How Local is the Local Inflation Factor?

Evidence from Emerging European Countries

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Working paper 08-2021
Version 03
May 2022

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This version: May 2022

Abstract

We consider whether inflation is a 'global phenomenon' for European emerging market economies, as has been claimed for advanced or high-income countries. We find that a global inflation factor accounts for more than a half of the variance in the national inflation rates, and show that forecasting models of national headline inflation rates that include global inflation factors generally produce more accurate path forecasts than Phillips Curve-type models, and models with local inflation factors. Our results are qualitatively unaffected by allowing for sparsity and non-linearity in the factor forecasting models. We also provide some insight as to why global factors are an important determinant of domestic inflation, by considering the country-level characteristics which tend to increase the importance of global factors over domestic.

Keywords: Global inflation, Common factors, Forecasting, Inflation spillovers, Machine learning, Variable selection.

JEL Classification: E31, E52, F42, F62.

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Declaration of interest: None

1. Introduction

Over the last decade or so there has been much debate in the literature about the relative importance of global factors and domestic factors (including a country's monetary policy) as determinants of countries' inflation rates. As argued by Ciccarelli and Mojon (2010), the international character of economic fluctuations is not new (see, e.g., Kose et al. (2003)) but the recognition that inflation might also be a global phenomenon has come more slowly, with Ciccarelli and Mojon (2010) being an important contribution, along with Neely and Rapach (2011a) and Mumtaz and Surico (2012), *inter alia*.[1] Ciccarelli and Mojon (2010) show that a common factor accounts for nearly 70% of the variance of inflation of 22 OECD countries, capturing trend components and cyclical variation. The importance of the 'globalisation of inflation' has not gone undisputed, both in terms of the implications for the effectiveness of domestic monetary policy,[2] as well as for the appropriate way of modelling and forecasting inflation.

Much of the research has focused on the U.S. and the developed countries of the OECD, with fewer studies of developing and emerging economies. This is not surprising, with the superior availability of data for advanced economies such as the U.S. supporting the application of appropriate econometric techniques to investigate the effects of global factors on inflation. However, it is unfortunate for at least two reasons. Firstly, less advanced countries typically experience more variable inflation rates, putting a premium on the accurate modelling and forecasting of inflation in those countries, both for the conduct of policy by the monetary authorities, as well as for the savings and investment decisions of private-sector agents. Secondly, recent research by Kamber and Wong (2020) suggests that global factors play a more important role in determining trend inflation (as opposed to cyclical inflation) in emerging economies than in developed economies. They suggest (referring to Draghi (2015)) that although global factors affect the inflation gap in both emerging and developed countries, central banks will 'look through' foreign shocks that only have transitory effects (that is, only affect the inflation gap). Hence for the conduct of monetary policy, determining the effects of foreign shocks on developing countries may be a more pressing concern than for developed economies, especially if these shocks do have a greater effect on trend inflation in developing economies.

In this paper, we directly address the relevance of the globalisation of inflation phenomenon for emerging

[1] That said, it has long been recognised that the Phillips curve (Phillips (1958)) relationship between the real-side of the economy (the unemployment rate, or an activity variable or measure of slack more generally) and price or wage inflation, ought to be supplemented with a role for international developments, such as oil prices or import prices (see, e.g., Franz and Gordon (1993) and Roberts (1995)).

[2] See, e.g., Carney (2015), Draghi (2015) and Jordan (2015).

market economies, by analysing a number of emerging European economies. We address a number of key issues that might affect the findings. Firstly, in the context of the emerging European economies, what is an appropriate 'global' inflation factor? A factor could be extracted from all the countries taken together (i.e., emerging and developed), or from the subset of emerging countries, or from the developed countries. The shared geographic location of the emerging European countries, and their close ties in terms of cultural, political and industrial development might suggest an emerging-country factor, but equally we might expect the EU member countries to be affected by European-wide, or even global, inflation. We regard this as an empirical question, and we allow the data to choose between these possibilities based on which generates the best forecasts. Related to the choice of factor, how to calculate the factor(s) turns out to matter. We estimate factors using partial least squares, rather than the oft-used principal component analysis. As we explain, this makes it more likely that the factors will be able to predict national inflation rates.

The second main consideration is the choice of forecasting model in which to determine any potential benefits from including factors. The forecasting models in which 'global' effects are included can affect the importance we attribute to global developments, as can the benchmark models we use as comparators,[3]and the failure to model domestic influences might misleadingly point to an important role for external factors in forecasting domestic inflation. We attempt to guard against finding a role for 'global inflation', because of the omission of relevant domestic sources, by including a factor calculated from a large set of domestic variables, which includes the traditional Phillips curve determinants. We use a factor to capture a wide range of possible domestic influences.

At least for the U.S. evidence has accumulated against the traditional Phillips curve, with the 'missing disinflation' in the US following the 2008 Financial Crisis (see, e.g., Stock (2011) and Coibion and Gorodnichenko (2015)), and the recent low rates of inflation despite low rates of unemployment (see, e.g., Ball and Mazumder (2019)). Coupled with the apparent flattening in the Phillips curve, McLeay and Tenreyro (2019) argue that the actions of the monetary authorities will diminish the observed responsiveness of prices to slack. Atkeson and Ohanian (2001) had earlier found that a simple average of the four quarterly inflation

[3]A case in point is the study by Gillitzer and McCarthy (2019), which shows that a head-to-head comparison of the forecast performance of the global inflation model of Ciccarelli and Mojon (2010) with the 'no change' benchmark of Atkeson and Ohanian (2001) (discussed further below in the main text) does not favour the former. The benchmark model of Atkeson and Ohanian (2001) happens to closely correspond to the model of Stock and Watson (2007) for U.S. inflation for a particular epoch. However, adding the global factor to the model of Atkeson and Ohanian (2001) was found to improve accuracy at longer horizons. This can be understood in terms of the concept of forecast encompassing: a model can be less accurate than another but still carry useful incremental information for forecasting (see, e.g., Chong and Hendry (1986) and Ericsson and Marquez (1993)).

rates up to the forecast origin was more accurate than forecasts obtained from Phillips Curve specifications. That said, our ”Phillips curve” model is broader than a simple relationship between inflation and unemployment rate or the output gap, and captures a broad range of domestic influences. We also allow the domestic variables to have a non-linear or time-varying influence on inflation, consistent with the view that the Phillips curve might exhibit important non-linearities (see, e.g., Hooper et al. (2019)).

The literature also suggests an important distinction between core and headline inflation, where the former excludes food and energy prices. Global determinants of commodity prices will likely influence domestic energy and food prices, and hence headline inflation. But the ‘globalisation of inflation’ phenomenon as sometimes understood goes beyond this direct effect, to refer to an effect on core inflation. While food and energy prices will affect the headline figure, they may not be closely related to the domestic level of activity, so that Phillips curve specifications may not work well for the headline rate.[4] We unpack these issues as follows. Our primary focus is on headline inflation rates, and we check whether a global factor has predictive power once we have separately controlled for commodity (food and energy) prices. We then consider whether our findings change when headline inflation is replaced with core inflation.

The recent literature presents a mixed picture. In addition to the papers cited above, Auer et al. (2017) argue that greater international interconnectedness, as measured by global value chains, has led to an increase in the importance of ‘global slack’ (relative to domestic conditions) in determining national inflation rates. Kabukçuoğlu and Martínez-García (2018) find that modelling cross-country inflation spillovers also improves upon traditional ‘closed’ Phillips Curve forecasting models. Yet the importance of global factors (with the exception of commodity prices) in determining advanced economies’ national inflation rates is contested by Mikolajun and Lodge (2016). They show that in Phillips Curve models for the period of relative stability from the mid 1990s onwards, global factors other than commodity prices tend to be of little importance, especially once forward-looking expectations are included to capture long-term trends. (Altansukh et al., 2017, p.2) suggest ‘the observed convergence in aggregate and core inflation may be the product of many economies sharing a similar inflation target concurrently, rather than due to a global transmission factor’.

