Do local and global factors impact the emerging markets' sovereign yield curves? Evidence from a data-rich environment

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October 2020

Abstract

This paper investigates the relation between yield curve and macroeconomic factors for ten emerging sovereign bond markets using the sample from January 2006 to April 2019. To this end, the diffusion indices obtained under four categories (global variables, inflation, domestic financial variables, and economic activity) are incorporated by estimating dynamic panel data regressions together with the yield curve factors. Besides, in order to capture dynamic interaction between yield curve and macroeconomic/financial factors, a panel VAR analysis based on the system GMM approach is utilized. Empirical results suggest that the level factor responds to shocks originated from inflation, domestic financial variables and global variables. Furthermore, the slope factor is affected by shocks in global variables, and the curvature factor appears to be influenced by domestic financial variables. We also show that macroeconomic/financial factors captures significant predictive information over yield curve factors by running individual country factor-augmented predictive regressions and variable selection algorithms such ridge regression, LASSO and Elastic Net. Our findings have important implications for policymakers and fund managers by explaining the underlying forces of movements in the yield curve and forecasting accurately dynamics of yield curve factors.

Keywords: Yield Curve, Macroeconomic Factors, Nelson Siegel Model, Panel VAR, Forecasting, Variable Selection.

JEL Classification: C1, C5, F2, F3, F4, G1.

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This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1002/for.2763

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1. Introduction

In conformity with the experienced wave of globalization and financial development in emerging markets (EM) for the last decades, local bond markets of those economies have gained prominence regarding the financing of economic entities. In recent years, monetary policies of advanced economies have been designed on the expansionary front coupled with unconventional measures leading to abundant liquidity in the financial system. This leads to a swift decline in policy rates and puts downward pressure on the yields of financial assets. Given the ”search for yield” behavior of global investors and relatively higher yields offered by EM financial assets, there have been observed voluminous capital inflows to EM economies through debt securities. Furthermore, differentiation of local economic factors in EM countries from developed counterparts creates potential diversification benefits and a strong appetite for this asset class (Miyajima et al. (2015)). Apart from this, broadening and deepening of cross-border financial links reinforced by the behavior of global market participants, financial liberalization attempts of local authorities and economic integration actions of supranational organizations have resulted in rising momentum of local EM bond markets (Wooldridge et al. (2003), Garcia-Herrero and Wooldridge (2007)).

Accordingly, prominent foreign interest in EM debt securities has brought financial deepening in the market structure. International bond issuance from the selected EM group appear to increase dramatically since the beginning of the 2000s (Figure 1). On the other hand, domestic bond markets mostly consisted of local currency issuance also grew in size[1]. Although these markets were historically dominated by sovereign entities, non-financial corporations also started to obtain financing through local debt markets (Figure 1).

– Insert Figure 1 about here. –

Given the relevance of macroeconomic fundamentals with yield curve modeling parameters, recently, the academic literature has focused on extensions of yield curve models that incorporate macroeconomic variables (see Exterkate et al. (2013), Ullah et al. (2013), Ullah (2016), Yang (2020)). Diebold et al. (2006) combine the Nelson-Siegel (NS) model with inflation, output and the policy rate to provide new insights into the relationship between the term structure of interest rates and the US economy. They show that the level factor is somewhat correlated with inflation whereas the slope factor is related to economic activity. Unlike the level and the slope factors, the curvature factor appears to be unrelated to any of the main US

[1]This data corresponds to the summation of the notional outstanding amount of selected EM countries comprising the sample of this study. Details about countries are provided in Section 2.

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macroeconomic variables. Lu and Wu (2009) examine the interactions between the US Treasury yield curve and 17 macroeconomic data and find that shocks on inflation-related variables such as consumer prices and producer prices have a sizeable positive impact on the yield curve, resulting in a parallel shift across different maturities. On the other hand, shocks on real activity variables such as GDP growth, industrial production, and capacity utilization have broader impacts on the short end than on the long end of the yield curve, thus resulting in a flatter or a steeper yield curve. Hännikäinen (2017) evaluates the predictive content of yield curve factors for US real activity in a data-rich environment. It is shown that while predictive power is subject to alterations from a historical perspective, slope emerges as a key parameter in understanding the real economic fluctuations. By covering the advanced economies such as US, Germany, Canada, and UK, Argyropoulos and Tzavalis (2016) provide evidence supporting the importance of slope and curvature for future changes in economic activity. As a recent study, Paccagnini (2016) interpolates the term structure of the US Treasury Rates for the period 1984-2007 with the help of three yield curve parameters. It is founded that term structure informs policymakers about how macroeconomic shocks are related to yield curve dynamics.

While there exists profound literature about developed markets, few studies directly examine EM yield curve parameters and their interaction with the macroeconomic environment. Kanjilal (2013) examines the debt market in India over the period 1997-2011. By applying NS methodology, the sovereign yield curve is estimated and almost all of the movements across the yield curve are found to be explained by latent level, slope, and curvature factors. Rodriguez et al. (2011) utilize the dynamic version of the NS model to reproduce stylized facts of Brazil's term structure and find that the model fits the data well. Kaya (2013) conducts the same exercise for the Turkish economy and find similar results. In a more recent study, Prasanna and Sowmya (2017) analyze the contemporaneous relation between macroeconomic factors and yield curve movements in nine Asian sovereign bond markets. They indicate that increases in the policy rate and inflation affect the slope of the term structure while the output growth has a significant influence on the long-term rates in the region.

The purpose of this paper is to extend the empirical evidence addressing the question of how yield curve factors are related to macroeconomic factors for ten emerging sovereign bond markets using the large set of macroeconomic and financial variables unlike the previous studies that use only a limited set of explanatory variables. To this end, firstly, we extract the yield curve factors by employing the NS methodology. Secondly, we estimate dynamic panel data regressions between yield curve factors and latent factors that

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are constructed on a relatively large set of economic indicators, namely global variables, domestic financial variables, economic activity, and inflation-related variables. Furthermore, we provide a characterization of the dynamic interactions between the yield curve and macroeconomics factors via estimating panel VAR model and computing impulse response functions. Finally, utilizing an individual factor augmented predictive regressions and variable selection algorithms for each emerging market, we investigate whether macroeconomic/financial factors have predictive ability for yield curve factors.

Our findings can be summarized as follows. First, it is observed that a shock coming to the inflation factor is being transmitted to a positive response in the level factor of the yield curve. Second, one unit shock of innovation to the factor representing economic activity brings about an increase in the slope component leading to steepening in EM countries' yield curve shape. Third, the response of the slope factor to the shocks in the global factor is negative and significant after around the first month which has a lasting effect on the slope factor. This finding implies that global factors have the power to explain movements in the yield curves of emerging markets, in addition to the local factors. Fourth, macroeconomic/financial factors capture significant predictive information over yield curve factors. Fifth, employing variable selection algorithms improves the forecast accuracy of the model further.

This paper is organized as follows: Section 2 provides detailed information about utilized data sets. Section 3 covers the dynamic factor model to summarize macroeconomic and financial forces, NS methodology to estimate yield curve factors of individual countries as well as dynamic panel regressions and panel VAR model constructed to assess the interaction between yield curve factors and macroeconomic forces. Section 4 presents empirical results, and Section 5 concludes the discussion.

