Macro Factors in Bond Risk Premia

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Are there important cyclical fluctuations in bond market premiums and, if so, with what macroeconomic aggregates do these premiums 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 commonly employed affine term structure models where the forecastability of bond returns and bond yields is completely summarized by the cross-section of yields or forward rates. An important implication of these findings is that the cyclical behavior of estimated risk premia in both returns and long-term yields depends importantly on whether the information in macroeconomic factors is included in forecasts of excess bond returns. Without the macro factors, risk premia appear virtually acyclical, whereas with the estimated factors risk premia have a marked countercyclical component, consistent with theories that imply investors must be compensated for risks associated with macroeconomic activity. (*JEL* E0, E4, G10, G12)

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

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30% and 35% 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.

This article addresses two empirical questions. First, do the movements in bond market risk premia bear any direct relation to cyclical macroeconomic activity? And second, if so, do macroeconomic fundamentals contain information about risk premia that is not already embedded in bond market data?

The first question is central to whether models with rational, utility-maximizing investors can explain the predictable variation in financial market returns that we observe in the data. Such economic theories almost always imply that investors must be compensated with risks associated with recessions, and macroeconomic activity more generally. For example, Campbell and Cochrane (1999) theorize that risk premia vary with the difference between consumption and a slow-moving habit, where this difference is driven by shocks to aggregate consumption. In this model, financial market risk premia rise when the economy is growing slowly or contracting.[1] The second question is important for understanding the types of restrictions such models would require to ensure that the equilibrium return on bonds varies over time in a manner consistent with both macroeconomic and financial market data.

Yet, despite the growing body of theoretical work rationalizing asset market risk premia, there is little direct evidence of a link between business cycle activity in macroeconomic variables and risk premia in bond markets. The empirical evidence cited above 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.

[1] Campbell and Cochrane focus on equity risk premia. 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 premiums) should vary with the same macroeconomic shocks that drive the Campbell-Cochrane model. Brandt and Wang (2003) argue that risk premia are driven by shocks to inflation, as well as shocks to aggregate consumption. Other models of rational, utility-maximizing investors imply that risk premia fluctuate with countercyclical movements in macroeconomic uncertainty (e.g., Bansal and Yaron 2004; Bansal, Khatchatrian, and Yaron 2005).

This article 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 by estimating common factors from a monthly panel of 132 measures of economic activity. 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* vary with macroeconomic fundamentals.

Our results indicate that excess bond returns are indeed forecastable by macroeconomic fundamentals, and we find marked countercyclical variation in bond risk premia. The magnitude of the forecastability that we find associated with macroeconomic activity is not only statistically significant, but it also is economically significant. The estimated factors have their strongest predictive power for two-year bonds, explaining 26% 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 by CP_t, explains 31% 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 estimated as the principal components of the yield covariance matrix. For example, when both CP_t and a linear combination of our estimated macro factors are included together as predictor variables, each variable is strongly marginally statistically significant, and the regression model can explain as much as 44% of next year's two-year excess bond return, an improvement of 13% 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 yield curve. This behavior is ruled out by the unrestricted (and commonly employed) no-arbitrage affine term structure models, where the forecastability of bond returns and bond yields is completely summarized by the cross-section of yields or forward rates. This behavior is not, however, ruled out by restricted affine term structure models (e.g., Duffee 2008). We discuss this further below.

Our results can be used to decompose long-term bond yields into an expectations component and a (yield) risk-premium component. We show that the cyclical behavior of the risk-premium component, both in yields and in returns, depends importantly on whether the predictive information contained in the estimated factors is included when forecasting excess bond returns. When the information in macro factors is ignored, both return and yield risk premia are virtually acyclical, exhibiting a correlation with real industrial production growth that is close to zero. This is true even if CP_t is used as a predictor variable for returns. By contrast, when the information in the estimated factors is included, bond risk premia have a marked countercyclical component and are found to be substantially higher in recessions. These findings underscore the importance of using information beyond that contained in the yield curve to uncover business-cycle variation in risk premia associated with real macroeconomic activity.

By tying time-varying risk premia directly to macroeconomic fundamentals, the findings presented here are, to the best of our knowledge, the first of their kind for bond market data that are consistent (in a particular way) with rational, utility-maximizing models, which almost always imply that investors must be compensated for risks associated with recessions, and macroeconomic activity more generally. The findings also demonstrate the importance of including the information in macro factors in accounting properly for risk premia, especially in recessions. When this information is ignored, too much of the business cycle variation in long-term yields is attributed to expectations of future nominal interest rates, and too little is attributed to changes in the compensation for bearing risk.

The rest of this article is organized as follows. In the next section, we briefly review the 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 risk premia in bond yields implied by our bond return forecasts. This analysis is conducted in Section 4. Section 5 concludes. Additional results, extended to more maturities and an updated sample, will be available in Ludvigson and Ng (2009).

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, 2006). Dynamic factor analysis with large N and large T is preceded by a literature studying classical factor analysis for the case where N is relatively small and fixed but $T \to \infty$. See, for example, Sargent and Sims (1977); Sargent (1989); and Stock and Watson (1989, 1991). By contrast, Connor and Korajczyk (1986, 1988) pioneered techniques for undertaking dynamic factor analysis when T is fixed and $N \to \infty$.

The presumption of the dynamic factor model is that the covariation among economic time series is captured by a few unobserved common factors. Stock and Watson (2002b) show that consistent estimates of the space spanned by the common factors may be constructed by principal components analysis. A large and growing body of literature has applied dynamic factor analysis in a variety of empirical settings. Stock and Watson (2002b and 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 (VAR) framework to study the macroeconomic effects of policy interventions, patterns of comovement in economic activity, or term structure dynamics (Bernanke and Boivin 2003; Bernanke, Boivin, and Eliasz 2005; Giannone, Reichlin, and Sala 2002, 2005; Stock and Watson 2005;

Mönch 2007). Boivin and Giannoni (2005) use dynamic factor analysis of large datasets to form empirical inputs into dynamic stochastic general equilibrium models. Ludvigson and Ng (2007) 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 the possible empirical linkages between macroeconomic variables and bond prices in a no-arbitrage factor model of the term structure of interest rates. Building on 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.[2] The investigation of this article differs because we 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 premiums are forecastable by macroeconomic fundamentals. We view our investigation as complementary to that of Ang and Piazzesi. Finally, in a very recent work, Duffee (2008) presents evidence of a latent bond market factor that, like our constructed factors, predicts future yields and future returns but is not revealed by the cross-section of bond yields or forward rates. As in our investigation, he finds that the factor is related to fluctuations in real economic activity.

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 2002a, 2002b, 2004). Our notation for excess bond returns and yields closely follows that in Cochrane (2005). We refer the reader to those articles 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 article is to assess whether there is palpable forecastable variation in

[2] A closely related approach is taken in a 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, 2005), use affine models to link the term structure to perceptions of monetary policy.

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 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 as $rx_{t+1}^{(n)} \equiv r_{t+1}^{(n)} - y_t^{(1)}$, 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.[3]

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

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

by least squares. For example, Z_t could include the individual forward rates studied in Fama and Bliss (1987), the single forward factor studied in Cochrane and Piazzesi (2005) (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 premiums and macroeconomic fundamentals. In particular, suppose we observe a $T \times N$ panel of macroeconomic data with elements x_{it}, $i = 1, \ldots N$, $t = 1, \ldots, T$, 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 combinations to consider. Furthermore, letting x_t denote the $N \times 1$ vector of panel observations at time t, estimates from the regression

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

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

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

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

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

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

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

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

As common factors are not observed, we replace f_t by $\widehat{f}_t$, estimates that, when $N, T \to \infty$, span the same space as f_t. (Since f_t and λ_i cannot be separately identified, the factors are identifiable only up to an $r \times r$ matrix.) In practice, f_t are estimated by principal components analysis (PCA).[5] Let the Λ be the $N \times r$ matrix defined as $\Lambda \equiv (\lambda_1', \ldots, \lambda_N')'$. Intuitively, the estimated time t factors $\widehat{f}_t$ are linear combinations of each element of the $N \times 1$ vector $x_t = (x_{1t}, \ldots, x_{Nt})'$, where the linear combination is chosen optimally to minimize the sum of squared residuals $x_t - \Lambda f_t$. Throughout the article, 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 Bayesian information criterion (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.[6] The vector Z_t contains additional

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

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

where M is a constant.

