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Do Macroeconomic Variables Forecast Bond Returns?

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Abstract

This paper studies time varying bond returns via macroeconomic variables. We find that a single macro index consisting of inflation, real activities and money can predict annual excess bond returns of 1-5 year maturities with R^2 up to 37%. The macro factor has a symmetric tent-shape, when projected onto forward rates. In addition, i) it predicts longer-term bond returns better than shorter-term returns, ii) it is countercyclical and independent of each bond yield and iii) it predicts excess stock returns. Results are robust to measurement errors and lags. Through detailed analyses, we argue that macroeconomic variables could account for the information in long-maturity forward rates almost entirely in light of return predictability.

(JEL G0, G1, E0, E4)

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1 Introduction

This paper studies time varying bond returns via macroeconomic variables. We find that a single macroeconomic index made of variables describing inflation, real activities and monetary aggregates can predict one-year excess holding period returns on US government bonds of one- to five-year maturities with R^2 up to 37%. Contributions to total forecasting power by each category are roughly equal. The macro factor is a linear combination of 15 macroeconomic variables which forecasts average movements of returns on bonds. We select variables which are frequently used in academic literature and professional forecasting.

The existing literature mostly focuses on asset price variables to find a good predictor for bond returns. Fama and Bliss (1987) showed that the spread between n-year forward rate and the one-year yield predicts excess return on n-year maturity bond. Cochrane and Piazzesi (2005) set a new standard for return predictability by finding out a single factor which is a linear combination of forward rates and one-year interest rate. However, there exist few studies which link the findings aforementioned to macroeconomic variables. Given the abundance of theoretical works that derive asset returns using macroeconomic fundamentals and only limited empirical successes, it is important to verify if we could account for the information that asset prices contain in predicting bond returns using macroeconomic variables. The major contribution of the paper is that we could generate stylized facts regarding time-varying bond risk premia purely out of macroeconomic variables.

We not only match predictability of bond returns equivalent to the level attained by the forward-rates based factor identified by Cochrane and Piazzesi (2005) but also find that the macro factor is quite similar to their factor (henceforth C-P factor) in qualitative aspects as well: The macro factor has a symmetric tent-shape when projected onto forward rates. In addition, the macro factor predicts longer-term bond returns better than shorter-term returns displaying highest R^2 value at 4-year maturity bond return. Therefore this factor correctly captures the difference between 5-year and 4-year yields which matters in forecasting returns.

It is countercyclical, i.e. it predicts low returns at good times and high returns at bad times.

The single macro factor predicts excess stock returns as well, with R^2 value of 11 percent. Furthermore when we run an unrestricted regression for one-year ahead stock returns, R^2 increases up to 33 percent. We discuss implications of this in terms of a process for stochastic discount factor. We show that our empirical findings are robust to lags and measurement errors. Through detailed analyses, we argue that macroeconomic variables could account for the information in long-maturity forward rates almost entirely in light of return predictability.

This paper proceeds as follows. Next, we review related literature. Section 3 explains data series we will use for our estimations. Then we run several regressions of excess bond returns onto macroeconomic variables. Section 5 analyzes the empirical findings by comparing with the C-P factor in an attempt to link macroeconomic variables to forward rates. Section 6 concludes.

2 Related literature

Bond return predictability has been extensively studied in the context of forward rates. Fama and Bliss (1987) and Stambaugh (1988) are two important early contributions. Cochrane and Piazzesi (2005) show that a tent shaped linear combination of forward rates could forecast bond returns significantly better than term premiums or simple slope of yields. Existence of bond return predictability implies that the expectation hypothesis is not true. One might account for it by deviating from rationality of investors. However the major strand of literature ascribes it to predictability of time varying risk premia. Thus our paper provides additional evidences against the expectation hypothesis from a macroeconomic perspective. Furthermore, we provide a tighter description about predictability pattern: A single macro index model can predict the excess bond returns of one- to five-year maturities very well, consistent with the finding with forward rates by Cochrane and Piazzesi (2005).

Fama and French (1989) show that expected returns on stocks and long-term bonds have comovements with business cycles (countercyclical patterns). They use financial market variables such as term premiums or default premiums as their right hand side variables. This paper links macroeconomic variables displaying business cycles directly to the expected excess returns on both bonds and stocks.

Estrella and Mishkin (1997) and Evans and Marshall (1998) run vector autoregressions (VAR) of bond yields and macroeconomic variables to relate yield movements to macro shocks (real shocks, price shocks, and monetary policy shocks). Ang and Piazzesi (2003) impose no arbitrage restrictions to VAR models so that they could compare unobservable yield factors and macroeconomic variables in a more systematic way because most latent factor models assume no arbitrage restriction while VAR models do not. Our paper focuses on return predictability of bonds rather than explaining term structure of yields. However the existence of return predictability consisting only of macroeconomic variables has an implication on bond pricing formula similar to Ang and Piazzesi (2003).

Lastly our paper is related to macroeconomics based asset pricing models such as consumption based models. Our empirical results suggest that general equilibrium models could account for return predictability provided that they explicitly consider monetary sectors and investment behaviors of firms as well as more detailed specifications about consumption expenditures. Cochrane (2005) is an excellent survey in this regard.

3 Data

We use the Fama-Bliss data of zero coupon bond prices with maturities from 1 to 5 years, obtained from CRSP to effectively compare our macro factor with the C-P factor. The Fama-Bliss bond data covers the period from 1964 to 2003 and our monthly macro data covers the period from 1964 to 2002, which allows us to forecast excess holding period returns during the period between 1965 and 2003. Excess holding period return of n-year bond is defined as the return from purchasing n-year bond with borrowing at one year rate, selling next year. We have chosen 15 macro variables that can capture real activities, inflation, and monetary sectors. First, real activities can be explained by using the unemployment rate and the growth rate of the following seven macro variables: the real personal consumption expenditures on non-durable goods (FRED: PCENDC96), durable goods (FRED: PCEDGC96) and service (FRED: PCESVC96), the consumer credit outstanding by commercial banks (Federal reserves Statistics: G.19), the loan investment by all commercial banks (FRED: LOANINV), the unemployment rate (IFS: 11167R.ZF.), and the new privately owned housing units started (http://www.census.gov/const/startsua.pdf). Every growth rate is annualized. Secondly, we measure inflation by using the annualized inflation of the following three macro variables: the chain-type price index for personal consumption expenditure (FRED: PCEPI), PPI/WPI (IFS: 11163.ZF.), and the spot oil price (FRED: OILPRICE). Thirdly, we find that the following four money macro variables help considerably in predicting the bond returns: the log ratios of M2 (IFS: 11159MB.ZF.) to M1 (IFS: 11159MA.ZF.), and M1 to MB (IFS: 11119MA.ZF), the annualized growth rate of M1, and the difference between annualized growth rates of M3 (IFS: 11159MC.ZF.) and M2. We attempt to measure velocity shifts as well as money growth rates in selecting monetary variables. Each data source is indicated in parenthesis where FRED stands for the Federal Reserve Bank of St. Louis and IFS stands for the IMF International Financial Statistics. Our study contains most of the variables that have been used in a variety of macroeconomic literature, asset pricing models and professional forecasting. For instance, the chain-type price index for personal consumption expenditure, civilian unemployment rate, and housing starts are used in the survey of professional forecasters of Federal Reserve Bank of Philadelphia, Blue Chip Consensus and Congressional Budget Office. In order to verify whether our macro factor can forecast excess holding period return on stocks, we use NYSE value-weighted annual returns, obtained from CRSP.

4 Bond returns and macro variables

This section estimates and analyzes return forecasting factor using only macroeconomic variables. Following Cochrane and Piazzesi (2005) we identify our single return forecasting factor in two steps. First, we compute an average value of one-year ahead holding period returns in excess of the one-year interest rate over maturities of 2-5 years. Then, we forecast the average holding period excess return using our macroeconomic variables representing a subset of information variables for bond market traders. We call the explained part of this estimation as the macro factor and run one-year ahead, individual bond return regressions onto this factor. We estimate unrestricted equations as well, i.e. we forecast the excess bond returns with all the macroeconomic variables in order to check the legitimacy of the two-step estimation procedure. After verifying the significance of our estimates, we analyze and compare our factor with the forward-rates based factor that predicts bond returns.