2. Data

We have a balanced panel dataset of monthly observations between January 2006 and April 2019 for ten emerging markets[2]. The dataset includes a large set of indicators that are selected to represent a broad range of macroeconomic variables that can be classified into the following four categories:

- *Real Economic activity:* unemployment, industrial production, balance of payments statistics, retail trade, vehicle productions, completed buildings recorded and new orders;
- *Prices:* producer prices and consumer prices;

[2]Brazil, Hungary, India, Malaysia, Mexico, Poland, Russia, South Africa, Thailand, and Turkey

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- *Domestic Financial variables:* interest rates, exchange rates, implied volatility, money supply and stock prices;
- *Global variables:* Economic activity and financial market variables on global scale such as US term premium, US economic policy uncertainty, EU industrial production, ISM manufacturing PMI, MSCI emerging markets indices and Nomura China stress indicator;

– Insert Table 1 about here. –

Table 1 shows the final number of series in each category, as well as the total number of series for each country. The final selection of the variables for each country is determined based on data availability. We consider the series of indicators that are followed most closely by market participants. It is thus fairly comprehensive as the data include both supply-side and demand-side indicators. All variables are subject to preliminary transformations to induce stationarity as needed. Detailed descriptions of the individual macroeconomic variables are provided in the Tables A1-A10 of the appendix.

In addition to the above set of macroeconomic and financial indicators, which are used in our construction of local and global factors, we collect monthly zero-coupon yields of maturities 3, 6, 12, 24, 36, 48, 60, 72, 84, 96, 108 and 120 months to estimate the yield curve factors for each emerging markets in our sample. All data is downloaded from the Bloomberg terminal.

3. Empirical Methodology

3.1. Extraction of common factors using dynamic factor model

In our analysis, we separately extract potentially useful common factors from our four datasets (i.e., real economic activity, prices, domestic variables and global variables) for each country. To do this, we utilize the widely used dynamic factor model (DFM) of Giannone et al. (2008). As is typical in such models, individual variables are represented as the sum of components that are common to all variables in the economy (i.e., the factors) and an orthogonal idiosyncratic part.

Formally, the DFM can be written as a system of equations: a measurement equation (i.e., Eq. (1)) that links the observed variables to the unobserved common factor to be estimated, and transition equation (Eq. (2)) that describe the dynamics of the common factor. Once Eqs. (1)-(2) are written in state space form, we employ the Kalman filter and smoother in order to extract the common factors and generate projections for all of the variables in the model.

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We start by characterizing the dynamics for the monthly data. Let $X_{i,t}$ denote panel of observable economic variables where i shows the cross-section unit of macroeconomic variables, $i = 1, ..., N$ and t indicates the monthly time index, $t = 1, ..., T$. We assume that $X_{i,t}$ has the following factor model representation:

$$X_t = \Lambda F_t + \xi_t, \qquad \xi_t \sim N(0, \Sigma_e), \tag{1}$$

$$F_t = \sum_{i=1}^{p} \Psi_i F_{t-i} + u_t, \qquad u_t \sim N(0, Q), \tag{2}$$

where F_t is an $r \times 1$ vector of unobserved common factors with zero mean and unit variance, that reflect "most" of the co-movements in the variables, Λ is a corresponding $N \times r$ factor loading matrix, and the idiosyncratic disturbances, ξ_t, are uncorrelated with F_t at all leads and lags, and have a diagonal covariance matrix, Σ_e. The common factors are modeled as a stationary vector autoregressive (VAR) process of order p driven by the common shocks, $u_t \sim N(0, Q)$, and that the Ψ_i are $r \times r$ matrices of autoregressive coefficients. Also, the common shocks, u_t, and the idiosyncratic shocks, ϵ_t, are assumed to be serially independent and independent of each other over time. We estimate the model using the two-step approach proposed by Giannone et al. (2008)[3] and select the first factor that explains the highest variation in each dataset[4]. The lags of the factors are chosen via use of Schwarz information criteria. In particular, four diffusion indexes (i.e., factors) are constructed. While three of the four factors that are separately extracted using the datasets belonging to real economic activity, prices, domestic variables are called local factors, the factor extracted from the set of global variables is called global factor.

3.2. Estimation of yield curve factors: Nelson-Siegel Model

The yield curve factors are obtained using NS model where the zero rates can be described explicitly by the following functional form:

$$y_t(m) = \beta_1 + \beta_2 \left(\frac{1 - e^{-\frac{m}{\tau}}}{\frac{m}{\tau}} \right) + \beta_3 \left(\frac{1 - e^{-\frac{m}{\tau}}}{\frac{m}{\tau}} - e^{-\frac{m}{\tau}} \right) \tag{3}$$

Accordingly, $y_t(m)$ denotes the continuously compounded zero-coupon nominal yield at time t of a bond with maturity m, and β_1, β_2, β_3 and τ are NS parameters to be estimated. Eq.(3) represents a four-component

[3]see, Doz et al. (2011) for details.

[4]Explanatory powers of extracted first three factors are presented in Table A11 of the Appendix. The expanatory power of first factors range between 22% and 53%.

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approximation to the cross-section of yields at any time. Diebold and Li (2006) interpret the NS parameters as the level (β_1), slope (β_2) and curvature (β_3). The coefficient τ, which is frequently referred to as the shape parameter, determines both the steepness of the slope factor and the location of the hump (Annaert et al. (2013)). The parameters are estimated using non-linear least squares where the objective function is to minimize the squared difference between duration-inverse weighted actual and fitted prices.

However, employing the non-linear least squares optimization leads to non-smooth parameter estimates, especially for the slope and curvature parameters. Therefore, we estimate level, slope and curvature parameters by Ordinary Least Squares (OLS) fixing τ parameter to reduce the volatility of these parameters as proposed by Diebold and Li (2006). We run a grid search to find the optimal τ parameter, which gives us the smallest Root Mean Squared Error (RMSE) for each emerging markets in our sample[5].

3.3. *Dynamic Panel Data Estimations*

Before undertaking dynamic interaction between yield curve factors and macroeconomic/financial determinants, an initial empirical investigation is performed by using an estimation technique exploiting the longitudinal nature of the data which also incorporates the timewise autoregressive structure of yield curve factors. In this context, difference generalized method of moments (GMM) approach developed by Holtz-Eakin et al. (1988) and Arellano and Bond (1991) is implemented where explained variables are dynamic (meaning they are being dependent on their own past realizations) and explanatory variables are not strictly exogenous (meaning they are correlated with the past and present realizations of the error term).

Arellano-Bond estimation involves a transformation of regressors (mostly by differencing) and an application of GMM. Modeling through fixed effects, despite the fact that underlying data generating process is dynamic by nature, creates a correlation between error term and regressors because of the demeaning attempt of dependent and independent variables in fixed effects estimation. Since demeaning operation creates a set of regressors which are not distributed independently of the disturbance term, coefficient estimator for lagged dependent variable is inconsistent (Nickell, 1981). The solution to this evident problem is to apply a transformation to the model. First differencing to the original model is mostly used in practice to remove the unobserved individual effect. When model is transformed, then it becomes eligible for instrumental variable estimation. Difference GMM method is doing this by establishing a system of equations (for each time period) and by economizing internal instruments (lagged values of instrumented variables)

[5] For this purpose, the estimations are iterated for more than one million times.

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to make the estimation. Hence, our methodological framework entails the use of one-step difference GMM method of Arellano and Bond (1991).