[5] To be precise, the $T \times r$ matrix $\widehat{f}$ is $\sqrt{T}$ times the r eigenvectors corresponding to the r largest eigenvalues of the $T \times T$ matrix $xx'/(TN)$ in decreasing order. Let Λ be the $N \times r$ matrix of factor loadings $(\lambda_1', \ldots, \lambda_N')'$. 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).

[6] 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

(nonfactor) 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 Equation (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 Equation (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 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 $N, T \to \infty$ with $\sqrt{T}/N \to 0$, Bai and Ng (2006) showed that $(\hat{\alpha}, \hat{\beta})$ obtained from least squares estimation of Equation (5) are $\sqrt{T}$ consistent and asymptotically normal, and the asymptotic variance is such that the 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). 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

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.

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 1964:1–2003:12, the same sample that was 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 1964:1–2003:12. The economic series are provided by James Stock and Mark Watson and used in 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 ensure 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. This is important because business cycle fluctuations in the aggregate economy—the sort of cyclical variation we are interested in—consist of substantial co-movement in financial and real variables. Presumably, such fluctuations are driven by a small number of primitive shocks that affect both financial markets and aggregate quantities. Because these common movements are likely to be among the most important sources of variation in cyclical macro variables, one would not want to remove variables classified as "financial" from the dataset. As we argue below, the important findings are not what variables we have included in our large dataset but rather, first, that the estimated factors are highly correlated with real macroeconomic activity (and not highly correlated with financial indicators) and, second, that they contain business cycle information about future excess bond returns that is not in the bond market data previously found to have substantial forecasting power for bond returns.

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

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 factor 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.

in individual yield spreads and forward spreads 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 is 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.[7] 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% 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 has 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.[8] 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 $F_t = \overrightarrow{F6}_t = (\widehat{F}_{1t}, \widehat{F}_{1t}^3, \widehat{F}_{2t}, \widehat{F}_{3t}, \widehat{F}_{4t}, \widehat{F}_{8t})'$ 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 estimated factor. The estimated factors $\widehat{F}_{5t}$ and $\widehat{F}_{6t}$ exhibit little forecasting power for excess bond returns. When CP_t is included, by contrast, the five-factor subset $F_t \subset f_t$ given by $F_t = \overrightarrow{F5}_t = (\widehat{F}_{1t}, \widehat{F}_{1t}^3, \widehat{F}_{3t}, \widehat{F}_{4t}, \widehat{F}_{8t})'$ 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 premiums 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 by $F6_t$ and $F5_t$, respectively:

$$\frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)} = \gamma_0 + \gamma_1 \widehat{F}_{1t} + \gamma_2 \widehat{F}_{1t}^3 + \gamma_3 \widehat{F}_{2t} + \gamma_4 \widehat{F}_{3t} + \gamma_5 \widehat{F}_{4t} + \gamma_6 \widehat{F}_{8t} + u_{t+1},$$
$$F6_t \equiv \widehat{\gamma}' \overrightarrow{F6}_t, \tag{7}$$

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

[8] 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.

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

$$F5_t \equiv \widehat{\delta}' \overrightarrow{F5}_t, \tag{8}$$

where $\widehat{\gamma}$ and $\widehat{\delta}$ denote the 6×1 and 5×1 vectors of estimated coefficients from Equations (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. Table 2 presents results from in-sample forecasting regressions of the general form (5), for two-, three-, four-, and five-year log excess bond returns.[9] 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 Equation (5) given in Equation (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. A subsection 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 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 ensure that the procedure fully corrects for the MA(12) error structure.

First, consider the top panel of Table 2, which shows the results of predictive regressions for excess returns on the two-year bond $rx_{t+1}^{(2)}$. As a benchmark, row *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, $g_t^{(2)}, g_t^{(3)}, \ldots, g_t^{(5)}$, is strongly statistically significant and explains 31% of next year's two-year excess bond return. By comparison, row *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 marginally statistically significant at the 5% or better level. Together, these factors are statistically significant predictors of bond returns and explain 26% of the variation one year ahead in the two-year return. Although the second factor, $\widehat{F}_{2t}$, is strongly statistically

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

Table 2
Regression of monthly excess bond returns on lagged cactors

Model: $rx_{t+1}^{(n)} = \beta_0 + \beta_1' \widehat{F}_t + \beta_2 CP_t + \epsilon_{t+1}$,

		$\widehat{F}_{1t}$	$\widehat{F}_{1t}^3$	$\widehat{F}_{2t}$	$\widehat{F}_{3t}$	$\widehat{F}_{4t}$	$\widehat{F}_{8t}$	CP_t	$F5_t$	$F6_t$	$\bar{R}^2$
	(a)							**0.45**			0.31
								(8.90)			
	(b)	**−0.93**	**0.06**	**−0.40**	**0.18**	**−0.33**	**0.35**				0.26
		(−5.19)	(2.78)	(−3.10)	(2.24)	(−2.94)	(4.35)				
	(c)	**−0.74**	**0.05**	0.08	**0.24**	**−0.24**	**0.24**	**0.41**			0.45
		(−4.48)	(2.70)	(0.71)	(3.84)	(−2.51)	(2.70)	(5.22)			
$rx_{t+1}^{(2)}$	(d)	**−0.93**	**0.06**		0.18	**−0.33**	**0.35**				0.22
		(−4.96)	(2.87)		(1.87)	(−2.65)	(3.83)				
	(e)	**−0.75**	**0.05**		**0.24**	**−0.25**	**0.24**	**0.40**			0.45
		(−4.71)	(2.71)		(3.85)	(−2.61)	(2.89)	(5.89)			
	(f)								**0.54**		0.22
									(5.52)		
	(g)									**0.50**	0.26
										(6.78)	
	(h)							**0.39**	**0.43**		0.44
								(6.0)	(5.78)		
	(a)							**0.85**			0.34
								(8.52)			
	(b)	**−1.59**	**0.11**		0.19	**−0.53**	**0.64**				0.18
		(−4.68)	(3.12)		(1.05)	(−2.23)	(3.73)				
	(c)	**−1.22**	**0.10**		**0.30**	**−0.36**	**0.44**	**0.76**			0.44
		(−4.39)	(2.96)		(2.78)	(−2.12)	(2.74)	(6.13)			
$rx_{t+1}^{(3)}$	(d)								**0.91**		0.19
									(5.28)		
	(e)									**0.89**	0.24
										(6.57)	
	(f)							**0.75**	**0.69**		0.44
								(6.16)	(5.55)		
	(a)							**1.24**			0.37
								(8.58)			
	(b)	**−2.05**	**0.16**		0.18	−0.63	**0.95**				0.16
		(−4.49)	(3.20)		(0.68)	(−1.77)	(3.75)				
	(c)	**−1.51**	**0.14**		**0.35**	−0.37	**0.64**	**1.13**			0.45
		(−4.20)	(3.08)		(2.22)	(−1.50)	(2.83)	(6.40)			
$rx_{t+1}^{(4)}$	(d)								**1.19**		0.17
									(5.08)		
	(e)									**1.20**	0.23
										(6.57)	
	(f)							**1.11**	**0.87**		0.45
								(6.30)	(5.39)		
	(a)							**1.46**			0.34
								(7.90)			
	(b)	**−2.27**	**0.18**		0.18	−0.78	**1.13**				0.14
		(−4.10)	(3.06)		(0.55)	(−1.80)	(3.68)				
	(c)	**−1.63**	**0.15**		**0.38**	−0.48	**0.76**	**1.34**			0.41
		(−3.86)	(2.95)		(1.92)	(−1.54)	(2.76)	(6.00)			
$rx_{t+1}^{(5)}$	(d)								**1.36**		0.14
									(4.80)		
	(e)									**1.41**	0.21
										(6.47)	
	(f)							**1.32**	**0.98**		0.42
								(5.87)	(5.08)		

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 1964:1–2003:12.

significant in row b, row 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%. Thus, 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 separate predictors.

