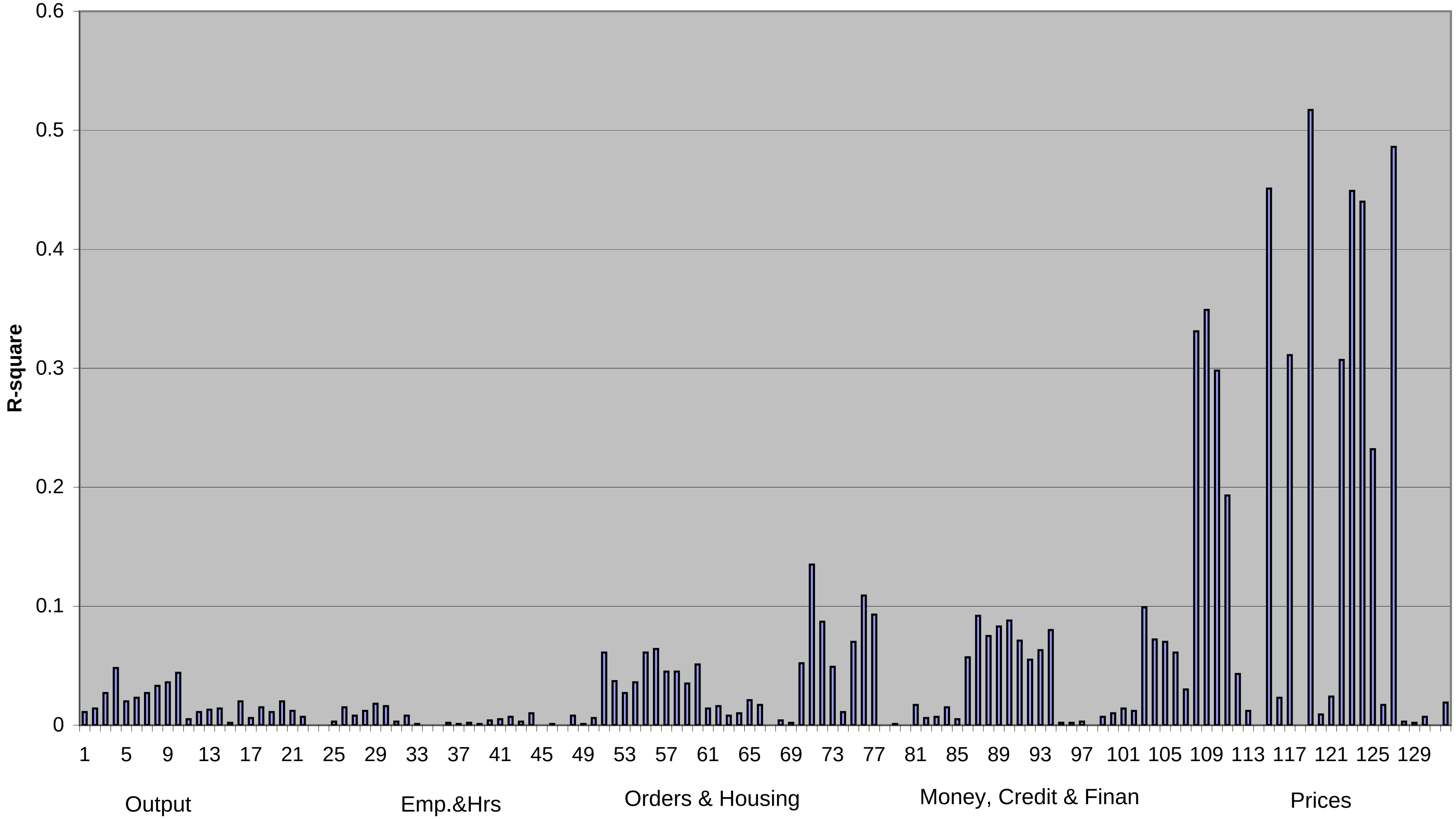
Notes: Chart shows the R-square from regressing the series number given on the x-axis onto F_1. See the appendix for a description of the numbered series. The factors are estimated using data from 1964:1-2003:12.