For this study, we utilize following series of specifications in which yield curve components are defined as dependent variables and static factors describing inflation, economic activity, local financial conditions and global financial outlook are added as explanatory variables in an incremental manner. As the most comprehensive specification, the final model includes all the macroeconomic/financial factors.

$$YC_{it} = \rho \sum_{s=1}^{2} YC_{it-s} + \gamma_1 Inflation_{it} + u_i + e_{it} \tag{4}$$

$$YC_{it} = \rho \sum_{s=1}^{2} YC_{it-s} + \gamma_2 Activity_{it} + u_i + e_{it} \tag{5}$$

$$YC_{it} = \rho \sum_{s=1}^{2} YC_{it-s} + \gamma_3 Financial_{it} + u_i + e_{it} \tag{6}$$

$$YC_{it} = \rho \sum_{s=1}^{2} YC_{it-s} + \gamma_4 Global_{it} + u_i + e_{it} \tag{7}$$

$$YC_{it} = \rho \sum_{s=1}^{2} YC_{it-s} + \gamma_1 Inflation_{it} + \gamma_2 Activity_{it} + \gamma_3 Financial_{it} + \gamma_4 Global_{it} + u_i + e_{it} \tag{8}$$

where YC_{it} refers to the yield curve components which are level, slope and curvature. ρ stands for the auto-regressive parameters obtained from the first and second lags of yield curve components included as covariates[6]. γ coefficients measure the impact of macroeconomic and financial dynamics on yield curve formation.

3.4. Dynamic Common Correlated Effects

Dynamic panel data models with system GMM estimations have advantages such as accounting from dynamic structure in the variable of interest and capability to handle endogeneity problems (Roodman (2006, 2009), Labra and Torrecillas (2018)). However, as noted by Ruiz-Porras (2012), applying this methodology on data structures with longer time dimensions (T) and shorter cross-sectional dimension (N) could result in the over-identification of the model.[7] Furthermore, it does not account for unobserved

[6]Lag-length is chosen based on SIC criteria.

[7]We thank the anonymous referee for pointing out this issue and suggesting alternative estimation technique.

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dependencies between cross-sectional units in the examined data set. Despite the fact that in system GMM estimations we tried to mitigate over-identification problem by limiting the number of lags of instruments in level and difference equations, specifications described above are also estimated by utilizing dynamic common correlated effects for robustness.[8]

In this context, estimation procedure conceptualized by Chudik and Pesaran (2015) and operationalized by Ditzen (2018) is implemented. Following empirical identification is considered:

$$Y_{i,t} = \lambda_i Y_{i,t-1} + \beta_i X_{i,t} + \sum_{k=0}^{P} \gamma'_{i,k} \bar{Z}_{t-k} + \varepsilon_{i,t}, \qquad \bar{Z}_t = \left(\bar{Y}_t, \bar{X}_t\right) \tag{9}$$

where Y and X describe dependent and independent variables, whereas $\beta_i = \beta + v_i$, $v_i \sim IID\,(0, \Omega_v)$ and $\lambda_i = \lambda + \zeta_i$, $\zeta_i \sim ID\left(0, \Omega_f\right)$ represent heterogeneous coefficients which are randomly distributed around a common mean. As quoted in Ditzen (2018), Pesaran (2006) in static models with no lagged dependent variable terms as additional explanatory variables, estimations will be consistent by approximating the unobserved common factors with cross-section averages $\bar{Y}_t$ and $\bar{X}_t$ under strict exogeneity. On the other hands, in dynamic models, Chudik and Pesaran (2015) show that estimator gains consistency if $P = \sqrt[3]{T}$ lags of the cross-sectional averages are incorporated into the specification.

We follow this methodology to obtain coefficient estimations for level, slope and curvature factors. In addition to this, we also implement Pesaran (2015) test for cross-sectional dependence to evaluate dependencies across countries[9].

3.5. *Panel VAR model using a system GMM approach*

In the following part of our empirical setting, we exploit the informative content of yield curve parameters and macroeconomic factors within the context of panel VAR model. This class of modelling framework has been increasingly utilized to study interdependencies, particularly in the fields of macroeconomics and finance such as economic activity, business cycle tendencies, and transmission of financial shocks among many others (Canova and Ciccarelli (2013)).

To assess the dynamic relation between yield curve components and macro-factors, we utilize a panel VAR model using generalized method of moments (GMM) approach as described by Abrigo and Love

[8]As it does not vary over cross-section units, the variable termed "global" is excluded from these estimations.

[9]The test results are presented in Table A12 of the Appendix.

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(2016). The estimated system of equations referring for the panel VAR model of order p with country-specific fixed effects can be specified as the following:

$$
\begin{aligned}
Y_{it} &= A_1 Y_{it-1} + A_2 Y_{it-2} + ... + A_p Y_{it-p} + u_i + e_{it} \\
E[e_{it}] &= 0, \qquad\qquad E[e'_{it} e_{it}] = \Sigma, \\
& \qquad\qquad E[e'_{it} e_{is}] = 0, fort > s
\end{aligned}
\tag{10}
$$

where Y_{it} is a $(1xm)$ vector of endogenous variables (prices, economic activity, domestic financial, global, level, slope, curvature), u_i and e_{it} represent the $(1 \times m)$ dependent variable specific panel fixed effects and idiosyncratic errors, respectively. The idiosyncratic disturbances e_{it} have a diagonal covariance matrix, Σ. As mentioned before, variables are obtained from yield curve factors by utilizing Nelson and Siegel (1987) methodology and the common factors related to each category (prices, economic activity, domestic financial, global) are extracted by applying dynamic factor model based on the large sets of variables included in each category.

The ordering in panel VAR is chosen to reflect the transmission channel for EM in which originated global shocks are propagated to local financial conditions and, in the next step, they are incorporated in the formulation of yield curve dynamics to characterize the influence on economic activity and pricing behavior. In this framework, ordering of the variables does not alter the coefficient estimates for the panel VAR, while it is expected to affect the impulse-response functions (IRFs). However, it is found that IRFs are not subject to alterations when order of the variables is changed.

Empirical analysis with panel VAR model is multifaceted for which the initial results are obtained for the stationarity of variables to make reliable inferences. In this context, we benefit from the panel unit root testing procedures of Im et al. (2003) and Levin et al. (2002). Additionally, consistent moment and model selection criteria of Andrews and Lu (2001) as well as the Hansen (1982) J-statistics of over-identifying restrictions are reviewed to decide on the optimal lag length of the mode. While IRFs are utilized to gain deeper insight about the dynamic inter-relation of yield curve factors with macro-forces in the EM countries, the stability conditions of panel VAR estimates are also checked by calculating the modulus of eigenvalues of the estimated model.

3.6. Out-of-sample forecasting exercise for individual countries

Apart from investigating dynamic interdependencies, we employ factor augmented predictive regressions commonly used in the empirical finance studies, for investigating the predictability of yield curve

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factors separately for each countries. Specifically, we construct our predictive regressions of the following form:

$$y_{t+1} = \alpha_0 + \beta' Z_t + \varepsilon_{t+1} \tag{11}$$

where y_{t+1} is the yield curve factors in period $t + 1$ and Z_t includes factors (prices, economic activity, domestic financial) extracted using the dynamic factor model approach of Giannone et al.(2008). We select the benchmark model as random-walk (RW) model since comparing our model results with this model will tell us whether macroeconomic factors add value to forecasting of yield curve factors. Out-of-sample forecasting exercise over the period January, 2012 to April, 2019, with an in-sample period of January, 2006 to December, 2011, is employed recursively to provide insight into the predictive ability of macroeconomic and financial factors for yield curve factors. For each month, we produce a sequence of six h-month-ahead forecast for $h = 1, 2, 3, 4, 5, 6$. To assess the statistical significance of forecast performance of different models compared to our benchmark model, the Diebold and Mariano (2002, DM) test is utilized using quadratic loss function.