The evidence for emerging or low income countries in favour of globalisation of inflation is also equiv-

[4] See e.g., Ball and Mazumder (2019), who argue that large relative price changes may also occur in industries other than food and energy, suggesting measuring inflation using the weighted median of price changes across industries (proposed as a measure of core inflation by Bryan and Cecchetti (1993)).

ocal. Duncan and Martínez-García (2019) consider a range of models for 14 emerging market economies, including open-economy Phillips Curve models, and generally find they are outperformed by the Atkeson and Ohanian (2001) benchmark. Parker (2018) comes to a similar conclusion for middle and low income countries. His findings match those of Ciccarelli and Mojon (2010) in that global inflation matters for high-income countries, but accounts for only 10% or so of the variation in national inflation rates for low income countries (and only 15-20% for middle income countries). (Parker, 2018, p.175) argues that in high income countries it is 'the lower average inflation, lower inflation volatility, higher GDP per capita, deeper financial development and more transparent monetary policy that explain a greater role for global inflation factors'. Jašová et al. (2019) find a diminished role for global inflation in determining emerging markets national inflation rates following the global financial crisis, in contrast to their evidence for developed countries. Finally, both Hałka and Szafranek (2016) and Lovin (2020) offer a more positive assessment of the effects of global factors on emerging market economies. Hałka and Szafranek (2016) find central and eastern European countries inflation rates are affected by inflation in the euro area, and Lovin (2020) finds a role for euro area inflation and output gap for European emerging countries' inflation rates, although core CPI was less affected than food and energy.

Looking ahead: we find that global factors play an important role in determining European emerging market national headline inflation rates, in addition to the explanatory power provided by local, domestic factors: 'inflation is a global phenomenon' for the European emerging market countries' just as it has found to be for advanced economies. This finding is tempered somewhat when we forecast core inflation instead. For forecasting headline national inflation rates, global inflation is found to have predictive power beyond the information carried by the factor regarding commodity prices.

Our findings are based on linear factor forecasting models, but are shown to carry over to factor-selection methods that enforce sparsity, as well as a machine-learning method that allows for a non-linear relationship between national inflation rates and the sets of factors. We consider alternative methods of evaluating forecast performance, including looking at path forecasts, but the bottom-line is essentially unchanged.

Finally, we undertake two additional sets of analyses, with the aim of furthering our understanding of why inflation appears to be a global phenomenon for emerging market economies. The first considers whether we can explain national inflation rates better (in terms of generating more accurate forecasts) if we make an allowance for the different degrees of "connectedness" between countries when we calculate the global inflation factor. For shorter and medium horizon forecasts allowing for network effects yields improvements for some countries. However, for some EM countries at all horizons, and for most counties at longer horizons, allowing for network effects is not beneficial. The second casts light on the country-level characteristics that make a country's inflation rate more responsive to global inflation, as opposed to domestic factors. That is, we explore the potential propagation channels of global factors on domestic inflation rates for emerging markets.

2. Data

We collect a large set of macro-economic indicators on the central and eastern European countries: Bulgaria, Czech Republic, Greece, Hungary, Poland, and Romania (hereinafter referred to as EM European). We select the EM European countries which have made the largest strides in terms of globalization in recent years.[5] The data-set includes both 'hard indicators' and country level survey data. In the hard indicators, we have supply-side variables, such as construction, industrial production indices, and demand-side variables, such as energy usage. Among the survey variables, we have consumer confidence indices, European Commission economic sentiment index and Market PMI survey, etc. To capture the potential vulnerability of EM European countries to external factors, we also consider the current account balance, and export and import value indices. The macroeconomic indicators are downloaded from Bloomberg.

In addition to the macroeconomic indicators, we employ a large dataset of disaggregated harmonized indices of consumer prices (HICP), up to product-level, for our sample of countries. This is a higher level of disaggregation than sector-specific price data, and includes product series such as 'meat', 'milk', 'package holidays', and 'dental services', etc. The number of HICP components ranges from 73 and 89 indices across countries, since not all items are not available for all countries.[6] The disaggregated price data are obtained from the Euro-stat database. To construct a proxy for global inflation, we collect a large panel of headline consumer price indices for a set of 98 countries, including the 71 advanced countries, and 27 emerging markets. Hence, our dataset covers inflation rates for countries in different regions such as the Middle East, Asia, Africa, and Europe. The selection of countries is based on data availability: earlier-period high-quality data are not available for some countries we would otherwise have included. The country-level headline consumer price indices are taken from the IMF database.

[5]See Gygli et al. (2019).

[6]We only utilized the indices that have available data for our whole sample period.

Our complete monthly dataset covers the period January 2002 to January 2020: the starting date being determined by data availability. All series are adjusted for seasonality (where relevant), and made stationary as appropriate by either differencing, year-over-year differencing, or log-differencing. Table 1 summarizes the number of variables in each data group across countries.

– Insert Table 1 about here. –

3. Methodology

3.1. Constructing the local and global factors using Partial Least Squares (PLS)

In much of the existing literature, a proxy for global inflation is constructed as a common factor of a group of country inflation rates, often either as a static factor resulting from the application of principal component analysis (PCA) or from dynamic factor models estimated using Bayesian methods (Ciccarelli and Mojon, 2010; Mumtaz et al., 2011; Parker, 2018). Unlike those studies, we use partial least squares (PLS) to extract common factors, and calculate factors from our three separate datasets. The first is a country-specific macroeconomic indicators dataset, the second a country-specific dataset of disaggregated CPI indices, and finally we calculate a number of factors from a dataset of national inflation rates, as described below. PLS reduces the large number of variables in each of these datasets to a small number of factors, which have maximum explanatory power for a given target variable. As indicated by (Fuentes et al., 2015; Groen and Kapetanios, 2016), PLS estimates the latent factors by maximizing the co-variance between the target forecast variable and predictor variables. The explicit consideration of the target forecast variable counters the main criticism of PCA: it ensures that the resulting factors are related to the target variable.

In this paper, the PLS method is utilized by following the two-step approach proposed by Friedman et al. (2001). For each dataset X, the algorithm standardizes each predictor variables x_j $(j = 1, \ldots, n)$ to have zero mean and unit variance.[7] Then, univariate regression coefficients $\widehat{\gamma_{1j}} = \langle x_j, y \rangle$ are stored for each j, where y alternatively represents the headline inflation rates of our EM European countries. Using these coefficients, the first PLS direction $z_1 = \sum_j \widehat{\gamma_{1j}} x_j$ is determined as the weighted sum of the original set of predictor variables, where the weights are given by the vector of univariate regression coefficients. Accordingly, the

[7] For each country, the dataset X alternatively represent the aggregated harmonized indices of consumer prices, the set of macroeconomic indicators, headline inflation rates for 98 countries, headline inflation rates of 71 advanced countries and headline inflation rates of 27 emerging markets.

estimation of the PLS direction incorporates the degree of association between target variable y and the predictor variables. Subsequently, the target variable y is regressed on z_1, resulting in a coefficient θ_1, and then all inputs are orthogonalized with respect to z_1. This process is repeated until PLS constructs a sequence of $k < n$ orthogonal directions, $\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_k$. Hence, PLS attempts to capture the directions that have high variance and high correlation with the target variable concurrently. In particular, the p^{th} PLS direction $\widehat{\gamma_p}$ solves the following optimization problem:

$$\begin{aligned} &\max_{\alpha} && Corr^2(y, X_\alpha)Var(X_\alpha), \\ &\text{subject to} && \|\alpha\| = 1, \quad \alpha' M \widehat{\gamma_k} = 0, \quad k = 1, ..., p-1 \end{aligned} \tag{1}$$

where M denotes the sample covariance matrix of the x_j. The conditions $\alpha' M \widehat{\gamma_k} = 0$ ensures that $\mathbf{z}_k = \mathbf{X}\alpha$ is uncorrelated with all the previous linear combinations $\mathbf{z}_k = \mathbf{X}\widehat{\gamma_k}$.