The estimated factors have statistically and economically significant predictive power beyond that contained in the forward-rate factor CP_t. This is evident in rows d through h, which display estimates of the marginal predictive power of the estimated factors in $\overrightarrow{F5}_t$ and the single predictor factors $F5_t$ and $F6_t$. Notice that when $F5_t$ is included in the regression with CP_t, both variables have strongly statistically significant predictive power, with asymptotic t-statistics of around 6 for each variable. These results demonstrate that the estimated factors contain information about future returns that is not contained in yields or forward spreads subsumed in CP_t. The 45% $\bar{R}^2$ 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 ($\bar{R}^2 = 44\%$).

Notice also that the single predictor factors (linear combinations of the individual factors in $\overrightarrow{F5}_t$ and $\overrightarrow{F6}_t$) 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% of next year's excess bond return; both $\overrightarrow{F5}_t$ and $F5_t$ explain 22%.

The results in the remaining panels of Table 2 are for excess returns on three-, four-, and five-year bonds. They are broadly similar to those reported in the top panel for two-year bonds. In particular, (i) the single factors $F5_t$ and $F6_t$ predict future bond returns just as well as 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 the results in the top panel. 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 (row c of the last three panels). Moreover, the single factors $F5_t$ and $F6_t$ remain strongly statistically significant predictors of excess returns on bonds of all maturities regardless of whether the forward factor CP_t is included, and continue to deliver high $\bar{R}^2$. $F6_t$ alone explains 24%, 23%, and 21% of next year's excess return on the three-, four-, and five-year bonds, respectively; $F5_t$ explains 19%, 17%, and 14% of next year's excess returns on these bonds, and $F5_t$ and CP_t together explain 44%, 45%, and 42% of next

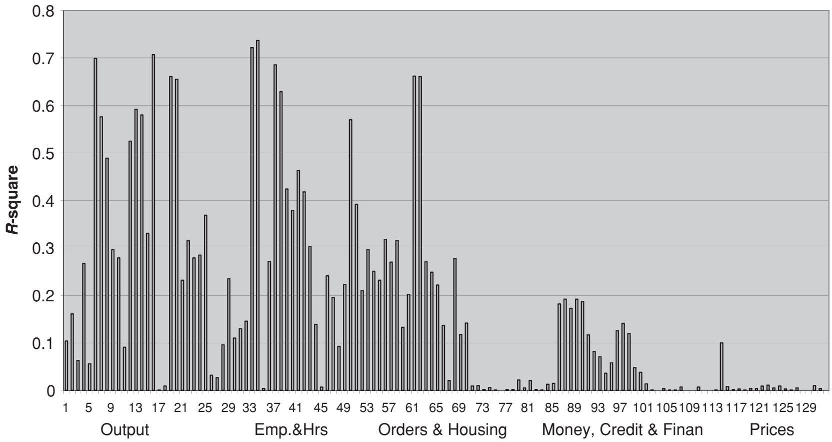

Figure 1
Marginal R-squares for F_1
Note: Chart shows the R-square from regressing the series number given on the x-axis onto F_1. See the Appendix for a description of the numbered series. The factors are estimated using data from 1964:1 to 2003:12.

year's 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.

Economic interpretation of the factors. What economic interpretation can we give to the predictor factors? Because the factors are identifiable only up to an $r \times r$ matrix, a detailed interpretation of the individual factors would be inappropriate. Moreover, we caution that any labeling of the factors is imperfect, because each is influenced to some degree by all the variables in our large dataset and the orthogonalization means that no one of them will correspond exactly to a precise economic concept like output or unemployment, which are naturally correlated. Nonetheless, it is useful to show that the factors capture relevant macroeconomic information. We do so here by briefly characterizing the factors as they relate to the underlying variables in our panel dataset.

Figures 1–5 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 a 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

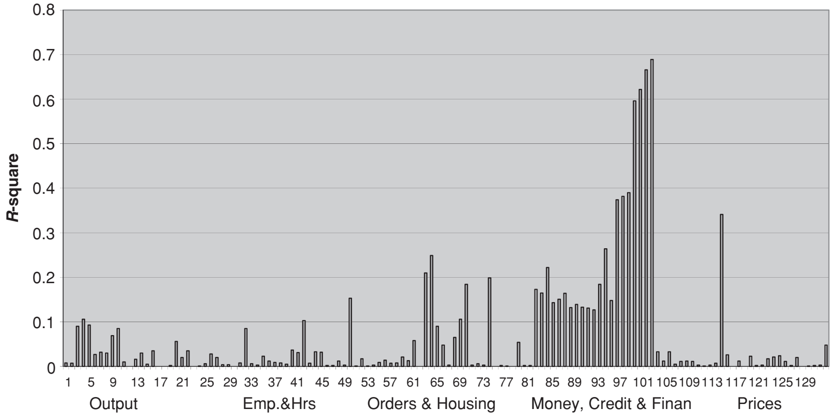

Figure 2
Marginal *R*-squares for F_2
Note: See Figure 1.

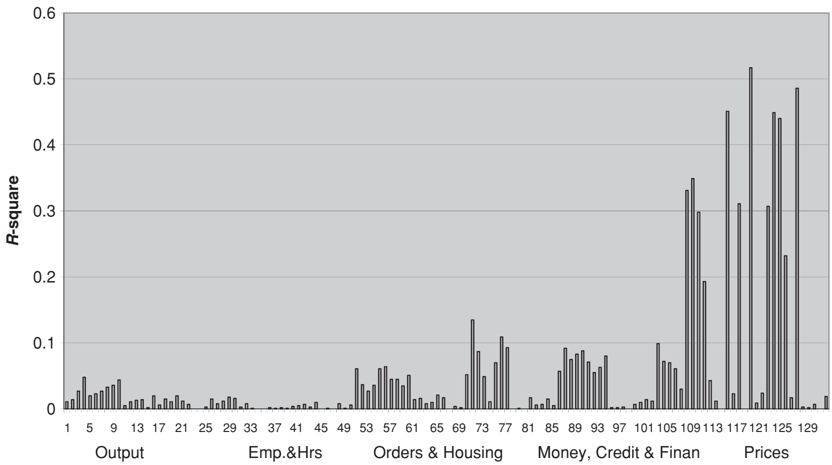

Figure 3
Marginal *R*-squares for F_3
Note: See Figure 1.

of −45%, loads heavily on several interest rate spreads (Figure 2), explaining almost 70% 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. Figures 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*.

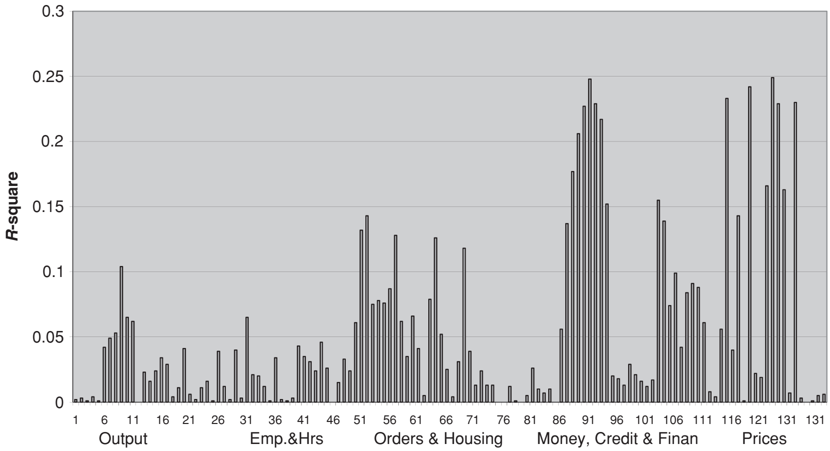

Figure 4
Marginal *R*-squares for F_4
Note: See Figure 1.

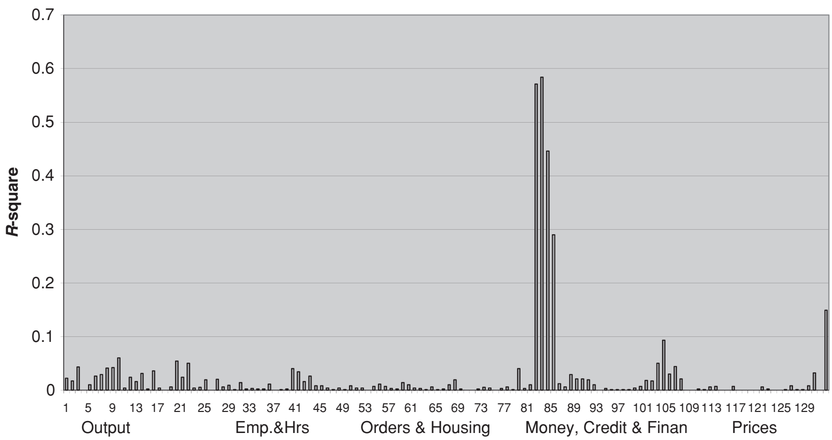

Figure 5
Marginal *R*-squares for F_8
Note: See Figure 1.

