Macro Factors in UK Excess Bond Returns: Principal Components and Factor-Model Approach

Erdemlioglu, Deniz

Louvain School of Management and K.U.Leuven

2009

Macro Factors in UK Excess Bond Returns: Principal Components and Factor-Model Approach

Deniz Erdemlioglu *

Louvain School of Management, Belgium

This Version: October 5, 2009

Abstract

We use factor augmented predictive regressions to investigate the relationship between excess bond returns and the macro economy. Our application is for the case of United Kingdom. The dimension of the large data set with 127 variables is reduced by the method of principal components and the Onatski (2009) procedure is used to determine the number factors. Our data covers the period 1983:09 - 2006:10. We find that variation in the one year ahead excess returns on 2 to 5-year UK government bonds can be modeled by macroeconomic fundamentals with R^2 values varying from 34 percent to 44 percent. Specifically, three macro factors "unemployment" factor, "inflation" factor and "stock market" factor have significant predictive power in explaining the variation in the excess bond returns. Our results provide new evidence against the expectations hypothesis for the case of UK. We contribute to the literature by analyzing the direct link between macroeconomic variables and excess bond returns for a European market rather than the US. Unpredictability of excess bond returns is not the case in the UK either.

Keywords: Principal Components Analysis (PCA), Expectations Hypothesis, Excess Bond Returns, Factor Models.

***JEL Classification*:** G10, G12, E0, E4.

---

* *Correspondence*: Louvain School of Management-FUNDP. Email: deniz.erdemlioglu@fundp.ac.be. This paper is conducted as a dissertation of advanced studies in economics program at Catholic University of Leuven. I would like to thank Alexei Onatski from Columbia University for providing me computer program to determine the number of factors. I also thank Stefano Siviero from Bank of Italy for answering my questions regarding the Bai and Ng (2002) procedure. I am thankful to Leonardo Iania for his suggestions throughout the paper. I am especially grateful to my promotor Hans Dewachter for his helpful comments, suggestions and idea in writing this thesis at Catholic University of Leuven.

1 Introduction

The Expectations hypothesis (EH) of the term structure of interest rate states that the long-term interest rates are determined by the market's expectations of the future short-term interest rates plus a constant risk premium (Thornton 2005). This definition of the expectation hypothesis also posits that excess returns cannot be predicted and risk premia do not change over time (Cochrane and Piazzesi 2005, Ludvigson and Ng 2005). Regarding the empirical tests of the expectations hypothesis, most of the finance and applied macroeconomic research literature found evidence that EH does not hold and excess returns are forecastable. Among these studies, Fama and Bliss (1987) found that the spread between n-year forward rate and the one-year yield predicts excess returns on n-year maturity bond. Campbell and Shiller (1991) find that the Treasury yield spreads have forecasting power for the excess returns on US government bonds. Cochrane and Piazzesi (2005) examine the time-variation in expected excess bond returns and show that a single forward factor predicts one-year excess returns on US government bonds. A possible link between excess returns and macroeconomic aggregates has been also investigated in the literature. Campbell and Cochrane (1999) show that excess stock returns vary with the slow-moving consumption habit. Wachter (2006) proposes a consumption-based model and connects nominal bonds to consumption growth. Kim and Moon (2005) investigate time varying US bond returns via macroeconomic variables. Their finding indicates that a single macro index constructed from macroeconomic variables can forecast annual excess bond returns of one to five maturities with R^2 up to 37%. Brandt and Wang (2003) link aggregate risk aversion to inflation finding a time-varying risk aversion which responses to news about inflation. Ludvigson and Ng (2005) show that macroeconomic fundamentals have indeed important forecasting power for future excess bond returns on US government bonds.

In this work, we investigate the direct link between excess bond returns and macro economy. We follow Ludvigson and Ng (2005) and examine whether the excess bond returns are forecastable by macroeconomic factors. However, instead of investigating this empirical question for the US market, we apply our study to the UK economy. This application also enables us to re-visit the expectations hypothesis for the case of UK. Our findings show that variation in one-period ahead excess returns on 2-, 3-, 4-, and 5-year nominal UK government liability bonds can be, indeed, predicted via macroeconomic aggregates with an R^2 statistics varying from 34 percent to 44 percent. We find three important factors which help explaining the variation in the excess bond returns. These factors are "unemployment" factor (as a real factor), "inflation" factor, and "stock market" factor. These results also indicate that the expectations hypothesis does not hold in the case of UK. Our main contribution to the literature is to show that the excess returns on UK government bonds can be modeled via macroeconomic factors.

The paper is organized as follows. In the next section, we review the literature related to excess bond returns and our methodology. In Section 3, we describe the econometric framework of the paper. Section 4 introduces the data set employed in the empirical study and Section 5 analyzes our empirical findings. Section 6 concludes.

2 Related Literature

The literature on excess bond returns mostly focuses on modeling the variation in the expected excess returns (e.g. time-varying bond risk premia) and forecasting future changes in the bond yields. A broad class of these models are called term structure models which are developed to better explain the term structure movements and understand the behavior of the expected excess returns. Among these models, standard term structure models identified the determinants of the yield curves as factors called "level", "slope", and "curvature" factors (See Litterman and Scheinkman (1991)). Following the standard models, affine term structure models in which the bond yields are considered as *affine* functions of some state vector are characterized by the work of Duffie and Kan (1996). Dai and Singleton (2000) investigate the differences and similarities among affine term structure models and find that some class of affine models are better than the others in explaining the bond yields. Moreover, regarding the empirical fact of time-varying bond risk premia, Dai and Singleton (2002) use affine (and quadratic-Gaussian) dynamic term structure models to explain the variation in the expected excess bond returns. Duffie (2002) examines the forecasting ability of the affine term structure models. He introduces the "essentially affine" term structure model which provides better forecasts of future changes in Treasury yields than the standard "completely affine" models. Unfortunately, the standard term structure models suffer from economic interpretation even though they are capable of providing some explanation for the time-varying behavior of the excess bond returns. Ang and Piazzesi (2003) examine the relationship between macroeconomic variables and the dynamics of the yield curve using a no-arbitrage term structure factor model. Specifically, Ang and Piazzesi use a term structure factor model in which the macro factors are inflation, economic growth and other latent factors. They find that macro factors explain most of the movements in the short and middle parts of the yield curve. Furthermore, Ang and Piazzesi show that the "level" and "slope" factors are related to macro factors, especially to inflation. Piazzesi and Swanson (2004) find that excess returns (on federal funds futures) are countercyclical. They also find that excess returns can be forecasted by macroeconomic indicators such as employment growth and financial business-cycle indicators. Kozicki and Tinsley (2005) present an affine term structure model which is able to explain the empirical facts regarding to the monetary policy transmission mechanism. Recently, Duffie (2008) shows that there is a "hidden" factor containing information about the expected future yields. The hidden factor is related to real activity and "expectations" which are in turn crucial in explaining the behavior of the excess returns.

Regarding our methodology, we use factor model structure and estimate latent factors using Principal Components Analysis (PCA).[1] This approach gives us two main advantages.

[1] Ludvigson and Ng (2008) examine macro factors in bond risk premia using both the *static* factor model and the *dynamic* factor model structure. The use of different factor model structure i.e. either static or dynamic, does not change the main result that the excess returns on US bonds are forecastable. Hence, we choose to use static factor model representation in our empirical study for UK.

First, we can summarize the information in a large set of variables (127 variables in our case), allowing us to use a richer information set for examining the variations in excess returns. Second, instead of relying on the variables consumption and inflation to explain the excess returns, we obtain a better chance to capture the unobservable information sets of investors. (See Ludvigson and Ng (2005)).

Factor models have been widely used in finance and macroeconomics literature in order to address various types of questions. Starting in the 1970's, Geweke (1977) introduced approximate dynamic factor analysis in modeling economic time series. Following Geweke (1977), Sargent and Sims (1977) developed the exact factor model, and Chamberlain and Rothschild (1983) proposed the static approximate factor models. The literature of factor models in both theoretical and empirical aspects is vast. Quah and Sargent (1993) use factor models in order to show that the dynamics of employment in the US can be explained by two unobservable factors. Forni and Reichlin (1996, 1998) develop a factor model based procedure for analyzing large cross-sections of observations and apply this procedure to question economic growth and business cycle dynamics. Following these studies, Forni *et al.*, (2000, 2004) propose the generalized dynamic factor model. The generalized dynamic factor model is characterized in Forni and Lippi (2001), and the dynamic principal components is introduced as a method for extracting dynamic and latent factors through spectral density matrix estimations. Based on the generalized dynamic factor model framework imposing less restrictive assumptions, Forni *et al.*, (2001) extract Euro area coincident and leading indicators from a large panel of economic variables for many countries.[2] Next to these developments, factor models have many other empirical applications. Boivin and Giannoni (2005) propose a new empirical method which combines dynamic factor analysis with a DSGE modeling. Bernanke and Boivin (2003) employ a factor-model approach and estimate policy reaction functions for the Fed as summarizing the information in a large data set. Bernanke *et al.*, (2005) combine structural standard VAR framework with factor analysis

[2] See Stock and Watson (1998, 2002a, 2002b), Bai and Ng (2002) for the procedure in detail.

(i.e. FAVAR) to re-explore the effect of monetary policy on the US economy. Giannone *et al.*, (2005), using a factor model and VAR approach, analyze a large panel of variables for the US and find two aggregates that capture the interactions among US macroeconomic variables. The implications of dynamic factor models for VAR analysis have been also studied in the literature (See for example Stock and Watson (2005)). In recent years, many authors use factor-model approach for forecasting purposes. Forni *et al.*, (2003, 2005) use two alternative factor model structure and examine whether financial variables help forecasting inflation and real activity in the Euro area.[3] Stock and Watson (1999, 2002a, 2000b) develop a forecasting method in which the information in a large data set can be summarized by relatively few estimated factors through principal components. This method is proposed as approximate dynamic factor model to forecast macroeconomic time series in two steps. This forecasting procedure involving factor model is also used in Ludvigson and Ng (2005, 2008) to seek whether US excess bond returns are forecastable by macroeconomic fundamentals. In this paper, we investigate this empirical question for the case of United Kingdom.

3 Econometric Framework

This section describes the econometric framework of the paper. We first introduce the notations and definitions related to bond returns, yields, as well as forward rates. We then introduce the predictive regressions used to examine whether the macroeconomic variables have predictive power for the UK excess bond returns. To avoid huge number of regressors, we use the factor model and extract macro factors using the method of principal components. These estimated factors hence summarize the information in our data set and can be used as explanatory variables in the predictive regressions. We provide the estimation results of our predictive regressions in Section 5. Specifying the number of factors is a crucial task. We explain the procedures for determining the number of factors in the Appendix.

[3]One factor model representation is the generalized dynamic factor model, and the other so-called Stock and Watson (1999) model is the approximate dynamic factor model.

3.1 Bond Returns and Predictive Regressions

Following the notation and the data generating process of Cochrane (2005), Ludvigson and Ng (2005), continously compounded excess bond returns can be defined as

$$rx_{t+1}^{(n)} \equiv r_{t+1}^{(n)} - y_t^{(1)} \tag{3.1}$$

where for $t = 1, 2, ..., T$, $rx_{t+1}^{(n)}$ is the log excess bond return on an n-year discount bond in period $t+1$, $r_{t+1}^{(n)}$ is the log holding period return from buying an n-year discount 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. The log holding period return, $r_{t+1}^{(n)}$ can be also defined as

$$r_{t+1}^{(n)} \equiv p_{t+1}^{(n-1)} - p_t^{(n)} \tag{3.2}$$

where $p_{t+1}^{(n-1)}$ is the log price of an $n-1$ year discount bond at time $t+1$ and $p_t^{(n)}$ is the log price of an n-year discount bond at time t. The log yield on the n-year bond at time t is defined

$$y_t^{(n)} \equiv -(1/n)p_t^{(n)} \tag{3.3}$$

From (3.3), the log price of the n-year zero coupon bond at time t can be hence written as

$$p_t^{(n)} \equiv -y_t^{(n)}(n) \tag{3.4}$$

and substituting (3.2) into (3.1) gives

$$rx_{t+1}^{(n)} \equiv p_{t+1}^{(n-1)} - p_t^{(n)} - y_t^{(1)} \tag{3.5}$$

The intuition of the latter expression is as follows. An investor purchases an n-year zero coupon bond at time t. After one period (i.e., one year later), the investor sells the n-year zero coupon bond as an $n-1$ year bond and hence receives his holding period return on that bond. The investor then subtract his holding period return from the yield on one year Treasury bill to see how much excess bond return he obtained from these transactions.

Note that log excess bond returns can be also obtained from the yields on those bonds. By rearranging (3.5) and using (3.4), we can obtain the expression:

$$rx_{t+1}^{(n)} \equiv y_t^{(n)} - y_t^{(1)} - (n-1)\big(y_{t+1}^{(n-1)} - y_t^{(n)}\big) \tag{3.6}$$

where $rx_{t+1}^{(n)}$ is the log excess return on an n-year zero coupon government bond at time t+1, $y_t^{(n)}$ is the log yield on an n-year bond at time t, $y_{t+1}^{(n-1)}$ is the log yield on an $n-1$ year bond at time $t+1$, and $y_t^{(1)}$ is the log yield on an one-year Treasury bill at time t.[4] For instance, the log excess return on a 3-year UK government bond *today* is equal to the log holding period return from buying this 3-year government bond *twelve months* ago and selling it as a 2-year bond today; subtracted from the log yield on a 1-year (twelve months) UK Treasury bill. We use government liability UK bond yields to calculate the excess returns based on the expression (3.6).