In our forecasting exercise, we first make use of a factor that summarizes the information contained in a broad set of macroeconomic indicators for each of the EM European countries in our sample. We label these PLS-factors as ‘Local macro factors’ (LocalMACRO) since they are based on only local or ‘own-country’ variables. Similarly, using the highly-disaggregated CPI data for a given country, we extract PLS-factors for each country, which will be highly correlated with that country’s headline inflation rate. We name these ‘Local (domestic) inflation factors’ (LocalCPI).

Three competing measures of ‘global inflation’ are considered. We partition our dataset of headline inflation rates, covering countries across the globe, into three sets: ‘Global’ (includes all countries), ‘Emerging’ (includes only EM countries) and ‘Developed’ (includes only DM countries). Each subset is used to generate a PLS factor that may prove instrumental in capturing global inflation dynamics. These new PLS-factors are called the ‘Global inflation factor’ (GlobalCPI) - constructed using inflation rates of all countries, the ‘EM inflation factor’ (EMCPI) - constructed using only inflation rates of emerging countries, and the ‘DM inflation factor’ (DMCPI) - constructed using only inflation rates of developed countries.

*3.2. **Forecasting experiment: factor-augmented predictive regressions***

To evaluate the predictive ability of global and local factors for the year-over-year inflation rates of emerging European countries, we specify factor-augmented predictive regressions, where factors are extracted using both PCA and PLS approaches. We utilize both a recursive and 84-months fixed length rolling window forecasting scheme to generate forecasts from the different specifications. We design a set of models which allows us to isolate any accuracy gains from the incorporation of either country-specific or global inflation factors, conditional on the model already including Phillips Curve-type variables (proxied by the LocalMACROhttps://www.overleaf.com/project/5f0c677d2c68ac0001776f4f factor). That is, we are not so much interested in whether a model with a global factor (say) is better or worse than a Phillips curve model, as whether the global factor has any additional incremental predictive ability when added to a Phillips curve model. Note that the method of construction of the factors does not impose orthogonality between the factors in different groups (e.g., between the factors in the LocalMACRO and LocalCPI groups). Hence any potential improvement from adding a LocalCPI factor, say, may be tempered to the extent that the LocalCPI factor is correlated with the included LocalMACRO factors. Nevertheless our suite of models facilitates encompassing-type comparisons (see footnote 3) and will allow us to discern improvements from adding factors conditional on the factors already included, even though some care is required over the interpretation. Hence the forecasting exercise consists of the following models:[8]

- **Specification 1**: Local macro factor model

  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \varepsilon_{t+h}$

- **Specification 2**: Local inflation factor model

  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \varepsilon_{t+h}$

- **Specification 3**: EM inflation factor model

  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \theta' F_t^{EMCPI} + \varepsilon_{t+h}$

- **Specification 4**: DM inflation factor model

  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \theta' F_t^{DMCPI} + \varepsilon_{t+h}$

- **Specification 5**: Augmented inflation factor model

  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \theta' F_t^{EMCPI} + \delta' F_t^{DMCPI} + \varepsilon_{t+h}$

- **Specification 6**: Global inflation factor model

  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \theta' F_t^{GlobalCPI} + \varepsilon_{t+h}$

where y_t, alternatively, is year-over-year inflation rates of European emerging countries, and L^p is shorthand for a pth order lag polynomial, and F_t^j for j = [LocalMACRO, LocalCPI, EMCPI, DMCPI, GlobalCPI]

[8]Lag length is selected via the Schwarz information criterion (SIC) for benchmark AR model.

represents the estimated country-specific common factors described in Section 3.1.[9] The lag length p of the AR component of each specification type is selected based on SIC criteria. While the specification types 1-2 enable us to assess the importance of local inflation and macro factors in addition to lags of the inflation rate and constant, specification types 3-6 are extensions that include global inflation factors. All models are re-estimated at each step using the information available up to time t. We use exactly 50% of the sample period to assess out-of-sample forecasts, giving us 103-h observations where forecast horizons are evaluated for h = 1, 2 3, 4, 5, 6, 9, 12 step-ahead forecasts. Furthermore, we compare forecast accuracy using the mean squared forecast error (MSFE).

In addition to these models, we also examine the usefulness of various time-varying parameter and shrinkage models defined in Section 3.3. These models are designed to be flexible enough to capture some forms of structural change and parameter non-constancies (Korobilis, 2019). The use of a rolling-window forecasting scheme will allow some model adaptation, but we also investigate the potential for time-varying parameter models to improve on the linear factor models.

3.3. ***Time-varying parameter and shrinkage models***

3.3.1. Variational Bayes Dynamic Variable Selection (VBDVS) algorithm

Koop and Korobilis (2020) introduce the dynamic extension of variational Bayes (VB) to tackle high-dimensional problems where the number of predictors may exceed the number of time-series observations. The main advantage of the VBDVS algorithm is that it is computationally less demanding than Markov chain Monte Carlo (MCMC) algorithm, while achieving estimation accuracy equivalent to that of MCMC.

The VBVDS model of Koop and Korobilis (2020) has the following form:

$$\begin{aligned} y_t &= x_t\beta_t + \varepsilon_t \\ \beta_t &= \beta_{t-1} + \eta_t \end{aligned} \tag{2}$$

where y_t is the dependent variable, $\beta_t = \left(\beta_{1,t}, \ldots, \beta_{p,t}\right)'$ is a $p \times 1$ vector of time-varying parameters, x_t is a $1 \times p$ vector of predictor variables and lagged dependent variables. Moreover, $\varepsilon_t \sim N\left(0, \sigma_t^2\right)$ with σ_t^2 time-varying variance parameter, $\eta_t \sim N\left(0, W_t\right)$ with $W_t = \text{diag}\left(w_{1,t}, \ldots, w_{p,t}\right)$ is a $p \times p$ diagonal matrix.

[9] For each country, all the common factors are re-estimated at each forecast origin using the information available up to time t to prevent the look-ahead bias.