Figure 2: Marginal R-squares for F_2



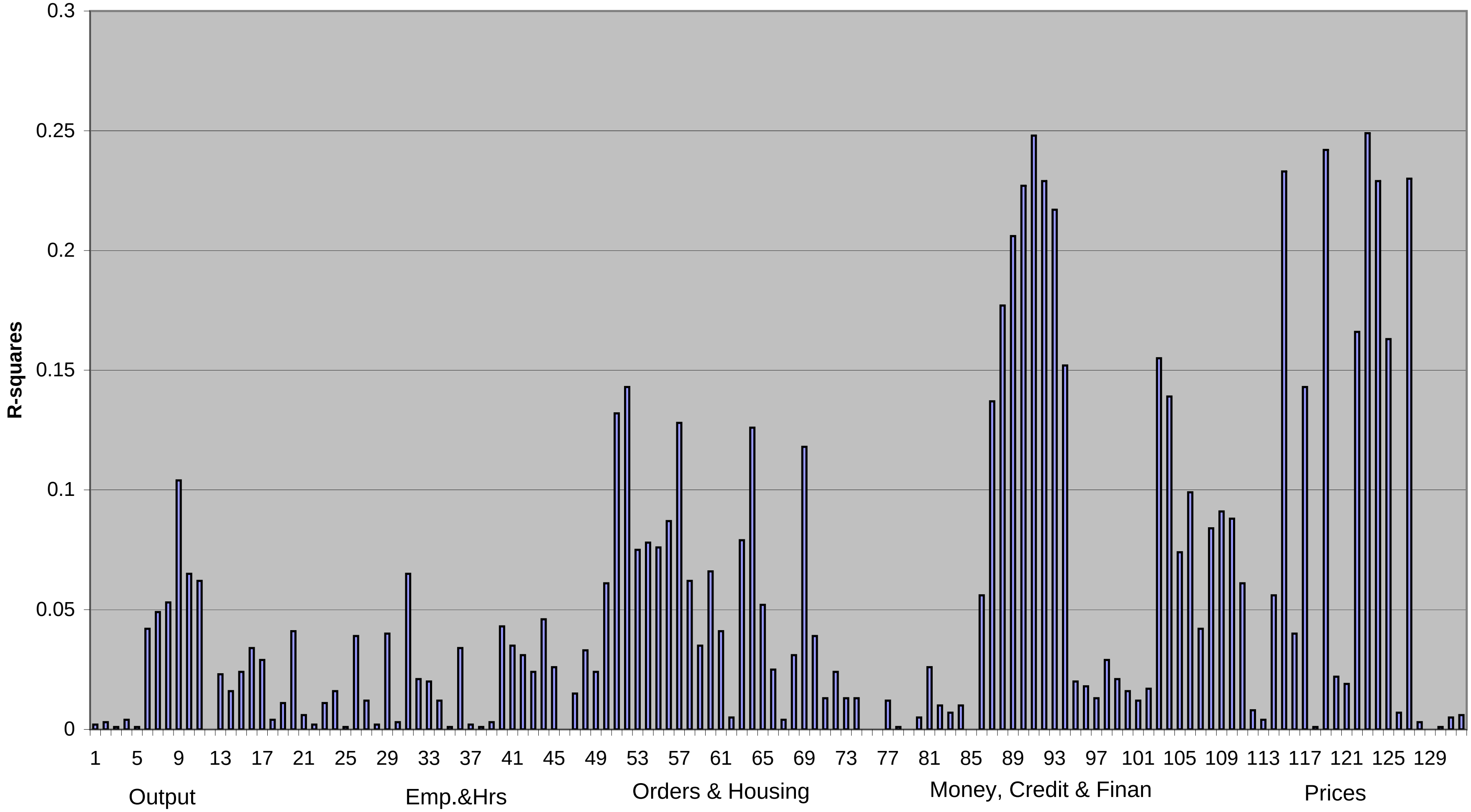
Notes: See Figure 1.