4. Empirical Results

4.1. Relation between yield curve factors and extracted common factors

Before moving into dynamic panel estimations, it is informative to visually investigate the co-movements between macroeconomic factors and yield curve parameters. By pooling cross-sectional dimensions of sample countries with historical time series, Figure 2 depicts the scatterplots of yield curve factors with macro-forces that are theoretically known to be relevant. Here, it is seen that there exists a positive correlation between level factor of EM sovereign yield curves and inflation factor extracted from CPI and PPI series of sample countries. Hence, we suspect that price pressures entailing high inflation rates can be preemptively associated with higher level of the yield curve. While the degree of association is lower compared to level-inflation case, there is a negative linear relation between slope factor and local macroeconomic activity component. In other words, steepening in yield curves can be relevant to the loss of momentum in growth tendencies. Lastly, as a striking finding, we demonstrate a relation between curvature factor and local financial factor as a common pattern in EM countries.

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4.2. *Dynamic Panel Estimation Results*

First of all, dynamic panel estimations reveal that, as expected, autoregressive dependence on time dimension is evident for yield curve components. When level, slope and curvature factors are defined as dependent variables, corresponding regressions support the expectation that lags of the explained variables are statistically significant.

For the univariate specifications for level factor, it is seen that inflation factor is an important determinant of long-term component of the yield curve. In particular, upward movements in inflation factor tracking the price pressures in EM countries create significant and positive impact on level factor. In addition to this, local financial factors, for which increases are corresponding to deterioration in financial indicators and volatility in financial markets, turn out to be associated with level factor as well.

In univariate cases, economic activity and global factors are found to be somewhat significant supporting the expectation that growth outlook and global forces might have an influence the formation of slope component. However, when multivariate case is considered, while economic activity retains its significance, local financial conditions emerge as a significant determinant of slope factor. In terms of curvature factor, unlike most of the studies in the previous literature, local financial conditions is found to be an important driver.

– Insert Table 2 about here. –

– Insert Table 3 about here. –

– Insert Table 4 about here. –

4.3. *Dynamic Common Correlated Effects Results*

Results obtained from dynamic common correlated effects estimations are vastly in line with system GMM results. Lag dependence structure of level factor is still evident. Univariate specifications for level equation shows that inflation and economic activity factors are significantly associated with level component of EM yield curves in which former is positively and latter is negatively related with long-term yield curve factor entailing long-term interest rates. When we change the estimation technique, previously documented significant role of domestic financial conditions in explaining level dynamics disappear. In full specification, as expected, only significant explanatory variable for level equation is inflation outlook. In the second step, similar estimations are conducted for slope component. Here, in contrast to previous estimations, the predictive power of the equations regarding in-sample context is improved, as manifested

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by statistically significant effects of inflation and financial factors, on top of theoretically and empirically suggested economic activity factor. Significance is also retained in the broadest specification.

Lastly, curvature factor is considered. As it is not widely observed in the empirical literature, dynamic common correlated effects estimations indicate that curvature component of EM yield curves is significantly driven by the course of domestic financial conditions. Hence, any movements in sub-components of domestic financial conditions including credit growth, exchange rates, stock market outlook and capital flows will have implications on the yield curve formations.

For each yield curve factor, Pesaran (2015) test results in broadest specifications show that null hypothesis of weak cross-sectional dependence is vastly rejected pointing out the fact that common correlated effects estimations controlling for unobserved dependencies across EM countries are reliable in this setting[10].

– Insert Table 5 about here. –

– Insert Table 6 about here. –

– Insert Table 7 about here. –

4.4. Panel VAR results

As stated in Section 3.5, the stationarity behavior of variables utilized in panel VAR model are evaluated with IPS and LLC panel unit root test. When level values are assessed with these tests (with only constant and with both constant and trend terms in test specifications), there appears to be some evidence pointing out non-stationarity. Hence, we proceed with transformation of variables into first differences yielding stationarity before conducting estimations[11]. In terms of the selection of lag length, the informative content of Hansen's J-statistic and information criterion are considered. In this case, overwhelming evidence is the use of one lag in the specification of panel VAR model[12].

To analyze the interaction among common factors and yield curve factors, we perform impulse response functions. Figure 3 presents the cumulative orthogonalized impulse-response functions from the estimated panel VAR. 95% confidence interval to analyze the statistical significance are created by using 1000 Monte Carlo simulation draws. The forecast horizon is determined as 12 months. It is observed that a shock coming

[10]The test results are reported in Table A13 of the Appendix.

[11]Results of panel unit root tests are provided in Table A14 in the appendix.

[12]Information criterion results are given in Table A15 in the appendix.

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to inflation factor is being transmitted to a positive response in the level factor of yield curve. The impact that occurs following the inflationary shock lasts almost 6 months, whereas it losses the significance after 3rd month. Thus, it supports the argument that level is the long term factor in the yield curve formulation which reflects the inflationary dynamics as well as inflation expectations.

– Insert Figure 3 about here. –

Impulse-response functions also reveal the statistically significant relation between economic growth and slope component of the yield curve. Following one unit shock to the factor representing the economic activity, the slope component increases leading to steepening in EM countries' yield curve formation. The impact seems to peak around 6-months horizon. It is interesting to note that local financial conditions in EM countries are found to be strongly associated with curvature component of yield curve. In particular, one unit impulse given to the factor summarizing local financial dynamics is tracked to have a statistically significant influence on curvature factor, while the majority of the impact occurs within a shorter period of time.

The response of slope factor to shocks in global factor is negative and significant after around 1st month and also these shocks have a lasting effect on the slope factor. This result supports the findings of Jotikasthira et al. (2015), that U.S. yield factor have power to explain movements in the curves of other countries. The inverse relation between global and slope factor might indicate that a shock to the global factor may increase the expectations of raising the short-term policy rate by central banks. Hence, this situation puts upward pressure on short-term government bonds, thereby resulting in a negative relationship. This is often seen as a bag sign for the economy since the yield spread is historically narrowed ahead of recessions.

We also examine the impulse-response among yield curve factors themselves from the estimated panel VAR model (Figure 4). It could be seen that shocks coming to level factor significantly and negatively affect slope and curvature factors in the examined horizon. Impulse-response function also depicts the strong influence of slope factor on level factor, whereas no significant result is obtained for the impact of slope on curvature. Lastly, impulse-response functions display that shocks coming to curvature does not produce statistically significant responses for level factor. On the other hand, impulses occurred to curvature is tracked to create slightly significant responses on slope parameter. Overall, our results highlight the relevance of local and global factors for better understanding the movements of yield curves in emerging markets.