This approach is implemented with a dynamic variable selection (DVS) prior of the form:

$$
\begin{aligned}
\beta_{j,t} \mid \gamma_{j,t}, \tau^2_{j,t} &\sim \left(1-\gamma_{j,t}\right) N\left(0, c \times \tau^2_{j,t}\right) + \gamma_{j,t} N\left(0, \tau^2_{j,t}\right) \\
\gamma_{j,t} \mid \pi_t &\sim \text{Bernoulli}\left(\pi_{0,t}\right) \\
\frac{1}{\tau^2_{j,t}} &\sim \text{Gamma}\left(g_0, h_0\right) \\
\pi_{0,t} &\sim \text{Beta}(1,1)
\end{aligned}
\tag{3}
$$

where (j, t) subscripts represent the j^{th} element of a time varying parameter at time t. Furthermore, g_0, h_0 and c denote the prior hyper-parameters where $c \to 0$ resulting in shrinkage of first component prior of $\beta_{j,t}$ to posterior towards zero. Given these prior settings, the posterior distributions are obtained by maximizing the log-marginal likelihood:

$$
q^{\star}\left(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t}\right) = \underset{q\left(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t}\right)}{\arg\max} \int q\left(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t}\right) \log\left(\frac{q\left(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t}\right)}{p\left(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t}\right)}\right) \tag{4}
$$

where subscripts $(1 : t)$ indicate observations of a state variable from period 1 up to period t.[10]

3.3.2. Gaussian process regression (GPR)

Gaussian process regression is a machine learning method based on non-parametric kernel-based probabilistic models. The GPR can be used to determine whether inflation can be represented by a time-varying parameter model or whether a more complex type of non-linear model is required. Given that a linear regression model is of the form:

$$
y = x^T \beta + \varepsilon, \qquad y = f(\mathbf{x}) + \varepsilon \tag{5}
$$

where $\varepsilon \sim N\left(0, \sigma^2\right)$, then the GPR model predicts the value of a dependent variable $y_i \in \mathbb{R}$ given the new input vector $x_i \in \mathbb{R}^d$ and the training data $\{(\mathbf{x}_i, y_i) \mid i = 1, \ldots n\}$. In particular, the GPR estimates the response of y defining latent variables, $f\left(x_i\right), i = 1, 2, \ldots, n$, from a Gaussian process (GP), and explicit basis functions ϕ. In other words, contrary to standard Bayesian approach based on the probability distribution of parameters of a specific function, GP is a distribution over functions $\mathcal{GP}\left(m(\mathbf{x}), k\left(\mathbf{x}, \mathbf{x}'\right)\right)$ with a fully specified mean function $m(x) = E(f(x))$ and co-variance function $k\left(x, x'\right) = E(f(x) - m(x))\left(f\left(x'\right) - m\left(x'\right)\right)$. As

[10] See Koop and Korobilis (2020) for more technical details.

suggested by Rasmussen and Williams (2006), we utilize the commonly used covariance function which is called squared exponential kernel:

$$k(x, x') = \sigma_f^2 \exp\left(-\frac{1}{2\ell^2}\left\|x - x'\right\|^2\right) \tag{6}$$

where $\|x - x'\|$ denotes the Euclidean distance between points x and x'; ℓ is correlation length; σ_f^2 is signal variance. These hyper-parameters can be estimated from the data while training the GPR model.

In particular, the GPR changes the simple linear regression model into a new space:

$$\phi(x)^T\beta + f(x) \tag{7}$$

where $f(x) \sim GP(0, k(x, x'))$, indicating that $f(x)$ are from zero mean GP with $k(x, x')$. Then, $\phi(x)$ are a set of basis functions that map the input vector $x_i \in \mathbb{R}^d$ into a new feature vector $\phi(x)$ in $\mathbb{R}^p$. Intuitively, the GPR projects the inputs into high dimensional space using the set of basis functions and then estimate the linear model in this high dimensional space rather than directly on the inputs themselves. Thus, this model represent a GPR model and the response y can be defined as:

$$P(y_i \mid f(x_i), x_i) \sim N\left(y_i \mid \phi(x_i)^T\beta + f(x_i), \sigma^2\right) \tag{8}$$

Furthermore, the joint distribution of latent variables $f(x_1), f(x_2), \ldots, f(x_n)$ is denoted as follows:

$$P(f \mid X) \sim N(f \mid 0, K(X, X)) \tag{9}$$

To estimate the GPR model, we use the Matlab toolbox GPML developed by Rasmussen and Nickisch (2010).

3.3.3. *Least absolute shrinkage operator (LASSO)*

We also employ the LASSO approach introduced by Tibshirani (1996). Unlike the ridge estimator, LASSO imposes an ℓ_1-norm penalty on the regression coefficients for possible shrinkage. The LASSO estimator is denoted below:

$$\hat{\beta}^{lasso} = \min_{\beta} \quad \|Y - X\beta\|_2 + \lambda \sum_{j=1}^{N} |\beta_j|, \tag{10}$$

where λ is a tuning parameter that adjusts the strength of the ℓ_1-norm penalty. Given that objective function in the LASSO is not differentiable, we implement the efficient iterative algorithm (shooting algorithm) proposed by Fu (1998) for numerical optimization.

3.3.4. Elastic Net (ENET)

Tibshirani (1996) finds that the LASSO's predictive accuracy is often worse than the forecast performance of the ridge regression in the presence of highly correlated variables. Zou and Hastie (2005) overcome this problem by incorporating a hybrid version of the estimators LASSO and Ridge, known as the elastic net estimator (ENET). The ENET estimator is represented as follows:

$$\hat{\beta}^{EN} = \min_{\beta} \quad ||Y - X\beta||_2 + \lambda_1 \sum_{j=1}^{N} |\beta_j| + \lambda_2 \sum_{j=1}^{N} {\beta_j}^2, \tag{11}$$

where λ_1 and λ_2 are tuning parameters controlling the two penalty functions. Similar to the LASSO, the ENET also results in possible shrinkage of coefficients to zero.

3.4. ***Forecast evaluation***

3.4.1. Forecast accuracy: Multi horizon forecast comparison

A key focus of our evaluation of forecast performance is the forecast path. We suppose the forecast user (e.g., the central banker) is more interested in the forecast path than performance at given horizons in isolation. Hence we compare the different specifications (and thus the incremental usefulness of 'global inflation') in terms of their ability to produce accurate forecast paths (Jordà and Marcellino, 2010). This preempts the practical difficulties which arise when one model fares better at some horizons, and a rival model is better at other horizons - that is, we obtain incoherent inferences. It also allows us to side-step issues to do with multiple testing, arising from comparing forecast accuracy at many horizons, and the appropriate way of dealing with this (see, e.g., (Hansen, 2005; Patton and Timmermann, 2012; Quaedvlieg, 2021) on this and related issues).

We utilize the multi-horizon superior predictive ability (SPA) test of Quaedvlieg (2021), in addition to Diebold and Mariano (1995) test (DM), which compares model performances at each horizon separately. In particular, we denote the variable of interest at time t as y_t over the time period $t = 1, \ldots, T$. Since our aim is to compare the forecast path of 1 to H-step ahead forecasts, we define $\hat{\boldsymbol{y}}_{i,t} = \left[\hat{\boldsymbol{y}}^1_{i,t}, \ldots, \hat{\boldsymbol{y}}^H_{i,t}\right]'$ where $\hat{\boldsymbol{y}}^h_{i,t}$ represents the point forecasts of a model i at horizon $h = 1, \ldots, H$. We also describe a loss function $\boldsymbol{L}_{i,t} = L\left(\boldsymbol{y}_t, \hat{\boldsymbol{y}}_{i,t}\right) = (y_t - \hat{\boldsymbol{y}}_{i,t})^2$ which maps prediction errors into an H-dimensional vector where $L^h_{i,t} = L\left(\boldsymbol{y}_t, \hat{\boldsymbol{y}}^h_{i,t}\right)$ represents a typical element. Based on the squared error loss, we compared models regarding their loss differential by using:

$$\boldsymbol{d}_{ij,t} \equiv \boldsymbol{L}_{i,t} - \boldsymbol{L}_{j,t}, \tag{12}$$

where $\boldsymbol{d}_{ij,t}$ is an H-dimensional vector with elements $d^h_{ij,t}$. Following Quaedvlieg (2021), we use expected loss differentials $E\left(\boldsymbol{d}_{ij,t}\right) = \boldsymbol{\mu}_{ij,t}$ in our hypothesis, where $\boldsymbol{\mu}_{ij} \equiv \lim_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{\mu}_{ij,t}$.[11] Firstly, we test the following hypothesis to compare models prediction performance at a single horizon h which corresponds to a standard DM test:

$$H^{\mathrm{DM}} : \mu^h_{ij} = 0 \tag{13}$$

$$t^h_{\mathrm{DM},ij} = \frac{\sqrt{T}\bar{d}^h_{ij}}{\hat{\omega}^h_{ij}} \tag{14}$$

where $\bar{d}^h_{ij} = \frac{1}{T}\sum d^h_{ij,t}$, and $\omega^h_{ij} = \boldsymbol{\Omega}^{1/2}_{ij,hh}$ denotes the square root of the diagonal element in the h^{th} horizon. We test the null hypothesis using a standard t-test with HAC-type standard errors.