4.1 Return-forecasting factor using macro variables

We denote log bond price at t with maturity n as

$$p_t^n.$$

Then the log yield is defined as

$$y_t^n \equiv -\frac{p_t^n}{n}.$$

The log of one-period holding period return from purchasing the n-period bond at t and selling it at $(t+1)$ is expressed as

$$hpr_{t+1}^n \equiv p_{t+1}^{n-1} - p_t^n.$$

Now the log return in excess of one period yield, i.e. excess holding period return is

$$hprx_{t+1}^n \equiv hpr_{t+1}^n - y_t^1.$$

Similarly, we express the log forward rate at time t for one period loans between $(t+n-1)$ and $(t+n)$ as

$$f_t^n \equiv p_t^{n-1} - p_t^n.$$

Abusing notations slightly, $hprx_{t+1}$, y_t, and f_t without superscripts stand for vectors of the excess returns, yields, and forward rates respectively. We denote X_t as a $(k+1)\times 1$ vector of regressors, where $X_t = [1, x_{1t}, \cdots, x_{kt}]'$ and $\{x_{it}\}_{i=1}^k$ refers to macroeconomic variables. In our estimations, we use $k = 15$ variables. A linear regression to forecast excess bond returns with macroeconomic variables will be of the form,

$$hprx_{t+1}^n = \delta_0^n + \sum_{i=1}^{15} \delta_{1i}^n x_{it} + \epsilon_{t+1}^n, \tag{1}$$

where $\delta_1^n = [\delta_{11}^n, \cdots \delta_{1k}^n]$ and $n = 2, \cdots, 5$. We call them unrestricted regressions.

Alternatively, we can form a single factor by projecting the average of excess returns over maturities on macroeconomic variables,

$$\begin{aligned}\frac{1}{4}\sum_{n=2}^{5} hprx_{t+1}^n &= \gamma_0 + \sum_{i=1}^{15} \gamma_{1i} x_{it} + \epsilon_{t+1} \\ &= \gamma' X_t + \epsilon_{t+1},\end{aligned}$$

where $\gamma = [\gamma_0, \gamma_{11}, \cdots, \gamma_{1k}]'$. Table 1 (step 1) shows the results which we discuss later. Then we can identify factor loadings for the single index $(\gamma' X_t)$ by estimating the following equations,

$$hprx_{t+1}^n = b_n(\gamma' X_t) + \epsilon_{t+1}^n, \tag{2}$$

for $n = 2, ...5$. The coefficients are normalized so that the sum of b_n over n is equal to four. We denote the specification (2) as restricted regressions. Table 1 (step 2) displays the results from the specification (2).

R^2 values are around 34% to 37% with our synthetic single factor, which is equivalent to or slightly higher than those from the forward rate based factor identified by Cochrane and Piazzesi (2005). R^2 increases as maturity gets longer, becomes highest at four-year bond. Estimates of

b_n are [0.47, 0.87, 1.21, 1.44], showing a upward sloping curve. With the C-P factor in the right hand side, we obtain $[0.47, 0.87, 1.24, 1.43]$, displaying virtually identical loadings. Standard errors are corrected in Newey-West way with 18 lags and they are also quite similar. Figure 1 presents the ex-post excess holding period returns and our macroeconomic return-forecasting factor $\gamma' X_t$. There are hits and misses, but one can see that our forecasting factor formed one year ago is in good sync with the realized excess bond returns invested last year.

It has been noted that forward rates or bond returns show co-movements with macro variables dictating business cycles. However it was difficult to match predictability of excess bond returns that the factor mimicking portfolios can attain. The C-P factor consists entirely of the bond prices of one- to five-year maturities. Therefore, our result suggests that a linear combination of macroeconomic variables can forecast fluctuations of excess bond returns with different maturities equally well as bond prices can. Given the results, it is an appealing conjecture that macroeconomic variables entail the information in forward rates in terms of return predictability. The next section will discuss it in further detail. We verify robustness of our findings in the below.

High R^2 might come from the number of the right hand side variables. Almost identical adjusted R^2 shows that our forecasting is not spurious and χ^2-tests for joint significance strongly confirm that the excess returns are predictable. It would be great if there exists one macroeconomic variable capturing the level movement of bond returns. However, figure 2 suggests that it is not the case. We plot R^2 by increasing right hand side variables gradually to check if there is any single macro variable performing exceptionally. To the contrary, forecastability increases slowly but surely to achieve 37 percent of R^2.

In addition, figure 3 displays bi-variate coherences between macroeconomic variables and average excess bond return. Bi-variate coherence is the ratio of a squared covariance to the product of two variances at a specific frequency (or a cycle of period).

As Sargent (1987) put, one could understand bi-variate coherence as R^2 statistic at each frequency or period. Therefore, if we could find that coherence patterns are similar across the different pairs, we could presumably reduce the number of macroeconomic variables for return forecasting equations. However, figure 3 shows that highest coherences prevail at rather heterogeneous frequencies for each pair.[1] For instance, the coherence between M1 growth rate and the average excess return in panel (x_{14}, AXR) shows highest coherence of 0.61 at the lowest frequency, or the full sample period while the one with the non-durable consumption growth rate [panel (x_1, AXR)] reveals 0.3 around quarterly period. This suggests that different macroeconomic variables play an independent role in shaping up return-forecasting factor according to both figure 2 and figure 3. Another notable observation is that money appears to matter.

If our variables represent a subset of information set for bond market participants, it is not surprising that they will use more than ten variables given the vast amount of statistics releases freely available nowadays. At least, our macro factor or the C-P factor illustrates that one synthetic factor could capture all excess bond returns in a stable manner.

Now we check if our single factor is consistent with unrestricted regressions. We run unrestricted regressions for (1) and figure 4 plots factor loadings on macro variables for the excess holding period returns of two to five year maturities in both the restricted and the unrestricted regressions. Horizontal axis represents maturities of excess bond returns. They are very close across each other, showing that the single factor approach captures successfully almost all of the return forecasting done by the unrestricted estimations. We also run regressions onto single lag of each variables to find out that the coefficients are similarly estimated and highly jointly significant. The predictability measured in R^2 stays around 34 to 36 percent steadily when lagging the macroeconomic variables.[2] Since macroeconomic variables are persistent over

[1] Horizontal axis for the coherence is between $(0, \pi)$ in terms of frequency. Since $2\pi/\omega$ is the period, where ω is the frequency, lowest frequency implies the whole sample, the highest frequency refers to two month and a value around 0.5 refers to a year.

[2] However, once lag reaches over seven months, then R^2 declines. We do not report the results with single lags, for there is little change.

time, this result shows that serially uncorrelated measurement errors cannot be the reason for forecastability.

Step1 in table 1 reports corrected standard errors with Hansen-Hodrick procedure with 12 lags, Newey-West way with 18 lags, and nonoverlapping sample in an attempt to handle overlapping data structure and cross correlations and autocorrelations of the macro variables, though the latter two issues are less serious than those of the forward rates.[3] Estimates are reasonable, although some of them are volatile. Given the proximity of our results with Cochrane and Piazzesi (2005), we believe that the estimates are not misleading. However we run through most of the tests performed by them and still decisively reject the hypothesis that returns are unpredictable with $\chi^2(15)$ at one percent critical value, 31. All of the results imply that return predictability by the single factor does exist. Interestingly enough, our synthetic macro factor appears to have good resemblance with the forward-rates based factor according to our empirical findings. This naturally leads us into further investigating this factor in various regards. Then, we attempt to connect the macro factor to the C-P factor.

5 Analyzing the macro factor

5.1 Stock return forecasting

Fama and French (1989, 1993) and Cochrane and Piazzesi (2005) show that a bond return forecasting factor will predict stock returns as well. Our results support this view. Table 2 reports that the single macro factor forecasts stock returns with 11 percent of R^2, slightly higher than the C-P factor. The estimated coefficient is 2.19 and statistically significant. Term spread also forecasts stock returns, yet only with 3 percent of R^2. When we predict stock

[3] In correcting standard errors with nonoverlapping data, we follow the method by Cochrane and Piazzesi (2005). We compute the average covariance matrix for parameters, for there are twelve ways of constructing nonoverlapping monthly observations of annaul returns. Heteroskedasticity is corrected as well.

returns using both the macro factor and term spread, there exists no change in R^2, while the term spread becomes insignificant. The last regression compares the macro factor with the C-P factor. R^2 is 11 percent and both coefficients become noisier, the loading of the macro factor is 1.84, somewhat lower than that of the first regression.