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4.5. *Out-of-sample forecasting results*

The ratios of root mean squared errors (RMSEs) for our set of forecasting models are presented in Table 8 for each of the forecast horizons. Models that yield the lowest RMSE values at each horizon are denoted in bold. Overall, the entries in Table 5 in general are less than unity, which reveals that the factor-augmented predictive regressions usually produce better forecasts than the benchmark RW model. This finding is further supported by the DM test, indicating statistically significant improvements in forecast accuracy compared to the RW model. Our results also suggest that the RMSE values generally increase with the forecast horizon, confirming the out-of-sample predictive power of macro and financial factors especially for short term horizons. In particular, the predictive power of macro/financial factors is notable for Brazil, Hungary, India, Mexico, Poland and Thailand. Surprisingly, the factor augmented predictive regressions yield better forecasts for curvature factor in 7 countries out of 10 with a limited number of exceptions. This can be seen from Table 8 by noting that the lowest RMSEs are denoted in bold. However, while the RMSEs of factor type predictions are lower more than 40% compared to those of RW model for Hungary and Poland, their forecast performances are relatively poor in Russia and South Africa particularly for level and slope factors.

Furthermore, it is important to choose appropriate predictors prior to estimation of predictive regressions since the model and parameter uncertainty may adversely affect the explanatory variables' marginal predictive content (see, Bai and Ng (2008), Kuzin et al. (2011), Cepni and Guney (2019), Cepni et al. (2018, 2020), Fraooq et al. (2019), Terui and Li (2019) and Mascio et al. (2020)). In this respect, as an robustness check, we investigate alternative variable selection methods namely, the Elastic-Net, the Least Absolute Shrinkage Operator (LASSO), and the Ridge regression in order to pre-select variables prior to the predictions[13]. Accordingly, for each month, we recursively choose predictors from the set of our four macroeconomic and financial factors, instead of using all of them. As presented in Tables A16-A18 of appendix, machine learning algorithms are useful for selecting predictors when constructing predictions. Put differently, variable selection methods results in predictive gains by providing sparsity for model estimation compared to the predictive regressions utilizing all macroeconomic and financial factors simultaneously for each month. This can be seen from Tables A16-A18 of the appendix by noting that the entries in general are less than unity.

– Insert Table 5 about here. –

[13]We give detailed information on how the variables selection algorithms are implemented in the appendix.

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5. Conclusion

This paper investigates the relative importance of the local and global factors in driving movement in term structure of interest rates in emerging markets. For this purpose, initially, the yield curve factors are extracted using the NS methodology for the 2006:01- 2019:04 period. Rather than analyzing the effect of macroeconomic variables by using a few empirical proxies for price developments, growth and monetary policy stance, the macroeconomic and financial variables are classified as global variables, economic activity, domestic financial developments and inflation. Then, a panel VAR model is employed to explore the dynamics of the yield curve factors and macroeconomics factors.

Empirical results suggest that the level factor responds positively to the shocks originating from inflation developments as well as financial variables. However, the effect of domestic financial variables on the level factor tends to be larger in size compared to inflationary shocks. Whereas slope factor is affected by shocks in global variables, curvature factor appears to be influenced by domestic financial variables. Besides, utilizing an individual factor augmented predictive regressions and variable selection algorithms also confirm thst macroeconomic/financial factors have predictive power for yield curve factors.

Our findings indicate that macroeconomic and global financial variables are informative in terms of explaining changes in yield curve of emerging markets countries. Given the unconventional monetary policy implementations and low-rate environment in developed countries, the emerging market domestic bond rates tend to be exposed to the swings in global financial conditions, which weakens the monetary policy transmission mechanism in emerging markets. Hence, policymakers should take into account the possible implications of shocks stemming from global financial framework as well as economic activity and local financial variables. Additionally, deciphering the relation among macroeconomic forces and each particular factor of yield curve enables to anticipate the changes in the yield curve through the evolvement in those forces and creates a better environment for producing accurate forecasts. Given the tremendous growth of emerging market bonds, and hence, the importance of accurate yield forecasts in the computation of optimal investment positions, our findings suggest that incorporating local and global factors in forecasting models can help to improve the design of portfolios that include emerging market bonds.

Conflicts of interest

The authors declare no conflict of interest.

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Data Availability Statement

The data that support the findings of this study are available from Bloomberg terminal. Restrictions apply to the availability of these data, which were used under license for this study. However, we shared the corresponding tickers in Tables A1 - A10 of the online appendix. Hence anyone who has a Bloomberg account can easily download the same data.

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Table 1: Number of indicators by type for selected emerging markets.

Categories	Brazil	Hungary	India	Malaysia	Mexico	Poland	Russia	South Africa	Thailand	Turkey
Real economic activity	63	47	48	20	60	28	31	61	31	44
Prices	16	13	11	15	17	20	17	17	14	16
Domestic financial variables	29	38	37	26	37	32	32	37	26	40
Global variables	48	48	48	48	48	48	48	48	48	48
Total	156	146	144	109	162	128	128	163	119	148

Table 2: Dynamic panel estimation results : Level factor

Dependent Variable : Level	(1)	(2)	(3)	(4)	(5)
L.Level	1.133***	1.196***	1.153***	1.178***	1.097***
	(0.064)	(0.063)	(0.054)	(0.059)	(0.068)
L2.Level	-0.288***	-0.313***	-0.272***	-0.300***	-0.277***
	(0.054)	(0.057)	(0.052)	(0.054)	(0.053)
Inflation	0.0794***				0.0642***
	(0.029)				(0.023)
Activity		-0.0114			-0.0173
		(0.016)			(0.013)
Financial			0.0548**		0.0382
			(0.027)		(0.027)
Global				-0.0152	-0.0015
				(0.010)	(0.006)
Observations	1340	1340	1340	1340	1340
Number of country	10	10	10	10	10

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

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Table 3: Dynamic panel estimation results : Slope factor

Dependent Variable : Slope	(1)	(2)	(3)	(4)	(5)
L.Slope	1.186***	1.137***	1.176***	1.177***	1.110***
	(0.052)	(0.044)	(0.062)	(0.047)	(0.051)
L2.Slope	-0.352***	-0.308***	-0.353***	-0.327***	-0.307***
	(0.051)	(0.047)	(0.056)	(0.042)	(0.049)
Inflation	0.005				-0.009
	(0.019)				(0.024)
Activity		0.038***			0.048***
		(0.014)			(0.017)
Financial			0.025		0.045***
			(0.022)		(0.015)
Global				0.014*	-0.005
				(0.008)	(0.009)
Observations	1340	1340	1340	1340	1340
Number of country	10	10	10	10	10

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Dynamic panel estimation results : Curvature factor

Dependent Variable : Curvature	(1)	(2)	(3)	(4)	(5)
L.Curvature	1.065***	1.046***	1.050***	1.058***	1.041***
	(0.083)	(0.088)	(0.084)	(0.091)	(0.084)
L2.Curvature	-0.347***	-0.343***	-0.345***	-0.346***	-0.341***
	(0.083)	(0.083)	(0.082)	(0.087)	(0.083)
Inflation	0.007				-0.029
	(0.045)				(0.048)
Activity		0.037			0.022
		(0.030)			(0.019)
Financial			0.087**		0.095**
			(0.037)		(0.040)
Global				0.008	-0.005
				(0.026)	(0.025)
Observations	1340	1340	1340	1340	1340
Number of country	10	10	10	10	10

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

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Table 5: Dynamic common correlated effects estimation results : Level factor