Utilizing the DM test may lead to situations where model i yields better forecasts than those of the model j at some specific horizons, while the model j generates significantly better forecasts for other specific horizons. In this case, the DM test may not present a clear picture of which model we should choose. To address this issue, Quaedvlieg (2021) proposes two types of SPA test: uniform superior predictive ability (uSPA) and average superior predictive ability (aSPA). While the uSPA requires superior forecasts at each individual horizon, the aSPA compares the weighted average loss across horizons by considering the relative importance of superior forecast performance at one horizon against inferior prediction ability at another. The loss difference can be defined as $\mu^{(\text{Uniform})}_{ij} = \min_h \mu^h_{ij}$ for the uSPA and $\mu^{(\text{Avg})}_{ij} = w'\mu_{ij} = \sum_{h=1}^{H} w_h \mu^h_{ij}$ with weights $\boldsymbol{w} = [w_1, \ldots, w_H]'$ for the aSPA.

To test the uniform superior predictive ability, we test the following null hypothesis:

$$H_{0,\mathrm{uSPA}} : \mu^{(\text{Unif})}_{ij} \leq 0 \tag{15}$$

$$t_{\mathrm{uSPA},ij} = \min_h \frac{\sqrt{T}\bar{d}^h_{ij}}{\hat{\omega}^h_{ij}} \tag{16}$$

against the one-sided alternative that $\mu^{(\text{Uniform})}_{ij} > 0$ using the t_{uSPA} test statistic which is the minimum of DM test statistics defined in equation (14). Similarly, the associated null for the aSPA test can be written as:

$$H_{0,\mathrm{ASPA}} : \mu^{(\text{Avg})}_{ij} \leq 0 \tag{17}$$

[11] See, Quaedvlieg (2021) for assumptions regarding the properties of $\boldsymbol{d}_{ij,t}$.

$$t_{\text{aSPA},ij} = \frac{\sqrt{T}\bar{d}_{ij}}{\hat{\zeta}_{ij}} \tag{18}$$

with the alternative $\mu_{ij}^{(\text{Avg})} > 0$, where $\bar{d}_{ij} = \boldsymbol{w}'\overline{\boldsymbol{d}}_{ij}$ and $\zeta_{ij} \equiv \sqrt{\boldsymbol{w}'\boldsymbol{\Omega}_{ij}\boldsymbol{w}}$. Since these 't-statistics' do not follow a Student t distribution in either case, inference is based on the moving block bootstrap techniques of Kunsch (1989), as suggested by Quaedvlieg (2021).

3.4.2. Encompassing test: Forecast informativeness

In some instances the policy maker may be interested in a relatively long-horizon, and of interest is how far ahead our models can forecast. Forecasts are said to be informative up to the horizon at which the forecast error variance is no longer smaller than the unconditional variance of the target variable. (The assumption being that the forecasting model, which makes use of forecast-origin information, will initially fare better than the unconditional mean, but that the relative advantage will diminish in the forecast horizon as the role of the conditioning data wanes). In our context it seems reasonable to suppose that long-horizon forecast performance will measure the ability of the models to forecast core inflation, and that short-horizon performance will bear more on the ability to forecast more cyclical or short-acting components such as food.

Following the work of Breitung and Knüppel (2018), we test that the forecast $\hat{y}_{t+h|t}$ is not informative for y_{t+h} using the null hypothesis:

$$H_0: \quad \mathbb{E}\left(e_{t+h|t}^2\right) \geq \mathbb{E}\left(y_{t+h} - \mu\right)^2 \tag{19}$$

where $e_{t+h|t} = y_{t+h} - \hat{y}_{t+h|t}$ is the forecast error. Then, the maximum forecast horizon h^* can be defined as $h^* = h_{\min} - 1$ where $h_{\min}$ is the lowest forecast horizon which satisfies the condition given in the null hypothesis. In other words, we sequentially test the H_0 for $h = 1, 2, \ldots, h_{\max}$ until the H_0 is not rejected for the first time. Then we select the previous horizon as maximum forecast horizon. Equivalently, we can write our null hypothesis as:

$$H_0': \quad \mathbb{E}\left(y_{t+h} - \mu\right)\left(\hat{y}_{t+h|t} - \mu\right) = 0 \tag{20}$$

This means that the forecast is rational if $\mathbb{E}\left(y_{t+h} - \hat{y}_{t+h|t} \mid \hat{y}_{t+h|t}\right) = 0$. Subsequently, we can reject the null hypothesis if y_{t+h} and $\hat{y}_{t+h|t}$ are positively correlated. This leads to a one sided t-test of the null hypothesis $\beta_{1,h} = 0$ against the alternative $\beta_{1,h} > 0$ with the constant $\alpha_{0,h} = \mu$ is left unrestricted in the Mincer-Zarnowitz regression defined in Mincer and Zarnowitz (1969). Hence, this test can be interpreted as an encompassing test – whether the model forecast adds useful information relative to simply using the unconditional mean (estimated by the sample average).

4. Results

4.1. Do global inflation factors drive local inflation rates ?

Figure 1 shows the percentage of the variance in the inflation rates of EM European countries explained by global and local inflation factors, where the factors are obtained using the PLS and PCA methods. As can be seen in Figure 1, there is a notable rise in the variance explained by the first common factor, especially for the Czech Republic and Poland, when the factors are extracted utilizing the PLS approach. This finding shows the importance of considering the degree of association between the inflation rate (our target variable) and the predictor variables to construct the common factors. Hence, the PLS-approach results in a better proxy for capturing the local and global price dynamics, although previous studies used PCA (Ciccarelli and Mojon, 2010; Mumtaz et al., 2011; Parker, 2018) A closer look to Figure 1 shows that although the local CPI factor estimated based on disaggregated CPI date explains more than 75% of the variance in inflation rates, the global CPI factor accounts for more than 50% of the variance of national inflation rates, indicating a clear role for global factors in driving the headline inflation in EM European countries, in addition to local price dynamics. In particular, the importance of global factors in driving national inflation rates is more pronounced for Bulgaria since the shares of inflation explained by Global CPI and EM CPI factors are slightly higher than the local CPI factor.

In terms of how 'global' is global, we note the higher level of the variance explained by the (PLS-based) EM CPI factor compared to the DM CPI factor, that we observe in all countries.[12] Some of the recent literature would appear to suggest that our European Union member countries might be more affected by DM developments. In particular, recent empirical studies provide evidence that global investors tend to see emerging markets as a single asset class, resulting in correlated investment patterns in emerging markets (Miyajima and Shim, 2014). This results in an increase in the convergence of emerging market economies' response to global and domestic monetary policy shocks, making them more connected. Furthermore, although our sample countries are members of the EU, they do not use the euro as their currency (except for Greece), which may play an essential role in the exchange rate pass-through into inflation during large capital outflows from emerging markets. Hence, decomposing the global price dynamics into emerging and developed market components expands on the existing literature by exploring the different facets of inflation

[12]Unsurprisingly, while the first factors of EMCPI and DMCPI are tend to be highly correlated for each country, the correlation coefficients start to decline in the higher number of factors. For instance, the fourth factor of EMCPI and the fourth factor of DMCPI is even negatively correlated for Greece (-0.25) and Romania (-0.03).

dynamics, which yields interesting nuances.