The lower R^2 for stock return forecasting with the single macro factor implies that there exists other sources of risk premia in the case of stock returns. Since our macro factor $\gamma' X_t$ is built up so that it predicts average movements of bond returns, roughly the common variations between stock returns and bond returns will be captured by the macro factor. Fama and French (1993) report that there exist variables that specialize in accounting for expected excess stock returns. Macroeconomic variables might have some additional explanatory power over the expected excess stock returns, independent of the part that forecasts bond returns. Pursuing the idea, we run an unrestricted regression of the excess stock returns onto all the macroeconomic variables we have. This yields an R^2 of 33 percent. When we run a regression consisting only of a few variables describing real activities especially, it still presents an R^2 value of 25 to 30 percent. In addition, we check if the explained part of the regression has any forecasting power toward excess bond returns, which turns out that it is very small. Following the literature we interpret that there exists a common variation of excess returns predicting both kinds of assets, but stock returns also contain some independent risk premia due to cash flow risks as suggested by Fama and French (1993), Cochrane and Piazzesi (2005). Macroeconomic variables do affect both the common and idiosyncratic shocks. However, if one wants to have a macro factor structure predicting both stock returns and bond returns, our findings suggest that there exist two macro indices, one of which is entirely for stock returns, the other, mostly for bond returns but also helpful for the stock returns to some extent. Related, one interesting implication regarding empirical asset pricing models is that if we use these two factors to mimic the stochastic discount factor, we could obtain similar predictability over both stock returns and bond returns.

5.2 Term structures of yields

This section relates the macro return-forecasting factor to yield factors. Term structure of bond yields is well approximated by three yield factors called 'level', 'slope', and 'curvature'. The panel (c) of figure 5 presents the loadings of the three factors over maturities 1-5 years, extracted as the first three principal components of yields. The three yield factors account for almost all the variance of yields. We compare the macro factor by projecting it on yields and the top left panel (a) of figure 5 displays the loadings. The top right panel (b) presents the coefficients of the C-P factor expressed in terms of yields. One can easily see both the macro factor and the C-P factor share a pattern of yield curve, and it is very different from those of the three yield factors. As emphasized by Cochrane and Piazzesi (2005), the return forecasting factor is a small variation not explained by the usual yield factors.

Empirical finance literature has identified that term spreads have predictability over bond returns. It is possible that the macro factor could reflect the information that term spreads contain. Cochrane and Piazzesi (2005) found that when excess returns are projected onto forward rates, the estimated coefficients will feature symmetric tent shapes over maturities of forward rates. It is comforting that the panel (a) and (b) look quite different from the slope factor though, we would verify if the single macro factor could draw a tent shape over maturities of forward rates. We run regressions of all the forward rates on the macro factor. Then, we use the projected parts as regressors for the excess holding period returns. If the macro factor captures forward rates sufficiently, we could observe symmetric tent shapes of estimated coefficients as the forward rates factor.

The panel (d) reveals that this is the case. Although we do not report here, we experimented with different numbers of macroeconomic variables to see if a symmetric tent shape prevails with fewer variables. Once we include monetary variables after using variables representing real activities and inflation, tent shapes finally emerge. Alternatively, projecting the macro factor onto forward rates also results in a symmetric tent shape. Therefore, R^2 and the shapes of both yield curve and forward curve emulated by the macro factor imply that the macro factor predicts the excess holding period returns in an almost identical way as the forward rates do.

The punchline of Cochrane and Piazzesi (2005) is not to ignore the small factor, or the difference between five-year and four-year yield. Since yields, forward rates and returns are all linear functions of bond prices, if all the five yields are used for return forecasting, the same predictive power will prevail as that of C-P factor because five yields span the same space as five forward rates do. Even if the macro factor is on a par with the forward rates factor, the macro factor uses a different basis. Therefore a natural question arises: How does the macro factor perform together with yields?

When all five yield factors as well as a constant are used to predict the excess returns, R^2 value is 35%. Adding the macro factor, one can observe an increase in R^2 to 48%.[4]

To summarize, our single factor constructed from macroeconomic variables predicts the excess bond returns to virtually the same extent that all five yields can. Figure 5 displays that this return-forecasting factor is also quite similar to the forward-rates factor qualitatively. However the yield factors cannot drive out the macro factor. Rather, it appears that forecasting power strengthens when we include the macro return-forecasting factor to all the yields. Alternatively one can suspect that all five yield factors could predict bond returns that the macro factor can not capture. To verify if this conjecture is plausible, we test the null hypothesis that adding five yields to the macro factor has no significance,

$$\frac{1}{4}\sum_{n=2}^{5} hprx_{t+1}^{n} = \gamma' X_t + \sum_{n=1}^{5} \alpha_n y_t^n + \epsilon_{t+1}.$$

That is, we test if $\alpha_1 = \cdots = \alpha_5 = 0$.

Table 4 documents that with Newey-West standard error correction, an increase in R^2 from 35% to 48% by including all five yields as additional regressors could be statistically significant. However tests with nonoverlapping data cannot reject the null hypothesis at 5% critical level,

[4]Table 3 reports the case with the five latent factors extracted from the principal component analysis. Obviously, we have the same increase in R^2 when we add all 5 yields.

implying that the macro factor suffices to forecast average bond return.

Thus, spaces spanned by either the macro factor or all five yields may represent slightly different dimensions of future expectations regarding bond prices respectively, yet they are almost the same across each other both qualitatively and quantitatively. Next section further explores the macro factor. In so doing we perform robustness checks of our empirical findings as well.

5.3 Macro factor and forward rates

5.3.1 Lags and measurement error

We start by displaying regression results with both the macro factor and the C-P factor. Table 5 documents that R^2 increases up to 47 percent and both factors are jointly significant. However recall that the macro factor captures what all five yields do in delineating common variations of expected returns according to the test results in table 4. Since the forward-rates based factor should span the same space as the one that all five yields do, adding the C-P factor to the macro factor may not be as impressive as it looks. Note also that factor loadings of two factors are almost identical and smoothly upward sloping.

In their analysis, Cochrane and Piazzesi (2005) report highest R^2 around 44 percent when they include multiple lags of their factor. They argue that this is a sign of measurement error, and a good linear predictor of the true factor will be the standard Kalman filtered estimate, i.e. a moving average representation of the factor. We verify how lags of the macro factor affect return predictability. The table 6-(i) reveals that the macro factor is quite robust to multiple lags. R^2 or adjusted R^2 do not change and the estimated lag coefficients are insignificant. We also run regressions to predict bond returns using both the macro factor and the C-P factor with lags of each factor. Table 6-(iii) documents that adding three lags of both factors does not help in forecasting returns when compared with the result with no lags.

In addition, the results on stock return forecasting in table 2 are insightful in this regard.

The forecasting power of stock returns over one year yield increases when we use a moving average of the Cochrane-Piazzesi factor. The resultant R^2 (10%) is virtually the same as what the macro factor could achieve ($R^2 = 11\%$).

Therefore we argue that the macroeconomic variables could account for what bond prices reflect in terms of return predictability. Of course they are not identical. Bond prices are the future conditional expectations of nominal stochastic discount factor. We presumably miss some important variables that reflect the expectations of bond market participants. We support this view due to the evidence that the macro factor is insensitive to lags, thereby less affected by measurement errors. We showed that missing variables could be all of the whole term structure of yields, but test results are not strong and reversed with nonoverlapping sample correction.[5]

The main point of the paper is that usual suspects in macroeconomic literature could form a good basis for the information set used by asset market participants. Moreover, a single, macro index characterization works well for all excess returns we considered. A related message is that macroeconomic models of asset pricing consistent with return predictability must entail a richer set of variables such as monetary variables and investments as well as consumption variables.