Figure 3: Marginal R-squares for F_3



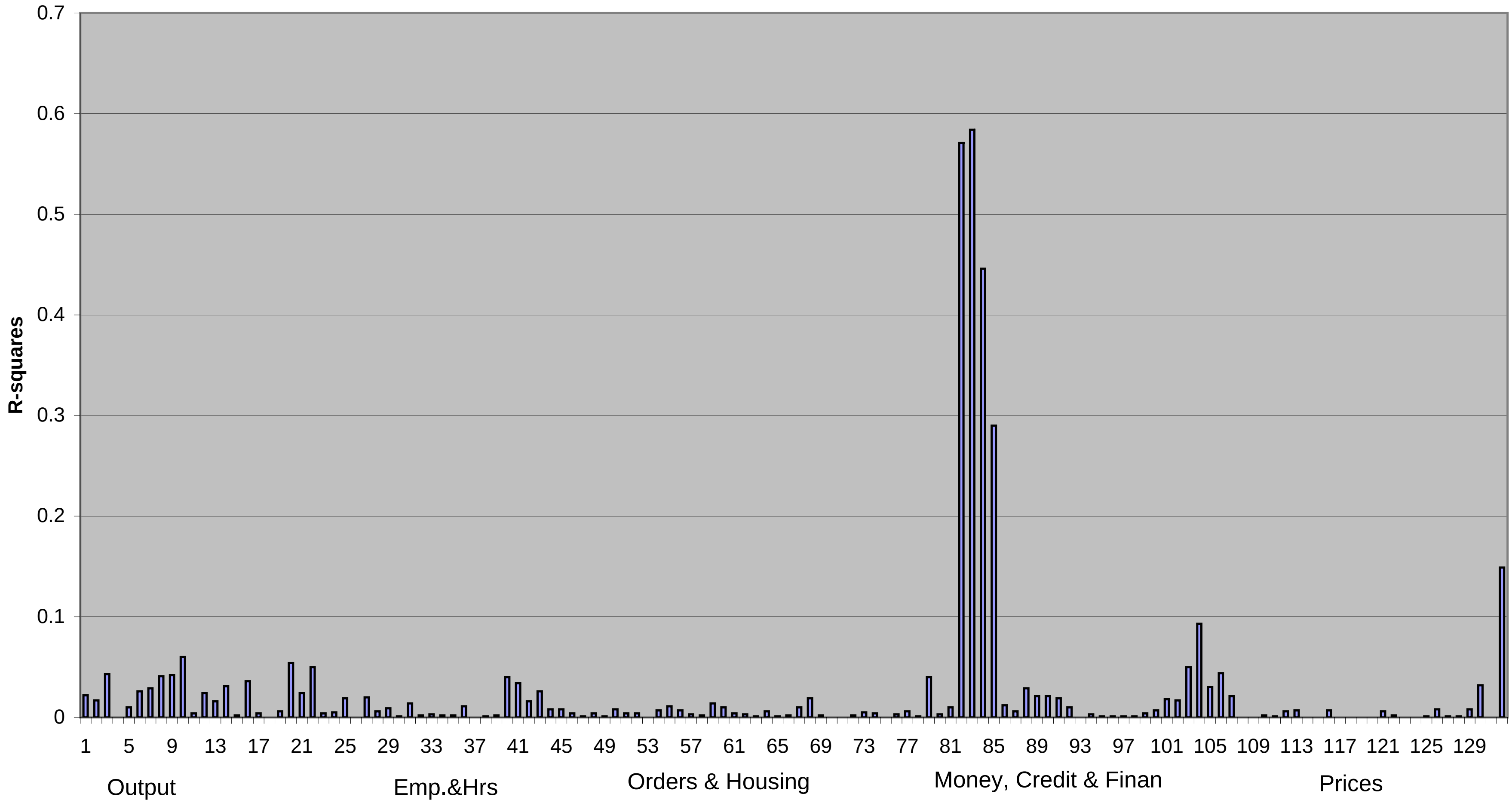
Notes: See Figure 1.