We define log forward rate at time t for the loans between time t+$n-1$ and t+n as

$$f_t^{(n-1\to n)} \equiv p_t^{(n-1)} - p_t^{(n)} \tag{3.7}$$

Using (3.4), the above expression becomes

$$f_t^{(n-1\to n)} \equiv y_t^{(n)}(n) - y_t^{(n-1)}(n-1) \tag{3.8}$$

$$\equiv y_t^{(n-1)} + (n)\big(y_t^{(n)} - y_t^{(n-1)}\big) \tag{3.9}$$

where $f_t^{(n-1\to n)}$ is the log forward rate at time t for the loans between time $t+n-1$ and $t+n$, $y_t^{(n)}(n)$ is the log yield and duration on an n-year bond at time t, and $y_t^{(n-1)}(n-1)$ is

[4]Note that using monthly observation implies to go back to 12 months. Thus (t-1) can be understood as (t-12) for monthly observations.

the log yield and duration on an $n-1$ year bond at time t.

The objective of the paper is to investigate the link between excess bond returns and macroeconomic fundamentals. To do this, consider the following predictive regression model:[5]

$$rx_{t+1}^{(n)} = \gamma' X_t + \theta' Z_t + \varepsilon_{t+1} \tag{3.10}$$

where the log excess return on an n-year zero coupon UK government bond at time $t+1$ is regressed on a set of explanatory variables at time t, given by the predetermined K x 1 variable vector $Z_t = (Z_{1t}, Z_{2t}, ..., Z_{Kt})'$, and N observed macroeconomic variables grouped in X_t, $X_t = (X_{1t}, X_{2t}, ..., X_{Nt})'$. Predetermined variables contained in vector Z_t can be forward rates, yield spreads, and yield factors. Cochrane and Piazessi (2005) and Ludvigson and Ng (2008) use a single forward factor in their predictive regressions. Following Ludvigson and Ng (2008), we use a single forward factor (LN_t, henceforth) as a predetermined variable Z_t. Note that our data set consists of 127 variables with 278 monthly time series observations. To summarize the information in our large number of macroeconomic series, we consider that the macroeconomic variables in X_t can be described by relatively few factors.[6] Together with the LN_t factor, (3.10) can be then written as

$$rx_{t+1}^{(n)} = \alpha' F_t + \beta'(LN_t) + \varepsilon_{t+1} \tag{3.11}$$

which is considered as a predictive Factor-Augmented Regression Model (i.e. FAR) and can be estimated by least squares.[7] The factors F_t are unobservable and can be extracted from the data, LN_t is observable and it can be calculated as a simple weighted average of the one year Treasury bill and four forward rates. Following Bai and Ng (2002), the forecasting

[5]For other use of predictive regressions, see, for example, Cochrane and Piazessi (2005), Ludvigson and Ng (2005, 2008).

[6]See Section 3.2 for the factor model structure in detail.

[7]Note that the factors which describe the variation in the data may not be necessarily important for explaining the variation in excess bond returns. Thus, we consider F_t as a subset of all common factors. See also Ludvigson and Ng (2005) page 8.

procedure for excess bond returns then involves two steps:[8] In the first step, we extract F_t from the large macroeconomic data and denote it $\hat{F}_t$. Second, we regress $rx_t^{(n)}$ on $\hat{F}_{t-1}$ and LN_{t-1} to obtain coefficients $\hat{\alpha}'$ and $\hat{\beta}$. Thus, the forecast of the log excess return on an n-year UK government bond is given by:

$$\hat{r}x_{T+1|T}^{(n)} = \alpha'\hat{F}_t + \beta'(LN_t) \tag{3.12}$$

where $\hat{F}_t$ is the vector of estimated factors and LN_t is the additional observable explanatory variable. (3.12) is considered as a form of *diffusion index forecasting* in the literature (See, for example, Bai and Ng (2002)). Stock and Watson (2002) apply this procedure to forecast a number of real and nominal time series for different horizons. Their finding shows that the diffusion index forecasts outperform other forecasting models such as univariate autoregressions and small VAR models.

3.2 Estimation of Latent Factors

Following the factor model structure used in Ludvigson and Ng (2005, 2008), Stock and Watson (2002a, 2002b), Bai and Ng (2002), Breitung and Eickmeier (2005), let N be the number of cross-section units and T be the number of time series observations. For $i = 1, 2, ...N,\ t = 1, 2, ...T$, let X be the T x N data matrix and X_{it} be the observed data for i^{it} cross-section unit at time t (See Bai and Ng (2002)). The *static* factor model then can be written as

$$X_{it} = \lambda_{i1}F_{1t} + \lambda_{i2}F_{2t} + \ldots + \lambda_{ir}F_{rt} + e_{it} \tag{3.13}$$

or equivalently,

$$X_{it} = \lambda_i' F_t + e_{it} \tag{3.14}$$

[8]See Stock and Watson (1998, 2002a, 2002b), Bai and Ng (2002) for the procedure in detail.

In matrix notation, (3.14) can be written as

$$\underset{(Nx1)}{\begin{pmatrix} X_{1t} \\ X_{2t} \\ \vdots \\ X_{Nt} \end{pmatrix}} = \underset{(Nxr)}{\begin{pmatrix} \lambda_{11} & \lambda_{12} & \dots & \lambda_{1r} \\ \lambda_{21} & \lambda_{22} & \dots & \lambda_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{N1} & \lambda_{N2} & \dots & \lambda_{Nr} \end{pmatrix}} \underset{(rx1)}{\begin{pmatrix} F_{1t} \\ F_{2t} \\ \vdots \\ F_{rt} \end{pmatrix}} + \underset{(Nx1)}{\begin{pmatrix} e_{1t} \\ e_{2t} \\ \vdots \\ e_{Nt} \end{pmatrix}}$$

or simply,

$$X_t = \Lambda F_t + e \tag{3.15}$$

where the vector $X_t = (X_{1t}, X_{2t}, ..., X_{Nt})'$ is the observed data for N cross-sections, $\Lambda = (\Lambda_1, \Lambda_2, ..., \Lambda_N)'$ are the factor loadings, and $e = (e_{1t}, e_{2t}, ..., e_{Nt})'$ is the vector representing N idiosyncratic components of X_t . Note that equation (3.15) is the factor model representation of the data where X is observable, but the factors, their loadings as well as idiosyncratic components are not observable. Both cross-sectional and serial correlation in the idiosyncratic components can be allowed in factor model structures.[9] The objective is to extract the factors from the observable data set X_{it} and use them as regressors in the predictive regressions of the excess returns on UK government bonds.

4 Data

The macroeconomic data representing the UK economic activity is obtained from Datastream, IMF's Financial Statistics, Bank of England Statistics and OECD Statistics databases. The yields data set is constructed from the interest rate sections of Datastream.

[9] Orthogonality between factors and errors, and uncorrelated idiosyncratic components are assumed in the classical factor analysis and *exact dynamic factor models*. Chamberlain and Rothschild (1983) allow some correlated idiosyncratic components in their static *approximate factor models*. Cross-sectional and serial dependence in idiosyncratic components, cross-sectional and serial heteroscedasticity, weak dependence between factors and errors are allowed in the work of Bai and Ng (2002). Forni *et al.*, (1999) develop *generalized dynamic factor model* allowing a dynamic relationship between observable data and unobservable factors.

Having done the necessary corrections depending on the data availability, the data set contains monthly observations on 127 variables over the period 1983:09 - 2006:10. Note that the cross sectional units are chosen to represent the United Kingdom's industrial sector, labor market, money and credit market, stock market, prices, interest rates and exchange rates. All the series have been examined for stationarity and transformations have been conducted before any estimation. Regarding the data descriptions, variables and constructing sectoral groups, we mostly follow Cochrane and Piazzesi (2005), Cochrane (2005), Ludvigson and Ng (2005), Stock and Watson (2002a) and Artis *et al.*, (2001). The list of the data can be found in the Appendix.

The bond yields data set consists of UK government nominal yields with maturities of (n) 12, 24, 36, 48 and 60 months. This data is used to generate data for "holding period returns", "forward rates", as well as "excess bond returns".[10] A detailed description of the data used in the empirical part along with the sources and the transformations is given in the Data Appendix.

5 Empirical Results

We regress excess bond returns on a set of factors estimated by the method of principal components using our macroeconomic data set with 127 variables.[11] Principal components are the linear combinations that maximize variances. For instance, the first principal component is the first linear combination with maximum variance. Similarly, the first factor is the first regressor which explains the largest fraction of the total variation in the data set. Second factor is the second regressor which explains the largest fraction of the total variation in the data set, controlling the first factor, and so on (Ludvigson and Ng 2005, p.11). We determine the number of factors based on the Onatski (2009) procedure. This

[10]Forward rates have been calculated using yields instead of using log prices of the bonds. The data generating process regarding the forward rates is given in Section 3.1.

[11]The raw data is standardized prior to any estimation and hence the principal components are obtained from the correlation matrix of the macro aggregates.

procedure suggests us to use ten factors. For comparison, we also apply the Bai and Ng (2002) criterion to our data set. We find similar results in both procedures so that ten to eleven factors can describe the data quite well. Based on the Onatski procedure, we choose to set the number of factors equal to ten.[12] The results of the principal components analysis show that the first ten common factors of the data set account for about 40 percent of the variation in the macroeconomic series. This amount of variance ratio can be considered as a reasonable fit for macroeconomic panels (See, for example, Breitung and Eickmeieer (2005)). We could not find any contribution of the ninth and tenth common factor in explaining the variation in the excess returns and hence the estimations are reported for up to the eight common factors.

We start our empirical analysis by interpreting the macro factors. We first look at the correlation coefficients between each variable and predicted macro factors. By doing this, we aim to give some economic interpretation to the predicted factors based on their correlation with macroeconomic aggregates. Figure 1 to Figure 8 illustrate the correlation coefficients between each variable and the estimated factors. Figure 1 shows that the first factor is highly and negatively correlated with the variables of interest rates especially with nominal interbank rates, local authority interest rates and UK sterling certificates. The correlation coefficient is negative and close to 80 percent. Note that nominal interest rates may contain expectations about inflation (see, for example, Ludvgison and Ng (2005) p.17) and hence we call the first factor as an *inflation factor*. In these figures, we see that the second factor has correlations with the stock market, production prices along with export and import prices. Therefore, the second factor is also an *inflation factor* since it is related to price variables. The third factor is a *real* factor because it is mostly loaded on the industrial production, sales and orders. Figure 4 shows that the fourth factor we extract has correlations with the measures of labor market. Specifically, the fourth factor is positively correlated with the unemployment rates with a value around 40 percent. This means that high unemployment

[12] Details of the procedures and computation algorithm for the Onatski (2009) method are given in the Appendix.

rates (in recessions for example) are associated with the high values of the fourth factor. In addition, as we look at the Figure 4, the fourth factor also displays some negative correlation with retail sales and consumer prices. Therefore, we can call the fourth factor both *real* and *inflation factor*. The fifth factor loads on the measures of money & finance, prices, and employment variables. This factor has also negative correlation with the stock market variables such as UK market price index, FTA government stocks price index and FTSE 100 share price index. The correlation coefficient between the fifth factor and FTSE 100 is about -35%. We call this factor a *stock market factor*. Figure 6 shows that the sixth factor has correlations with the sales, orders and labor market variables. This factor is negatively correlated with the unemployment variables (about 34%), and positively correlated with the employment rates with a value around 38%, implying that the more the economy is doing well (i.e. booms and/or low unemployment rates), the higher the sixth factor values are. Due to these reasons, we call this factor a *real factor*. The seventh factor loads on interest rates, exchange rates, consumer and producer prices. The eighth factor has correlations with most of the variables in our macroeconomic data set as shown in Figure 8.

Having provided an insight about the extracted factors, we analyze the estimation results of the factor-augmented predictive regressions. In the regressions, independent variables are the eight macro factors and the LN_t factor. Note that the LN_t factor is the Ludvigson and Ng (2005) factor generated as a simple average of the one-year yield and four forward rates. Table 1 demonstrates the least squares estimation results of our predictive regressions.[13] In each table, the dependent variable $rx_{t+1}^{(n)}$ is the log excess return on the nominal n-year UK government liability bond. Estimated regression coefficients, heteroscedasticity and serial-correlation robust t-statistics, R^2 and adjusted R^2 statistics, F-test statistics and their probability values are reported in all tables.

[Table 1 here]

[13] Following Ludvigson and Ng (2008), other specifications such as quadratic and cubic forms of the variables, ninth and tenth common factors have been regressed as well. No statistical significance are found and thus no report is provided for those estimations.