5.3.2 Sub-periods and out-of-sample forecasts

It is clear that the macro factor is countercyclical from figure 1 and figure 3. Will the results go through in sub-samples and out-of-samples? This section provides some additional robustness checks to the return predicting regressions. Table 7 documents regression results when we divide the whole sample into three periods: 1964:1 to 1979:12, 1980:1 to 1989:12 and 1990:1 to 2003:12. We run both unrestricted and restricted regressions, which result in stable predictabilities across three periods. Unrestricted regressions outperform the restricted regressions, but the estimated coefficients (b) with the factor $\gamma' X_t$ derived from the full sample still show very robust perfor-

[5] Although we do not report, we also check the residual of our single factor regressions, showing that the residuals are explained by idiosyncratic bond yields of their own maturities, consistent with Cochrane and Piazzesi (2005).

mances. This also implies that our results come from appropriately capturing level movement of excess bond returns, not from measurement errors.

Next, we display some results from out-of-sample forecasting for robustness check. That is, we estimate the return forecasting factor and its loadings recursively using the data from the beginning of the sample to t instead of the full sample. Following Cochrane and Piazzesi (2005), we use a trading rule such that one has a long position of an average maturity bond by the amount of the forecast $E_t\left(\frac{1}{4}\sum_{n=2}^{5} hprx_{t+1}^{n}\right)$ and short position of the one year bond by the same amount. Then, ex-post profits will be of the following equation:

$$\left[\frac{1}{4}\sum_{n=2}^{5} hprx_{t+1}^{n}\right] E_t(\frac{1}{4}\sum_{n=2}^{5} hprx_{t+1}^{n}) = \left[\frac{1}{4}\sum_{n=2}^{5} hprx_{t+1}^{n}\right](b'\gamma' X_t),$$

where $\gamma' X_t$ is the return forecasting factor. A correct prediction on average return will make the profit positive according to the trading rule. Thus, we can measure the performance of return-forecasting factors. In order to see how the macro factor performs in both the full sample and the real sample (out-of-sample) cases, we accumulate the profits. Then we can illustrate how small forecasting errors are piling up over time. Figure 6 displays the cumulated profits when one uses either the macro factor or the Cochrane-Piazzesi factor.

The macro factor in the out-of-sample forecasting shows a similar pattern to that of the full sample case, which implies that out-of-sample forecasts are doing well. However, accumulated differences result in lower performance compared to the full sample forecast. The Cochrane-Piazzesi factor shows a similar performance. Computed RMSE (Root Mean Squared Errors) are also similar around 0.5.

6 Conclusion

Do macroeconomic variables predict excess bond returns? We give a strong confirmation to this question. We find that our single factor composed by macro variables performs equally well compared to a tent-shaped linear combination of forward rates found by Cochrane and Piazzesi

(2005). In addition, the macro factor is quite robust to lags unlike the forward-rates factor in predicting excess bond returns.

Existing studies have documented that forward rates include future expectations about excess bond returns, but they did not give macroeconomic interpretations on this observation. Macroeconomic models of asset pricing dictate that bond prices will be described by macroeconomic variables, but there exist few empirical studies that link two stories in a unified way. The major contribution of the paper is that we abridge the gap empirically by showing that current macroeconomic variables could account for the information in long maturity forward rates very well in light of return predictability. We find that macroeconomic variables used in bond return prediction could be quite effective when predicting stock returns as well.

Therefore, our results suggest that macroeconomic asset pricing models could give sharper characterizations on expected asset returns provided that they explicitly consider monetary variables and investment behaviors of firms as well as consumption variables. We leave this important task to future research.

Appendix

A Data source

Real variables	Data specification and source
1. Real personal consumption expenditures for non-durable goods	(saar, Billions of Chained 2000 Dollars, Monthly) http://research.stlouisfed.org/fred2/series/PCENDC96/
2. Real personal consumption expenditures for durable goods	(saar, Billions of Chained 2000 Dollars, Monthly) http://research.stlouisfed.org/fred2/series/PCEDGC96/
3. Real personal consumption expenditures for services	(saar, Billions of Chained 2000 Dollars, Monthly) http://research.stlouisfed.org/fred2/series/PCESVC96/
4. Total Loans and Investments at All Commercial Banks	(sa, Billions of Dollars, Monthly) http://research.stlouisfed.org/fred2/series/LOANINV
5. Unemployment rate	(Percent per Annum, Monthly) IMF IFS - 11167R..ZF...
6.New Privately Owned Housing Units Started	(nsa, number of housing units in thousands, monthly) http://www.census.gov/const/startsua.pdf
7. Consumer Credit	(nsa, Millions of Dollars, Monthly) Federal reserves Statistics: G.19

Inflation variables	Data specification and source
1. Personal Consumption Expenditures: Chain-type Price Index	(sa, Index 2000=100, Monthly) http://research.stlouisfed.org/fred2/series/PCEPI/
2. PPI / WPI	(index number, Monthly) IMF IFS - 11163...ZF...
3. Spot Oil Price: West Texas Intermediate	(Dollars per Barrel, Monthly) http://research.stlouisfed.org/fred2/series/OILPRICE

Monetary variables	Data specification and source
1. Monetary Base	(Billions of Dollars, Monthly) IMF IFS - 11119MA.ZF..
2. M1	(Billions of Dollars, Monthly) IMF IFS - 11159MA.ZF..
3. M2	(Billions of Dollars, Monthly) IMF IFS - 11159MB.ZF...
4. M3	(Billions of Dollars, Monthly) IMF IFS - 11159MC.ZF...

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Table 1. Estimates of the macro single factor model

Step 1. Estimating the return forecasting factor, $\frac{1}{4}\sum_{n=2}^{5} hprx_{t+1}^{n} = \gamma' X_t + \epsilon_{t+1}$

	constant	$\inf_{pce}$	$\inf_{ppi}$	$\inf_{petroleum}$	$\Delta hstart$	Δccr
OLS estimates	-24.06	-0.72	-0.13	0.02	-0.03	0.13
HH, 12 lags	(10.67)	(0.50)	(0.19)	(0.01)	(0.02)	(0.10)
NW, 18 lags	(10.47)	(0.46)	(0.17)	(0.01)	(0.02)	(0.09)
No overlap	(15.38)	(0.59)	(0.28)	(0.02)	(0.03)	(0.10)

	Δc_{nd}	Δc_d	Δc_s	$\Delta unemp$	$unemp$	$\Delta linv$
OLS estimates	-0.19	0.04	0.13	0.06	0.33	-0.57
HH, 12 lags	(0.27)	(0.06)	(0.48)	(0.02)	(0.25)	(0.22)
NW, 18 lags	(0.24)	(0.06)	(0.44)	(0.02)	(0.26)	(0.21)
No overlap	(0.43)	(0.12)	(0.67)	(0.03)	(0.35)	(0.30)

	$m2/m1$	$m1/mb$	$\mu_3 - \mu_2$	μ_1	R^2	$\bar{R}^2$	$\chi^2(15)$
OLS estimates	14.93	10.31	0.54	-0.08	0.37	0.35	
HH, 12 lags	(5.48)	(5.70)	(0.28)	(0.10)			201.92
NW, 18 lags	(5.41)	(5.60)	(0.26)	(0.10)			157.25
No overlap	(8.06)	(8.20)	(0.40)	(0.14)			42.47

(See next page for Notes)

Table 1 Step 2: Individual bond regressions, $hprx_{t+1}^{n} = b_n(\gamma_F' F_t) + \epsilon_{t+1}^{n}$

$\gamma_F' F_t$	Macro			C-P		
n	b_n	NW18	R^2	b_n	NW18	R^2
2	0.47	(0.06)	0.34	0.47	(0.05)	0.31
3	0.87	(0.10)	0.36	0.87	(0.10)	0.34
4	1.21	(0.15)	0.37	1.24	(0.15)	0.37
5	1.44	(0.18)	0.36	1.43	(0.19)	0.34

(Notes for Step 1) The 10 percent, 5 percent, and 1 percent critical values for a $\chi^2(15)$ are 22.3, 25, and 30.1 respectively. p-values are close to zero. Standard errors are in parentheses, and computed using three ways: Hansen and Hodrick with 12 lags, Newey-West with 18 lags, and with non-overlapping sample for robustness.
$\inf_{pce}$, $\inf_{ppi}$, $\inf_{petroleum}$ are annualized inflation for personal consumption price index, PPI, and oil prices. Δc_{nd}, Δc_d, Δc_s denote growth rates for non-durable, durable, and services expenditures, respectively. $unemp$ denotes unemployment rate
$\Delta unemp$, $\Delta hstart$, Δccr, $\Delta linv$ are annual changes in unemployment rate, housing start, consumer credits, and loan investments by all commercial banks. $m2/m1$, $m1/mb$, $\mu_3 - \mu_2$, μ_1 refer to log ratios of M2 to M1, M1 to MB, money growth difference between M3 and M2, and money growth rate for M1. All data including annual bond returns are of monthly frequency during 1964-2003.