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 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 Equation (7).[10] Using data from 1964:1 to 2003:12, we find the following regression results (t-statistics in parentheses):

$$\frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)} = \underset{(2.96)}{1.03} - \underset{(-5.12)}{1.72} \cdot \widehat{F}_{1t} + \underset{(2.97)}{0.13} \cdot \widehat{F}_{1t}^{3} - \underset{(-3.90)}{1.01} \cdot \widehat{F}_{2t} + \underset{(1.18)}{0.18} \cdot \widehat{F}_{3t}$$
$$- \underset{(-2.40)}{0.56} \cdot \widehat{F}_{4t} + \underset{(4.56)}{0.78} \cdot \widehat{F}_{8t} + u_{t+1},\ \bar{R}^2 = 0.224.$$

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 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.

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 $\widehat{F}_{1t}$ and IP_t over time (panel A), and the vector $F5_t$ and IP growth over time (panel B). Shaded bars indicate 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%. 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 $\widehat{F}_{1t}$. The linear combination

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

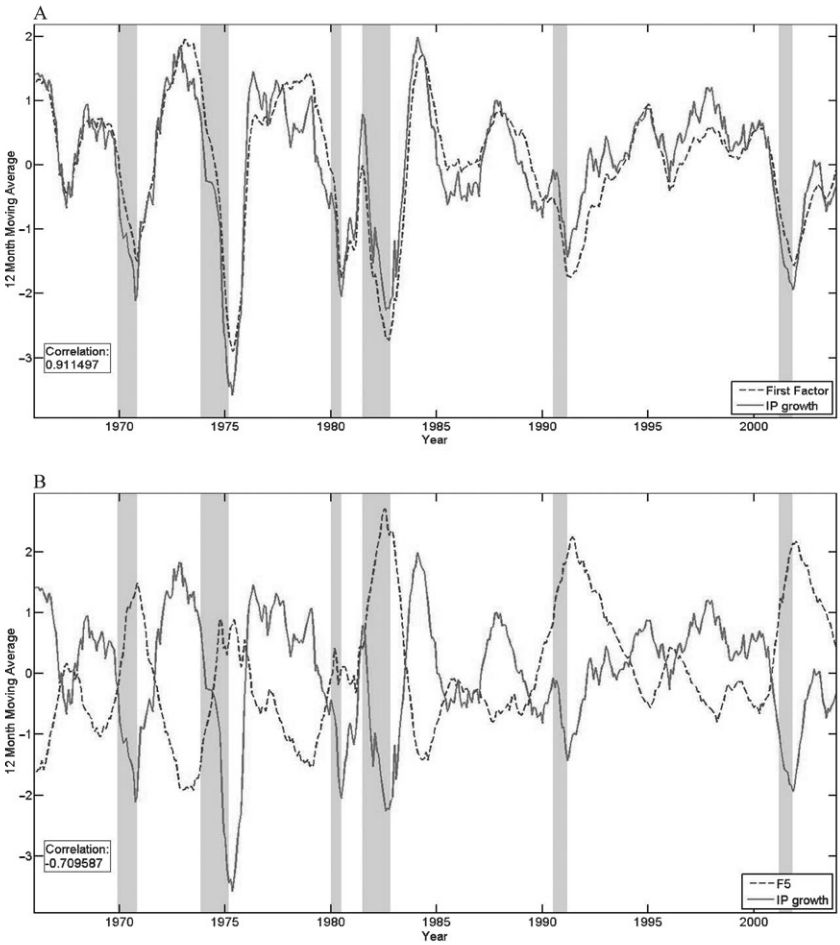

Figure 6
A: First factor and IP growth. B: *F*5 and IP growth
Note: Standardized units are reported. Shadings denote months designated as recessions by the National Bureau of Economic Research. "First factor" denotes the first estimated factor, F_1t. $F5$ denotes the linear combination of five factors, written in the text as $F5_t$.

of five factors, $F5_t$, also displays marked cyclical variation but has a negative correlation with IP growth: the correlation between the moving averages of IP growth and $F5_t$ is -71%.

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* and when $F5_t$ is *high* (Table 2). Since $\widehat{F}_{1t}$ is strongly positively correlated with IP growth, and $F5_t$ strongly negatively correlated, these findings imply that return forecasts have a strong countercyclical component—much stronger than what would be implied ignoring the factors—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.

Implications for affine models. The results reported in Table 2 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 the 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 of the Cochrane-Piazzesi factor, suggesting that CP_t summarizes a large body of information about economic and financial activity.

The main finding, however, is that measures of real activity and inflation in the aggregate economy captured by estimated factors contain economically meaningful information about future bond returns that is not contained in CP_t, and therefore not contained in contemporaneous 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.) Indeed, since the factors contain information about future excess returns that is not contained in CP_t our findings imply that the predictive information contained in the factors is not in the yield curve.

These findings are ruled out by unrestricted (and commonly employed) affine term structure models, where the forecastability of bond returns and bond yields is completely summarized by the cross-section of yields or forward rates. In such models, the continuously compounded yields on zero-coupon bonds are linear functions of K state variables. Thus, assuming the matrix that multiplies the state vector in the affine function for log bond yields is invertible, we can express the vector of K state variables as an affine function of K bond yields. It follows that bond yields themselves can serve as state variables and will contain any forecasting information that is in the state variables, regardless of whether those state variables are observable macro variables or treated as latent factors (see Cochrane 2005, chap. 19; Singleton 2006, chap. 12). Since bond returns, forward rates, and yields are all linear functions of one another, unrestricted affine models imply that any of these variables should contain all the forecastable information about future bond returns and yields; other variables should have no marginal predictive power. The findings reported above suggest that commonly employed affine models may conflict with an important aspect of bond data.

There are a number of potential resolutions to this conflict that are worthy of exploration in future work. First, the affine models themselves could be amended. For example, in affine term structure models, where the forecastability of bond returns and bond yields is completely summarized by yields, it is implicitly assumed that if there are K state variables, then there exist exactly K bond yields that are measured without error (while the other yields have nonzero measurement error). In this way, the matrix that multiplies the state vector in the affine function for the K log bond yields measured without error is invertible, and we can express the vector of K state variables as an affine function of K bond yields. As an alternative, Ang, Piazzesi, and Dong (2007) suggest modeling all yields as measured with error, in which case the inversion just described can't be implemented, so that the K state variables are no longer a linear function of K bond yields. It remains an open question as to whether a plausibly calibrated model of measurement error can account for the quantitative findings reported here.

More recently, Duffee (2008) addressed the question of whether factors that are orthogonal to the yield curve can still have important forecasting power for future yields and future returns in affine models. He shows that they can, as long as certain restrictions are placed on the model. Specifically, restrictions must be placed on the dynamics of the state vector to ensure that risk premia rise when expected future short rates fall. Consistent with these restrictions, Duffee finds evidence using Kalman filtering estimation of a factor that has an imperceptible effect on yields but nevertheless has substantial forecasting power for future yields and returns. As in this article, the factor he uncovers is related to short-term fluctuations in economic activity.

A second possible way to reconcile the findings here with theory is by considering term structure models characterized by unspanned stochastic volatility (e.g., Collin-Dufresne and Goldstein 2002). Additional work would be required, however, to develop a model of unspanned stochastic volatility that would generate the results above because we don't know the source of the volatility risk that cannot be perfectly hedged by only taking positions in bonds, or how that risk is related (if at all) to the real and inflation factors studied here.

Finally, nonlinear pricing kernels may in principle be capable of generating the results documented here, since in such models there is no implication that yields are linear functions of the state variables. We leave these interesting theoretical investigations to future research.

