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# THE MACROECONOMY AND THE YIELD CURVE: EVIDENCE FROM AN INTERNATIONAL PANEL DATASET

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#### Abstract

This paper provides cross-country empirical evidence on the dynamic interactions between macroeconomy and the yield curve by utilizing two-step estimation approach. In the first step three latent yield factors are estimated using Dynamic Nelson Siegel Model and in the second step dynamic relationship between these factors and macro factors are investigated by employing a Panel VAR model. The results suggest that there is a bidirectional link between macro variables and the yield curve.

Keywords: yield curve, macroeconomic variables, Nelson-Siegel, panel data

JEL classification: C5, E4, G1

## I. INTRODUCTION

It is well recognized that there is a close connection between real economy and financial conditions. Given that the interest rate is at the interconnection of the finance and the macro literature, a growing body of research investigates the relationship between the term structure of interest rates and macroeconomics. As stated by Aquiar-Conrari et al. (2012) the relationship between yield curve and macroeconomic variables is relavant for economic agents in a twofold sense: first, the yield curve may contain valuable information for growth, inflation and monetary policy in the future; second, the response of yield curve may contain valuable information for the dynamic impact of shocks on the macroeconomy.



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Early studies on this subject mainly concentrate on the unidirectional link from the yield curve to macroeconomic variables. Mishkin (1990), Esrella and Hardouvelis (1991), Estrella and Mishkin (1998) and Chinn and Kucko, (2010) among others, investigate the predictive power of the slope of the yield curve on growth and/or inflation. The findings in this literature suggest that the slope of the yield curve is usefull for predicting business cylces, growth and inflation<sup>1</sup>. On the other hand, a group of studies focuses on the unidirectional link from macro measures to the yield curve. For example, Ang and Piazzesi (2003), Hördahl et al. (2006), and Evans and Marshall (2007) show that macro factors have considerable effects on the yield curve. As discussed in Wu (2002) and, Smith and Taylor (2009) monetary policy changes also significantly influence the term structure of interest rates. However, as suggested by Ang, Dong, and Piazzesi (2007) when interactions are constraint to be unidirectional from macro-to-yield, the effect of macro factors on the dynamics of the yield curve may not be accurately estimated.

An alternative literature, mainly employs arbitrage-free models following Ang, Piazzesi and Wei (2006) or Dynamic Nelson Siegel Models following Diebold, Rudebusch, and Aruoba (2006)<sup>2</sup>, documents that there ise a bidirectional linkage between the macroeconomic variables and the yield curve. For example Diebold, Rudebusch, and Aruoba (2006) (henceforth DRA) find strong evidence of the effects of macro variables on the future movement in the yield curve and rather weak evidence for a reverse influence. In addition to DRA, Dewatcher and Lyrio (2006) and Rudebusch and Wu (2008), among others, report evidence for a significant bidirectional link between the term structure of interest rates and macroeconomic variables<sup>3</sup>. However, nearly all of the studies in this literateure use single, particularly US, country data.

This paper provides further evidence for the bidirectional link between macreconomic factors and the yield curve by using an international panel data set and utilizing a Dynamic Nelson Siegel Model following DRA. The use of panel data serves useful vehicle as it offers more accurate inference for model parameters and generates more accurate predictions by pooling data. A panel dataset of nine industrialized countries is used and a two-step estimation approach is employed. In the first step, three latent yield factors (level, slope and curvature) are estimated and in the second step, using the estimated latent yield factors dynamic relationship between these factors and macro factors are investigated by employing a Panel VAR model. To the best of my knowledge, this is the first paper that empirically investigates the aforementioned

<sup>&</sup>lt;sup>1</sup> For a review see Stock and Watson (2003)

<sup>&</sup>lt;sup>2</sup> Christensen, Diebold and Rudebusch (2009) combine the both approach and specify a generalized no-arbitrage Nelson-Siegel model.

<sup>&</sup>lt;sup>3</sup> For an overwiev of macro-finance literature see Gurkaynak and Wright (2012)

interactions by using a panel data.

The rest of the paper is as follows. Section two introduces the model. Section three presents the data. Section four provides estimation method and the results. Section five concludes.