Figure 4: Marginal R-squares for F_4



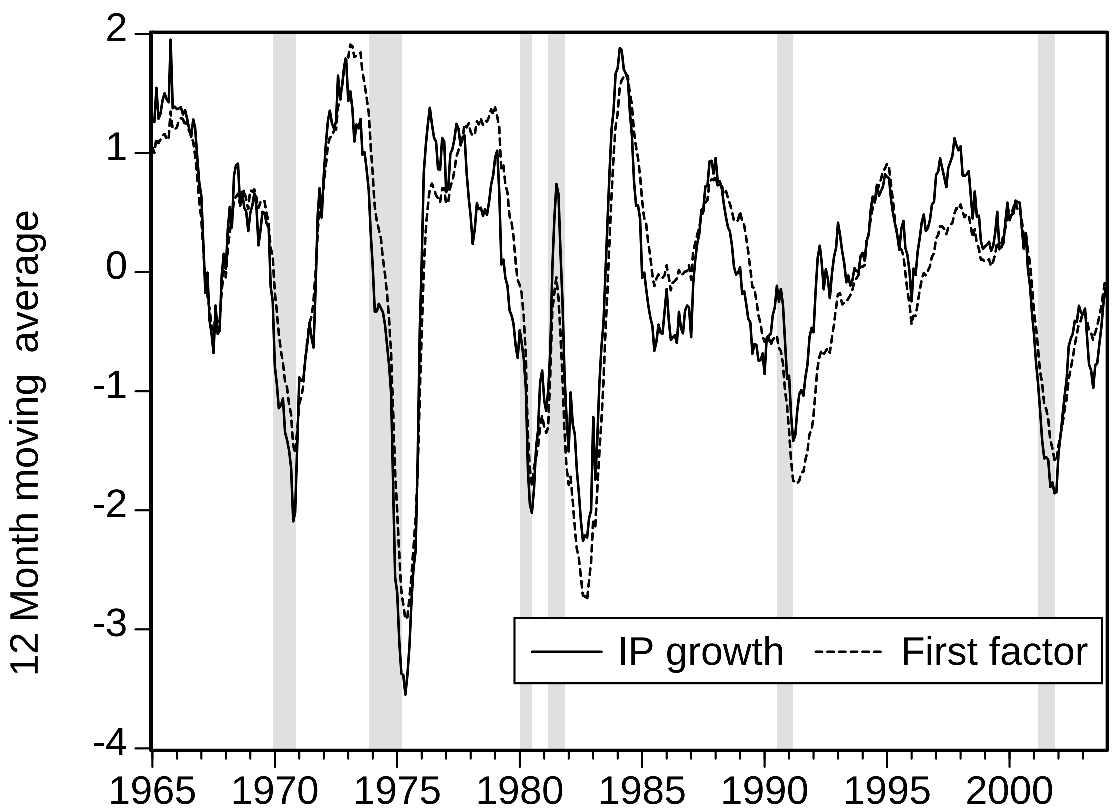
Notes: See Figure 1.