In all maturities, the fourth factor $\hat{F}_{4t}$ has the largest slope coefficient in absolute terms. This implies that it is the most important factor among the other factors estimated. Note that the fourth factor is positively correlated with the unemployment rates and negatively correlated with the retail sales. The coefficients of the fourth factor for all maturities are positive showing that the excess returns are high when unemployment rates are high and low when unemployment rates are low. Moreover, the loading of the fourth factor increases as maturities rise. The coefficient of this factor is the largest for the 5-year bond with a value of 8.72. The first factor $\hat{F}_{1t}$ is the second important factor while displaying high and negative correlations with the variables of interest rates (Correlation coefficient is about -80%). Similar to the loadings of the fourth factor, the estimated coefficients of the first factor also go up from 2.15 to 6.91 as maturities increase. The intuition behind this might be that since interest rates also contain information about investors' inflation expectations, for higher maturities say 5-year, inflation expectations become more important in explaining the variation in excess bond returns. The sixth factor $\hat{F}_{6t}$, as a *real factor*, is the third important factor in Table 1 for all maturities from 2-year to 5-year.[14] Note that the sixth factor exhibits negative correlation with the unemployment variables, and positive correlation with the UK employment rates. Not surprisingly, the sign of the estimated coefficient of the sixth factor is negative. This means that excess returns on UK government bonds decrease in good times (i.e. high employment rates or booms) and increase in bad times (i.e. low employment rates or recessions). Similar to the $\hat{F}_{1t}$ and $\hat{F}_{4t}$, the loadings of the sixth factor $\hat{F}_{6t}$ rise with bond maturities, indicating that the expected excess returns on longer maturity bonds have stronger relationship with the unemployment rates than that of shorter maturities. In other words, excess returns on longer maturity bonds are more counter-cyclical than shorter maturity bonds. The Ludvigson and Ng factor LN_t, as a simple average of the one year yield and four forward rates, is statistically significant only for the predictive regressions of 2-year excess returns (see the column of (n=2)).

[14] Except for the 5-year bond.

R^2 values in Table 1 show that the power of the macro factors in explaining the variation in excess bond returns decreases with maturities. For example, we obtain R^2 values around 44% in the predictive regressions of excess returns on 2-year bonds, whereas this value declines to 34% for 5-year bonds. Despite this fact, as we look at the estimation results of the average excess returns (across maturities, i.e. the column of (n=av)) our eight macro factors along with the LN_t factor explain about 36% of the variation in the excess returns on UK government bonds. Once we consider 2-year maturity bonds, we find that our macro factors and LN_t factor explain the variation in excess bond returns with an R^2 around 44%.

In addition to these estimations given in Table 1, we also perform different specifications for our factor-augmented predictive regressions. We use five different specifications for each predictive regressions by including and excluding the macro factors.[15] The estimation results are given in Table 2 - Table 6. In these specifications, we first regress excess returns only on the Ludvigson-Ng LN_t factor (i.e. specification (a) in the tables). The LN_t factor is statistically significant at 5 percent only for the 2-year maturity bonds. On average, it explains about 14 percent variation in one-year ahead excess returns on 2-year UK government bonds. For the 3-, 4-, 5-year, and average maturities, the coefficient of the LN_t factor is not statistically significant. We then run the predictive regressions including the estimated factors from $\hat{F}_{1t}$ up to $\hat{F}_{8t}$. This specification is done for all maturities and represented as specification (b) in each table from Table 1 to Table 6. Note that Ludvigson-Ng factor is excluded in those regressions to examine the *unconditional* predictive power of macroeconomic factors on excess UK bond returns.

We find that four factors $\hat{F}_{1t}$, $\hat{F}_{4t}$, $\hat{F}_{5t}$, and $\hat{F}_{6t}$ play an important role in explaining the variation in the excess bond returns. Through the factor $\hat{F}_{1t}$, interest rates and hence inflation expectations help explaining the variation in excess bond returns, showing that expected excess returns (i.e. bond risk premia) vary with inflation. The fourth factor $\hat{F}_{4t}$ is a *real* factor. It has positive correlations with unemployment rates and its slope coefficient

[15] The estimation results of the specification (c) are same as the results given in Table 1.

is positive. This has an important interpretation such that the excess bond returns might increase as the unemployment rates go up. If we consider that unemployment rates are high in bad times (or in recessions), then we can say that excess returns are high during bad times and low during good times. Intuitively, it is likely that investors must be compensated for risk related to bad times such as recessions (Ludvigson and Ng 2005)). The slope coefficient of the fifth factor $\hat{F}_{5t}$ is significant for the higher maturity bonds such as for the 4-year and 5-year bonds. Note that the fifth factor $\hat{F}_{5t}$ is related to the stock market variables. We find that stock prices may be important macro factors for explaining excess returns variations. The other macro factor having a significant factor loading for the 2-, 3-, 4-year bonds is the sixth factor $\hat{F}_{6t}$. Recall the sixth factor is a *real* factor exhibiting positive correlations with the UK employment rates. The estimated slope coefficient of the sixth factor is negative and it implies that as the employment rates rise (or unemployment rates fall), excess bond returns decrease. Specification (b)s in Table 2 to Table 6 show that the eight macro factors - all together - explain about 30% of the variation in next year's excess returns, on average. For comparison, we introduce two alternative specifications: specification (d) and specification (e).[16] The former specification includes four regressors that are $\hat{F}_{1t}$, $\hat{F}_{4t}$, $\hat{F}_{5t}$, and $\hat{F}_{6t}$, whereas the latter specification has one additional regressor which is the LN_t. For 2-year maturity bonds, $\hat{F}_{1t}$, $\hat{F}_{4t}$, $\hat{F}_{6t}$, and LN_t are statistically significant and together with the fifth factor, these macro factors explain about 42% of the variation in the excess returns on UK government liability bonds (See specification (e) in Table 2).[17] The LN_t factor is not significant at 5 percent for the other maturities. For the 3-year maturity bonds, we obtain R^2 statistics of 37%. For the 4-year and 5-year bonds, the fifth factor $\hat{F}_{5t}$ becomes statistically significant at 5 percent. However, the slope coefficient of the sixth factor $\hat{F}_{6t}$ is significant at 10 percent for the 5-year maturity bonds. The variation in the excess bond returns explained by these four macro factors $\hat{F}_{1t}$, $\hat{F}_{4t}$, $\hat{F}_{5t}$, $\hat{F}_{6t}$ is about 31% and 32% for the 4-year and 5-year bonds (See specification (d) in Table 4 and 5).

[16] Note that the estimation results of the specification (c) are same as the results given in Table 1.
[17] LN_t is significant at 10 percent level.

[Table 6 here]

To sum up, Table 6 presents the estimation results of the predictive regression of average excess UK bond returns. The table shows that the four macro factors $\hat{F}_{1t}$, $\hat{F}_{4t}$, $\hat{F}_{5t}$, and $\hat{F}_{6t}$ explain about 31 percent variation in the average excess bond returns. This implies that these factors contain predictive power for one-year ahead average excess bond returns. The macro factors $\hat{F}_{1t}$, $\hat{F}_{4t}$, $\hat{F}_{5t}$, $\hat{F}_{6t}$ have three economic interpretations in our study. First, expected excess bond returns vary with inflation. Second, excess returns on UK government bonds are high in bad times (such as periods with high unemployment rates) and low in good times (such as periods with high employment rates). Third, stock market and thus stock prices matter in explaining the variation in the excess bond returns. Actual and fitted values of the average excess return regressions are displayed in Figure 9. This result also suggests that the excess bond returns can be predicted via macroeconomic factors, providing evidence against the expectations hypothesis.

[Figure 10 here]

Figure 10 shows the pattern of the coefficients in a regression of excess bond returns on the four macro factors $\hat{F}_{1t}$, $\hat{F}_{4t}$, $\hat{F}_{5t}$, and $\hat{F}_{6t}$. Y axis represents the values of the estimated coefficients of the macro factors. X axis gives the number of the variable.[18] The maturity of the bond is represented by the legend (2, 3, 4, 5). The figure illustrates that longer maturities have greater factor loadings than shorter maturities. The pattern in the figure is also consistent with our previous findings such that the fourth factor $\hat{F}_{4t}$ - having the largest slope coefficients in absolute terms for all maturities- is the most important factor among the other factors estimated. From the figure, we can also see that the first factor $\hat{F}_{1t}$ (named as variable 1 in Figure 10) is the second important macro factor. $\hat{F}_{5t}$ and $\hat{F}_{6t}$ are the other factors whose loadings are shown in Figure 10. This figure along with the estimation results of the predictive regressions discussed before show that the excess returns on UK

[18] Variable 1 is the $\hat{F}_{1t}$, variable 2 is the $\hat{F}_{4t}$, variable 3 is the $\hat{F}_{5t}$, and variable 4 is the $\hat{F}_{6t}$.

government liability bonds can be modeled via macroeconomic factors. These factors are the *real* factors (such as unemployment factors), *inflation* factors (via interest rate expectations and consumer prices) and *stock market* factors.

6 Conclusion

We revisit the expectations hypothesis and examine whether the excess bond returns are forecastable by macroeconomic factors. Our objective is to investigate the link between excess returns on government bonds and the macroeconomic aggregates. We apply our study to the UK economy. Static factor model structure is used and latent factors are estimated by the principal components analysis (PCA). We use the Onatski (2009) procedure, and also perform the Bai and Ng (2002) criterion to determine the number of factors.

Our findings show that variation in the one year ahead excess returns on 2 to 5-year UK government bonds can be modeled by macroeconomic fundamentals with R^2 values varying from 34 percent to 44 percent. Specifically, three macro factors that are "unemployment" factor, "inflation" factor and "stock market" factor have predictive power in explaining the variation in the excess bond returns. If we consider that unemployment rates are high in bad times (or in recessions), then we can say that excess returns are high during bad times and low during good times. This also means that investors must be compensated for risk related to bad times such as recessions or high unemployment periods.

The estimation results of the predictive regressions do not support the Expectations hypothesis in the sense that nothing should forecast excess bond returns. We contribute to the literature by showing that unpredictability of excess bond returns is not the case in the UK. We examine whether macro factors have predictive power for explaining the variation in the excess bond returns and a future research may shed light upon finding the main reason of the linkage among macro factors and excess returns on UK government bonds.

References

[1] Anderson, N., Sleath, J. (2001). "New Estimates of the UK Real and Nominal Yield Curves", *Bank of England Working Paper*, (2001), pp. 1-41.

[2] Ang, A., M. Piazzesi (2003). "A No-Arbitrage Vector Autoregression of Term Structure Dynamics With Macroeconomic and Latent Variables", *Journal of Monetary Economics 50*, (2003), pp. 745-787.

[3] Artis, M., A. Banerjee and M. Marcellino (2005). "Factor Forecasts for the U.K.", *Journal of Forecasting 24*, (2005), pp. 279-298.

[4] Bai, J., Ng, S. (2002). "Determining the Number of Factors in Approximate Factor Models", *Econometrica 70*, (2002), pp. 191-221.

[5] Bernanke, B. S., J. Boivin, (2003). "Monetary Policy in a Data-Rich Environment", *Journal of Monetary Economics 50 (3)*, (2003), pp. 525-546.

[6] Bernanke, B. S., J. Boivin, and P. Eliasz (2003). "Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach", *Working Paper*, (2003), pp. 1-48.

[7] Boivin, J., and M. Giannoni (2005). "DSGE Models in a Data-Rich Environment", *Unpublished paper*, Columbia University.

[8] Breitung, J., Eickmeier, S. (2005). "Dynamic Factor Models", *Deutsche Bundesbank Discussion Paper No: 38/2005*, (2005), pp. 1-40.

[9] Brandt, M. W., K. Q. Wang (2003). "Time Varying Risk Aversion and Unexpected Inflation", *Journal of Monetary Economics 50*, (2003), pp. 1450-1498.

[10] Brillinger, D. R. (1981). "Time Series Data Analysis and Theory", *Holt, Rinehart and Winston, (1981), New York.*

[11] Campbell, J. Y., J. H. Cochrane (1999). "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behaviour", *Journal of Political Economy 107*, (1999), pp. 205-251.

[12] Campbell, J. Y., R. J. Shiller (1991). "Yield Spreads and Interest Rates: A Bird's Eye View", *Review of Economic Studies 58*, (1991), pp. 495-514.

[13] Chamberlain, G. and Rothschild, M. (1983). "Arbitrage, Factor Structure and Mean-Variance Analysis in Large Asset Markets", *Econometrica 51*, pp. 1305-1324.

[14] Cochrane, J. H. (2005). "Asset Pricing", Revised Edition. *Princeton University Press Princeton, NJ*, (2005).

[15] Cochrane, J. H., and M. Piazzesi (2005). "Bond Risk Premia", *The American Economic Review, 95(1)*, (2005), pp. 138-160.

[16] Dai, Q., K. Singleton (2002). "Expectation Puzzles, Time-Varying Risk Premia, and Affine Models of the Term Structure, *Journal of Financial Economics 63*, (2002), pp. 415-441.

[17] Duffie, G. R. (2002). "Term Premia and Interest Rate Forecasts in Affine Models", *Journal of Finance 57*, (2002), pp. 405-443.