### II. MODEL

One common way of analyzing the yield curve is the factor model approach which enables to express a large set of variables as a function of small set of unobserved factors. Since a factor representation can aggregate information from a large set of yields, it enables to analyze the yield curve dynamics in a convenient form. As DRA argue, one straightforward factor model is principal components approach. However, this approach restricts the factors to be orthogonal to each other, but it does not restrict factor loadings at all. Instead of this procedure, Nelson-Siegel form, which is very popular among practitioners and especially central banks, offers economically-motivated restrictions such as positive forward rates at all horizons and a discount factor approaches to zero as maturity increases.

The Nelson-Siegel representation is:

$$y_t(n) = \beta_1 + \beta_2 \left(\frac{1 - e^{-\lambda_t n}}{\lambda_t n}\right) + \beta_3 \left(\frac{1 - e^{-\lambda_t n}}{\lambda_t n} - e^{-\lambda_t n}\right)$$
(1)

where  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$ , and  $\lambda_t$  are parameters,  $y_t(n)$  is yield with maturity *n*. Diebold and Li (2006) (henceforth DL) show that allowing for the  $\beta_i$  coefficients to vary over time Nelson-Siegel yield curve representation becames a dynamic latent three-factor model. The Dynamic Nelson Siegel Model (DNS) is;

$$y_t(n) = \beta_{1t} + \beta_{2t} \left( \frac{1 - e^{-\lambda_t n}}{\lambda_t n} \right) + \beta_{3t} \left( \frac{1 - e^{-\lambda_t n}}{\lambda_t n} - e^{-\lambda_t n} \right)$$
(2)

The loadings  $\beta_{1,t}$ ,  $\beta_{2,t}$  and  $\beta_{3,t}$  are regarded as time varying level, slope and curvature factors, respectively. An increase in  $\beta_{1,t}$  increases the entire yield curve equally and therefore changes the level of the yield curve.  $\beta_{2,t}$  is closely related to the slope of the yield curve because short rates load on  $\beta_{2,t}$  is much more and an increase in  $\beta_{2,t}$  increases the short yields more than the long yields, thereby changes the slope of the yield curve. Lastly,  $\beta_{3,t}$  is closely related to the curvature because an increase in  $\beta_{3,t}$  increases the medium term very much but the short and long yields very small. The level, slope and curvature factors have ability to provide a good representation of the yield curve and empirically fit well (Chiristensen et al., 2011; DRA and DL).

To investigate the relationship between the yield curve and macroeconomy, as in DRA three macoeconomic variables (*output gap: OG, inflation: INF, and policy rate:PR*) are added to the model but loadings of the macro variables on the yields are restricted to be zero.

$$\begin{pmatrix} y_{i,t}(1) \\ y_{i,t}(12) \\ \vdots \\ \vdots \\ y_{i,t}(N) \end{pmatrix} = \begin{pmatrix} 1 & \frac{1-e^{-\lambda_t}}{\lambda_t} & \frac{1-e^{-\lambda_t}}{\lambda_t} - e^{-\lambda_t} & 0 & 0 & 0 \\ 1 & \frac{1-e^{-\lambda_t 2}}{\lambda_t 2} & \frac{1-e^{-\lambda_t 2}}{\lambda_t 2} - e^{-\lambda_t 2} & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \ddots & \vdots \\ 1 & \frac{1-e^{-\lambda_t N}}{\lambda_t N} & \frac{1-e^{-\lambda_t N}}{\lambda_t N} - e^{-\lambda_t N} & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \beta_{1i,t} \\ \beta_{2i,t} \\ \beta_{3i,t} \\ OG_{i,t} \\ PR_{i,t} \\ INF_{i,t} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1i,t} \\ \varepsilon_{2i,t} \\ \vdots \\ \vdots \\ \varepsilon_{Ni,t} \end{pmatrix}$$
(3)

i= Australia, ..., USA

The dynamic movement of the latent yield factors and the macro variables is assumed to follow a vector autoregressive process<sup>4</sup>;

$$X_{it} = \Gamma_0 + \Gamma_1(L)X_{it} + f_i + \epsilon_t \tag{4}$$

where  $X_{it} = \{OG_t, INF_t, PR_t, \beta_{1t}, \beta_{2t}, \beta_{3t}\}$  and  $\Gamma_1(L)$  is the matrix polynomial in the lag operator. The constraint that the time series relationship of dependent and explanatory variables is same for each cross-sectional unit which is likely to be violated in practice is relaxed by introducing fixed effects, denoted by  $f_i$  in (4). Fixed effects capture the countries' specifics and allows for individual heterogeneity in the levels of variables.