Figure 2 plots the PLS-based local and global inflation factors along with the actual inflation rates. An examination of these plots indicates that estimated factors tend to capture turning points relatively well. Both global and local factors stay high around the years 2007-2008 for almost all countries. However, since the onset of the global financial crisis in 2008-09, and again after the European sovereign debt crisis in 2011-12, there is a persistent decline in the global and local factors along with the inflation rates. It appears that low consumer price inflation has been a common feature of all EM European countries between 2014 and 2018. The national inflation rates move in tandem with the global factors reflecting the difficulty faced by the ECB in defusing global propagation channels that pose downside risks to the Euro area inflation outlook. Furthermore, the world economy has become increasingly integrated in recent years, which leads to an increase in the prevalence of global price shocks in domestic inflation dynamics after 2018. As shown in Figure 2, the inflation rates have become more interconnected to both global and local CPI factors after 2018, and they have started to move in a highly synchronized manner, especially in Bulgaria, Czech Republic, Greece, and Romania. [13]

– Insert Figures 1-2 about here. –

4.2. *Predictability of inflation rates: The role of global inflation factors*

Table 2 reports the recursive forecasting exercise results where model parameters are updated recursively on a monthly basis. While the entries in the row for the benchmark AR model denote the actual MSFEs, all other entries are the MSFEs relative to those of the AR model. As discussed in Section 3.2, there are six different specifications. Specifications 3-6 include the global factors in addition to local factors allowing us to quantify the importance of global factors for forecasting national inflation rates for the EM European countries. These factors are estimated using both PCA and PLS approach, where we set the number of factors to four for each dataset.[14] For the PLS approach, the first four factors of each dataset explain more than 82% variation in inflation rates for each country. The shares of variance explained by each individual factor are given in the Tables A1-A2 of the supplementary appendix. The entries in Table 2 lower than unity

[13]Figures A1 - A2 of the appendix provide the plots of local and global CPI factors over the sample period, where factors are obtained from using the PLS and PCA factor extraction methods. Although they show similar behavior most of the time, the factors estimated using the PLS approach capture inflation turning points relatively well.

[14]We also experimented with selecting the number of factors based on the criterion of Bai and Ng (2002), but found too many factors were chosen in terms of forecast performance.

indicate a better forecast performance than the AR benchmark. We produce a sequence of eight h-step ahead forecasts for each month, i.e., h = 1, 2, 3, 4, 5, 6, 9, 12. To make comparison and interpretation easier, the entries corresponding to the smallest MSFEs are highlighted in bold.

A closer examination of the results in Table 2 reveals a number of interesting findings. First, point forecasts from models that include both global and local CPI factors are generally superior to other models that only include local macro and local inflation factors. In particular, the specification types that include global factors perform better, especially for long-term forecast horizons (h= 9, 12), indicating the importance of spillover effects from global price dynamics for forecasting long-term inflation rates in EM European countries. For example, in Table 2 we see that the inclusion of global CPI factors (Specification-6) results in the lowest MSFE for 7 out of the 8 forecast horizons for Hungary and Poland. The forecast gains are also increasing in the horizon, and over a 70% reduction in MSFE relative to the benchmark is achieved for h=12, for both countries. Specification-6 achieves reductions on MSFE of 10% relative to adding local inflation factors (Specification-2), and of nearly 45% relative to the Phillips Curve (Specification-1 with macro factors), for Hungary at h=12. For Poland, the equivalent reductions in MSFE are even larger.

The picture is equally clear for Bulgaria, where the global CPI factor yields substantial predictive gains, and the "Local macro" (Specification-1) and "Local inflation" (Specification-2) forecasting models are the MSFE-best models in only 1 of the 8 cases.

Second, recall that we have eight forecast horizons and six countries, implying that there is a total of 48 comparisons. Of the various specification types, Specification-6, which augments global CPI factors, performs well in that it attains the top rank in 26 of the 48 cases. As a result, our inflation forecasting model exploiting the international information consistently outperforms the AR model. It is also worth remarking that Specification types 3-6 (which include at least one international factor, namely; EMCPI, DMCPI, or Global CPI factors) are best in three quarters (40 out of 48). Hence, Specification types 1-2 are not particularly useful for predicting headline inflation rates. For our sample of European EM countries, some measure of 'global inflation' tends to work well.[15]

Furthermore, we check whether the global inflation factor might simply be reflecting common shocks such as those related to commodity prices. The results in Tables A4-A5 of the supplementary appendix indi-

[15] As a robustness check, we examine the models performances during the euro area sovereign debt crisis (May 2010 - May 2012). Table A3 of the appendix shows that global factors play a significant role in driving local inflation rates since Specification types 3-6 attain the top rank in 33 out of 48 cases.

cate that Specification - 6 remains superior to the other models when these are augmented with commodity prices, for both recursive and rolling window forecasting schemes. Put differently, the explanatory power of global inflation does not disappear when we control for commodity prices: the global inflation factor does not simply proxy for commodity prices.[16]

Third, the plethora of rejections of the DM test in Table 2 (note that entries that are marked with either *, **, or ***, imply the rejection of the null hypothesis of equal predictive accuracy) confirms that the improvements in forecast accuracy are also statistically significant, compared to the AR model. Although the DM is commonly used as a test of equal predictive ability, and is reported here for that reason, because our comparisons involve nested models we also use the Giacomini and White (2006) test of conditional predictive ability. This is applicable for both nested and non-nested models. The findings are reported in Tables A6-A9 of the supplementary appendix, and are shown to give similar conclusions to the DM test.[17] For a detailed discussion of distribution of the test statistics and power of the DM test both in cases of parameter estimation uncertainty and nested models, refer to (McCracken, 2000; Clements and Hendry, 2005; Corradi and Swanson, 2007; Clements and Harvey, 2010; Clark and McCracken, 2012). Table A14 of the supplementary appendix shows the results for the same forecasting exercise as in Table 2, except that we now use an 84-month rolling window scheme instead of an expanding window.[18] The use of rolling windows leads to a deterioration in overall forecast accuracy relative to the expanding window scheme, with slightly fewer rejections of the null of equal accuracy with the benchmark.[19]

– Insert Table 2 about here. –

[16]When we undertake pairwise comparisons of Specification - 6 with a model which replaces global inflation factors with the commodity price index, we find Specification - 6 is superior (smaller MSFEs) in 38 cases out of 48. The picture is largely unchanged for the rolling window scheme (see Table A5). As a proxy for commodity prices, we use the Commodity Research Bureau BLS All Commodities Price Index, which measures the price movements of 22 commodities.

[17]Harvey et al. (1997) suggest that the DM test can be over-sized for empirical forecast errors for which the assumption of normality may not hold. Tables A10-A13 of the appendix presents the equality of mean squared forecast error test of Harvey et al. (1997). Again, the findings are similar to those for the DM test.

[18]As a robustness check, we repeat the same forecasting exercise using 60-month and 72-month rolling schemes. Similar results still continue to hold with slightly higher MSFEs.