[18] Duffie, G. (2008). "Information in (and not in) the Term Structure", *Unpublished paper, Haas School of Business, University of California Berkeley*, (2008).

[19] Fama, E., R. Bliss (1987). "The Information in Long-Maturity Forward Rates", *American Economic Review 77*, (1987), pp. 680-692.

[20] Favero, C., Marcellino, M., Neglia, F. (2005). "Principal Components at Work: The Empirical Analysis of Monetary Policy with Large Datasets", *Journal of Applied Econometrics 20, (2005)*, pp. 603-620.

[21] Forni, M., Hallin, M., Lippi, F., Reichlin L. (2000). "The Generalized Dynamic Factor Model: Identification and Estimation", *Review of Economics and Statistics 82*, (2001), pp. 540-554.

[22] Forni, M., Hallin, M., Lippi, F., Reichlin L. (2003). "Do Financial Variables Help Forecasting Inflation and Real Activity in the Euro Area", *Journal of Monetary Economics 50*, (2003), pp. 1243-1255.

[23] Forni, M., Hallin, M., Lippi, F., Reichlin L. (2004). "The Generalized Dynamic Factor Model: Consistency and Convergence Rates", *Journal of Econometrics 119*, (2004), pp. 231-255.

[24] Forni, M., Hallin, M., Lippi, F., Reichlin L. (2005). "The Generalized Dynamic Factor Model: One-Side Estimation and Forecasting", Consistency and Convergence Rates", *Journal of American Statistical Association 100*, (2005), pp. 830-840.

[25] Geweke, J. (1977). "The Dynamic Factor Analysis of Economic Time Series", ch. 19 in Aigner, D.J. and A.S. Goldberger (eds.), (1977), Latent variables in socio-economic models, *Amsterdam: North Holland.*

[26] Giannone, D., L. Reichlin, and L. Sala (2002). "Tracking Greenspan: Systematic and Unsystematic Monetary Policy Revisited", *CEPR Working Paper No. 3550*, (2002).

[27] Greenwood, R., Vayanos, D. (2008). "Bond Supply and Excess Bond Returns", AFA 2009 San Francisco Meeting Paper, (February 2008), pp. 1-49.

[28] Gurkaynak, R., Sack, B., Wright, J. H. (2007). "The U.S. Treasury Yield Curve:1961 to the Present", *Journal of Monetary Economics 54*, (2007), pp. 2291-2304.

[29] Hagan, P. S., West, G. (2006). "Interpolation Methods for Curve Construction", *Journal of Applied Mathematical Finance Vol. 13 No. 2*, (June 2006), pp. 89-129.

[30] Johnson, R. A., Wichern, D. W. (2007). “Applied Multivariate Statistical Analysis”, Asset Pricing”, *Sixth Edition, Pearson Education, Inc., NJ*, (2007).

[31] Kim, H., Moon, J. (2005). “Do Macroeconomic Variables Forecast Bond Returns?”, *Department of Economics, SUNY at Buffalo Working Paper*, (2005), pp. 1-36.

[32] Kozicki, S., and P. Tinsley (2005). “Term Structure Transmission of Monetary Policy”, *Federal Reserve Bank of Kansas city Working Paper 05-06*, (2005).

[33] Lanne, M. (1999). “Testing the Expectations Hypothesis of the Term Structure of Interest Rates in the Presence of a Potential Regime Shift”, *Bank of England Discussion Paper 20/99*,(1999), pp. 1-19.

[34] Lekkos, I., Milas, C. (2004). “Time-Varying Excess Returns on UK Government Bonds: A Non-Linear Approach”, *Journal of Banking and Finance 28*, (2004), pp. 45-52.

[35] Litterman, Robert, and Jose Scheinkman (1991). “Common Factors Affecting Bond Returns, *Journal of Fixed Income 1*, (1991), pp. 54-61.

[36] Ludvigson, S. C. and S. Ng (2005): “Macro Factors in Bond Risk Premia”, *forthcoming in the Review of Financial Studies.*

[37] Ludvigson, S. C., and S. Ng (2006). “The Empirical Risk-Return Relation: A Factor Analysis Approach”, *Journal of Financial Economics*, (2006), forthcoming.

[38] Onatski, A. (2009). “Determining the Number of Factors from Empirical Distribution of Eigenvalues”, *Columbia University Working Paper*, (2006), pp. 1-31.

[39] Piazzesi, M., E. Swanson (2004). “Futures Prices as Risk-Adjusted Forecasts of Monetary Policy”, *NBER Working Paper No. 10547*, (2004).

[40] Quah, D., Sargent, T. J. (1992). “A Dynamic Index Model for Large Cross Sections”, *Federal Reserve Bank of Minneapolis Discussion Paper 77*, (1992), pp. 1-32.

[41] Reijer, Ard H. J. (2005). "Forecasting Dutch GDP using Large Scale Factor Models", *DNB Working Paper No.28*, (February 2005), pp. 1-37.

[42] Steeley, J. M. (2004). "Estimating Time-Varying Risk Premia in UK Long-Term Government Bonds", *Journal of Applied Financial Economics*, (2004), pp. 367-373.

[43] Stock, J. H., Watson, M. W. (1998). "Diffusion Indexes", *NBER Working Paper 6702*, (August 1998), pp. 1-67.

[44] Stock, J. H., Watson, M. W. (1999). "Forecasting Infation", *Journal of Monetary Economics 44*, (1999), pp. 293-335.

[45] Stock, J. H., Watson, M. W. (2002a). "Macroeconomic Forecasting Using Diffusion Indexes", *Journal of Business and Economic Studies 20*, (2002a), pp. 147-162.

[46] Stock, J. H., Watson, M. W. (2002b). "Forecasting Using Principal Components form a Large Number of Predictors", *Journal of American Statistical Association 97*, (2002b), pp. 1167-1179.

[47] Stock, J. H., Watson, M. W. (2003). "Forecasting Output and Inflation: The Role of Asset Prices", *Journal of Economic Literature 41*, (2003), pp. 788-829.

[48] Stock, J. H., Watson, M. W. (2004). "Forecasting With Many Predictors", *Unpublished paper*, (2004), Princeton University.

[49] Stock, J. H., Watson, M. W. (2005). "Implications of Dynamic Factor Models for VAR Analysis", *NBER Working Paper 11467*, (2005), pp. 1-67.

[50] Thornton, D. L. (2005). "Predictions of Short-Term Rates and Expectations Hypothesis of the Term Structure of Interest Rates", *Federal Reserve Bank of St. Louis Working Paper 2004-010A*, (2005), pp. 1-30.

[51] Wachter, J. (2006). "A Consumption Based Model of the Term Structure of Interest Rates",*Journal of Financial Economics 79*, (2006), pp. 365-399.

[52] Wright, J. H., Faust, J. (2008). "Efficient Prediction of Excess Returns", *NBER Working Paper 14269*, (2008), pp. 1-50.

Appendix

A. Procedures for Determining the Number of Factors

We use the Onatski (2009) procedure to determine the number of factors. In this procedure, the number of factors are estimated using the empirical distribution of eigenvalues. The main advantage of the Onatski (2009) procedure is such that it works quite well (even in the small samples) when idiosyncratic components are correlated both cross-sectionally and over time (See Onatski (2009). Following this procedure[19], the family of operational estimators of the number of factors is defined as

$$\hat{r}(\delta) = \max\{i \leq r^n_{max} : \lambda_i - \lambda_{i+1} \geq \delta\} \tag{.1}$$

where r^n_{max} is the maximum possible number of factors with sample of size n, $\lambda_i - \lambda_{i+1}$ is the difference between i-th and i+1-th largest eigenvalues of the sample covariance matrix, and δ is a positive parameter. The estimator r^n_{max} is consistent and developed for determining the number of factors in the approximate factor models. Intuitively, r^n_{max} separates the diverging eigenvalues from the cluster and counts the number of separated eigenvalues. The number of separated eigenvalues then equals to number of factors. Following Onatski (2009), we compute the number of factors based on (.1) as follows:

Step-1: First compute eigenvalues $\lambda_1, \lambda_2, ..., \lambda_n$ of the sample covariance matrix XX'/T. Then, set $j = r_{max} + 1$.

Step-2: Regress $\lambda_j, \lambda_{j+1}, \lambda_{j+3}, \lambda_{J+4}$ on the constant and $(j-1)^{2/3}, ..., (j+3)^{2/3}$. Estimate the regressions by OLS and get $\hat{\beta}$. Then, set $\delta = 2|\hat{\beta}|$.

Step-3: Compute $\hat{r}(\delta) = \max\{i \leq r^n_{max} : \lambda_i - \lambda_{i+1} \geq \delta\}$, or if $\lambda_i - \lambda_{i+1} < \delta$ for all $i \leq r^n_{max}$, set $\hat{r}(\delta) = 0$.

[19]For proofs of the theorems and statistical (e.g. consistency) properties, see Onatski, A. (2009). "Determining the Number of Factors from Empirical Distribution of Eigenvalues", *Columbia University Working Paper*, (2009), pp. 1-31.

Step-4: Set $j = r^n_{max} + 1$. Repeat step-2 and step-3 until convergence.

To estimate of the number of factors, we set $r_{max} = 20$. We find that our estimate of the number of factors is "ten".

As an alternative and for comparison, we also apply the Bai and Ng (2002) procedure to our data set. This procedure is based on the minimization of the some information criterion functions. In our empirical work, we choose the following Bai - Ng criterion functions:

$$PC_{p1}(k) = V(k) + k\hat{\sigma}^2(\frac{N+T}{NT})\ln(\frac{NT}{N+T})$$

$$IC_{p2}(k) = \ln[V(k)] + k(\frac{N+T}{NT})\ln[\min\{N,T\}]$$

The estimated number of factors, $(\hat{k})$ is then obtained from minimizing the information criterion where the maximum number of factors is some pre-specified upper bound for the number of factors (from Breitung and Eickmeier 2005, p.14). We detect ten to eleven factors, which is closed to our Onatski procedure results.

B. Data Descriptions

Data spans the period 1983:09 - 2006:10. Table A1 lists the data codes (i.e. mnemonic of each series used in Datastream, "dot" representations are ignored), the transformation applied to the series, and a data description. All series are obtained from Datastream, and its sub-databases such as IMF's *Financial Statistics* and OECD's *Statistics*. Bond yields data is from the interest rate section of Datastream. In the table, ln denotes logarithm, $\triangle ln$ and $\triangle^2 ln$ denote first and second difference of the logarithm, lv denotes the level of the series, and $\triangle lv$ denotes the first difference of the level of the series.

Table A1: Data Sources, Transformations and Definitions

Group 1: Output and Industry

No.	Gp	Data Code	Trans	Description
1	1	UKIPTOTG	Δln	PRODUCTION INDEX - ALL
2	1	UKCKYXG	Δln	PRODUCTION INDEX - MINING
3	1	UKIPMANG	Δln	INDUSTRIAL PRODUCTION INDEX MANUFACTURING
4	1	UKCKYZG	Δln	INDUSTRIAL PRODUCTION INDEX - ELECT./GAS (S.A.)
5	1	UKAGVOG	Δln	INDUSTRIAL PRODUCTION INDEX - TEXTILE
6	1	UKAGXQG	Δln	INDUSTRIAL PRODUCTION INDEX - OTHER MAN.
7	1	UKAGXSG	Δln	INDUSTRIAL PRODUCTION INDEX - ALL ENG.
8	1	UKCKZOG	Δln	INDUSTRIAL PRODUCTION INDEX - EXT.OİL/GAS
9	1	UKCKZAG	Δln	INDUSTRIAL PRODUCTION INDEX - FOOD/DRİNK (S.A.)
10	1	UKCKZFG	Δln	INDUSTRIAL PRODUCTION INDEX - COKE/PET
11	1	UKCKZGG	Δln	INDUSTRIAL PRODUCTION INDEX - CHEM
12	1	UKCKZJG	Δln	INDUSTRIAL PRODUCTION INDEX - METAL
13	1	UKFTAQ	Δln	UK NUMBER OF PROPERTY TRANSACTİONS.