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

[11] Lettau and Ludvigson (2009) provide a review of the literature on in-sample versus out-of-sample forecasting of asset returns.

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. Second, we compare the out-of-sample forecasting performance of a specification that includes the same five macro factors plus 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.

The purpose of this analysis is to assess the out-of-sample predictive power of the particular combination of estimated factors $\overrightarrow{F5}_t$ for which we have found statistically significant in-sample predictive power. Notice that this question can only be addressed by holding the factors fixed throughout the out-of-sample forecasting exercise. A distinct question concerns whether different factors display out-of-sample forecasting power when the set of factors used to forecast returns is chosen in every out-of-sample recursion using only information available at the time of the forecast. We address this question below, where we combine an out-of-sample analysis using recursively chosen factors with a bootstrap procedure to assess the small-sample distribution of the out-of-sample test statistics. First we turn to the out-of-sample forecasting performance of the specific combination of factors $\overrightarrow{F5}_t$.

Out-of-sample forecasts using $\overrightarrow{F5}_t$. Table 3 reports results from one-year-ahead out-of-sample forecast comparisons of log excess bond returns, $rx_{t+1}^{(n)}$, $n = 2, \ldots, 5$. 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 $rx_{t+1}^{(2)}, \ldots, rx_{t+1}^{(5)}$, 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 $t = 1964{:}12, \ldots, 1984{:}12$ (dependent variable from $t = 1965{:}1, \ldots, 1984{:}12$, independent variables from $t = 1964{:}1, \ldots, 1983{:}12$) and the estimated parameters and values of the regressors at $t = 1984{:}12$ were used to forecast annual compound returns for 1985:12.[12] All parameters and

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

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	$\overrightarrow{F5}_t$ vs. *const*	0.794	50.07*	3.28
2	1995:1–2003:12	$\overrightarrow{F5}_t$ vs. *const*	0.838	21.83*	2.01
3	1985:1–2003:12	$\overrightarrow{F5}_t + CP$ vs. $const + CP$	0.810	45.77*	3.28
4	1995:1–2003:12	$\overrightarrow{F5}_t + CP$ vs. $const + CP$	0.884	14.04*	2.01
		$rx_{t+1}^{(3)}$			
5	1985:1–2003:2	$\overrightarrow{F5}_t$ vs. *const*	0.839	35.17*	3.28
6	1995:1–2003:2	$\overrightarrow{F5}_t$ vs. *const*	0.858	16.75*	2.01
7	1985:1–2003:2	$\overrightarrow{F5}_t + CP$ vs. $const + CP$	0.858	29.77*	3.28
8	1995:1–2003:2	$\overrightarrow{F5}_t + CP$ vs. $const + CP$	0.894	10.70*	2.01
		$rx_{t+1}^{(4)}$			
9	1985:1–2003:12	$\overrightarrow{F5}_t$ vs. *const*	0.874	26.28*	3.28
10	1995:1–2003:12	$\overrightarrow{F5}_t$ vs. *const*	0.888	14.05*	2.01
11	1985:1–2003:12	$\overrightarrow{F5}_t + CP$ vs. $const + CP$	0.891	21.86*	3.28
12	1995:1–2003:12	$\overrightarrow{F5}_t + CP$ vs. $const + CP$	0.913	9.00*	2.01
		$rx_{t+1}^{(5)}$			
13	1985:1–2003:12	$\overrightarrow{F5}_t$ vs. *const*	0.905	20.20*	3.28
14	1995:1–2003:12	$\overrightarrow{F5}_t$ vs. *const*	0.925	10.30*	2.01
15	1985:1–2003:12	$\overrightarrow{F5}_t + CP$ vs. $const + CP$	0.926	15.18*	3.28
16	1995:1–2003:12	$\overrightarrow{F5}_t + CP$ vs. $const + CP$	0.941	6.39*	2.01

*Significant at the 1% or better level.
Note: See next page.
Note: 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 $(\widehat{F}_{1t}, \widehat{F}_{1t}^{3}, \widehat{F}_{3t}, \widehat{F}_{4t}, \widehat{F}_{8t})'$. Rows that have "$\overrightarrow{F5}_t$ vs. *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 "$\overrightarrow{F5}_t + CP$ vs. $const + CP$" 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 $t = 1964{:}1, \ldots, 1984{:}12$ (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 $t = 1964{:}1, \ldots, 1994{:}12$. 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.

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 $t = 1964{:}1, \ldots, 1995{:}1$. 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% 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% of the constant expected returns benchmark for $rx_{t+1}^{(2)}, \ldots, rx_{t+1}^{(5)}$, respectively. The ENC-NEW test statistic always indicates that the improvement in forecast power is strongly statistically significant, at the 1% or better level. Moreover, the reduction in mean-squared 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 from 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 anywhere from 81% to 94% 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 1% or better level.

Small sample inference and out-of-sample forecasts using recursively chosen factors. To guard against inadequacy of the asymptotic approximation in finite samples, a Technical Appendix available on the authors' Web sites reports the results of a comprehensive bootstrap inference for specifications using four regression models. We first assess the finite sample behavior of our in-sample forecasting statistics. The bootstrap procedure takes into account the sampling variation attributable to the estimation of factors, as well as to the estimation of the forecasting relation. The results are contained in the Technical Appendix, and the bootstrap procedure is discussed in detail there. 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.

We also conduct a different out-of-sample investigation in which the factors are chosen optimally (using the BIC criterion, as in the in-sample exercise above) in each out-of-sample recursion, using only information available at the time of the forecast. The purpose of this exercise is to account for the sampling variation in finite samples that is attributable to the fact that different factors (identity and number) may be picked in different samples. We also guard here against the inadequacy of the asymptotic approximation of our test statistics in finite samples by using a bootstrap procedure to assess the finite-sample distribution of the out-of-sample test statistic used to gauge the improvement in out-of-sample predictability afforded by the recursively chosen factors.

The details of this procedure are provided in the Technical Appendix, with results contained in Table A5. Here we provide only a summary of the procedure and results. The results in Table A5 of the Technical Appendix show that the forecasting specifications using recursively chosen factors improve 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 85% to 95% of the constant expected returns benchmark mean-squared error, depending on the excess return being forecast and the forecast period. The test statistic (described in the Technical Appendix) indicates that the improvement in forecast power is statistically significant at the 5% or better level in every case but one (when forecasting the five-year excess bond return), where in this case it is statistically significant at the 10% level. These results show that even when we account for the sampling variation attributable to the fact that different factors may be chosen in different samples, it would be very unlikely that we would observe test statistics as large as those observed in the data if the null hypothesis were true and expected excess returns were constant.

4. A Decomposition of Yield Spreads

In this section we examine the quantitative importance of the factors by investigating the cyclical behavior of risk premia in both returns and yields implied by our excess bond return forecasts. The cyclical behavior of bond risk premia is of interest for at least two reasons. First, many economic models that rationalize time-varying risk premia imply that investors must be compensated for risks associated with the business cycle. In particular, they imply that risk premia should be higher in recessions than in expansions. We can use our results from the previous section to investigate the extent to which this is true in the data.

A second reason this issue is important is that the cyclicality of bond market risk premia is a matter of special concern to Federal Reserve policy makers, who routinely worry about the extent that fluctuations in long rates reflect investor expectations of future short-term rates versus changing risk premia. For example, in a speech given in July of 2005, Federal Reserve Governor Donald Kohn emphasized the importance of distinguishing between movements in long-term yields attributable to expectations of future short-term rates, and those attributable to movements in risk premia: “To what extent are long-term interest rates low because investors expect short-term rates to be low in the future . . . and to what extent do low long rates reflect narrow term premiums?"[13]

Federal Reserve Chairman Ben Bernanke argued similarly that the implications for monetary policy could be quite different depending on the extent to which the behavior of long-term yields reflects movements in the expectations of future short-term rates versus the term premium component.[14]

Notice that the n-period yield can be written as the average of expected future nominal short-rates plus an additional term $\varkappa_t^{(n)}$, which we refer to interchangeably as a *yield risk premium* or *term premium*:

$$y_t^{(n)} = \underbrace{\frac{1}{n} E_t\left(y_t^{(1)} + y_{t+1}^{(1)} + \cdots + y_{t+n-1}^{(1)}\right)}_{\text{expectations component}} + \underbrace{\varkappa_t^{(n)}}_{\text{yield risk premium}} . \tag{9}$$

The term premium $\varkappa_t^{(n)}$ 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. Under the expectations hypothesis, the yield risk premium, $\varkappa_t^{(n)}$, is assumed constant.