[19]Tables A15 - A16 summarize the results for the same forecasting exercise, but when factors are extracted using the PCA method. Several interesting conclusions can be drawn - in terms of forecast accuracy and significance - from a comparison of the results with Table 2. Immediately apparent is a notable deterioration in forecast performance of the competing models compared to the AR model. In particular, none of the competing models improve on the simple AR model (virtually all the entries exceed one) in Romania (in the recursive window) and in Bulgaria (in the rolling window). This is in sharp contrast to the results obtained when the factors are extracted by PLS. The DM test further shows that incorporating PCA-based factors worsens forecast accuracy. A consideration of the specific target when constructing factors is demonstrably better in our sample. PCA ignores the target variable when the factors are constructed, and this is shown to be costly for predicting European EM inflation rates.

The pairwise comparison of competing models using uSPA and aSPA tests is reported in Table 3. As stated by Quaedvlieg (2021), while this framework accommodates tests of nested models if we use rolling windows of data to estimate the models, it does not allow such comparisons using expanding windows. Hence, we report pairwise comparison results only for the rolling window scheme because of this limitation of the superior predictive ability tests. In particular, we perform the following pairwise tests of models: i) Specification-2 against Specification-1, ii) Specification-3 against Specification-2, iii) Specification-4 against Specification-2, iv) Specification-5 against Specification-4, v) Specification-6 against Specification-5 and vi) Specification-6 against Specification-2. In addition to comparing the accuracy of the complete path, we also investigate a range of additional hypotheses which might be of interest, namely different horizon ranges, i.e., short-, mid and long-term forecasts. In theses cases, the uSPA and aSPA tests are applied to subsets of horizons. Hence, we also implement the tests for a subset of horizons by grouping h= 1, 2, 3 for a short horizon, h= 4, 5, 6 for a medium horizon, and h= 9, 12 for a long horizon. This allows us to reap some of the benefits of path evaluation, while tailoring the paths such that we can determine whether the contribution of the added factors depends on the horizon.

– Insert Table 3 about here. –

An inspection of Tables 3 leads to several clear-cut conclusions.[20] Firstly, we find strong evidence in favor of Specification-3 being superior to Specification-2 across the aSPA and uSPA tests for all horizons together, in Bulgaria and Romania, implying that the EMCPI factor contains useful information not already included in the information set comprising Specification-2 (which has only local factors). This finding is in line with a speech made by ECB Governor Mario Draghi in October 2015, in which the inflation outlook was described as "less sanguine" for the Euro Area due to the external weakness in demand, and also highlighted the risks to emerging market economies emanating from weakness in China.[21] Secondly, the aSPA test, combining all horizons, is positive and statistically significant, suggesting that Specification-4 outperforms the Specification-2 in Hungary and Poland. Finally, although there are limited episodes favouring adding global factors for medium and long horizons, the picture is much clearer for short horizons. For all countries (with the exception of Hungary), models with global factors dominate those with only local factors for the

[20]Multi-horizon comparison test results for PCA approach are presented in Table A17 of the appendix.

[21]For access to full details of the press conference: https://www.ecb.europa.eu/press/pressconf/2015/html/is151022.en.html

shorter horizons.[22] The reason may be that the variance of the loss differential increases in forecast horizon h, limiting the ability of the tests to differentiate between competing models, as pointed out by Quaedvlieg (2021).

4.3. Do global inflation dynamics matter for predicting core inflation rates?

The global economy may influence domestic price developments in many ways. The routes may be direct, via imports of final consumer goods, or indirectly via commodities and/or intermediate goods imports, as well as by influencing the prices set by domestic producers who are also exporters. However, core inflation is defined as the change in the euro area HICP special aggregate ‘all items excluding energy, food, alcohol, and tobacco’. By excluding energy and food from the consumption basket, we are able to control for some of the channels through which global inflation might operate. A direct comparison of the influence of global CPI factors on core and headline inflation should be informative. If the main effects of global inflation on national inflation are confined to the effects of short-run seasonal/cyclical movements in food and energy, we would not expect global factors to contribute to meaningful reductions in forecast errors for core inflation.

Table 4 presents the results of the same forecasting exercise for core inflation rates. Specification-6 (which includes global CPI factors) still performs well, and attains the top rank in 16 of the 48 cases. But this marks a deterioration in performance relative to targeting headline inflation,when Specification - 6 was best in 26 of the 48 cases. On the other hand, if we focus on the set of Specifications (types 3-6) which include at least one global factor, these models are best on MSFE in 35 out of 48 cases (compared to 40 out of 48 for headline inflation). We conclude that although global factors still play an important role in determining European emerging market core inflation rates, local factors now play a more prominent role in driving price changes (relative to headline inflation rates).[23]

[22] Furthermore, the results of the forecast efficiency test of Mincer and Zarnowitz (1969) are reported in Tables A18-A19 of the supplementary appendix for both recursive and rolling forecasting schemes, for factors extracted using the PLS approach. In the recursive scheme, forecast efficiency varies across the countries. Efficient forecasts are found in Bulgaria, Czech Republic, Hungary, and Poland for horizons $h = 1, 2, 3, 4, 5$ where the null generally cannot be rejected. There is evidence that adding global factors (that is, using Specification-6) reduces forecast inefficiency. That is, generating forecasts from a model which accords a role to global inflation breaks the correlation between these forecasts and their corresponding errors. In Tables A20-A21 of the appendix, we also report the efficiency tests results for competing models where factors are based on the PCA approach. Unlike the PLS-based forecasting models, using PCA-based common factors in forecasting models yields inefficient forecasts for almost all horizons across the countries irrespective of the forecasting scheme. This provides further support for PLS over PCA for calculating factors for the purpose of forecasting a specific variable.

[23] In Table A22 of the supplementary appendix, we report the results for rolling forecasting scheme. Point forecasts from models that only have local factors are generally superior to other models that include global inflation factors. In particular, the specification

– Insert Table 4 about here. –

Drilling down a little deeper, comparing Specifications - 3 and - 4 in (Table 4) shows that the EMCPI factor produces smaller forecast errors relative to the DMCPI factor, especially for longer forecast horizons. An interesting conjecture for this difference is the following. A deprecation (appreciation) of EM currencies versus the Euro might precipitate a fall (rise) in import prices and ultimately act as a drag (push) on domestic consumer prices. On the contrary, the currency union of Euro area members creates an extra layer of protection against external shocks in the trading of goods and services within the European union, limiting the informativeness of the DMCPI factor. This stands in contrast to European emerging economies, which gravitate around the Euro bloc and usually exhibit higher exchange-rate pass-through.

4.4. ***Forecast informativeness: How far can we forecast?***

We address this question for all our models and for the benchmark, to determine the extent to which the inclusion of the different factors extends the horizon at which our models are informative about the inflation outlook. We use the recently proposed test of Breitung and Knüppel (2018) to determine the maximum forecast horizon of our models. Table 5 presents the maximum forecast horizons h^* suggested by the encompassing test. The results demonstrate that the AR model forecasts for inflation rates are not informative beyond 9-months when the recursive forecasting scheme is employed. The encompassing test also implies smaller values of h^* for the AR model if the rolling window approach is adopted, which renders inflation forecasts uninformative beyond 6-months ahead for any country.

– Insert Table 5 about here. –

By way of contrast, the models augmented with factors produce informative forecasts at horizons greater than the maximum forecast horizon of the AR model in most of the cases. For Romania there is no improvement in h^* (from 9 months) if only local factors are added (recursive scheme), but the horizon increases to 12 when global factors are included. For all other countries the informative horizon is at the maximum of 12 for all specifications. This finding supports the view that inflation is largely a global phenomenon and highlights the role of global inflation in local inflation dynamics (Duncan and Martínez-García, 2015).

types 1-2 useful for predicting core inflation rates in 23 out of 48 cases (7 out of 48 cases for headline inflation) under a rolling forecasting scheme.