Group 2: Sales, Orders and Registrations

No.	Gp	Data Code	Trans	Description
14	2	UKOSLI69G	Δln	UK SALES OF TOTAL MANUFACTURED GOODS (VOLUME) (S.A.)
15	2	UKOSLI78G	Δln	UK SALES OF EXPORTED MANUFACTURED GOODS (VOL.) (S.A.)
16	2	UKOSLI77G	Δln	UK SALES OF MANUFACTURED GOODS (VOLUME) (S.A.)
17	2	UKOODI54G	Δln	UK ORDERS FOR EXPORTED MAN. GOODS (VOLUME)
18	2	UKOODI53G	Δln	UK ORDERS FOR MAN. GOODS FROM DOM. MT. (VOLUME)
19	2	UKOODI45G	Δln	UK ORDERS FOR TOTAL MAN. GOODS (VOLUME)
20	2	UKOSLI07E	Δln	UK TOTAL RETAIL TRADE (VALUE) SADJ
21	2	UKOSLI15G	Δln	UK TOTAL RETAIL TRADE (VOLUME)
22	2	UKRTFOODG	Δln	UK RETAIL SALES: PRED. FOOD STORES - ALL BUSIN. (S.A.)
23	2	UKRTCFOTG	Δln	UK RETAIL SALES: TEXT.,CLOT. & FOOTWEAR- ALL BUS.
24	2	UKRTHOUSG	Δln	UK RETAIL SALES: HOUSEHOLD GOODS STORES - ALL BUS
25	2	UKRTONFDG	Δln	UK RETAIL SALES: OTHER NON-FOOD STORES - ALL BUS. (S.A.)
26	2	UKBCGT..	Δln	UK NEW REGISTRATIONS OF CARS (GB) (S.A.)
27	2	UKFFAO..	Δln	UK PASSENGER CAR PRODUCTION SADJ
28	2	UKJCYM..A	Δln	UK PASSENGER CARS TOTAL CURN (S.A.)
29	2	UKLNBU..P	Δln	UK MOTOR VEHICLE PRODUCTION (S.A.)
30	2	UKJCYG..A	Δln	UK COMMERCIAL VEHICLE TOTAL CURN (S.A.)
31	2	UKFFAQ..	Δln	UK COMMERCIAL VEHICLEPRODUCTION SADJ
32	2	UKOSLI12E	Δln	UK PASSENGER CAR REGIST. SADJ
33	2	UKOSLI12O	Δln	UK PASSENGER CAR REGISTRATIONS VOLA
34	2	UKOSLI12P	Δln	UK PASSENGER CAR REGISTRATIONS VOLN (S.A.)
35	2	UKCPTRRTF	Δln	UK CRUDE PETROLEUMREFINERY RECEIPTS - TOTAL (S.A.)
36	2	UKOUTPPDF	Δln	UK TOTAL OUTPUT OFPETROLEUM PRODUCTS (S.A.)
37	2	UKOBS084Q	Δlv	UK BUSIN. TEND. SURVEY: MFG. - FUTURE PROD. SADJ
38	2	UKOBS082Q	Δlv	UK BUSIN. TEND. SURVEY: MFG. - FUTURE SELLING PRICES SADJ
39	2	UKOCS002Q	Δlv	UK CONSUMER OPINION SURVEY: CONFIDENCE INDIC. SADJ

Group 3: Labor Market

No.	Gp	Data Code	Trans	Description
40	3	UKUNPTOTO	$\Delta^2 ln$	UK UNEMPLOYMENT CLAIMANT COUNT
41	3	UKUN%TOTQ	$\Delta^2 ln$	UK UNEMPLOYMENT RATE SADJ
42	3	UKYBTF..	$\Delta^2 ln$	UK LFS: POPULATION AGED 16-59/64, ALL
43	3	UKMGSF..	Δln	UK LFS: ECON. ACTIV. ANNUAL= SPRING QUART.(MAR-MAY)
44	3	UKMGWG..	Δln	UK LFS: ECONOMIC ACTIVITY RATE, ALL, AGED 16 & OVER (S.A.)
45	3	UKUN%O16Q	Δlv	UK LFS: UNEMPLOYMENT RATE, ALL, AGED 16 & OVER SADJ

46	3	UKYBSH..	Δln	UK LFS: UNEMPLOYED, ALL, AGED 16-59/64
47	3	UKYBTI..	Δln	UK LFS: UNEMPLOYMENT RATE, ALL, AGED 16-59/64 SADJ
48	3	UKMGSA..	Δln	UK LFS: IN EMPLOYMENT, MALE, AGED 16 & OVER
49	3	UKMGSR..	Δln	UK LFS: EMPLOYMENT RATE, ALL, AGED 16 & OVER SADJ
50	3	UKMGSS..	$\Delta^2 ln$	UK LFS: EMPLOYMENT RATE, MALE, AGED 16 & OVER (S.A.)
51	3	UKMGST..	Δln	UK LFS: EMPLOYMENT RATE, FEMALE, AGED 16 & OVER SADJ
52	3	UKYBUS..	$\Delta^2 ln$	UK LFS: TOTAL ACTUAL WEEKLY HOURS WORKED, ALL VOLN
53	3	UKYBUT..	$\Delta^2 ln$	UK LFS: TOTAL ACTUAL WEEKLY HOURS WORKED, MALE VOLN
54	3	UKYBUU..	Δln	UK LFS: TOTAL ACT. WKLY. HOURS WORKED, FEM. VOLN (S.A.)
55	3	UKOPRMNME	Δln	UK OUTPUT PER HEAD INDEX
56	3	UKOLC007E	$\Delta^2 ln$	UK WEEKLY EARNINGS:MANUFACTURING (S.A.)
57	3	UKOLC011F	Δln	UK WEEKLY EARNINGS - WHOLE ECONOMY (S.A.)
58	3	UKOLC023E	Δln	UK UNIT LABOUR COST- MANUFACTURING (S.A.)

Group 4: Money and Credit

No.	Gp	Data Code	Trans	Description
59	4	UKM0....B	Δln	UK MONEY SUPPLY M0: NOTES & COINS IN CIRC.OUTSIDE BOE
60	4	UKM2....A	Δln	UK MONEY SUPP. M2: RET. DEP. AND CASH IN M4 (EP) CURN (S.A.)
61	4	UKVQWU..	Δln	UK MONEY STOCK: RETAIL DEPOSITS & CASH IN M4 CURA
62	4	UKIMF4	Δln	UK M4: STOCK NATIONAL CURRENCY BILLIONS (S.A.)
63	4	UKAAPP..A	Δlv	UK RETAILERS CONS. CREDIT: NET LENDING: (SUSP.) CURN (S.A.)

Group 5: Interest Rates and Exchange Rates

No.	Gp	Data Code	Trans	Description
64	5	UKI60B..	Δlv	UK MONEY MKT. RATE (FED. FUNDS) (%) (PER ANNUM??)
65	5	UKI60D..	Δlv	UK EURODOLLAR RATE INLONDON (S.A.) (%)
66	5	UKI60P..	Δlv	UK LENDING RATE (PRIME RATE) (%)
67	5	UKOIR077R	Δlv	UK DISCOUNT RATE 3-MONTH T- BILLS (STERLING) (%) NADJ
68	5	UKOIR080R	Δlv	UK YIELD 10-YEAR CENTRAL GOVERN. SECURITIES (S.A.) (%)
69	5	UKOIR090R	Δlv	UK YIELD 20-YEAR CENTRAL GOV. BONDS (GILTS) (%) NADJ
70	5	LCBBASE	Δlv	UK CLEARING BANKS BASE RATE - MIDDLE RATE (%)
71	5	LDNIBON	Δlv	UK INTERBANK OVERNIGHT - MIDDLE RATE (S.A.) (%)
72	5	LDNIB1M	Δlv	UK INTERBANK 1 MONTH - MIDDLE RATE (S.A.) (%)
73	5	LDNIB7D	Δlv	UK INTERBANK 7 DAY - MIDDLE RATE (S.A.) (%)
74	5	LDNIB3M	Δlv	UK INTERBANK 3 MONTH - MIDDLE RATE (%)
75	5	LDNIB6M	Δlv	UK INTERBANK 6 MONTH - MIDDLE RATE (%)
76	5	LDNIB1Y	Δlv	UK INTERBANK 1 YEAR - MIDDLE RATE (S.A.) (%)
77	5	LDNLA1M	Δlv	UK LOCAL AUTH. DEPOSIT 1 MONTH - MIDDLE RATE (%) (S.A.)
78	5	LDNLA3M	Δlv	UK LOCAL AUTH. DEPOSIT 3 MONTH - MIDDLE RATE (%) (S.A.)
79	5	LDNLA6M	Δlv	UK LOCAL AUTHORITY DEPOSIT 6 MONTH - MIDDLE RATE (%)
80	5	LDNLA1Y	Δlv	UK LOCAL AUTHORITY DEPOSIT 1 YEAR - MIDDLE RATE (%)
81	5	LDNCD1M	Δlv	UK STERLING CERTS. 1 MONTH - MIDDLE RATE (%) (S.A.)
82	5	LDNCD3M	Δlv	UK STERLING CERTS. 3 MONTH - MIDDLE RATE (%) (S.A.)
83	5	LDNCD6M	Δlv	UK STERLING CERTS. 6 MONTH - MIDDLE RATE (%)
84	5	LDNCD1Y	Δlv	UK STERLING CERTS. 1 YEAR - MIDDLE RATE (%) (S.A.)
85	5	UKXAU$..	Δln	UK AUSTRALIAN $ TO UK£ (S.A.)
86	5	UKAJFV..	Δln	UK NEW ZEALAND $ TO UK £ NADJ (S.A.)
87	5	UKXCN$..	Δln	UK CANADIAN $ TO UK £ (S.A.)
88	5	UKXDKR..	Δln	UK DANISH KRONE TO UK£ (S.A.)
89	5	UKXYEN..	Δln	UK JAPANESE YEN TO UKPOUND (S.A.)
90	5	UKXNKR..	Δln	UK NORWEGIAN KRONER TO UK £
91	5	UKXSKR..	Δln	UK SWEDISH KRONA TO UK £
92	5	UKXSFR..	Δln	UK SWISS FRANCS TO UK£ (S.A.)
93	5	UKXUS$..	Δln	UK US $ TO £1 (S.A.)
94	5	UKSDR...	Δln	UK POUNDS TO SDR

Group 6: Stock Market

No.	Gp	Data Code	Trans	Description
95	6	UKSHRPRC	Δln	UK UK DATASTREAM MARKET PRICE INDEX (EP)
96	6	UKSHRPRCF	Δln	UK FT ALL SHARE INDEX (EP) NADJ
97	6	UKFTAGOV	Δln	UK FTA ALL GOVT. STOCKS PRICE INDEX (EP) (S.A.)
98	6	UKOSP001F	Δln	UK FTSE 100 SHARE PRICE INDEX NADJ

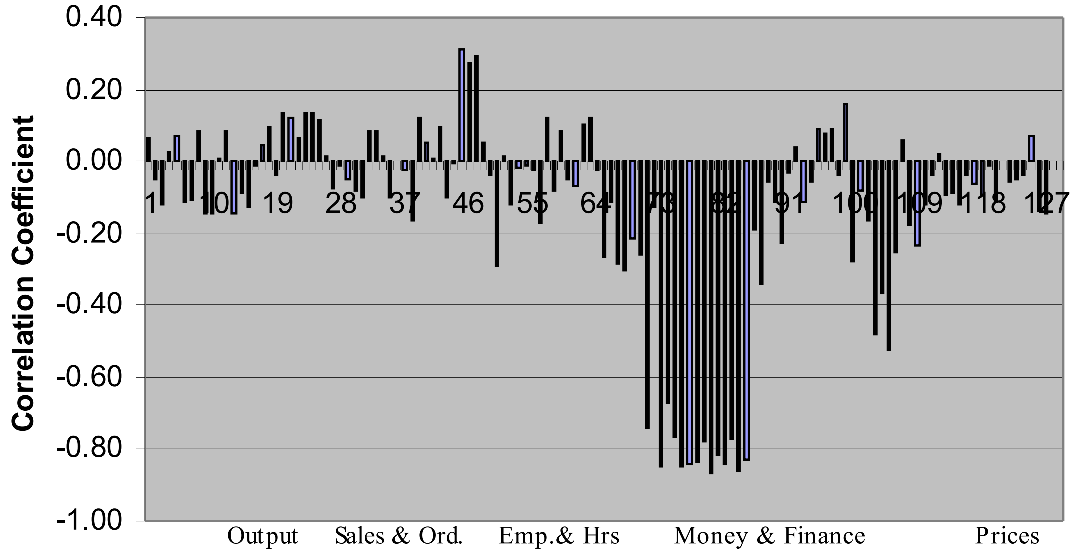
Group 7: Prices

No.	Gp	Data Code	Trans	Description
99	7	UKOCP009F	Δln	UK CPI (S.A.)
100	7	UKOCP019F	Δln	UK CPI - FOOD (S.A.)
101	7	UKOCP041F	Δln	UK CPI - ENERGY (S.A.)
102	7	UKOCP042F	Δln	UK CPI - EXCLUDING FOOD & ENERGY (S.A.)
103	7	UKOCP053F	Δln	UK CPI - HOUSING (S.A.)
104	7	UKOCP074F	Δln	UK RPI ALL ITEMS (S.A.)
105	7	UKOCP075F	Δln	UK RPI ALL ITEMS LESS MORTGAGE INTEREST RATES (S.A.)
106	7	UKOPP017F	Δln	UK PPI - MANUFACTURING OUTPUT (S.A.)
107	7	UKOPP012F	Δln	UK PPI - MANUFACTURING OUTPUT, FOOD (S.A.)
108	7	UKOPP054F	Δln	UK PPI - MANUFACTURING OUTPUT, CHEMICALS (S.A.)
109	7	UKOPP018F	Δln	UK PPI - MANUFACTURING OUTPUT EXCLUDING FOOD (S.A.)
110	7	UKOPP028F	Δln	UK PPI - MANUFACTURING INPUT EXCLUDING FOOD (S.A.)
111	7	UKOPP029F	Δln	UK PPI - MANUFACTURING INPUT, RAW MATERIALS (S.A.)
112	7	UKOPP026F	Δln	UK PPI - MANUFACTURING INPUT, FUEL (S.A.)
113	7	UKBQLJ..	Δln	UK BOP: EXPORTS - CHEMICALS (S.A.)
114	7	UKBQLK..	Δln	UK BOP: EXPORTS - MATERIAL MANUFAC. LESS ERRATICS (S.A.)
115	7	UKBQLY..	Δln	UK BOP: IMPORTS - CHEMICALS (S.A.)
116	7	UKBQLZ..	Δln	UK BOP: IMPORTS - MATERIAL MANUFAC. LESS ERRATICS (S.A.)
117	7	UKBQLM..	Δln	UK BOP: EXPORTS - CONSUMER GOODS OTHER THAN CARS (S.A.)
118	7	UKBQLN..	Δln	UK BOP: EXPORTS - INTERMEDIATE GOODS (S.A.)
119	7	UKBQLO..	Δln	UK BOP: EXPORTS - CAPITAL GOODS (S.A.)
120	7	UKBQPM..	Δln	UK BOP: EXPORTS - PASSENGER MOTOR CARS (S.A.)
121	7	UKBQMB..	Δln	UK BOP: IMPORTS - PASSENGER MOTOR CARS (S.A.)
122	7	UKBQMC..	Δln	UK BOP: IMPORTS - CONSUMER GOODS OTHER THAN CARS (S.A.)
123	7	UKBQMD..	Δln	UK BOP: IMPORTS - INTERMEDIATE GOODS (S.A.)
124	7	UKBQME..	Δln	UK BOP: IMPORTS - CAPITAL GOODS (S.A.)