It is straightforward to show that the yield risk premium is identically equal to the average of expected future return risk premia of declining maturity:

$$\varkappa_t^{(n)} = \frac{1}{n}\left[E_t\left(rx_{t+1}^{(n)}\right) + E_t\left(rx_{t+2}^{(n-1)}\right) + \cdots + E_t\left(rx_{t+n-1}^{(2)}\right)\right]. \tag{10}$$

Notice that each of the conditional expectation terms on the right-hand side of Equation (10) are forecasts of excess bond returns, multiple steps ahead. Thus, Equation (10) shows that the excess bond return forecasts presented previously have direct implications for risk premia in yields, as well as risk premia in returns.

Denote estimated variables with "hats." To form an estimate of the risk-premium component in yields, $\varkappa_t^{(n)}$, we must form estimates of the multistep-ahead forecasts that appear on the right-hand side of Equation (10), i.e.,

$$\widehat{\varkappa}_t^{(n)} = \frac{1}{n}\left[\widehat{E}_t\left(rx_{t+1}^{(n)}\right) + \widehat{E}_t\left(rx_{t+2}^{(n-1)}\right) + \cdots + \widehat{E}_t\left(rx_{t+n-1}^{(2)}\right)\right], \tag{11}$$

[13] Remarks by Governor Donald Kohn at the Financial Market Risk Premiums Conference, Federal Reserve Board, Washington, DC, July 21, 2005.

[14] In remarks made before the Economic Club of New York, March 20, 2006, Chairman Bernanke argued: "What does the historically unusual behavior of long-term yields imply for the conduct of monetary policy? The answer, it turns out, depends critically on the source of that behavior. To the extent that the decline in forward rates can be traced to a decline in the term premium . . . the effect is stimulative and argues for greater monetary policy restraint . . . However, if the behavior of long-term yields reflects current or prospective economic conditions, the implications for policy may be quite different—indeed, quite the opposite."

where $\widehat{E}_t(\cdot)$ denotes an estimate of the conditional expectation $E_t(\cdot)$ formed by a linear projection. Thus, estimates of the conditional expectations are simply linear forecasts of excess returns, multiple steps ahead.

To generate multistep-ahead forecasts we estimate a monthly pth-order vector autoregression (VAR). The idea behind the VAR is that multistep-ahead forecasts may be obtained by iterating one-step-ahead linear projections from the VAR.

In our most general specification, the VAR vector contains observations on excess returns, the Cochrane-Piazzesi factor, CP_t, and the five estimated factors in the vector $\overrightarrow{F5}_t$:

$$Z_t \equiv \left[rx_t^{(5)}, rx_t^{(4)}, \ldots, rx_t^{(2)}, CP_t, \overrightarrow{F5}_t\right]',$$

a (10×1) vector. For comparison, we will also form bond forecasts with a restricted VAR that excludes the estimated factors but still includes CP_t as a predictor variable:

$$Z_t \equiv \left[rx_t^{(5)}, rx_t^{(4)}, \ldots, rx_t^{(2)}, CP_t\right]'.$$

We use a monthly VAR with $p = 12$ lags, where, for notational convenience, we write the VAR in terms of mean deviations:[15]

$$\begin{aligned} Z_{t+1/12} - \mu = {} & \mathbf{\Phi}_1(Z_t - \boldsymbol{\mu}) + \mathbf{\Phi}_2(Z_{t-1/12} - \boldsymbol{\mu}) \\ & + \cdots + \mathbf{\Phi}_p(Z_{t-11/12} - \boldsymbol{\mu}) + \boldsymbol{\varepsilon}_{t+1/12}. \end{aligned} \tag{12}$$

Let k denote the number of variables in Z_t. The VAR (12) can be stacked in the first-order companion form to become a VAR (1):

$$\boldsymbol{\xi}_{t+1/12} = \mathbf{A}\boldsymbol{\xi}_t + \mathbf{v}_{t+1/12}, \tag{13}$$

[15] This is only for notational convenience. The estimation will include the means.

where

$$\underset{(kp\times 1)}{\boldsymbol{\xi}_{t+1/12}} \equiv \begin{bmatrix} Z_t - \boldsymbol{\mu} \\ Z_{t-1/12} - \boldsymbol{\mu} \\ \cdot \\ \cdot \\ \cdot \\ Z_{t-11/12} - \boldsymbol{\mu} \end{bmatrix},$$

$$\underset{(kp\times kp)}{\mathbf{A}} = \begin{bmatrix} \boldsymbol{\Phi}_1 & \boldsymbol{\Phi}_2 & \boldsymbol{\Phi}_3 & \cdot & \cdot & \boldsymbol{\Phi}_{p-1} & \boldsymbol{\Phi}_p \\ \mathbf{I}_n & \mathbf{0} & \mathbf{0} & \cdot & \cdot & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_n & \mathbf{0} & \cdot & \cdot & \mathbf{0} & \mathbf{0} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \cdot & \cdot & \mathbf{I}_n & \mathbf{0} \end{bmatrix},$$

$$\underset{(kp\times 1)}{\mathbf{v}_t} \equiv \begin{bmatrix} \boldsymbol{\varepsilon}_{t+1/12} \\ \mathbf{0} \\ \cdot \\ \cdot \\ \cdot \\ \mathbf{0} \end{bmatrix}.$$

Multistep-ahead forecasts are straightforward to compute using the first-order VAR:

$$E_t \boldsymbol{\xi}_{t+j/12} = \mathbf{A}^j \boldsymbol{\xi}_t.$$

When $j = 12$, the monthly VAR produces forecasts of one-year-ahead variables, $E_t \boldsymbol{\xi}_{t+1} = \mathbf{A}^{12} \boldsymbol{\xi}_t$; when $j = 24$, it computes two-year-ahead forecasts; and so on.

As a final piece of notation, we define a vector $e1$ that picks out the first element of $\boldsymbol{\xi}_t$, i.e., $e1'\boldsymbol{\xi}_t \equiv rx_t^{(5)}$. Analogously, define vectors $e2$ through $e4$ that pick out the second through fourth elements of $\boldsymbol{\xi}_t$, e.g., $e2'\boldsymbol{\xi}_t \equiv rx_t^{(4)}$. In the notation above, we have $e1_{(kp\times 1)} = [1, 0, 0, \ldots 0]'$, $e2_{(kp\times 1)} = [0, 1, 0, \ldots 0]'$, analogously for $e3$ and $e4$. Thus, given estimates of the VAR parameters $\mathbf{A}$, we may form estimates of the conditional expectations on the right-hand side of Equation (11) from the VAR forecasts of return risk premia. For example, the estimate of the expectation of the five-year bond, one year ahead, is given by $\widehat{E}_t(rx_{t+1}^{(5)}) = e1'\mathbf{A}^{12}\boldsymbol{\xi}_t$; the estimate of the expectation of the four-year bond, two years ahead, is given by $\widehat{E}_t(rx_{t+2}^{(4)}) = e2'\mathbf{A}^{24}\boldsymbol{\xi}_t$; and so on.