Dependent Variable : Level	(1)	(2)	(3)	(4)
L.Level	1.088***	1.105***	1.101***	1.024***
	(0.044)	(0.048)	(0.041)	(0.033)
L2.Level	-0.227***	-0.236***	-0.229***	-0.215***
	(0.054)	(0.051)	(0.049)	(0.049)
Inflation	0.029***			0.025**
	(0.007)			(0.012)
Activity		-0.027**		-0.015
		(0.011)		(0.011)
Financial			0.002	0.001
			(0.011)	(0.014)
Observations	1340	1340	1340	1340
Number of country	10	10	10	10

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Dynamic common correlated effects estimation results : Slope factor

Dependent Variable : Slope	(1)	(2)	(3)	(4)
L.Slope	1.116***	1.124***	1.123***	1.170***
	(0.056)	(0.046)	(0.053)	(0.052)
L2.Slope	-0.244***	-0.267***	-0.246***	-0.256***
	(0.045)	(0.048)	(0.046)	(0.046)
Inflation	0.022***			0.023**
	(0.008)			(0.011)
Activity		0.015***		0.015***
		(0.004)		(0.005)
Financial			0.016***	0.018***
			(0.006)	(0.006)
Observations	1340	1340	1340	1340
Number of country	10	10	10	10

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

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Table 7: Dynamic common correlated effects estimation results : Curvature factor

Dependent Variable : Curvature	(1)	(2)	(3)	(4)
L.Curvature	1.048***	1.063***	1.124***	1.107***
	(0.050)	(0.047)	(0.100)	(0.099)
L2.Curvature	-0.218***	-0.221***	-0.242**	-0.255**
	(0.054)	(0.055)	(0.111)	(0.110)
Inflation	0.033			0.049**
	(0.021)			(0.021)
Activity		-0.004		0.028
		(0.007)		(0.017)
Financial			0.031**	0.028**
			(0.012)	(0.011)
Observations	1340	1340	1340	1340
Number of country	10	10	10	10

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

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Table 8: Factor augmented predictive regressions : out-of-sample forecasting results

Brazil	h=1	h=2	h=3	h=4	h=5	h=6
RW	0.0187	0.0190	0.0193	0.0194	0.0195	0.0196
Level	**0.817*** **	**0.864** **	**0.909** **	**0.951***	**0.986***	1.011
Slope	**0.798*** **	**0.847*** **	**0.886** **	**0.913** **	**0.928** **	**0.933** **
Curvature	**0.970***	1.007	1.049	1.094	1.140	1.189
Hungary						
RW	0.0167	0.0169	0.0172	0.0173	0.0175	0.0177
Level	**0.732*** **	**0.761*** **	**0.787*** **	**0.815*** **	**0.841*** **	**0.862** **
Slope	**0.469*** **	**0.480*** **	**0.493*** **	**0.506*** **	**0.517*** **	**0.527*** **
Curvature	**0.527*** **	**0.540*** **	**0.556*** **	**0.566*** **	**0.574*** **	**0.582*** **
India						
RW	0.0147	0.01473	0.01477	0.01478	0.01461	0.01442
Level	**0.778*** **	**0.804*** **	**0.831** **	**0.850** **	**0.867** **	**0.875** **
Slope	**0.982***	1.011	1.034	1.046	1.054	1.067
Curvature	**0.726*** **	**0.751*** **	**0.778*** **	**0.803*** **	**0.825*** **	**0.846** **
Malaysia						
RW	0.0040	0.0041	0.0041	0.0041	0.0042	0.0042
Level	**0.880** **	**0.904** **	**0.917** **	**0.942** **	**0.969***	**0.993***
Slope	1.432	1.475	1.506	1.547	1.587	1.629
Curvature	1.090	1.133	1.170	1.203	1.225	1.250
Mexico						
RW	0.0116	0.0117	0.0118	0.0119	0.0119	0.0120
Level	**0.849*** **	**0.888** **	**0.919** **	**0.949** **	**0.979***	1.022
Slope	**0.929** **	**0.969***	**0.995**	1.009	1.021	1.034
Curvature	**0.873*** **	**0.909** **	**0.941** **	**0.960** **	**0.979***	**0.990**
Poland						
RW	0.0134	0.0136	0.0137	0.0139	0.0141	0.0142
Level	**0.501*** **	**0.521*** **	**0.540*** **	**0.559*** **	**0.572*** **	**0.583*** **
Slope	1.042	1.068	1.090	1.107	1.123	1.139
Curvature	**0.834** **	**0.883** **	**0.929***	**0.976***	1.018	1.058
Russia						
RW	0.0106	0.0107	0.0109	0.0110	0.0112	0.0112
Level	1.271	1.276	1.275	1.293	1.302	1.298
Slope	1.315	1.361	1.397	1.427	1.454	1.480
Curvature	**0.890** **	**0.921** **	**0.940***	**0.947***	**0.939***	**0.914** **
S.Africa						
RW	0.0065	0.0065	0.0065	0.0066	0.0066	0.0066
Level	1.144	1.161	1.169	1.175	1.179	1.184
Slope	1.079	1.105	1.129	1.149	1.177	1.208
Curvature	**0.833*** **	**0.851** **	**0.872** **	**0.888** **	**0.904** **	**0.919** **
Thailand						
RW	0.0097	0.0097	0.0097	0.0098	0.0098	0.0099
Level	**0.781*** **	**0.784*** **	**0.788*** **	**0.791*** **	**0.795*** **	**0.797*** **
Slope	1.144	1.212	1.259	1.296	1.318	1.327
Curvature	**0.950** **	**0.972***	**0.990**	**0.999**	1.003	**0.999**
Turkey						
RW	0.0269	0.0268	0.0268	0.0270	0.0273	0.0278
Level	1.156	1.192	1.227	1.258	1.270	1.284
Slope	**0.869*** **	**0.889*** **	**0.901** **	**0.904** **	**0.916** **	**0.932***
Curvature	1.038	1.058	1.067	1.064	1.056	1.037

Entries in the first row of the table are point RMSEs based on the benchmark random walk (RW) model, while the rest are relative RMSEs. Hence, a value of less than unity indicates that a particular model and estimation method is more accurate than that based on the RW model, for a given forecast horizon. Models that yield the lowest MSFE for each forecast horizon are denoted in bold. Entries superscripted with an asterisk (*** = 1% level; ** = 5% level; * = 10% level) are significantly superior than the RW model, based on the DM predictive accuracy test.