(Notes for Step 2) The left hand side is the excess holding period returns for bonds of maturities between two and five years, and the right hand side is either the macro factor estimated from the Step 1 or the C-P factor (Cochrane-Piazzesi) using forward rates.

Table 2. Forecasts of excess stock returns

	R.H.S.	Macro factor	C-P factor	Term Spread	R^2
1	Macro factor	2.19			0.11
	(standard error)	(0.99)			
2	C-P factor		1.73		0.05
	(standard error)		(0.61)		
3	C-P + C-P lags				0.10
4	Term Spread (TS)			3.87	0.03
	(standard error)			(1.64)	
5	Macro & TS	2.03		0.60	0.11
	(standard error)	(1.06)		(1.31)	
6	Macro & C-P	1.84	0.59		0.11
	(standard error)	(1.15)	(0.62)		
7	All the macro variables				0.33

(Notes) The left hand side is the one-year return on the value-weighted NYSE stock return minus 1-year bond yield. Standard errors use Newey-West correction with 18 lags.

Table 3. Macro return forecasting factor and term structure of yields:

$\frac{1}{4}\sum_{n=2}^{5} hprx_{t+1}^{n} = \xi\left(\gamma' X_t\right) + \beta' y_t + \epsilon_{t+1}^{xy}$, y_t : yield factors, $\gamma' X_t$: macro factor

Eq.\R.H.S.	level	slope	curvature	4th	5th	macro	R^2	$\bar{R}^2$	χ^2
1	0.45						0.03	0.03	
HH12	0.55								0.66
NW18	0.48								0.85
2	0.99	0.45					0.24	0.24	
HH12	0.41	0.11							17.83
NW18	0.37	0.10							22.85
3	0.82	0.42	-0.12				0.26	0.25	
HH12	0.42	0.12	0.06						36.58
NW18	0.37	0.10	0.06						42.43
4	0.89	0.43	-0.11	0.27			0.35	0.34	
HH12	0.33	0.10	0.06	0.03					336.13
NW18	0.30	0.09	0.05	0.05					102.58
5	0.88	0.43	-0.11	0.27	-0.03		0.35	0.34	
HH12	0.33	0.10	0.06	0.03	0.04				811.29
NW18	0.30	0.09	0.05	0.05	0.04				105.47
6	0.62	0.17	-0.07	0.21	-0.04	0.76	0.48	0.47	
HH12	0.26	0.10	0.05	0.04	0.04	0.13			263.13
NW18	0.24	0.09	0.05	0.05	0.04	0.12			164.63

(Notes) We add the macro factor only for the regression (6) because the macro return-forecasting factor dominates yield factors in all other cases.

Table 4. Tests for significance of yield factors

	Newey-West 18 lags	Nonoverlapping	
Macro factor	χ^2 <p-value>	χ^2 <p-value>	5% critical value
+ level	0.32 <57.20>	0.18 <66.72>	3.84
+ slope	0.65 <72.25>	0.27 <87.50>	5.99
+ curvature	7.41 <5.99>	1.59 <66.22>	7.81
+ 4th	45.71 <0.00>	4.79 <30.92>	9.49
+ 5th	51.40 <0.00>	5.05 <40.98>	11.07

(Notes) This table tests if adding yield factors to the macro factor is meaningful. Thus, we test $\alpha_1 = \cdots = \alpha_N = 0$, where $N = 1, \cdots, 5$ in regressions

$$\frac{1}{4}\sum_{n=2}^{5} hprx_{t+1}^{n} = \gamma' X_t + \sum_{k=1}^{N} \alpha_k y_{k t} + \epsilon_{t+1}.$$

$\gamma' X_t$ is the vector of return-forecasting macro factor and y_{k_t} denotes the k^{th} yield factor, where $k = 1, \cdots, 5$. The first column indicates right hand side variables in a cumulative way. For instance, '+ slope' refers to testing the null hypothesis that α_1 (level) and α_2 (slope) are jointly insignificant. NW 18 is the Newey-West correction with 18 lags and Nonoverlapping refers to the standard errors with nonoverlapping sample.

Table 5. Macro factor and Cochrane-Piazzesi factor

$$hprx_{t+1}^n = b_n(\gamma' X_t) + c_n(\delta' f_t) + \epsilon_{t+1}^n$$

	Macro (b_n)	Cochrane-Piazzesi (c_n)	R^2	χ^2
$hprx_{t+1}^2$	0.31	0.28	0.42	
HH12	0.06	0.06		112
NW18	0.06	0.06		118
N/O	0.18	0.23		43
$hprx_{t+1}^3$	0.57	0.52	0.45	
HH12	0.10	0.11		113
NW18	0.09	0.10		123
N/O	0.19	0.24		43
$hprx_{t+1}^4$	0.76	0.77	0.47	
HH12	0.12	0.15		108
NW18	0.12	0.14		120
N/O	0.19	0.25		44
$hprx_{t+1}^5$	0.93	0.86	0.45	
HH12	0.14	0.19		106
NW18	0.14	0.18		114
N/O	0.20	0.26		36

(Notes) This table plots regression results for excess returns on each bond onto both the macro factor and the C-P factor. HH12 refers to Hansen-Hodrick standard error correction with 12 lags, NW18, Newey-West standard error correction with 18 lags, and N/O, nonoverlapping sample correction, respectively.

Table 6. Macro factor, Cochrane-Piazzesi factor, and lags

(i) Macro factor

Lag	α_0	α_1	α_2	α_3	R^2	$\bar{R}^2$
0	1.00 (0.12)				0.37	0.37
1	0.86 (0.32)	0.14 (0.30)			0.37	0.37
2	0.88 (0.30)	-0.06 (0.15)	0.20 (0.32)		0.37	0.37
3	0.89 (0.28)	-0.06 (0.15)	0.10 (0.13)	0.10 (0.30)	0.37	0.37

(ii) Cochrane-Piazzesi (C-P) factor

Lag	α_0	α_1	α_2	α_3	R^2	$\bar{R}^2$
0	1.00 (0.12)				0.35	0.35
1	0.55 (0.08)	0.56 (0.10)			0.40	0.40
2	0.47 (0.10)	0.42 (0.07)	0.26 (0.10)		0.41	0.40
3	0.44 (0.11)	0.38 (0.06)	0.17 (0.06)	0.19 (0.11)	0.41	0.41

(iii) Macro factor, C-P factor, and lags of both factors

Lag	α_m	α_{cp}	α_{m1}	α_{m2}	α_{m3}	α_{cp1}	α_{cp2}	α_{cp3}	R^2	$\bar{R}^2$
0	0.64	0.60							0.46	0.46
1	0.64	0.35	-0.07			0.38			0.48	0.48
2	0.64	0.32	-0.15	0.06		0.32	0.13		0.48	0.48
3	0.64	0.30	-0.15	0.07	-0.02	0.29	0.09	0.10	0.48	0.47

(Notes) Panel (i) refers to the loadings when lags of the macro factor are added. Panel (ii), the same loadings for the C-P factor, and the panel (iii) displays those when we have both the macro and C-P factors with lags.