Group 8: Miscellaneous

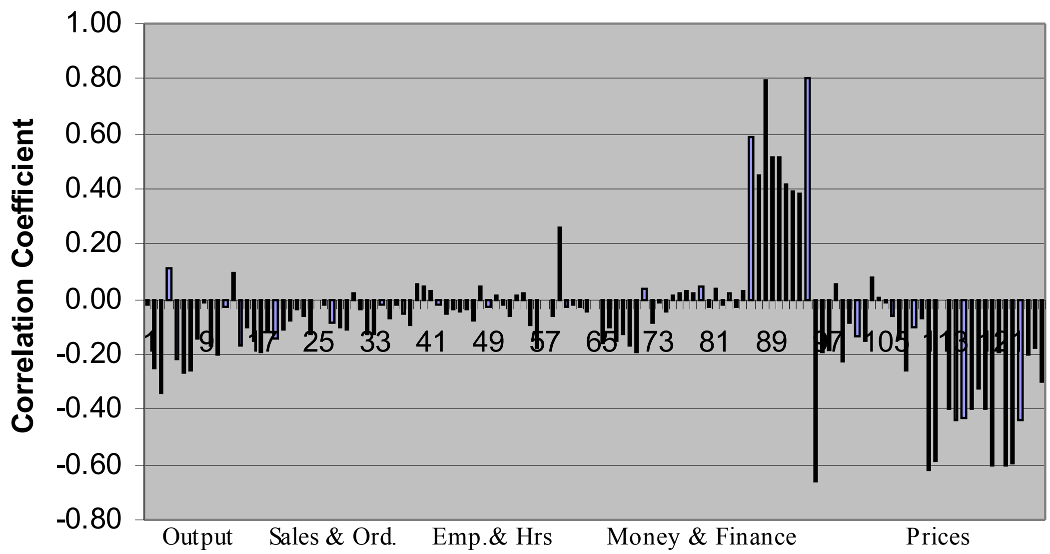
No.	Gp	Data Code	Trans	Description
125	8	UKEXPBOPB	Δln	UK EXPORTS - BALANCE OF PAYMENTS BASIS CURA (S.A.)
126	8	UKIMPBOPB	Δln	UK IMPORTS - BALANCE OF PAY. BASIS (S.A.)
127	8	UKNET	Δlv	UK NET - (EXPORTS - IMPORTS) (S.A.)

Figure 1: Correlations with F1



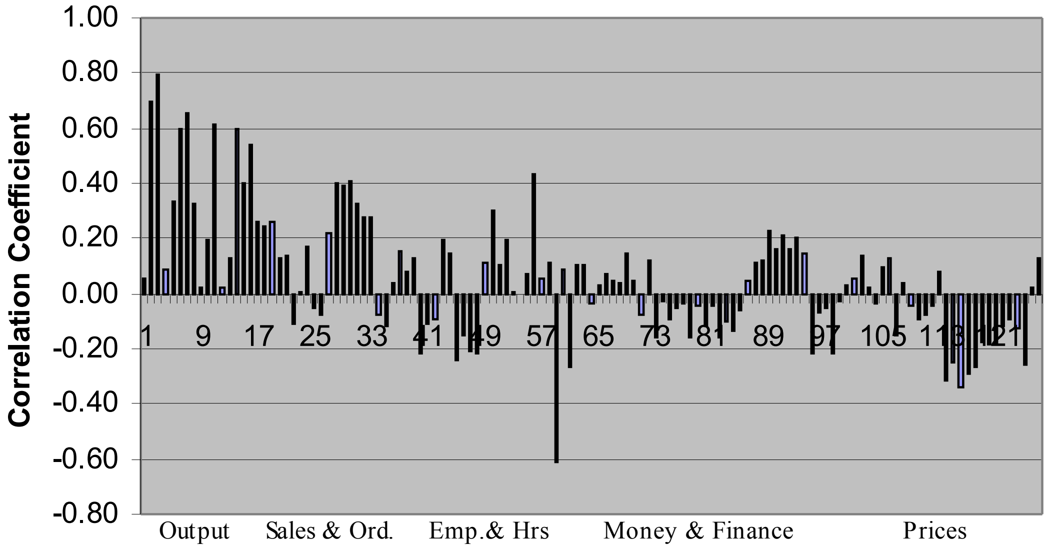
Notes: This chart shows the correlation coefficient between each variable and factor 1. Data covers 1983:09-2006:10. See appendix for a description of the numbered series.

Figure 2: Correlations with F2



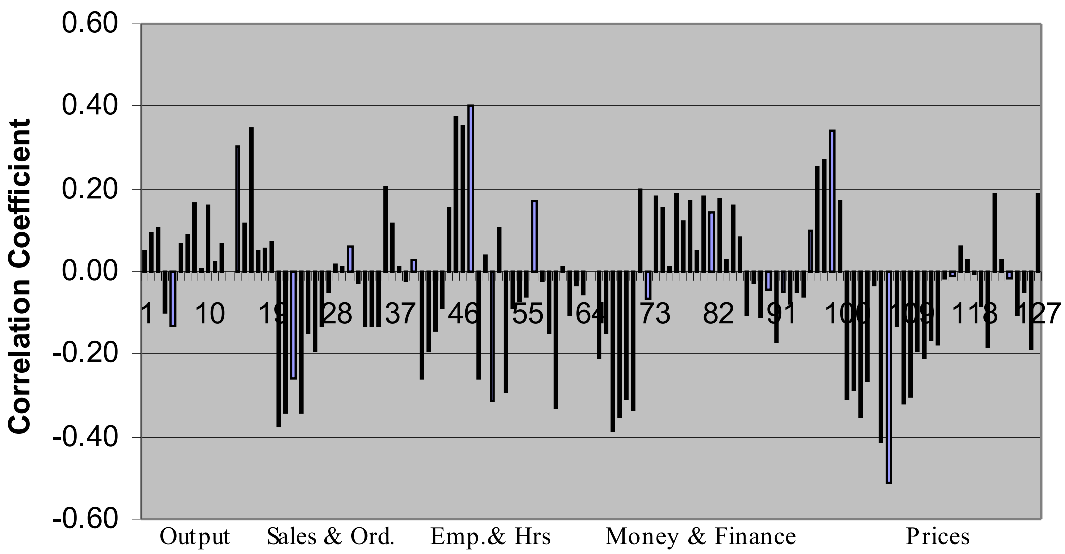
Notes: This chart shows the correlation coefficient between each variable and factor 2. Data covers 1983:09-2006:10. See appendix for a description of the numbered series.

Figure 3: Correlations with F3



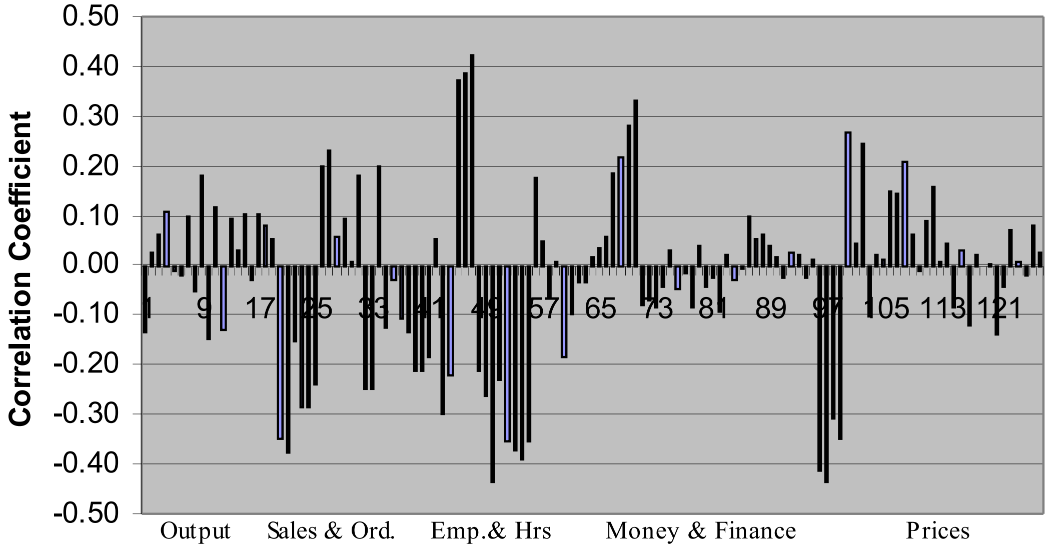
Notes: This chart shows the correlation coefficient between each variable and factor 3. Data covers 1983:09-2006:10. See appendix for a description of the numbered series.

Figure 4: Correlations with F4



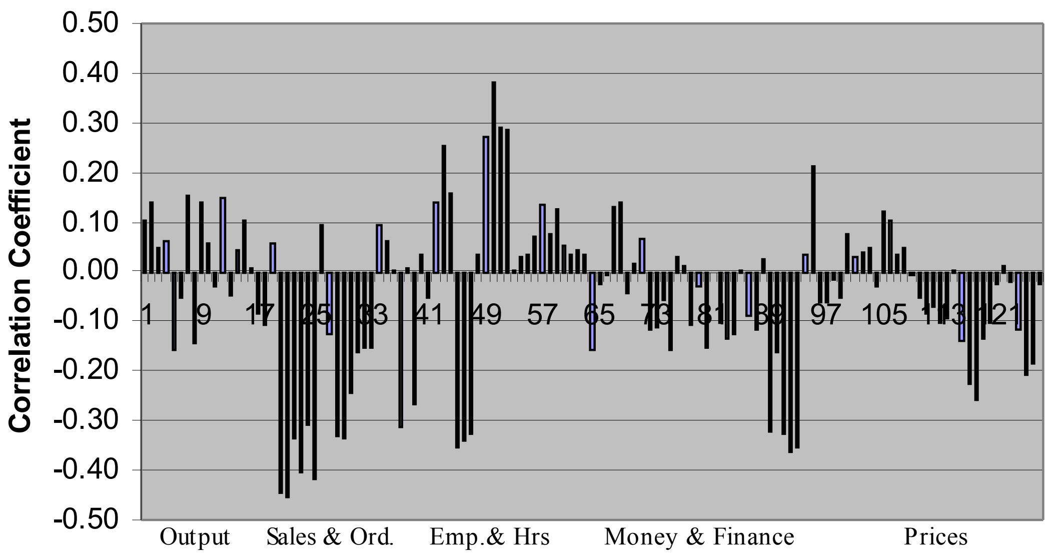
Notes: This chart shows the correlation coefficient between each variable and factor 4. Data covers 1983:09-2006:10. See appendix for a description of the numbered series.

Figure 5: Correlations with F5



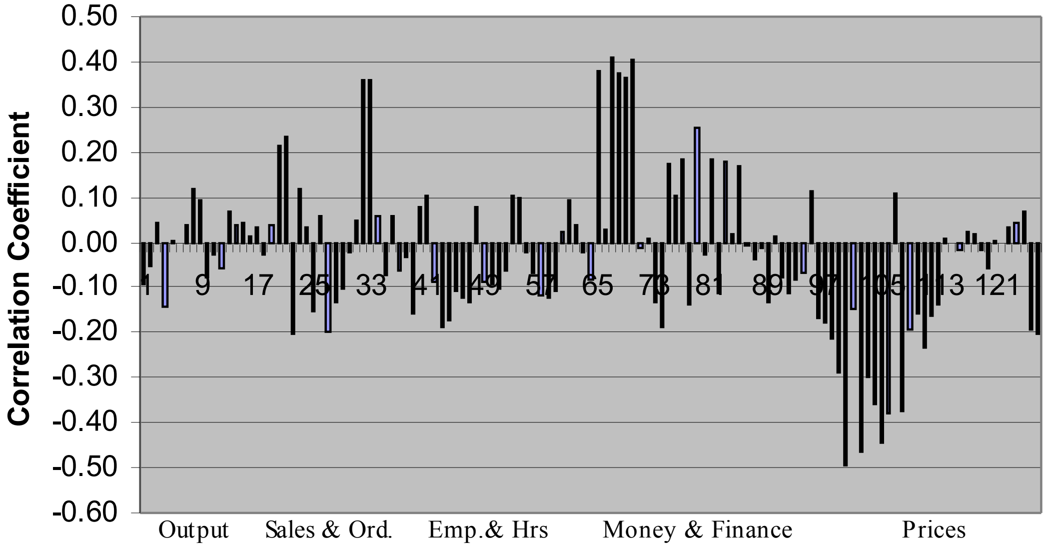
Notes: This chart shows the correlation coefficient between each variable and factor 5. Data covers 1983:09-2006:10. See appendix for a description of the numbered series.