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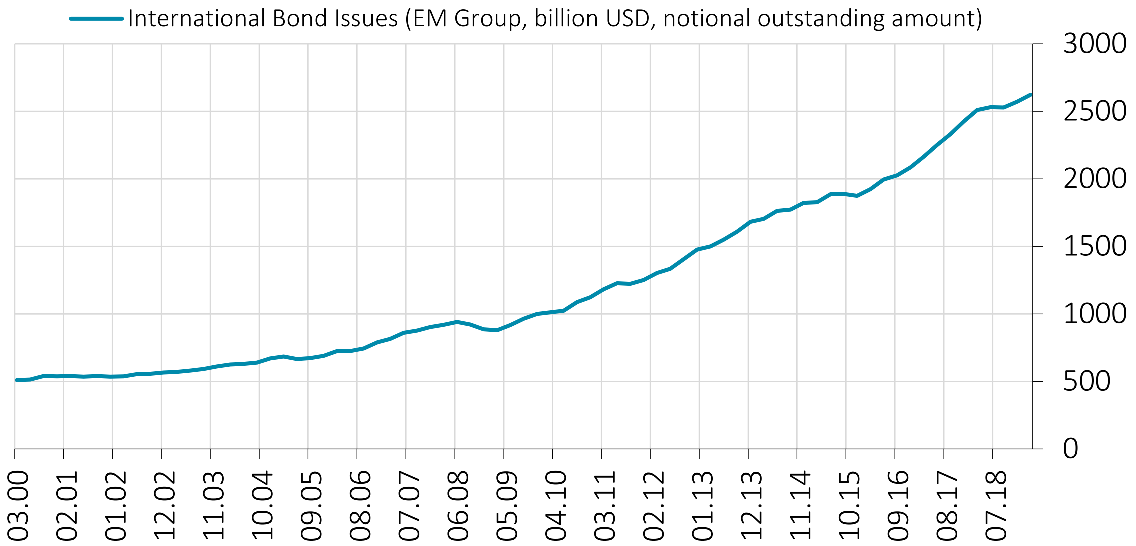
Figure 1: International bond issuances and EM domestic bond markets total size



Source:BIS

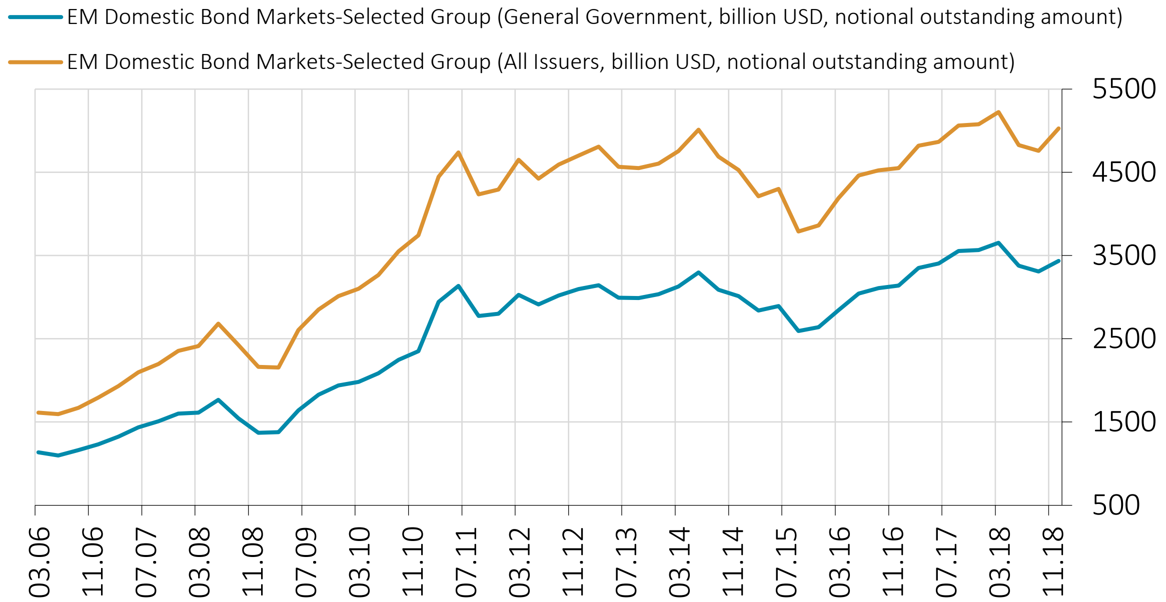


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Figure 2: Scatterplots of relation between yield curve factors and estimated common components

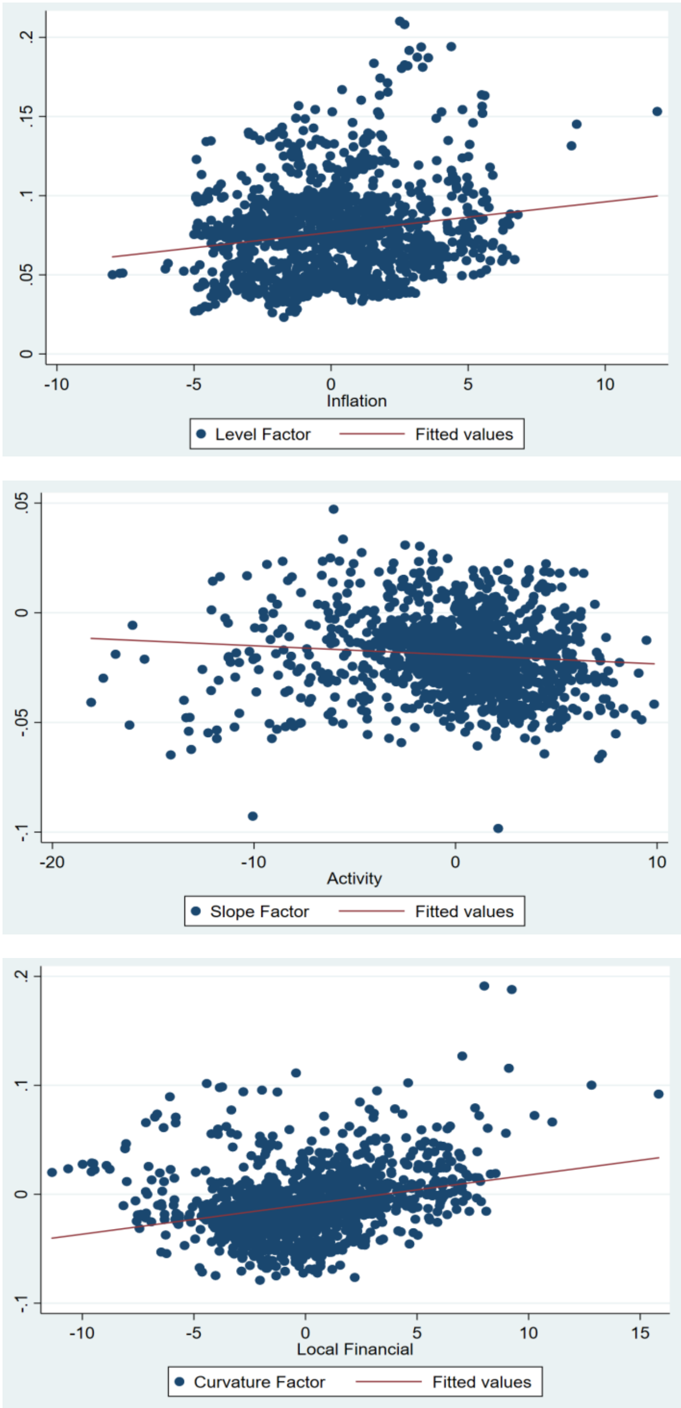

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Figure 3: Cumulative orthogonalized impulse-response functions