## III. DATA

In this research monthly data on zero-coupon government bond yields with maturities of 3, 6, 9, 12, 24, 36, 48, 60, 72, 84, 96, 108 and 120 months for nine industrial countries namely; Australia, Canada, Germany, Japan, Norway, Sweden, Switzerland, UK and US are used. The yields are from Wright data set which can be found at the author's personal webpage<sup>5</sup>. Following the Wright (2011), I start the sample with 1990 to account the trade-off between

<sup>&</sup>lt;sup>4</sup> In order to see the use of VARs to capture the dynamics of macro factors and the yield factors see Ang and Piazzesi (2003), DRA, Ang et al. (2007) and Moench (2012).

<sup>&</sup>lt;sup>5</sup> Which is http://econ.jhu.edu/directory/jonathan-wright/

maximizing sample size and minimizing the likelihood of a large structural break. Hence, the sample covers the period of 1990:1-2009:6. However, the yield data is not available before March 1998 for Norway and February 1993 for Sweden. The data refers to the yields on the last day of each month. All yields are continuously compounded.

For the macroeconomic measures three key variables; output gap  $(OG_t)$ , policy rate  $(PR_t)$  and annual price inflation  $(INF_t)$  are used. The first one represents the level of real economy relative to potential, the second one represents the policy instrument, and the last one represents the change in general price level. Therefore these three variables are widely considered to be the minimum set of fundamentals to capture the basic macroeconomic dynamics.

Output gap is calculated by detrending the log of industrial production index (IPI) using *Hodrick-Prescott* (*HP*) filter. The IPI data for countries is collected from International Financial Statistics (IFS) of IMF. Inflation rate is the 12-month percentage change in consumer price index (CPI). CPIs are collected from the IFS. Monthly CPI in Australia and monthly IPI in Australia and Switzerland are interpolated from quarterly data.

The description and sources of policy rates are given in Table 1.

| Country     | Policy rate   | Source                    |  |
|-------------|---|---------------------------|--|
| Australia   | Cash target rate  | Reserve Bank of Australia |  |
| Canada      | Overnight target rate   | Bank of Canada            |  |
| Germany     | Bundesbank discount rate and policy rate: main refinancing operations | Deutsche Bundesbank       |  |
| Japan       | Basic discount rate   | Bank of Japan             |  |
| Norway      | Sight deposit rate  | Norges Bank               |  |
| Sweden      | Repo rate   | The Riskbank              |  |
| Switzerland | SARON and call money rate   | Swiss National Bank       |  |
| UK          | Base rate   | Bank of England           |  |
| US          | Federal funds rate  | Federal Reserve Board     |  |

| Table 1: Policy | rates | and | their | sources |
|-----------------|-------|-----|-------|---------|
|-----------------|-------|-----|-------|---------|

## **IV. ESTIMATION AND RESULTS**

For the estimation, a two-step estimation procedure is employed. In the first step, the latent yield factors are estimated following the method of DL. In the second step, using the

Panel VAR estimation method of Love and Zicchino (2006), the Eq.4 is estimated.

As described in DL the parameters  $\theta = \{\beta_{1,t}, \beta_{2,t}, \beta_{3,t}\}$  can be estimated by OLS if  $\lambda_t$  can be fixed. One can find an appropriate value for  $\lambda_t$  if it is considered that  $\lambda_t$  determines the maturity at which the loading of the curvature factor,  $\beta_{3,t}$ , reaches its maximum. DL use 30 months for this purpose and determine  $\lambda_t$  as 0.0609. On the other hand, DRA utilizing a unified state-space modeling approach estimate  $\theta = \{\beta_{1,t}, \beta_{2,t}, \beta_{3,t}\}$ , and  $\lambda_t$  in one-step. DRA estimate  $\lambda_t$  as 0.0707, which implies that the loading on the curvature factor is maximized at a maturity of 23.3 months. Since the maturities of the yields used in this paper are very similar to the maturities of the yields used in DRA,  $\lambda_t$  is calibrated as 0.0707 and the latent yield factors for each country are estimated.