Figure 6: Correlations with F6



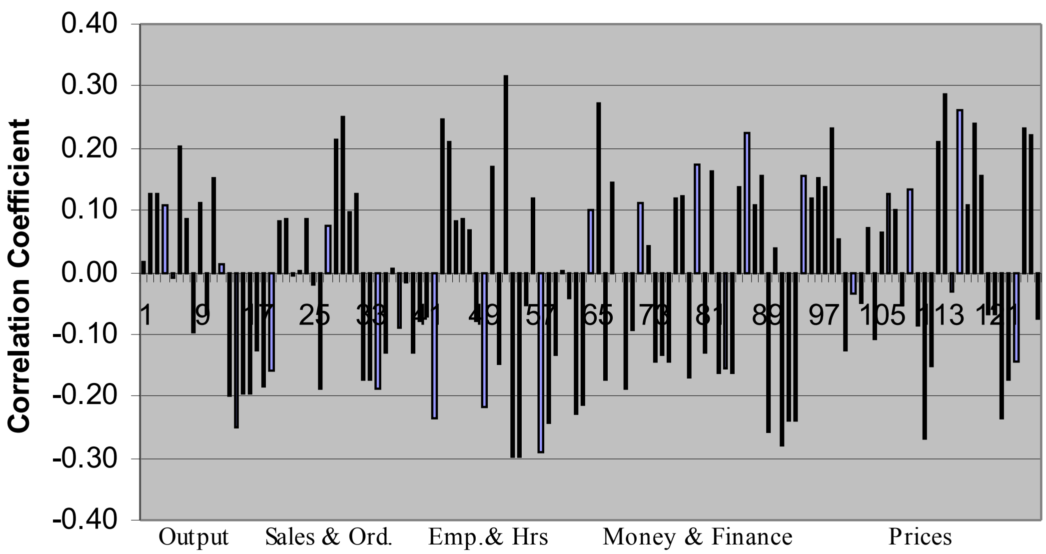
Notes: This chart shows the correlation coefficient between each variable and factor 6. Data covers 1983:09-2006:10. See appendix for a description of the numbered series.

Figure 7: Correlations with F7



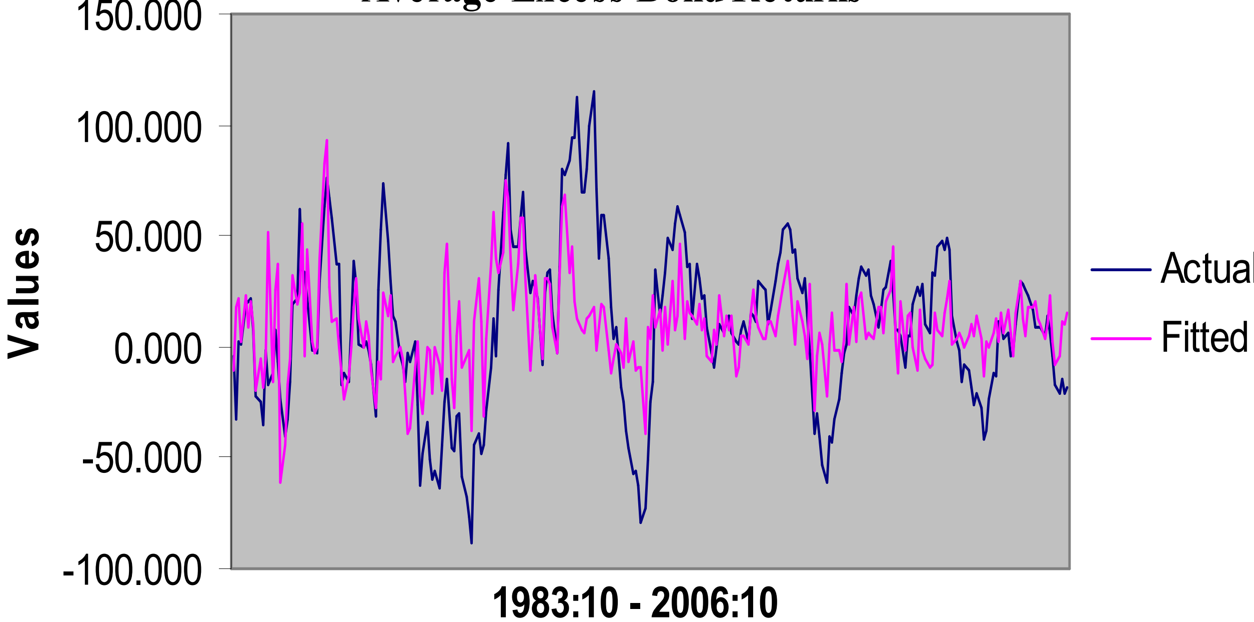
Notes: This chart shows the correlation coefficient between each variable and factor 7. Data covers 1983:09-2006:10. See appendix for a description of the numbered series.

Figure 8: Correlations with F8



Notes: This chart shows the correlation coefficient between each variable and factor 8. Data covers 1983:09-2006:10. See appendix for a description of the numbered series.

Figure 9: Actual and Fitted Values of Average Excess Bond Returns



Notes: The chart shows actual and fitted values of average excess bond returns obtained from predictive regressions.

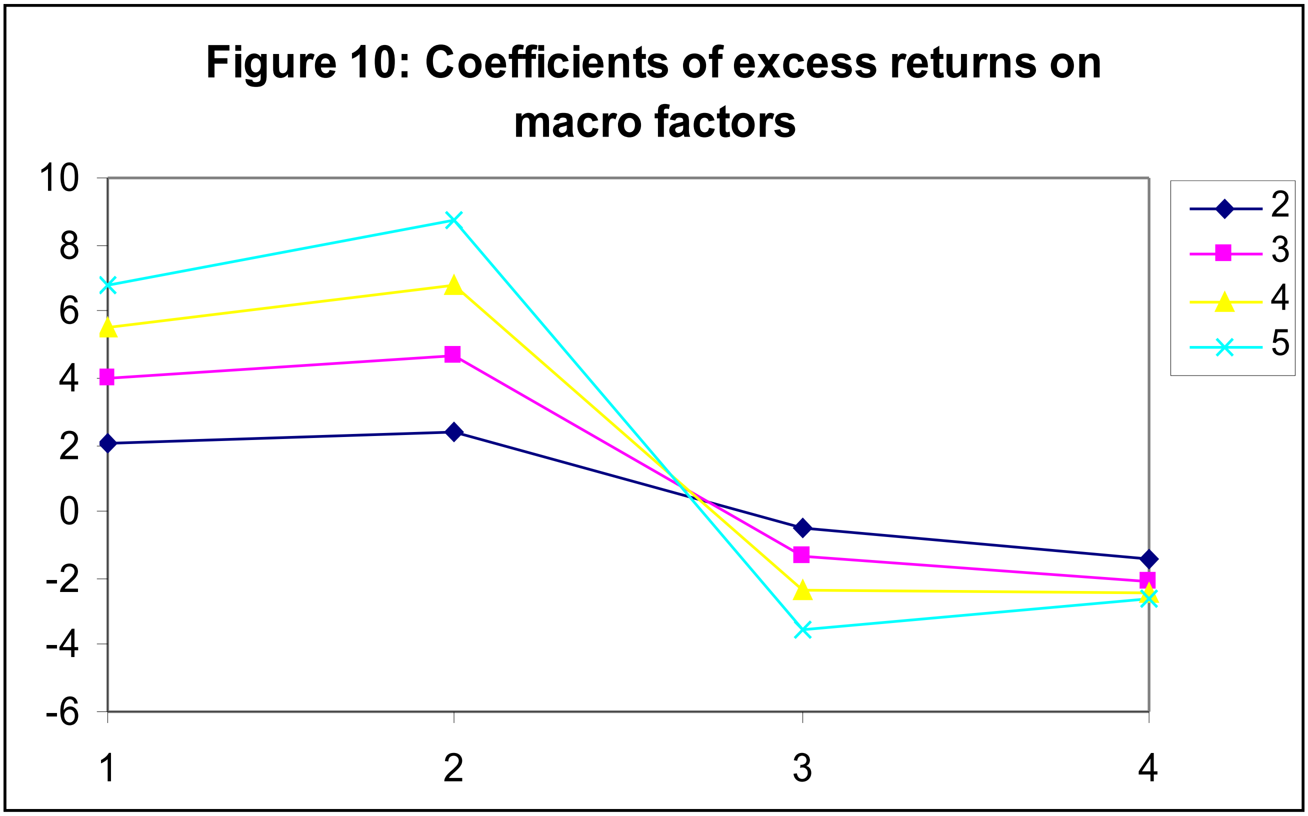


Figure 10: Coefficients of excess returns on macro factors
10
8
6
4
2
0
-2
-4
-6
1
2
3
4
2
3
4
5

Table 1: Regressions of Monthly UK Excess Bond Returns on Lagged Factors

Model: $rx_{t+1}^{(n)} = \beta_0 + \beta_1' \hat{F}_t + \beta_2(LN_t) + \varepsilon_{t+1}$

Regressor	(n=2)	(n=3)	(n=4)	(n=5)	(n=av)
intercept	-6.31	-4.54	-0.13	4.91	-1.52
	(-1.83)	(-0.73)	(-0.02)	(0.44)	(-0.21)
$\hat{F}_{1t}$	**2.15**	**4.07**	**5.66**	**6.91**	**4.70**
	(8.23)	(7.88)	(7.42)	(7.06)	(7.57)
$\hat{F}_{2t}$	-0.20	-0.16	-0.12	-0.09	-0.14
	(-0.63)	(-0.26)	(-0.13)	(-0.08)	(-0.20)
$\hat{F}_{3t}$	-0.46	-0.77	-0.95	-1.04	-0.81
	(-1.80)	(-1.55)	(-1.32)	(-1.13)	(-1.36)
$\hat{F}_{4t}$	**2.38**	**4.72**	**6.80**	**8.72**	**5.66**
	(6.73)	(7.38)	(7.55)	(7.63)	(7.56)
$\hat{F}_{5t}$	-0.30	-1.06	**-2.12**	**-3.32**	-1.70
	(-0.81)	(-1.45)	(-1.97)	(-2.38)	(-1.92)
$\hat{F}_{6t}$	**-1.23**	**-1.92**	**-2.26**	-2.42	**-1.96**
	(-3.32)	(-2.62)	(-2.16)	(-1.86)	(-2.28)
$\hat{F}_{7t}$	-0.66	-1.14	-1.39	-1.49	-1.17
	(-1.64)	(-1.49)	(-1.27)	(-1.07)	(-1.30)
$\hat{F}_{8t}$	-0.60	-0.76	-0.70	-0.54	-0.65
	(-1.66)	(-1.14)	(-0.76)	(-0.48)	(-0.86)
LN_t	**1.11**	1.34	1.26	1.12	1.21
	(3.10)	(1.90)	(1.27)	(0.91)	(1.47)
R^2	0.44	0.38	0.35	0.34	0.36
$\overline{R}^2$	0.42	0.36	0.33	0.31	0.34
F-stat	23.20	18.15	16.02	15.03	16.77
$prob(F)$	0.00	0.00	0.00	0.00	0.00

Notes: Table 1 reports estimates from OLS regressions of excess bond returns on the lagged variables named in the first column. The dependent variable rx_{t+1}^{n} is the log excess return on the n-year UK government liability bond. $\hat{F}_t$ denotes set of regressors estimated by the method of principal components using a macroeconomic data of UK with 127 variables. The monthly data covers the periods 1983:09-2006:10. The raw data is standardized prior to estimation of static factors by principal components. Thus, principal components are obtained from the correlation matrix of the macro aggregates. LN_t is the Ludvigson and Ng (2005) factor generated as a simple average of the one year yield and four forward rates. Data is checked for stationarity and all the necessary transformations are applied. Newey-West (1987) heteroscedasticity-consistent standard errors and covariances are calculated, t-statistics are reported in parentheses. Coefficients that are statistically significant at five percent or better level are highlighted in bold.