Figure 5: Marginal R-squares for F_8



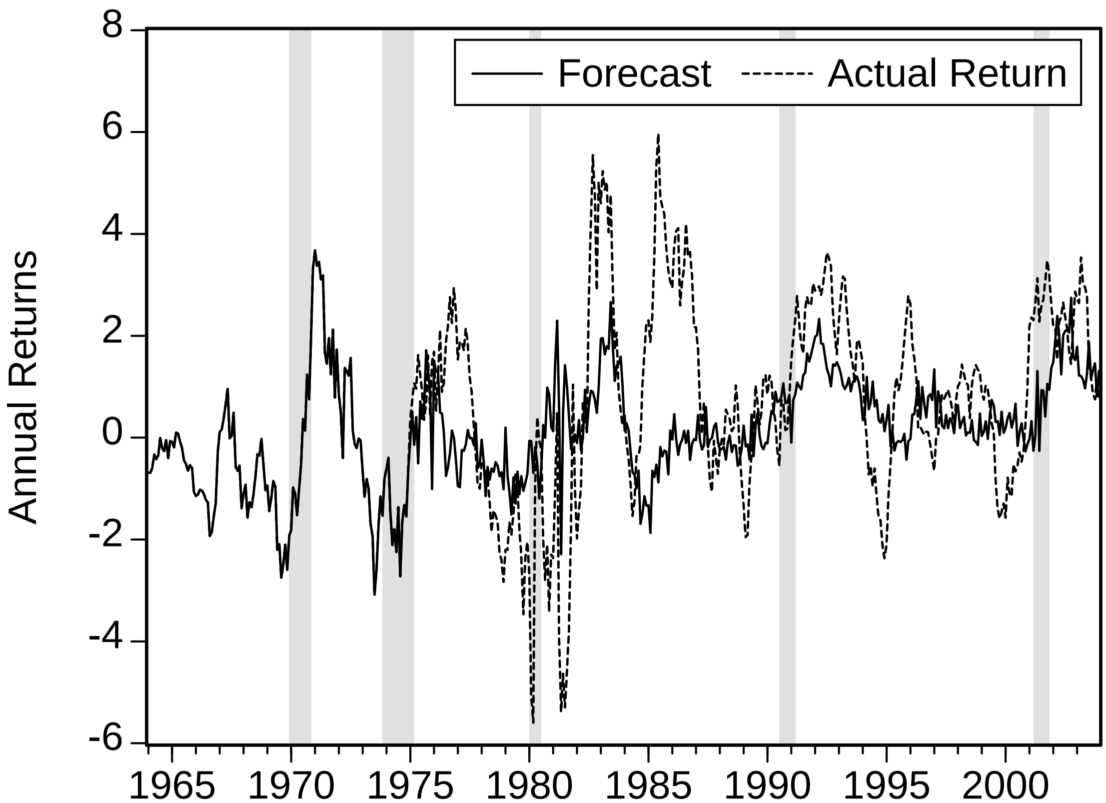
Notes: See Figure 1.