To estimate the Panel VAR model, Eq. (4), the method of Love and Zicchino (2006) is used. Given that the fixed effects are correlated with the regressors, the use of the meandifferencing procedure to eliminate the fixed effects creates biased coefficients. As discussed in Love and Zicchino (2006), removing only the forward mean, which is also known as *Helmert procedure*, enables to avoid biased coefficient problem (see Arellano and Bover, 2005). This transformation preserves the orthogonality between transformed variables and regressors and enables to use the lagged regressors as instruments. Thus, employing this procedure the coefficients are estimated by system GMM.

| 4 -0.01 |
|---------|
|         |
| 0.19    |
| 6 0.96  |
| 7 0.2   |
| 7 0.03  |
| 2 0.16  |
| 5 0.11  |
| -0.19   |
|         |
| 1       |
|         |

Table II: Simple Correlations

### The Macroeconomy and The Yield Curve

Table II displays correlation matrix of the estimated latent factors, empirical counterparts of these factors and, macro factors. Following DL and DRA, I use two empirical level factors, which are 10-year yield,  $y_t(120)$ , and the average of 10-year, 2-year and 3-month rate,  $[y_t(3) + y_t(24) + y_t(120)]/3$ . The high correlation between the level factor and the empirical counterparts verify that  $\beta_{1,t}$  can be regarded as a level factor. The correlation between the level factor and actual inflation is 0.55 which is consistent with the suggestion of the Fisher equation. Additionally, the correlation between  $\hat{\beta}_{1,t}$  and policy rate, 0.77, suggests that any increase in policy rate is associated with an increase in the entire yield curve.

The standard empirical slope factor employed in the literature is  $y_t(3) - y_t(120)$ . The correlation between the estimated level factor and the empirical slope factor is 0.99. This high correlation supports the interpretation of  $\beta_{2,t}$  as a slope factor. The correlation between the slope factor and cyclical dynamics of the economy which is measured by output gap does not worth to note, however, the correlation between  $\hat{\beta}_{2,t}$  and inflation and policy rate is 0.46 and 0.58, respectively.

The correlation between the estimated curvature factor and the empirical curvature factor, a commonly used one is  $[2y_t(24) - y_t(120) - y_t(3)]$ , is 0.96. This lends credibility to interpretation of  $\beta_{3,t}$  as a curvature factor. None of the macroeconomic variables appears to be correlated with the curvature factor.

#### **IV.I Impulse Responses**

To examine the dynamics of the relationship of the yield curve and macroeconomy impulse-response functions are used. Producing valid impulse responses requires an identification of the variance-covariance matrix of errors in a way that the residuals become orthogonal. The common practice for this purpose is to adopt a particular recursive causal ordering of the variables. DRA order the yield factors prior to the macro variables. They argue that such an ordering is plausible since the yield data used in their study are dated at the beginning of each month. They also argue that using the end-of-period yield data and ordering the macro variables first produces similar results. However, Sarno and Thornton (2004) points out that zero restrictions on impulse responses of financial variables to the contemporaneous macroeconomic shocks are inconsistent with the efficient market hypothesis. Moreover, Moench (2012) argues that an appropriate identification scheme must allow for the yield curve factors to contemporaneously respond to the macro shocks and this can be achieved ordering

the macro variables first. Since, in this paper the end-of-period yield data are used following both the experiment of DRA and, the arguments of Sarno and Thornton (2004) and Moench (2012) I order the macro factors first. The exact ordering is as follows;  $OG_t$ ,  $INF_t$ ,  $PR_t$ ,  $\beta_{1,t}$ ,  $\beta_{2,t}$ ,  $\beta_{3,t}$ . The standard errors and the confidence intervals for impulse responses are generated by the Monte Carlo simulations.

Table 3 presents the estimates of  $\Gamma_1$ . The results indicate that the macro variables and the yield factors are highly persistent<sup>6</sup>. Only the curvature factor appears to have a significant effect on output gap. In addition to their own lag effects, while inflation appears to be effected by only the macro variables, policy rate appears to be effected by only the yield factors. None of the macro factors appears to affect the yield curve factors.