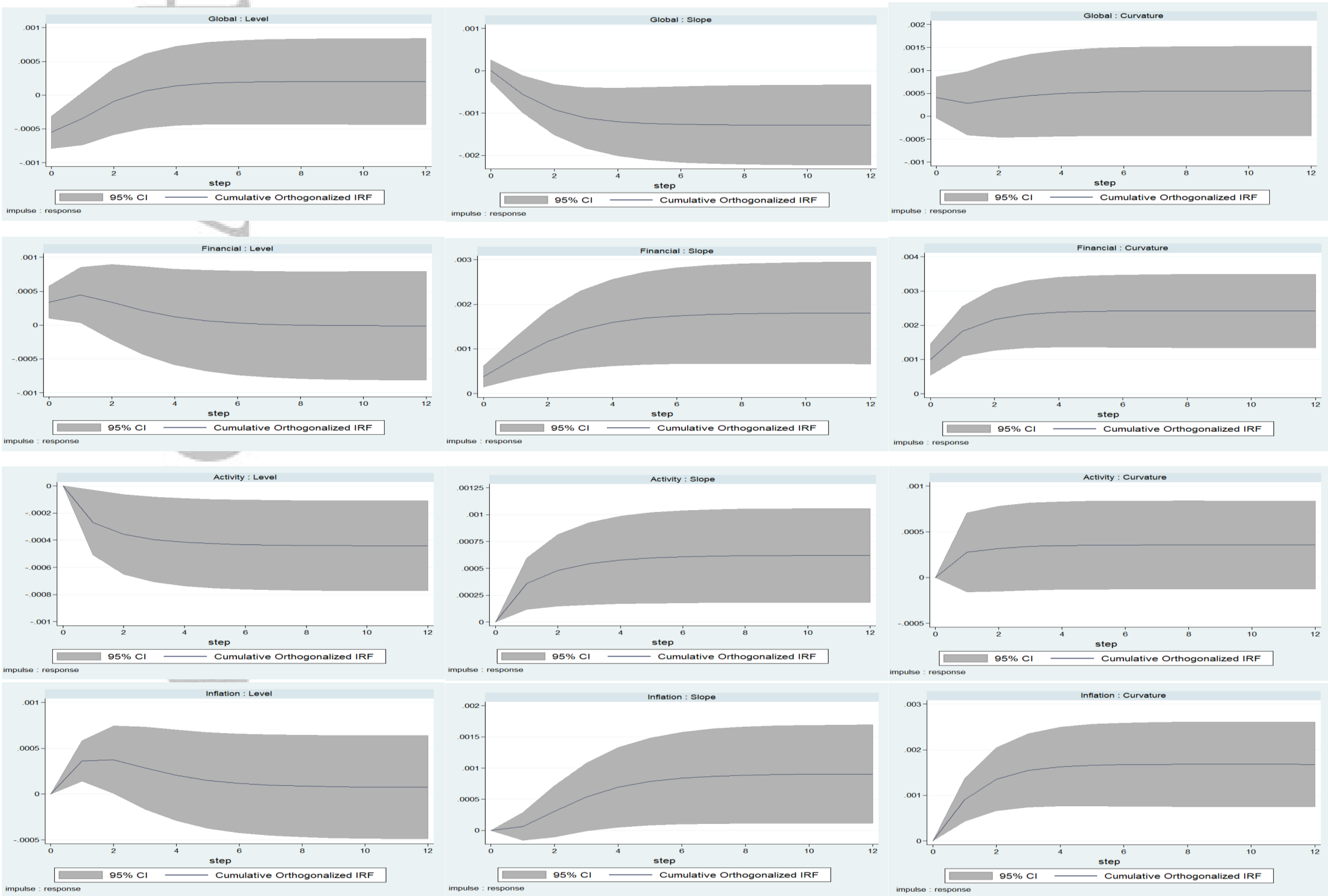

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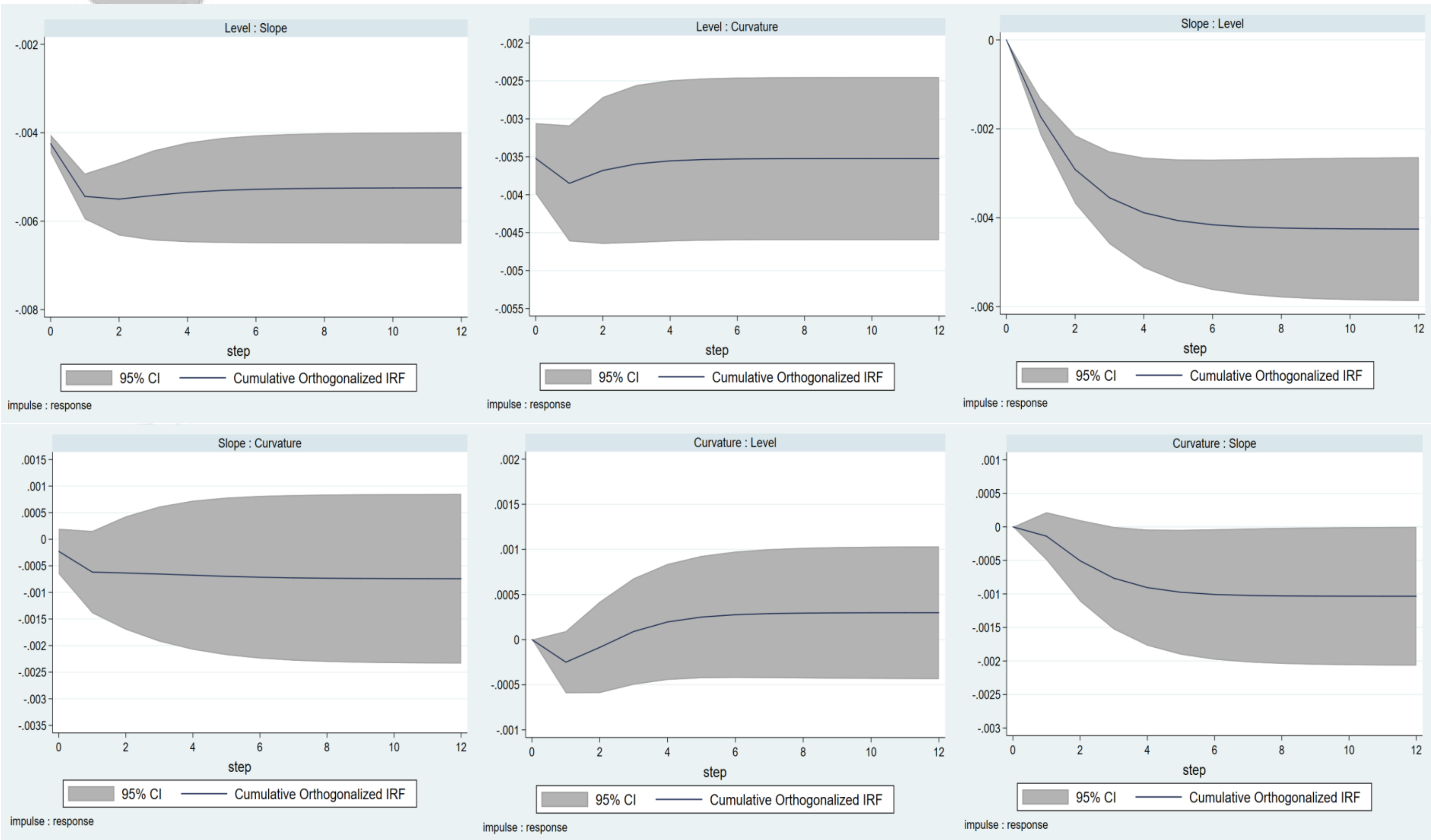
Figure 4: Accumulated impulse-responses among yield curve factors



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