Figure 6: First factor and IP growth



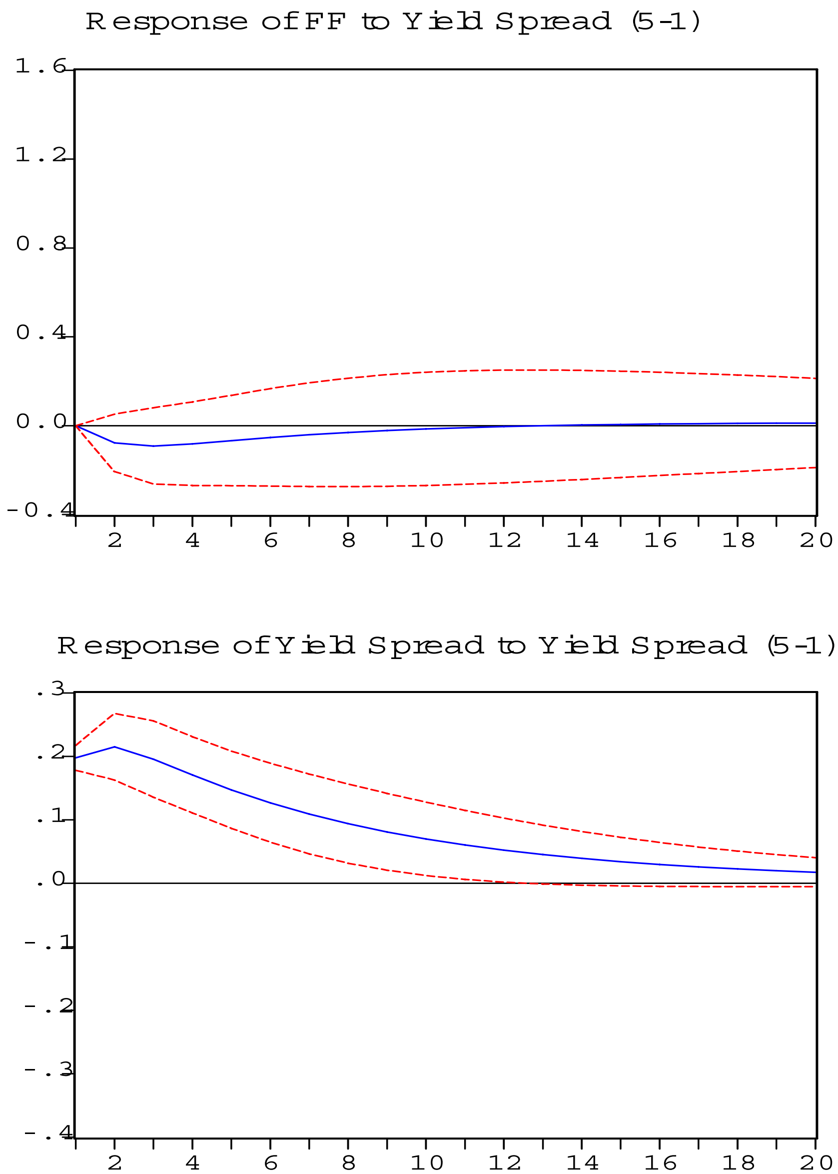
Note: Standardized units are reported. Shadings denote months designated as recessions by the NBER

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



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

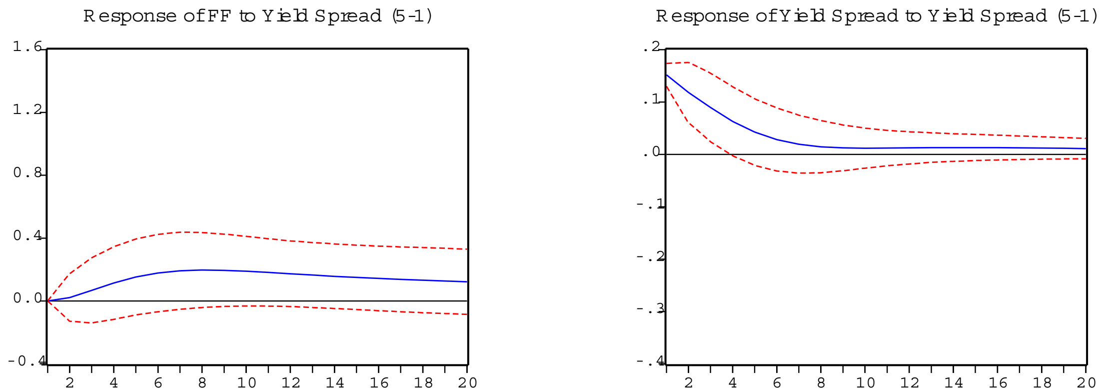
Figure 8: Impulse Responses, Full Sample