|                  | $OG_{t-1}$ | $INF_{t-1}$ | $PR_{t-1}$ | $\beta_{1,t-1}$ | $\beta_{2,t-1}$ | $\beta_{3,t-1}$ |
|------------------|------------|-------------|------------|-----------------|-----------------|-----------------|
| $OG_t$           | 0.871**    | 0.041       | -0.096     | 0.090           | 0.073           | 0.051**         |
|                  | (0.030)    | (0.035)     | (0.160)    | (0.145)         | (0.139)         | (0.017)         |
| INF <sub>t</sub> | 0.016**    | 0.930**     | -0.027     | 0.040           | 0.056*          | 0.006           |
|                  | (0.004)    | (0.012)     | (0.033)    | (0.030)         | (0.029)         | (0.005)         |
| $PR_t$           | -0.002     | -0.004      | 0.843**    | 0.138**         | 0.114**         | 0.055**         |
|                  | (0.002)    | (0.007)     | (0.026)    | (0.026)         | (0.024)         | (0.004)         |
| $\beta_{1,t}$    | -0.005*    | -0.006      | 0.025      | 0.960**         | -0.010          | 0.008*          |
|                  | (0.002)    | (0.008)     | (0.020)    | (0.020)         | (0.019)         | (0.004)         |
| $\beta_{2,t}$    | 0.009      | 0.006       | 0.071      | -0.081          | 0.869**         | 0.056**         |
|                  | (0.006)    | (0.011)     | (0.054)    | (0.052)         | (0.504)         | (0.006)         |
| $\beta_{3,t}$    | 0.019      | -0.008      | -0.123     | 0.130           | 0.121           | 0.895**         |
| -,-              | (0.012)    | (0.028)     | (0.112)    | (0.113)         | (0.108)         | (0.016)         |

Table 3: Parameter Estimates from Eq. (4)

Standard error appears in parenthesis.\*\* and \* denote parameter estimates significant at the 5 percent level and 10 percent level respectively. Variables are time demeaned.

Figure 1 shows impulse response functions along with the 95 percent confidence intervals. There are four groups of impulse responses; macro responses to macro shocks, macro responses to yield factors shocks, yield factors responses to macro shocks and lastly, yield factors responses to yield factors shocks.

<sup>&</sup>lt;sup>6</sup> Applying Andrews and Lu (2001) model selection criteria lag lenght is selected as 1.

#### The Macroeconomy and The Yield Curve

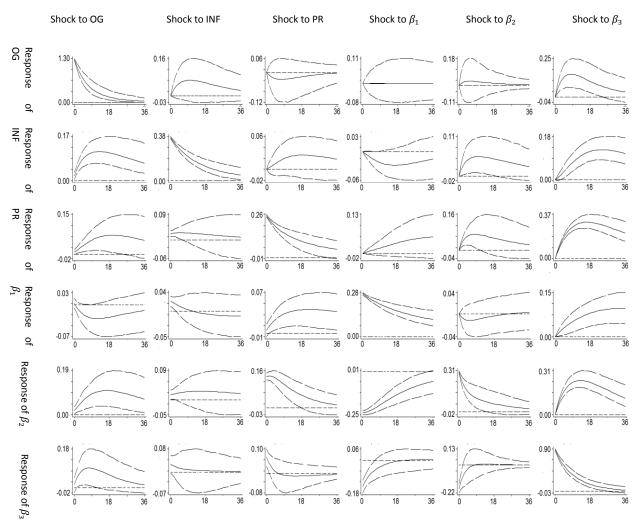


Figure 1: Impulse Responses

Note: Errors are 5% on each side generated by Monte-Carlo with 1000 replications.

Macro responses to macro shocks are similar to the typical responses in commonly used macro models in monetary policy analysis. While an increase in inflation increases the output gap over time, output gap gives no significant response to a policy rate shock. An increase in output gap leads to an increase in inflation which is the aggregate supply response of inflation to increased output gap. Policy rate rises in response to an increase in output gap and inflation. This finding is consistent with the monetary policy that follows the Taylor (1993) rule.

An increase in the level factor decreases inflation and increases policy rate, however, none of the effect is significant. As the expectation hypothesis argues, the long-term interest rate is the average of the expected short-term interest rates. Thus, an increase in the slope may indicate an increase in the expected short rates. By Fisher equation, this effect can be associated with an increase in inflation rate.

A positive shock to the slope factor leads to a rise in the policy rate. As suggested by

DRA there are two interpretations of such an effect. One is that, monetary policy authority may be reacting to the yields in setting the policy rate. The other one is likely that the yields are reacting to the macroeconomic information in anticipation of the action of monetary authorities.

All macro variables give pronounced and hump-shaped response to an unexpected rise of the curvature factor. While the general findings in the literature suggest that the macro factors are not related to the curvature factor, Dewatcher and Lyrio (2006) show that an increase in the curvature factor is positively related to a tougher monetary policy stance. Additionally, Moench (2012) finds that an unexpected increase in the curvature factor initially raises output growth sharply and then falls below zero almost one year after the shock. He argues that the curvature factor might be called as an early predictor of the recessions. Furthermore, the findings of Modena (2011), which is compatible with ours, show that the curvature factor reflects the cyclical fluctuation of economy and a negative shock to the curvature factor either anticipates or accompanies a slowdown in economic activity.