With these estimates in hand, we construct Figures 7–10, which illustrate the cyclical properties of term premiums and return risk premia implied by the bond

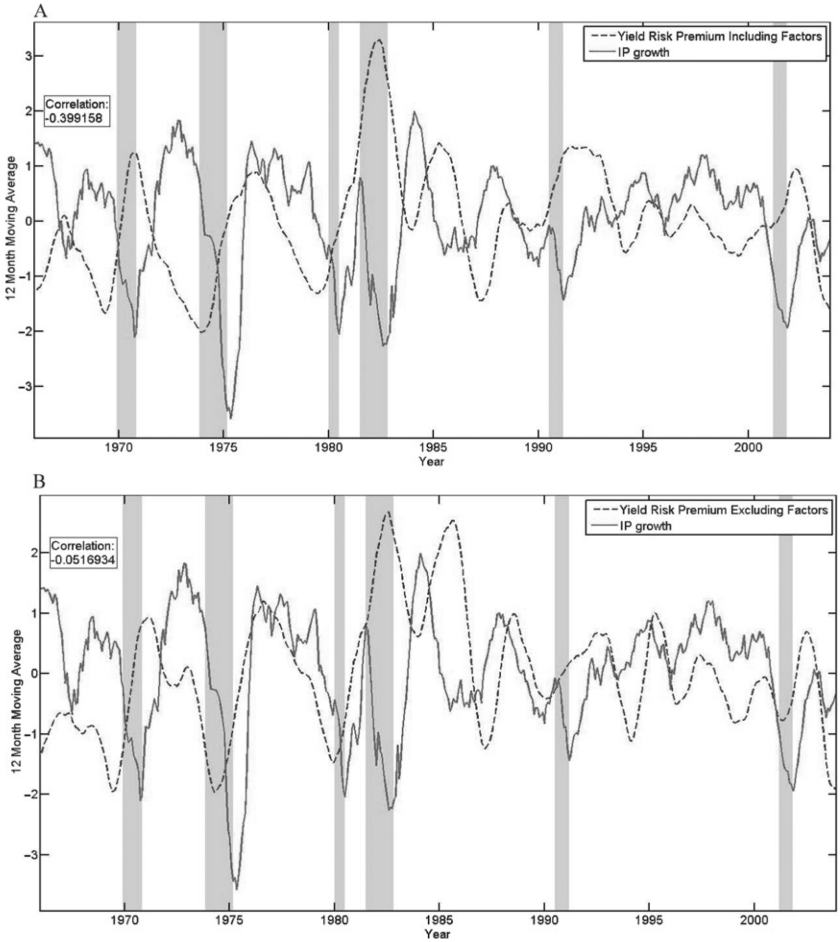

Figure 7
A: Yield risk premium including factors and IP growth. B: Yield risk premium excluding factors and IP growth (standardized).
Note: Standardized units are reported. Shadings denote months designated as recessions by the National Bureau of Economic Research.

return forecasts explored in this article. Two general aspects of all figures are noteworthy. First, both yield risk premia and return risk premia have a marked countercyclical component and reach greater values in recessions when factors are included in the estimation as compared with when they are omitted. Indeed, when they are omitted, risk premia appear almost acyclical. This is true even though, in the estimation where factors are omitted, CP_t is still included as a predictor variable. Second, yield risk premia and return risk premia are more volatile when factors are included in the estimation as compared with when they are omitted.

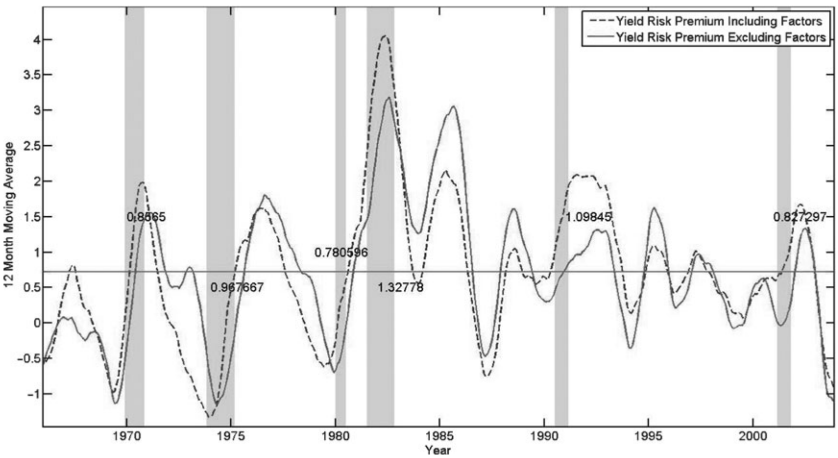

Figure 8
Yield risk premium including and excluding factors: 5-year bond
Note: Units in percent per annum are reported. Shadings denote months designated as recessions by the National Bureau of Economic Research. The red line denotes the mean risk premium of 0.72% per annum, including factors.

Figure 7 shows the 12-month moving average of the estimated yield risk premium over time for the five-year bond, $\widehat{\mathcal{H}}_t^{(5)}$, along with the 12-month moving average of industrial production growth. Panel A of the figure displays the estimate when factors $\overrightarrow{F5}_t$ are included in the VAR; panel B shows the same estimate when those factors are excluded, implying that only CP_t and lagged excess returns are used as predictors of future excess returns in the construction of $\widehat{\mathcal{H}}_t^{(5)}$. In both panels, the yield risk premium tends to rise over the course of a recession when IP growth is falling. However, when factors are included in the estimation (panel A), the yield risk premium has a distinct countercyclical component: it has a correlation with IP growth of -40%. By contrast, the yield risk premium is almost acyclical (correlation -0.05) when factors are excluded (panel B). While the means of the two yield risk premium measures are roughly the same in each panel (3.7% per annum in panel A, and 3.9% per annum in panel B), as suggested by the greater countercyclicality of the measure with factors, the term premium is more volatile when factors are included than when they are omitted (standard deviation equal to 1.02% in panel A and 0.93% in panel B).

Moreover, in most recessions, the estimated yield risk premium is significantly higher when information contained in the factors is included in the estimation than when it is omitted. Figure 8 plots the two estimates of the yield risk premium over time, with the maximum difference in risk premia with and without factors given in each recession. In the 1982–1983 recession, for example, the term premium including factors reached a level 1.33% per annum higher than the estimated term premium ignoring this information, a difference

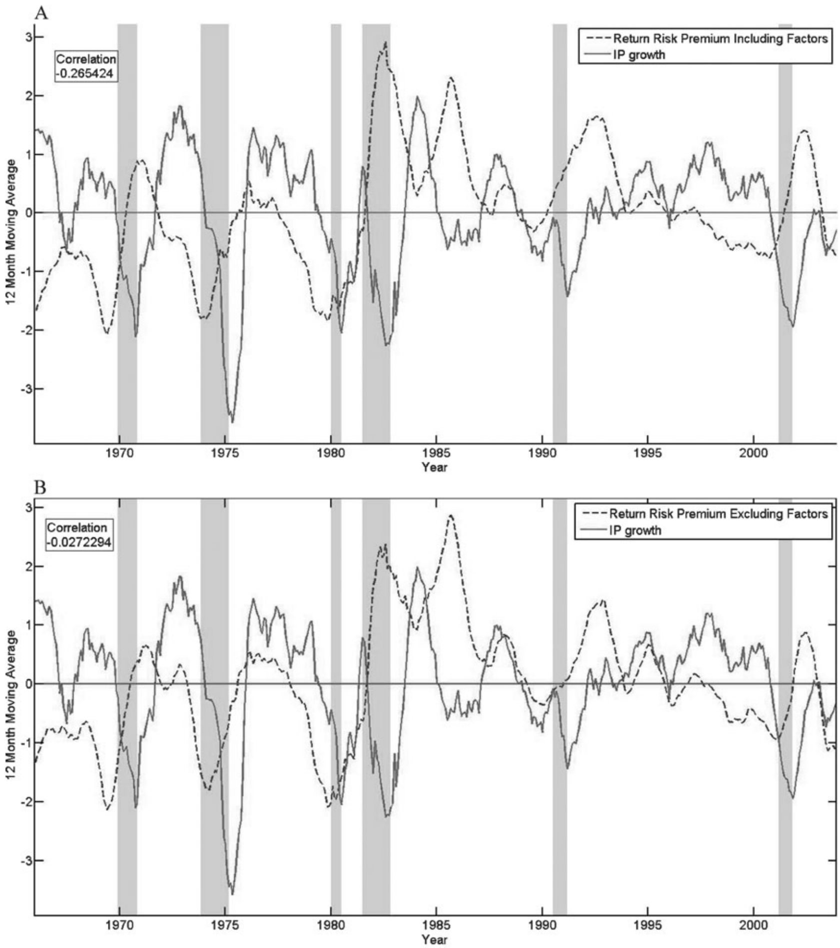

Figure 9
A: Return risk premium with factors and IP growth. B: Return risk premium without factors and IP growth
Note: Standardized units are reported. Shadings denote months designated as recessions by the National Bureau of Economic Research.

that is substantially greater than a one-standard-deviation movement in either risk premium measure. In the 1990–1991 recession, this difference was 1.10%, and it was 0.83% in the 2001 recession.