Table 2: Different Specifications of 2-year Bond Excess Return Regressions

Model: $rx_{t+1}^{(2)} = \beta_0 + \beta_1' \hat{F}_t + \beta_2(LN_t) + \varepsilon_{t+1}$

Regressor	(a)	(b)	(c)	(d)	(e)
intercept	-5.96	-3.66	-6.31	3.66	-6.31
	(-1.36)	(1.89)	(-1.83)	(1.88)	(-1.81)
$\hat{F}_{1t}$		**2.05**	**2.15**	**2.05**	**2.15**
		(7.07)	(8.23)	(6.45)	(7.53)
$\hat{F}_{2t}$		-0.31	-0.20		
		(-0.79)	(-0.63)		
$\hat{F}_{3t}$		-0.32	-0.46		
		(-1.19)	(-1.80)		
$\hat{F}_{4t}$		**2.34**	**2.38**	**2.35**	**2.38**
		(5.70)	(6.73)	(5.42)	(6.28)
$\hat{F}_{5t}$		-0.51	-0.30	-0.51	-0.30
		(-1.14)	(-0.81)	(-1.16)	(-0.83)
$\hat{F}_{6t}$		**-1.40**	**-1.23**	**-1.40**	**-1.24**
		(-2.89)	(-3.32)	(-2.91)	(-3.31)
$\hat{F}_{7t}$		-0.59	-0.66		
		(-1.33)	(-1.64)		
$\hat{F}_{8t}$		-0.86	-0.60		
		(-1.88)	(-1.66)		
LN_t	**1.07**		**1.11**		**1.11**
	(2.38)		(3.10)		(3.05)
R^2	0.14	0.29	0.44	0.27	0.42
$\overline{R}^2$	0.14	0.27	0.42	0.26	0.41
F-stat	45.78	13.57	23.30	25.31	39.86
$prob(F)$	0.00	0.00	0.00	0.00	0.00

Notes: Table 2 reports estimates from OLS regressions of excess bond returns on the lagged variables named in the first column. The dependent variable $rx_{t+1}^{n}$is the log excess return on the n-year UK government liability bond. $\hat{F}_t$ denotes set of regressors estimated by the method of principal components using a macroeconomic data of UK with 127 variables. The monthly data covers the periods 1983:09-2006:10. The raw data is standardized prior to estimation of static factors by principal components. Thus, principal components are obtained from the correlation matrix of the macro aggregates. LN_t is the Ludvigson and Ng (2005) factor generated as a simple average of the one year yield and four forward rates. Data is checked for stationarity and all the necessary transformations are applied. Newey-West (1987) heteroscedasticity-consistent standard errors and covariances are calculated, t-statistics are reported in parentheses. Coefficients that are statistically significant at five percent or better level are highlighted in bold.

Table 3: Different Specifications of 3-year Bond Excess Return Regressions

Model: $rx^{(3)}_{t+1} = \beta_0 + \beta_1' \hat{F}_t + \beta_2(LN_t) + \varepsilon_{t+1}$

Regressor	(a)	(b)	(c)	(d)	(e)
intercept	-3.84	7.51	-4.54	7.51	-4.48
	(-0.48)	(2.22)	(-0.73)	(2.22)	(-0.71)
$\hat{F}_{1t}$		**3.96**	**4.07**	**3.96**	**4.07**
		(7.38)	(7.88)	(6.92)	(7.46)
$\hat{F}_{2t}$		-0.29	-0.16		
		(-0.41)	(-0.26)		
$\hat{F}_{3t}$		-0.60	-0.77		
		(-1.21)	(-1.55)		
$\hat{F}_{4t}$		**4.68**	**4.72**	**4.68**	**4.72**
		(6.80)	(7.38)	(6.55)	(7.08)
$\hat{F}_{5t}$		-1.33	-1.06	-1.33	-1.07
		(-1.61)	(-1.45)	(-1.64)	(-1.49)
$\hat{F}_{6t}$		**-2.12**	**-1.92**	**-2.12**	**-1.92**
		(-2.46)	(-2.62)	(-2.49)	(-2.66)
$\hat{F}_{7t}$		-1.05	-1.14		
		(-1.35)	(-1.49)		
$\hat{F}_{8t}$		-1.07	-0.76		
		(-1.40)	(-1.14)		
LN_t	1.26		1.34		1.34
	(1.44)		(1.90)		(1.88)
R^2	0.06	0.31	0.38	0.30	0.37
$\overline{R}^2$	0.06	0.29	0.36	0.29	0.36
F-stat	17.42	15.29	18.15	29.49	31.66
$prob(F)$	0.00	0.00	0.00	0.00	0.00

Notes: Table 3 reports estimates from OLS regressions of excess bond returns on the lagged variables named in the first column. The dependent variable $rx^n_{t+1}$is the log excess return on the n-year UK government liability bond. $\hat{F}_t$ denotes set of regressors estimated by the method of principal components using a macroeconomic data of UK with 127 variables. The monthly data covers the periods 1983:09-2006:10. The raw data is standardized prior to estimation of static factors by principal components. Thus, principal components are obtained from the correlation matrix of the macro aggregates. LN_t is the Ludvigson and Ng (2005) factor generated as a simple average of the one year yield and four forward rates. Data is checked for stationarity and all the necessary transformations are applied. Newey-West (1987) heteroscedasticity-consistent standard errors and covariances are calculated, t-statistics are reported in parentheses. Coefficients that are statistically significant at five percent or better level are highlighted in bold.

Table 4: Different Specifications of 4-year Bond Excess Return Regressions

Model: $rx_{t+1}^{(4)} = \beta_0 + \beta_1' \hat{F}_t + \beta_2 (LN_t) + \varepsilon_{t+1}$

Regressor	(a)	(b)	(c)	(d)	(e)
intercept	0.84	**11.18**	-0.13	**11.18**	-0.00
	(0.07)	(2.42)	(-0.02)	(2.43)	(-0.00)
$\hat{F}_{1t}$		**5.55**	**5.66**	**5.55**	**5.66**
		(7.18)	(7.42)	(6.90)	(7.18)
$\hat{F}_{2t}$		-0.25	-0.12		
		(-0.25)	(-0.13)		
$\hat{F}_{3t}$		-0.79	-0.95		
		(-1.11)	(-1.32)		
$\hat{F}_{4t}$		**6.77**	**6.80**	**6.77**	**6.80**
		(7.23)	(7.55)	(7.09)	(7.40)
$\hat{F}_{5t}$		**-2.37**	**-2.12**	**-2.37**	**-2.13**
		(-2.06)	(-1.97)	(-2.10)	(-2.03)
$\hat{F}_{6t}$		**-2.44**	**-2.26**	**-2.44**	**-2.26**
		(-2.10)	(-2.16)	(-2.13)	(-2.20)
$\hat{F}_{7t}$		-1.30	-1.39		
		(-1.19)	(-1.27)		
$\hat{F}_{8t}$		-0.99	-0.70		
		(-0.98)	(-0.76)		
LN_t	1.15		1.26		1.25
	(0.93)		(1.27)		(1.25)
R^2	0.03	0.32	0.35	0.31	0.34
$\overline{R}^2$	0.02	0.30	0.33	0.30	0.33
F-stat	7.23	15.80	16.03	31.02	28.31
$prob(F)$	0.00	0.00	0.00	0.00	0.00

Notes: Table 4 reports estimates from OLS regressions of excess bond returns on the lagged variables named in the first column. The dependent variable $rx_{t+1}^{n}$is the log excess return on the n-year UK government liability bond. $\hat{F}_t$ denotes set of regressors estimated by the method of principal components using a macroeconomic data of UK with 127 variables. The monthly data covers the periods 1983:09-2006:10. The raw data is standardized prior to estimation of static factors by principal components. Thus, principal components are obtained from the correlation matrix of the macro aggregates. LN_t is the Ludvigson and Ng (2005) factor generated as a simple average of the one year yield and four forward rates. Data is checked for stationarity and all the necessary transformations are applied. Newey-West (1987) heteroscedasticity-consistent standard errors and covariances are calculated, t-statistics are reported in parentheses. Coefficients that are statistically significant at five percent or better level are highlighted in bold.

Table 5: Different Specifications of 5-year Bond Excess Return Regressions

Model: $rx_{t+1}^{(5)} = \beta_0 + \beta_1' \hat{F}_t + \beta_2(LN_t) + \varepsilon_{t+1}$

Regressor	(a)	(b)	(c)	(d)	(e)
intercept	6.04	**14.97**	4.91	**14.97**	5.10
	(0.43)	(2.61)	(0.44)	(2.64)	(0.46)
$\hat{F}_{1t}$		**6.81**	**6.91**	**6.81**	**6.91**
		(6.92)	(7.06)	(6.74)	(6.92)
$\hat{F}_{2t}$		-0.21	-0.09		
		(-0.17)	(-0.08)		
$\hat{F}_{3t}$		-0.89	-1.04		
		(-0.99)	(-1.13)		
$\hat{F}_{4t}$		**8.69**	**8.72**	**8.69**	**8.72**
		(7.43)	(7.63)	(7.40)	(7.61)
$\hat{F}_{5t}$		**-3.54**	**-3.32**	**-3.54**	**-3.33**
		(-2.42)	(-2.38)	(-2.46)	(-2.44)
$\hat{F}_{6t}$		-2.58	-2.42	-2.58	-2.42
		(-1.83)	(-1.86)	(-1.86)	(-1.89)
$\hat{F}_{7t}$		-1.42	-1.49		
		(-1.02)	(-1.07)		
$\hat{F}_{8t}$		-0.81	-0.54		
		(-0.66)	(-0.48)		
LN_t	0.99		1.12		1.10
	(0.65)		(0.91)		(0.89)
R^2	0.01	0.32	0.34	0.32	0.33
$\overline{R}^2$	0.01	0.30	0.31	0.31	0.32
F-stat	3.41	15.83	15.03	31.39	26.79
$prob(F)$	0.07	0.00	0.00	0.00	0.00

Notes: Table 5 reports estimates from OLS regressions of excess bond returns on the lagged variables named in the first column. The dependent variable $rx_{t+1}^{n}$is the log excess return on the n-year UK government liability bond. $\hat{F}_t$ denotes set of regressors estimated by the method of principal components using a macroeconomic data of UK with 127 variables. The monthly data covers the periods 1983:09-2006:10. The raw data is standardized prior to estimation of static factors by principal components. Thus, principal components are obtained from the correlation matrix of the macro aggregates. LN_t is the Ludvigson and Ng (2005) factor generated as a simple average of the one year yield and four forward rates. Data is checked for stationarity and all the necessary transformations are applied. Newey-West (1987) heteroscedasticity-consistent standard errors and covariances are calculated, t-statistics are reported in parentheses. Coefficients that are statistically significant at five percent or better level are highlighted in bold.

Table 6: Different Specifications of Average Excess Return Regressions

Model: $\frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)} = \beta_0 + \beta_1' \hat{F}_t + \beta_2(LN_t) + \varepsilon_{t+1}$

Regressor	(a)	(b)	(c)	(d)	(e)
intercept	-0.73	**9.33**	-1.52	**9.33**	-1.42
	(-0.08)	(2.42)	(-0.21)	(2.44)	(-0.19)
$\hat{F}_{1t}$		**4.59**	**4.70**	**4.59**	**4.70**
		(7.27)	(7.57)	(6.93)	(7.27)
$\hat{F}_{2t}$		-0.26	-0.14		
		(-0.32)	(-0.20)		
$\hat{F}_{3t}$		-0.65	-0.81		
		(-1.11)	(-1.36)		
$\hat{F}_{4t}$		**5.62**	**5.66**	**5.62**	**5.66**
		(7.15)	(7.56)	(7.00)	(7.39)
$\hat{F}_{5t}$		**-1.94**	-1.70	**-1.94**	**-1.70**
		(-2.01)	(-1.92)	(-2.05)	(-1.97)
$\hat{F}_{6t}$		**-2.13**	**-1.96**	**-2.14**	**-1.96**
		(-2.20)	(-2.28)	(-2.23)	(-2.32)
$\hat{F}_{7t}$		-1.09	-1.17		
		(-1.19)	(-1.30)		
$\hat{F}_{8t}$		-0.93	-0.65		
		(-1.10)	(-0.86)		
LN_t	1.12		1.21		1.20
	(1.10)		(1.47)		(1.45)
R^2	0.04	0.32	0.36	0.31	0.35
$\overline{R}^2$	0.03	0.30	0.34	0.30	0.34
F-stat	10.01	15.83	16.77	30.97	29.56
$prob(F)$	0.00	0.00	0.00	0.00	0.00

Notes: Table 6 reports estimates from OLS regressions of excess bond returns on the lagged variables named in the first column. The dependent variable $rx_{t+1}^{n}$is the log excess return on the n-year UK government liability bond. $\hat{F}_t$ denotes set of regressors estimated by the method of principal components using a macroeconomic data of UK with 127 variables. The monthly data covers the periods 1983:09-2006:10. The raw data is standardized prior to estimation of static factors by principal components. Thus, principal components are obtained from the correlation matrix of the macro aggregates. LN_t is the Ludvigson and Ng (2005) factor generated as a simple average of the one year yield and four forward rates. Data is checked for stationarity and all the necessary transformations are applied. Newey-West (1987) heteroscedasticity-consistent standard errors and covariances are calculated, t-statistics are reported in parentheses. Coefficients that are statistically significant at five percent or better level are highlighted in bold.