The responses of the yield factors to the macro variables indicates that the level factor gives little and temporary response to the inflation shock and no significant responses to the output gap shock. The findings suggest that, as discussed in Ang and Piazzesi (2003), inflation and real economic activity cannot shift the level of the yield curve. A shock to policy rate appears to lead a small but long-run boost to the level factor. If the level factor is regarded as the bond market's perception of long-run inflation, one may argue that not a surprise in inflation or real activity but in policy rate can induce to an expectation of higher future inflation.

The slope factor gives positive responses to the shocks in all three macro variables. These reactions are consistent with a Taylor (1993) rule based monetary policy responses that increases the short rate in response to an increase in output gap and inflation. An increase in the responses of the slope factor to a positive shock in policy indicates that the monetary policy surprises exert positive and short lived influence on the slope factor. Lastly, the curvature factor gives little and temporary positive responses to the macro shocks.

Lastly, I consider the yield factors responses to the yield factors shocks. All the yield factors show persistency. An increase in the level factor lowers the slope factor. Since the level factor is closely correlated with the long rate and can be interpreted as a higher inflation expectation, a shock in the level factor means an increase in the long-rate or higher inflation expectation which in turn decreases the slope factor. The curvature factor gives positive response to an increase in the level factor. This suggests that a surprise jump in the level factor raises the mid-term yields more relative to the short-term yields and the long-term yields. A

surprise increase in the slope factor significantly reduces the curvature factor. On the other hand, a positive shock in the curvature factor pushes up the level factor and the slope factor.

#### **IV.II Variance decompositions**

Table 3 reports variance decomposition of the yield and macro factors for 1, 12, 36 and 60 months forecast horizon in which percent of the variation in the row variable is explained by the column variable.

For one month forecasts the variations in the macro factors are driven by themselves which suggests that the short-term idiosyncratic variation in the macro factors are unrelated to the yield factors. However, for longer forecast horizons, the yield factors become more influential on inflation and especially on policy rate. For example, for 60-month forecast horizons, almost 28 percent of the variation in inflation and 74 percent of the variation in policy rate are driven by the curvature factor. This suggests that the curvature factor do predict a substantial fraction of the movement in policy rate.

|               | $OG_t$ | INF <sub>t</sub> | $PR_t$ | $\beta_{1,t}$ | $\beta_{2,t}$ | $\beta_{3,t}$ |
|---------------|--------|------------------|--------|---------------|---------------|---------------|
| 1 month ahea  | ad     |                  |        |               |               |               |
| $OG_t$        | 1.000  | 0.000            | 0.000  | 0.000         | 0.000         | 0.000         |
| $INF_t$       | 0.003  | 0.997            | 0.000  | 0.000         | 0.000         | 0.000         |
| $PR_t$        | 0.001  | 0.007            | 0.992  | 0.000         | 0.000         | 0.000         |
| $\beta_{1,t}$ | 0.000  | 0.005            | 0.000  | 0.994         | 0.000         | 0.000         |
| $\beta_{2,t}$ | 0.002  | 0.002            | 0.115  | 0.336         | 0.545         | 0.000         |
| $\beta_{3,t}$ | 0.000  | 0.001            | 0.005  | 0.025         | 0.042         | 0.927         |
| 12-month ah   | ead    |                  |        |               |               |               |
| $OG_t$        | 0.966  | 0.005            | 0.001  | 0.000         | 0.001         | 0.027         |
| $INF_t$       | 0.089  | 0.850            | 0.002  | 0.004         | 0.022         | 0.033         |
| $PR_t$        | 0.019  | 0.007            | 0.424  | 0.002         | 0.045         | 0.503         |
| $\beta_{1,t}$ | 0.008  | 0.002            | 0.012  | 0.952         | 0.002         | 0.025         |
| $\beta_{2,t}$ | 0.036  | 0.004            | 0.120  | 0.359         | 0.231         | 0.249         |
| $\beta_{3,t}$ | 0.019  | 0.001            | 0.002  | 0.018         | 0.017         | 0.943         |
| 36-month ah   | ead    |                  |        |               |               |               |
| $OG_t$        | 0.937  | 0.011            | 0.002  | 0.000         | 0.001         | 0.048         |
| $INF_t$       | 0.163  | 0.586            | 0.008  | 0.010         | 0.033         | 0.199         |
| $PR_t$        | 0.038  | 0.004            | 0.183  | 0.016         | 0.030         | 0.729         |
| $\beta_{1,t}$ | 0.012  | 0.002            | 0.031  | 0.818         | 0.001         | 0.136         |
| $\beta_{2,t}$ | 0.083  | 0.007            | 0.076  | 0.273         | 0.135         | 0.425         |
| $\beta_{3,t}$ | 0.030  | 0.001            | 0.002  | 0.017         | 0.015         | 0.935         |
| 60-month ah   | ead    |                  |        |               |               |               |
| $OG_t$        | 0.935  | 0.012            | 0.002  | 0.000         | 0.001         | 0.049         |
| $INF_t$       | 0.168  | 0.523            | 0.009  | 0.010         | 0.032         | 0.257         |
| $PR_t$        | 0.039  | 0.003            | 0.155  | 0.033         | 0.026         | 0.744         |
| $\beta_{1,t}$ | 0.010  | 0.003            | 0.037  | 0.741         | 0.001         | 0.209         |
| $\beta_{2,t}$ | 0.092  | 0.008            | 0.071  | 0.265         | 0.128         | 0.436         |
| $\beta_{3,t}$ | 0.030  | 0.001            | 0.002  | 0.017         | 0.015         | 0.934         |