Table 7: Sub-period regressions

	unrestricted R^2	unrestricted $\bar{R}^2$	restricted b	restricted R^2
1964:1-1979:12	0.66	0.63	0.92	0.29
1980:1-1989:12	0.68	0.64	1.04	0.25
1990:1-2003:12	0.58	0.54	1.02	0.30

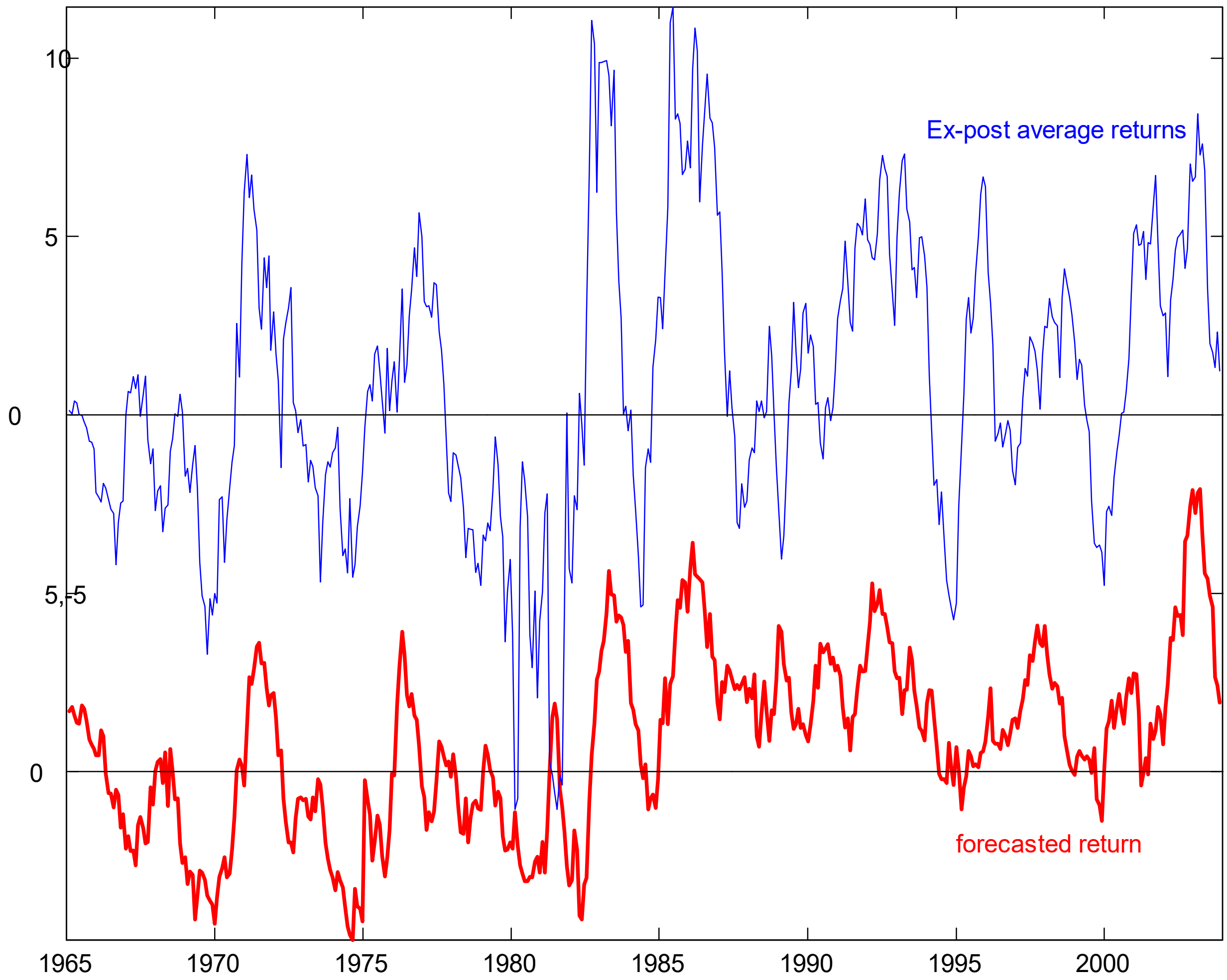
(Notes) Sub-period regression results of average excess return on macro variables.

Unrestricted regressions: $\frac{1}{4}\sum_{n=2}^{5} hprx_{t+1}^{n} = \gamma' X_t + \epsilon_{t+1}$

Restricted regression: $\frac{1}{4}\sum_{n=2}^{5} hprx_{t+1}^{n} = b(\gamma' X_t) + \varepsilon_{t+1}$

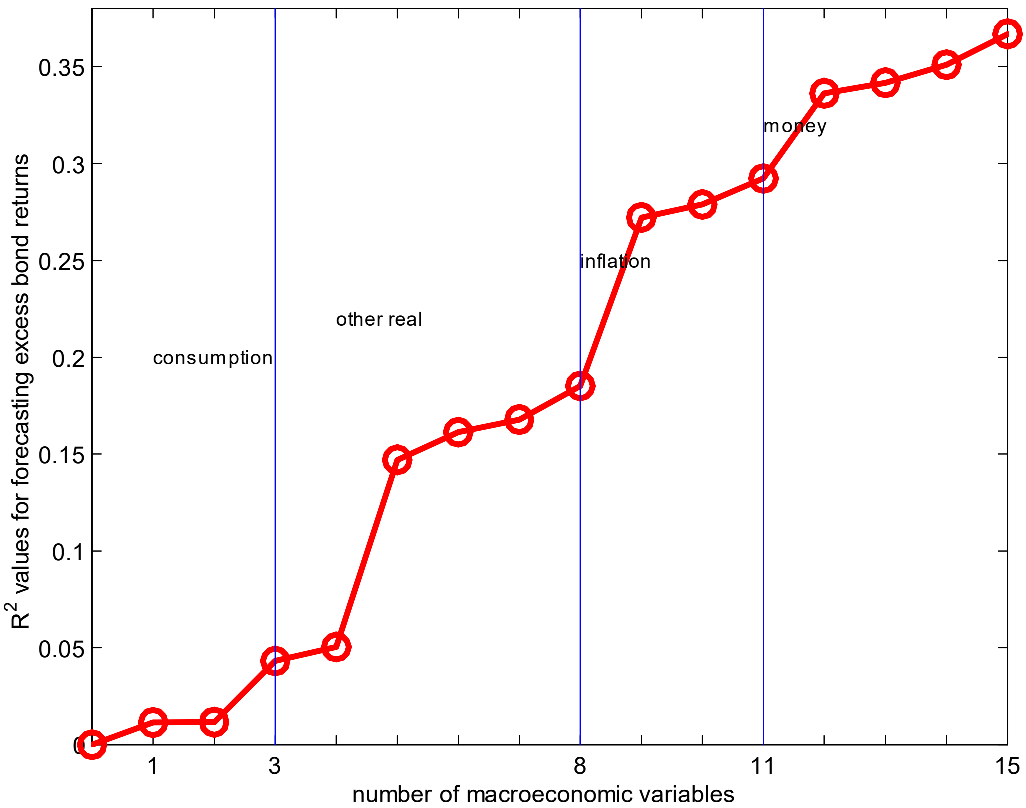
For the restricted regressions, $\gamma' X_t$ with the full sample is used to check if b is close to 1.