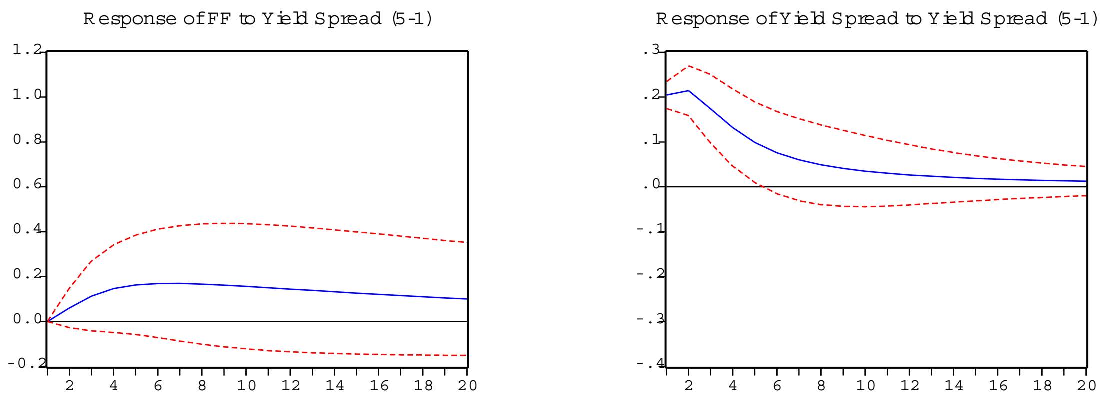
Notes: The Chart shows the 20-quarter response of variables to a one-standard deviation innovation in the spread on the five- minus one-year Treasury bond. The VAR residuals are orthogonalized using a Cholesky decomposition with the funds rate ordered first. The dashed lines represent two-standard error bands. The sample period is 1954:Q3-2005:Q4.