Figure 9 exhibits a similar pattern for return risk premia, again for the five-year bond. In panel A, where estimates include the information in factors, the return risk premium has a correlation with IP growth of −27%, while in panel B, this same correlation is close to zero (−0.03) when we exclude the information in factors. The return risk premium including factors is also more

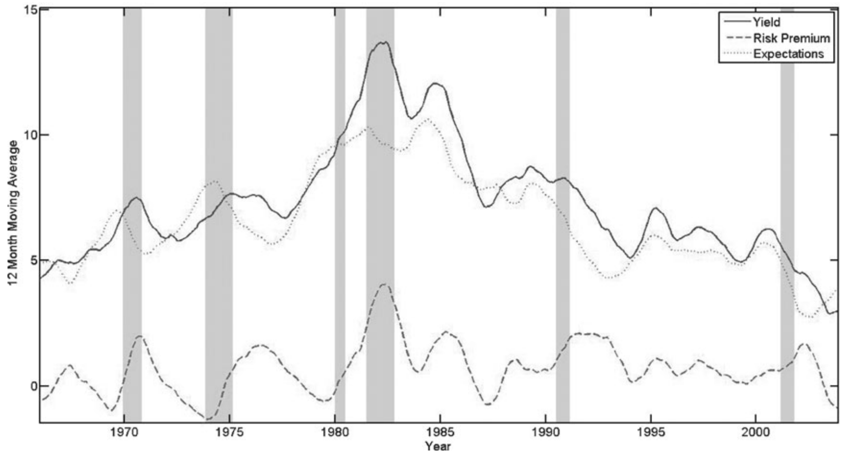

Figure 10
Five-year yield decomposition with factors
Note: Shadings denote months designated as recessions by the National Bureau of Economic Research. The line labeled "Yield" is the yield on the 5-year government bond. The lines labeled "Risk Premium" and "Expectations" are the estimated risk premium and expectations components of the 5-year yield.

volatile than the estimate obtained when the information on factors is ignored (standard deviation 3.1% per annum versus 2.7% per annum).

Finally, Figure 10 shows the five-year bond yield over time, decomposed into the term premium component and the expectations component, where the latter is measured as the residual $y_t^{(5)} - \widehat{\varkappa}_t^{(5)}$. In this figure, estimates of the term premium take into account the information in factors. The figure shows that recessions are periods during which risk premia account for the largest portion of the long-term yield. For example, risk premia were particularly high in the 1982–1983 recession, and almost as high during or shortly after the 1991 and 2001 recessions. Moreover, at the end of the sample, as the economy rebounded from recession in 2002 and 2003, risk premia declined significantly even as the expectations component rose.

When the economy is contracting, this marked countercyclicality of risk premia uncovered using macro factors contributes to a steepening of the yield curve even in periods when expectations of future short-term rates may be falling. Conversely, when the economy is growing, the countercyclicality of risk premia contributes to a flattening of the yield curve even in periods when expectations of future short-term rates may be rising. These results underscore the importance of the information in macro factors in accounting properly for risk premia, especially in recessions. When this information is ignored, too much of the variation in long-term yields is attributed to expectations of future nominal interest rates (and therefore expectations of future inflation and real rates), while too little is attributed to changes in the compensation for bearing risk. As one example, in the 2001 recession, the yield risk premium on the five-year bond was estimated to be 83 basis points higher using the information in factors than excluding that information. Since the expectations component is simply the difference between the long-term yield and the yield risk premium, this says that expectations of future economic conditions were actually much weaker in 2001 than what would be implied by a statistical model ignoring the information in the estimated factors.

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 literature, 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 unrestricted 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 is not just statistically significant but also economically important, with factors explaining between 21% and 26% 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. The results suggest that investors must be compensated for risks associated with recessions. Indeed, risk premia are found to be substantially higher in recessions when the macroeconomic factors are added to the information already contained in current bond market data. Moreover, without the macro factors, risk premia appear virtually acyclical, even when the information contained in current yields or the Cochrane-Piazzesi factor is included in the analysis.

An important aspect of these findings is that there is strong business cycle variation in expected excess bond returns that is not revealed in the yield curve. The other side of this coin is that the predictive factors we uncover are unlikely to help explain the yield curve, despite their predictive power for future excess returns. This is because the preponderance of information contained in the factors is not in bond yields, consistent with the observation of Kim (2008), who notes that macro factors such as those constructed here are less persistent and vary more at business cycle frequencies than do bond yields and bond returns, both of which are highly persistent variables. The findings underscore the importance of using information beyond that contained in the yield curve for uncovering countercyclical, business cycle-frequency variation in bond risk premia.

Data Appendix

Table A1 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 $\Delta^2\, ln$ 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 A1
Data sources, transformations, and definitions

Series Number	Short name	Mnemonic	Tran	Description
1	PI	a0m052	$\Delta\ln$	Personal Income (AR, Bil. Chain 2000 $) (TCB)
2	PI less transfers	a0m051	$\Delta\ln$	Personal Income Less Transfer Payments (AR, Bil. Chain 2000 $) (TCB)
3	Consumption	a0m224_r	$\Delta\ln$	Real Consumption (AC) a0m224/gmdc (a0m224 is from TCB)
4	M&T sales	a0m057	$\Delta\ln$	Manufacturing and Trade Sales (Mil. Chain 1996 $) (TCB)
5	Retail sales	a0m059	$\Delta\ln$	Sales of Retail Stores (Mil. Chain 2000 $) (TCB)
6	IP: total	ips10	$\Delta\ln$	Industrial Production Index - Total Index
7	IP: products	ips11	$\Delta\ln$	Industrial Production Index - Products, Total
8	IP: final prod	ips299	$\Delta\ln$	Industrial Production Index - Final Products
9	IP: cons gds	ips12	$\Delta\ln$	Industrial Production Index - Consumer Goods
10	IP: cons dble	ips13	$\Delta\ln$	Industrial Production Index - Durable Consumer Goods
11	IP: cons nondble	ips18	$\Delta\ln$	Industrial Production Index - Nondurable Consumer Goods
12	IP: bus eqpt	ips25	$\Delta\ln$	Industrial Production Index - Business Equipment
13	IP: matls	ips32	$\Delta\ln$	Industrial Production Index - Materials
14	IP: dble matls	ips34	$\Delta\ln$	Industrial Production Index - Durable Goods Materials
15	IP: nondble matls	ips38	$\Delta\ln$	Industrial Production Index - Nondurable Goods Materials
16	IP: mfg	ips43	$\Delta\ln$	Industrial Production Index - Manufacturing (Sic)
17	IP: res util	ips307	$\Delta\ln$	Industrial Production Index - Residential Utilities
18	IP: fuels	ips306	$\Delta\ln$	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	$\Delta\ln$	Civilian Labor Force: Employed, Total (Thous.,Sa)
24	Emp CPS nonag	lhnag	$\Delta\ln$	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	$\Delta\ln$	Unemploy. By Duration: Persons Unempl.Less than 5 Wks (Thous.,Sa)
28	U 5–14 wks	lhu14	$\Delta\ln$	Unemploy. By Duration: Persons Unempl. 5 to 14 Wks (Thous.,Sa)
29	U 15+ wks	lhu15	$\Delta\ln$	Unemploy. By Duration: Persons Unempl. 15 Wks + (Thous.,Sa)
30	U 15–26 wks	lhu26	$\Delta\ln$	Unemploy. By Duration: Persons Unempl. 15 to 26 Wks (Thous.,Sa)
31	U 27+ wks	lhu27	$\Delta\ln$	Unemploy. By Duration: Persons Unempl. 27 Wks + (Thous,Sa)
32	UI claims	a0m005	$\Delta\ln$	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.
59	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)

(*continued overleaf*)

Table A1
(Continued)

Series Number	Short name	Mnemonic	Tran	Description
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$,Sa)
74	M2 (real)	fm2dq	Δln	Money Supply - M2 in 1996 Dollars (Bci)
75	MB	fmfba	Δ^2ln	Monetary Base, Adj. tor Reserve Requirement Changes (Mil$,Sa)
76	Reserves tot	fmrra	Δ^2ln	Depository Inst Reserves:Total, Adj. tor 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: Intermed 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 Medical 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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