Figure 1. Average excess bond return and macro return forecasting factor



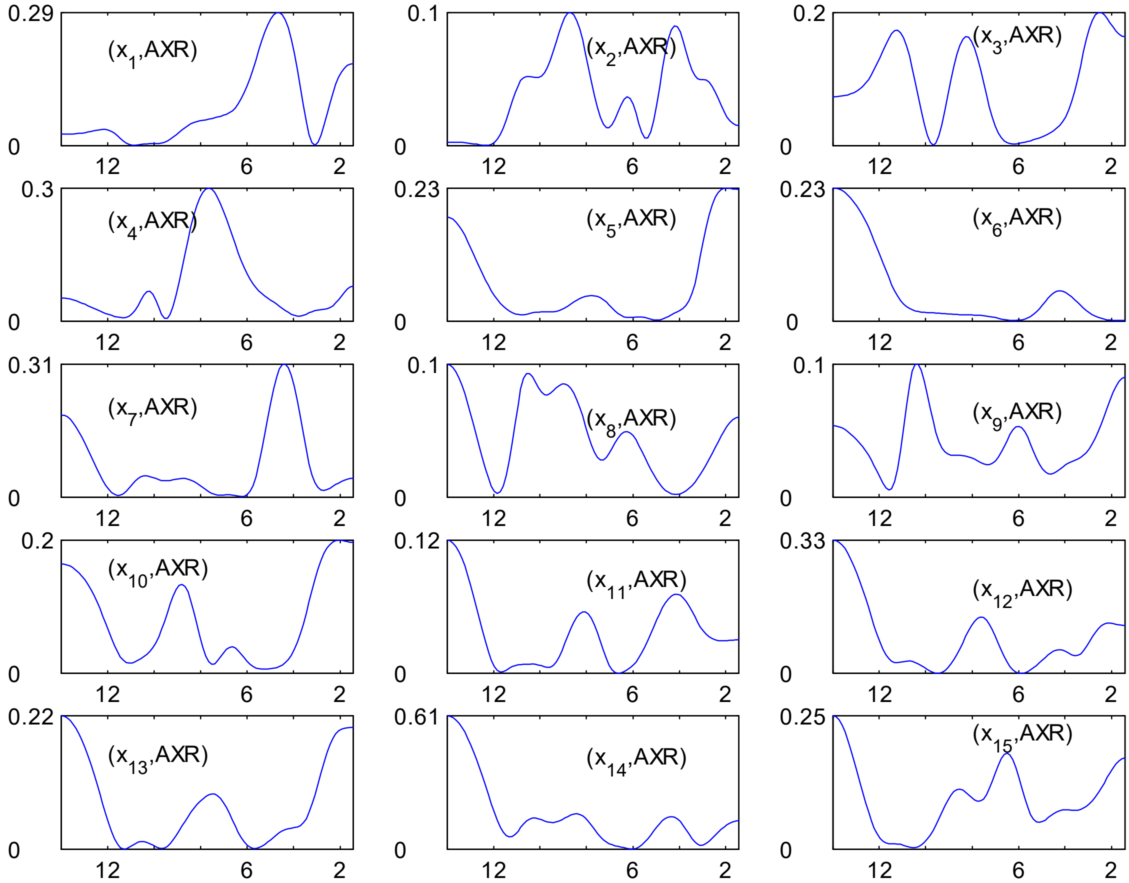
(Notes) The upper plots the actual realizations of average bond returns in excess of one-year bond yield, and the lower displays the forecasted return using macroeconomic variables.

Figure 2. Increase in R^2 When we add macro variables.



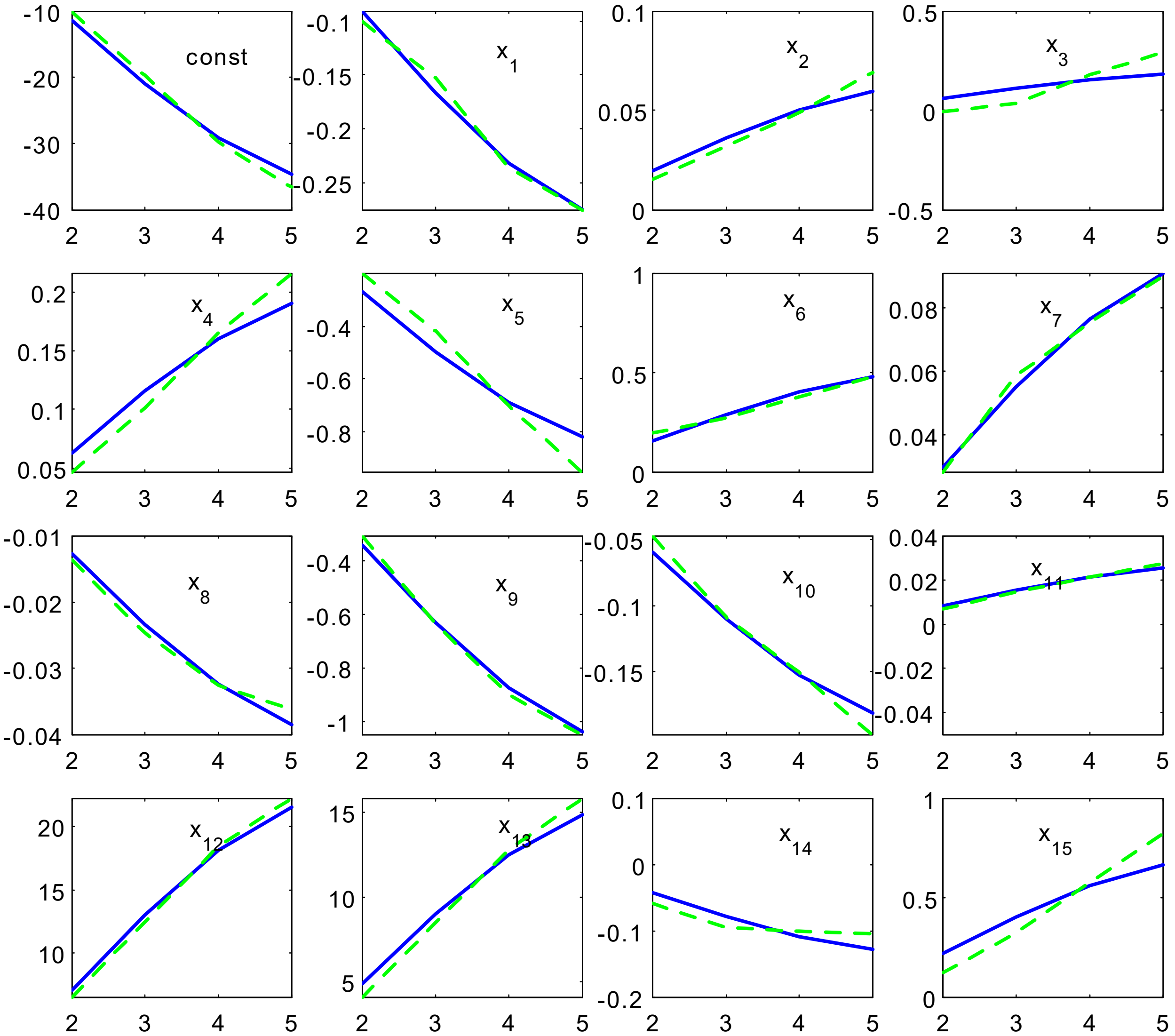
(Notes) The figure plots R^2 when macro variables increase from one to fifteen in the right hand side of the unrestricted forecasting equation. First three variables describe consumption expenditures. Next five variables represent other real activities. The third category contains variables related to inflation, and the last group variables are made with monetary aggregates. The results with adjusted R^2 shows virtually no change.

Figure 3. Coherences between macro variables and average excess holding period return