Figure 9: Impulse Responses, Subsamples

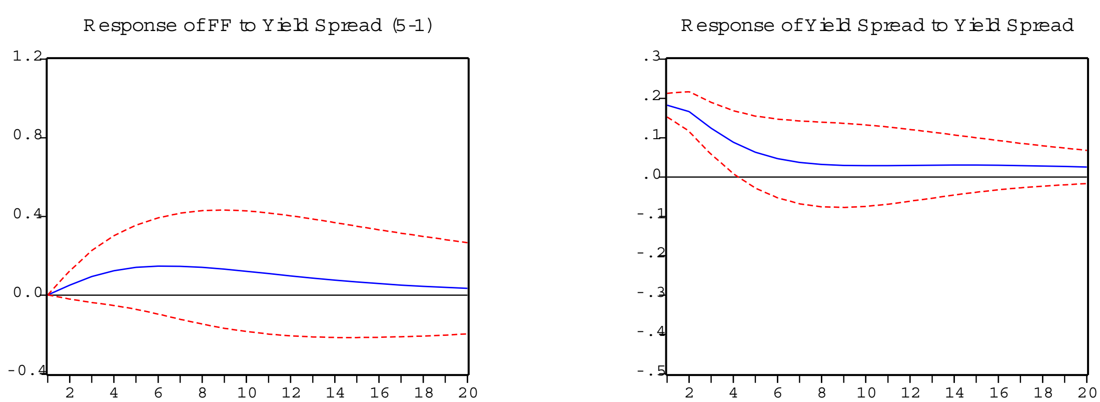
Pre-Volcker Period



Recent Period



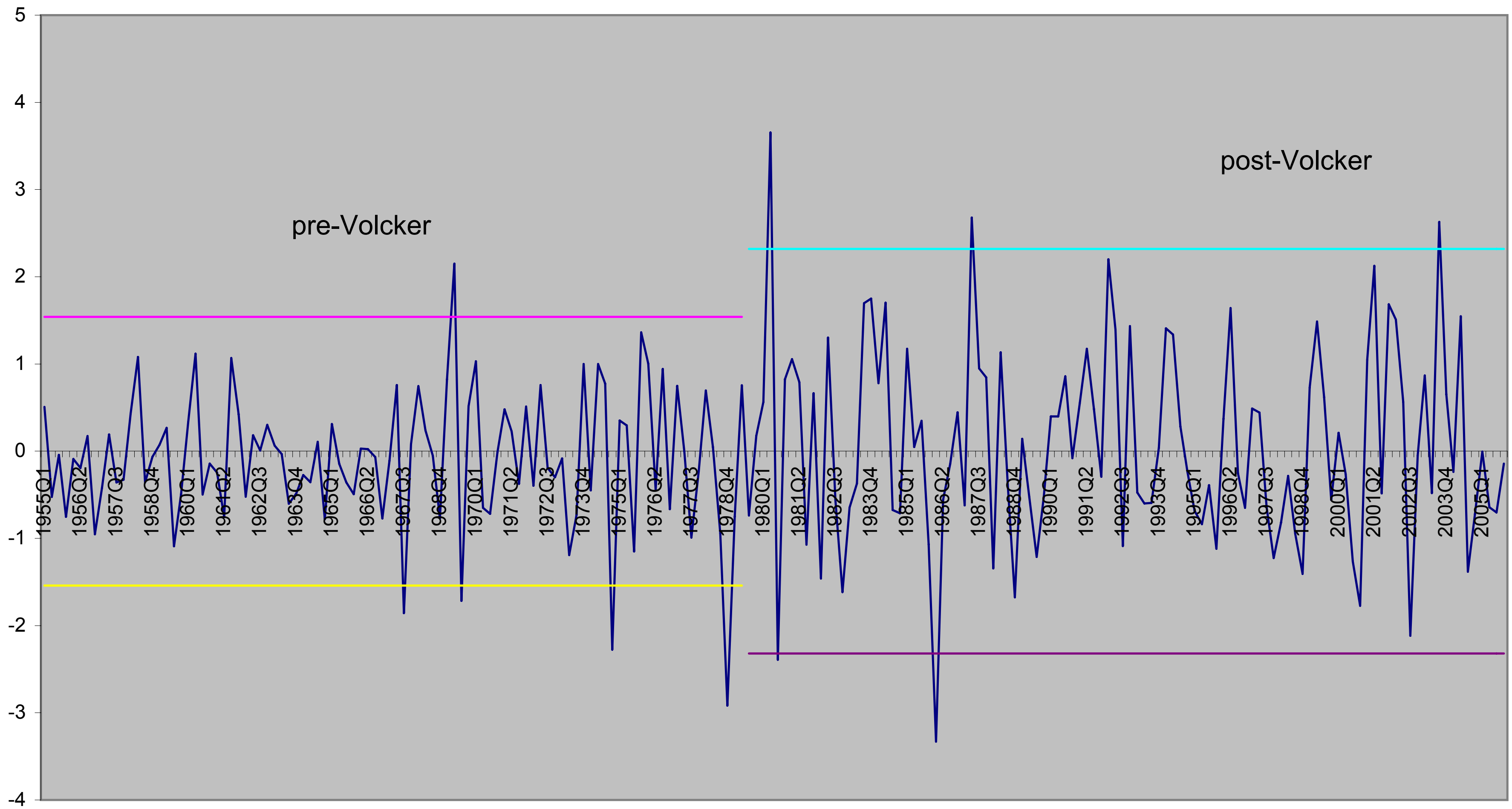
Greenspan Period



Notes: See next page.

Notes: The Chart shows the 20-quarter response of variables to a one-standard deviation innovation in the spread on the five- minus one-year Treasury bond. The VAR residuals are orthogonalized using a Cholesky decomposition with the funds rate ordered first. The dashed lines represent two-standard error bands. The sample period in the top panel is 1954:Q3-1979:Q2, in the middle panel is 1983:Q1-2005Q4, and in the bottom panel 1987:Q3-2005Q4.

Figure 10: Orthgonalized Residuals of Yield Spread (5-1)



Notes: The figure plots the residual for the yield spread (5-1) from a bivariate VAR of yields spreads and the federal funds rate. The VAR errors are orthgonalized so that the federal funds rate does not respond contemporaneously to a yield spread shock. Standardized units are reported. The lines in the plot represent plus and minus two-standard deviations in the pre- and post-Volcker regimes.