Table III: Variance Decomposition

Note: Percent of variation in the row variable is explained by column variable

Considering the effects of the macro factors on the yield curve movement, the results indicate that large amount of the variation in the yield curve factors are unrelated to the macro factors. Only for 1 month forecast horizon 11.5 percent of the variation in the slope factor is driven by policy rate, however, for long forecast horizons the influence of policy rate on the slope factor movement decreases and almost 9 percent of the variation in the slope factor is explained by output gap for 60-month forecast horizons.

As a consequence, the variance decomposition suggests that, contrary to DRA, the effects of the macro factors on the yield curve factors are less important than the effects of the yield curve on the macro factors. This indicates that, the assumption of the unidirectional link from macro to yield as in Ang and Piazzesi (2003) is highly restrictive. The curvature factor plays a crucial role in the movements of policy rate and somewhat on the movement of inflation. Considering what the yield curve would add to a standard small macro model, such as Rudebusch and Svensson (1999), DRA argue that the policy rate may be regarded as a sufficient statistics for interest rate affects in macro-dynamics. However, the findings in this paper suggest that this argument cannot be generalized and the yield curve appears to have a valuable content for such a small macro model.

## **V. CONCLUSION**

As stated by Piazzesi (2010) describing the dynamic interactions between the yield curve and macroeconomic variables is important for bond pricing, investment decisions and public policy. This research investigates the empirical interactions between the macroeconomy and the yield curve by using a panel dataset which consists of nine industrialized countries. For this purpose, I estimate latent yield factors (level, slope and curvature) by employing DNS and then employ a panel VAR which enables to incorporate the yield factors and macroeconomic variables (inflation, output gap and policy rate) simultaneously. I find strong evidence for bidirectional link between the yield factors and the macroeconomic variables. While the level of the yield curve is affected only by policy rate, the slope of the yield curve is affected by all three macroeconomic variables. On the other hand, evidence suggests that the level of the yield curve is ineffective on macro variables, however, the slope of the yield curve has a short-lived effect on inflation and policy rate. I also find strong evidence for that the curvature of the yield curve has a sound effect on the future macroeconomic developments.

The obtained results provide usefull information for policy making. For example, in

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many countries, the central banks are able to effect the short end of the yield curve, however, for aggregate demand long-term yields are more important. The results suggest that an increase in policy rate and the curvature factor leads to an increase in the level factor which closely related to long-term yields. The findings also indicate that the curvature factor may serve as a forward-looking indicator for the state of economy. Additionally, the results are usefull for banks to foresee how the price of derivative securities, such as swaps, futures and options on interes rates, computed from the yield curve depends on the macroeconomic conditions.