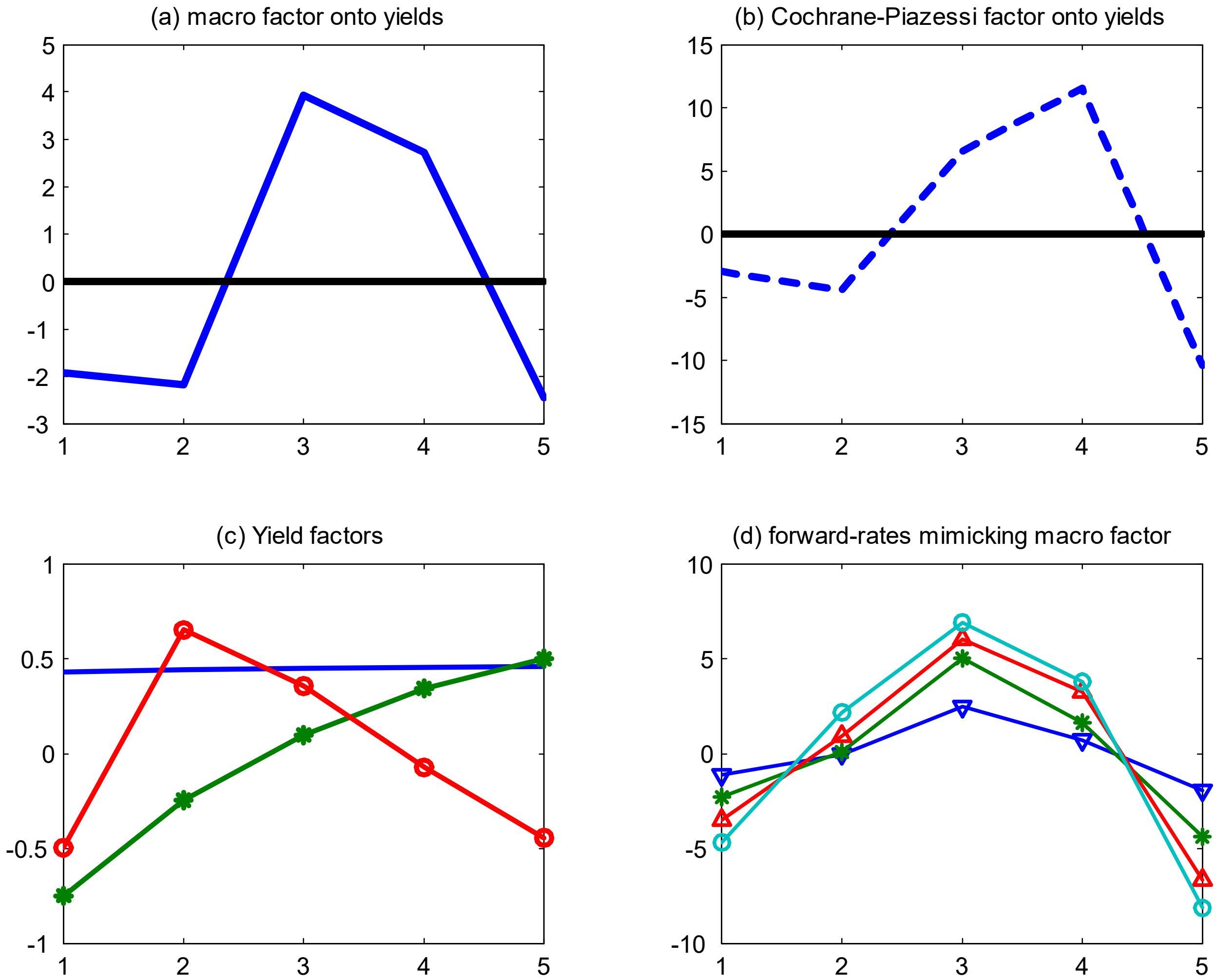
(Notes) Horizontal axis refers to periods (months) computed from frequency using the formula $2\pi/\omega$=period, where $\omega \in [0, \pi]$ is frequency. AXR denotes average excess bond return: Regarding $\{x_i\}_{i=1}^{15}$, one can consult notes in the figure 4 for the names of corresponding variables.

Figure 4. Unrestricted vs. Restricted Regressions of excess bond returns onto macro variables



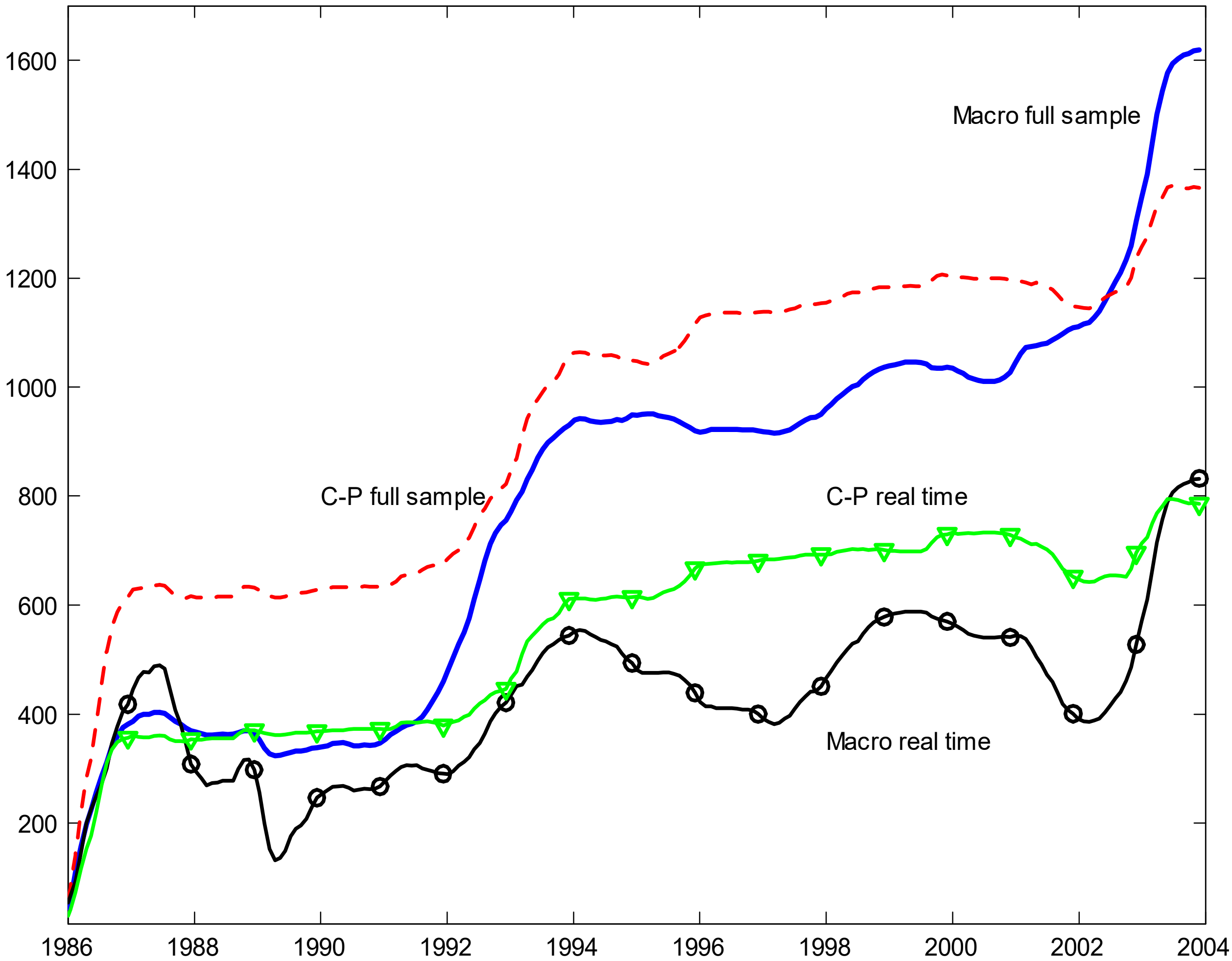
(Notes) const: constant, x_1,x_2,x_3 : growth rates of non-durable, durable and service expenditures, x_4:consumer credit outstanding by banks, x_5 : growth rate of loan investment by banks, x_6: unemployment of non-farm payroll, x_7: growth rate of unemployment rate, x_8 : growth rate of housing start, x_9 : inflation for chain-type price index for personal consumption expenditure, x_{10}: inflation for PPI, x_{11}: inflation for oil price, x_{12}: log(m2/m1), x_{13}: log(m1/mb), x_{14}: growth rate of M1 (Δm_1), x_{15}: Δm_3-Δm_2, Straight line : restricted regression, dashed line : unrestricted regression. All growth rates: annaulized. Horizontal axis: maturities of excess returns.

Figure 5. Yield factors and the macro factor



(Notes) Panel (a) plots the estimated coefficients of projected macro factor onto yields. Panel (b) displays estimated coefficients of Cochrane-Piazzesi factor onto yields. Panel (c) shows level (straight line), slope (asterisk), and curvature (circle) factors describing yields of one- to five-year maturities. Principal component analysis is used. Panel (d) depicts loadings of $hprx_{t+1}^{n}$ onto forward-rates mimicking macro factor. This factor is made as the explained part of projecting forward rates onto the macro factor. Horizontal axis represents maturity.

Figure 6: Trading rule: cumulated profits: Full sample versus real time sample



(Notes) Cumulative profits from trading rules using full sample and real time sample (out-of-sample) following Cochrane and Piazzesi (2005). Each line displays the cumulative value of $(1/4)\sum_{i=2}^{5} hprx_{t+1}^{n} \times E_t\{(1/4)\sum_{i=2}^{5} hprx_{t+1}^{n}\}$, where the latter term represents the amount of investment and could be using the full sample (1964-2003) or the real time sample (1964-t). That is, the conditional expectation term is recursively estimated every t. C-P refers to the Cochrane-Piazzesi factor, and the Macro denotes the macro factor.