### REFERENCES

- Andrew, D.W.K., & Lu. B. 2001. Consistent model and moment slection precedures for GMM estimation with application to dynamic panel data models. *Journal of Econometrics*, 101: 123-164.
- Ang, A., Boivin, J.S.D., % Loo-Kung, R. 2011. Monetary Policy Shifts and the Term Structure. *The Review of Economic Studies*, 78: 429-57.
- Ang, A., Dong, S., & Piazzesi, M. 2007. No-arbitrate Taylor rule. *NBER Working Paper No.* 13448. National Bureau of Economic Research.
- Ang, A., & Piazzesi, M. 2003. A no-arbitrage vector autoregression of term structure dynamics with macroeconomic and laten variables. *Journal of Monetary Economics*, 50: 745-87.
- Ang, A., Piazzesi, M., & Wei, M. 2006. What does the yield curve tell us about GDP growth. *Journal of Econometrics*, 131: 359-403.
- Arellano, M., & Bover, O. 1995. Another look at the instrumental variable estimation of error component models. *Journal of Econoetrics*, 68: 29-51.
- Bernanke, B., Reinhart, V., & Sack, B. 2004. Monetary policy alternatives at the zero bouns: an empirical assessment. *Brooking Papers on Economic Activity*, 2: 1-78.
- Chinn, M.D., & Kucko, K.J. 2010. The predictive power of the yield curve across countries and time. *NBER Working Paper*, No: 16398.
- Christensen, J. H., Diebold, F. X., & Rudebusch, G. D. 2009. An arbitrage Nelson–Siegel term structure model. *The Econometrics Journal*, 12(3).
- Christensen, J., Diebold, F., & Rudebusch, G. 2011. The affine arbitrage-free class of nelsonsiegel term structure models. *Journal of Econometrics*, 161: 4-20.
- Dewachter, H., & Lyrio, M. 2006. Macro Factors and the Term Structure of Interest Rates. *Journal of Money, Credit and Banking*, 38: 119-40.
- Diebold, F., & Li, C. 2006. Forecasting the term structure of government bond yields. *Journal* of Econometrics, 130: 337-64.
- Diebold, F., Rudebusch, & G., Aruoba, S. 2006. The macroeconomy and the yield curve: a dynamic latent factor approach. *Journal of Econometrics*, 131: 309-38.
- Estrella, A., & Mishkin, F. 1998. Predicting US recessions: financial variables as leading indicators. *Review of Economics and Statistics*, 80: 45–61.
- Estrella, H., & Hardouvelis, G. 1991. The term structure as a predictor of real economic activity. *Journal of Finance*, 46: 555–576.
- Evans, C.L., & Marshall, D.A. 2007. Economic determinants of the nominal treasury yield curve. *Journal of Monetary Economics*, 54: 1986-2003.
- Love, I., & Zicchino, L. 2006. Financial development and dynamic investment behavior:

-free generali

evidence from panel VAR. *The Quarterly Review of Economics and Finance*, 46: 190-210.

- Mishkin, F., 1990. What does the term structure tell us abut future inflation? *Journal of Monetary Economics*, 25: 77-95.
- Modena, M., 2011. A Macroeconomic Analysis of the Latent Factors of the Yield Curve. In Gregoriou, G. & Pascalau, R. *Financial Econometrics Modelling: Derivatives Pricing and Hedge Funds and Term Structure Models*. Palgrave-MacMillan.
- Moench, E. 2012. Term structure surprises: the predictive content of curvature, level, and slope. *Journal of Applied Econometrics*, 27(4), 574-602.
- Rudebusch, G., & Swensson, L., 1999. Policy rules for inflation targeting. In Taylor, J. *Monetary policy rules*. Chicago: University of Chicago Press. 203-46.
- Piazzesi, M. 2010. Affine term structure models. *Handbook of financial econometrics*, 1: 691-766.
- Rudebusch, G.D., & Wu, T. 2008. Macro-finance model of the term structure, monetary policy, and the economy. *The Economic Journal*, 118: 906-26.
- Sarno, L., & DL, T. 2004. The efficient market hypothesis and identification in structural VARs. *Federal Reserve Bank of St Louis Review*, 86: 49–60.
- Smith, J.M., & Taylor, J.B. 2009. The term structure of policy rules. *Journal of Monetary Economics*, 56: 907-17.
- Taylor, J., 1993. Discretion versus policy rules in practice. *Carnegie-Rochester Conference* Series on Public Policy, 39: 195–214.
- Wright, J.H., 2011. Term Premia and Infation Uncertainty: Empirical Evidence from an International Panel dataset. *American Economic Review*, 101: 1514-1534.
- Wu, T., 2002. Monetary policy and the slope factor in empirical term structure estimations. *FRB San Francisco Working Paper*, 2002-07.