However, the maximum horizon of 12 is reached for all specifications, so that we are not able to determine the extent to which informativeness is sensitive to the different measures of global inflation.

Note that none of the specifications leads to an increase in the maximum forecast horizon for Romania under the rolling window scheme, which confirms our previous finding that a recursive scheme leads to superior forecasts in these classes of model. However, for all other countries the results do not depend on whether we adopt a rolling or recursive scheme.

*4.5. **Time-varying parameter and shrinkage models: Is there a room for further improvement?***

We now turn to the time-varying parameter and data shrinkage (TVP) models, and a consideration of whether they yield improvements in forecast performance. We estimate the Specification - 6 using four different TVP models to impose sparsity on the local and global factors in the forecasting models. Table 6 presents the comparison of the out-of-sample results of the different TVP models for the recursive window procedure. While the VBVDS algorithm, LASSO, and ENET are sparsity-inducing shrinkage methods that place zero coefficients on potentially irrelevant factors, the GPR is a flexible non-parametric specification that enables us to determine the role of non-linearity more generally for inflation forecasting, by admitting non-sparse solutions. Table 6 is partitioned vertically into six panels presenting the results for our EM European countries. The first row of each panel is the MSFEs of the AR model, and all other MSFEs are presented as ratios to the MSFE of the AR model. In the second row of each panel we record the best-MSFE outcome for a given forecast horizon across all the constant parameter Specifications (1 to 6). The values for the best of all models are emboldened.

An inspection of Table 6 shows that most of the entries are smaller than one, which indicates that the TVP-models have a superior forecasting performance to the benchmark AR model. Furthermore, it can be seen that the forecast improvements provided by the TVP-models are also statistically significant compared to the AR, based on application of the DM test. The accuracy gains from implementing TVP models are increasing with the forecast horizon. Apart from a few short horizons, where either ENET or VBVDS delivers the smallest ratios, the GPR method is the overall winner, being superior to the other time-varying parameters and shrinkage models for the majority of forecast horizons and countries. In particular, recall that we have a total of 48 cases (eight forecast horizons and six countries): the GPR is the MSFE-best model in 20 of the 48 cases, suggesting that it is possible to improve on the constant-parameter models. The outstanding performance of the GPR model suggests that taking non-linearities into account is key to improving inflation forecasts. The fact that the GPR computes the probability distributions from all suitable functions that fit the data (function view), rather than defining the distributions over specific function parameters, makes it a very flexible way to capture the potential non-linearities between the factors and inflation. There are several sources of non-linearity (as pointed out by Medeiros et al. (2021)) which might account for the good performance of the GPR model. The relation between inflation and the local macro factors might be non-linear if it depends on the degree of economic slackness. Economic uncertainty is another possible reason, raising the prospect of choosing to delay irreversible economic decisions (Bloom, 2009). In the presence of such uncertainties, key macroeconomic variables may well have non-linear effects on inflation. We do however find that the GPR performance deteriorates at short horizons, suggesting that the benefits of introducing non-linearity may be limited for shorter horizons.

– Insert Table 6 about here. –

Taken together, sparsity-inducing methods do not provide marked gains compared to the models without shrinkage, supporting the notion of ”the illusion of sparsity” in economic forecasting, as discussed by Giannone et al. (2018); Fava and Lopes (2020); Cross et al. (2020). For example, we find that among the 'sparse' models, ENET is the best, but achieves the best performance overall in only 5 of the 48 cases outperforming the competing models. The VBVDS performs poorly, and generates the MSFE-best outcome in only one case.[24] Furthermore, Table 7 summarizes the MSFE-best models from Table 6. For each country and forecast horizon, it shows the pair of model specification (in terms of factors) and factor selection-modelling method (constant parameter, TVP or GPR) which gives the lowest MSFE. It is clear that the superiority of the GPR model comes from its coupling with Specification-6. That is, when Specification-6 is estimated by the GPR method, the MSFE-best forecasts are obtained more often than not.

Finally, we pay special attention to the GPR model and compare the importance of global and local factors for the GPR. To measure each factors' importance, we follow the approach of Medeiros et al. (2021) and compute the relative importance measure by multiplying the average coefficient size with the respective standard deviations. Figure 3 presents the influence of each of the factor groups (local macro, local CPI and global CPI) on inflation for the GPR method. The values in the graphs are normalized to sum one.

[24] In Table A24, we report the results of the same forecasting exercise for the rolling window procedure. Overall, the story is similar, as the GPR method attains the top rank in 28 out of 48 cases, followed by the VBVDS algorithm. This evidence again strongly supports the use of GPR methods for inflation forecasting because of the potential non-linearities.

Figure 3 reveals that the relative importance of the factor groups varies across country and forecast horizon. For instance, in Hungary, global CPI factors are gaining importance as the forecast horizon increases where relative importance measure reaches to 0.58 (for h=6) from the initial level 0.10 (for h=1). On the other hand, local and global factors seem to equally important across the forecast horizons for Czech Republic. Despite these differences, overall we find the relative importance of the global factor is generally as important as the local CPI factor for all countries with the exception of Greece. And in addition, the importance of local macro factors group is low for almost all countries and forecast horizons. This is consistent with our forecasting findings, that Specification 1 is generally not as good as the models with inflation factors (local or global). If we interpret the model with local macro factors as an approximation[25] to a Phillips Curve-type relationship, then our findings favour global inflation explanations of EM national inflation rates.

– Insert Figure 3 about here. –

5. Estimating global inflation factor through international inflation spillovers

Up to this point we have worked with a pre-determined designation of countries as developed or emerging market when we construct the global inflation factors, but this may not correspond to an economic grouping. In this section we make use of a measure of economic connectedness to determine the group structure. We utilize the time-varying parameter VAR (TVP-VAR) model of Antonakakis et al. (2020) to identify inflation spillovers across countries.[26] We calculate a pairwise directional connectedness (spillover) index for every pair of countries, based on the share of the 10-step ahead forecast error variance of a country's inflation rate that is accounted for by shocks to the other country. [27]

In Figure 4, we depict the network analysis of inflation spillovers for each country. Each edge between two nodes denotes the net pairwise spillovers between two countries, the arrow's direction indicates which country received shocks from which country on average. The thickness of the edge between two countries shows the strength of the propagation of shocks between countries. Similarly, each node's size represents the overall magnitude of net total directional connectedness for each country, implying that a larger node

[25] An 'approximation' in the sense that it includes a wide range of domestic variables in addition to a simple activity variable such as the unemployment rate or the output gap

[26] Technical details of TVP-VAR model and connectedness measures are provided in a supplementary online appendix.

[27] We also calculated the time-varying total connectedness of the network where its average sample value is 90.1%, implying that there is significant convergence in inflation rates across countries.

size has a significant role as sender/receiver of shocks within the network. We highlight with red (green) if a country is a net transmitter (receiver) of the shocks within the system.

Our results highlight the global nature of the spillovers of the inflation shocks from European countries (especially; Spain, Italy, France) to the rest of the world. On the contrary, Japan, Norway and Mexico are the highest net receivers inflation shocks in the network.[28] We identify the top 40 countries in terms of the transmission of inflation shocks to the EM European countries in our sample. We generate four different PLS factors using the set of top 10, top 20, top 30, and top 40 countries. Then, we estimate the Specification - 6 using these "tailored" global factors.

Table 8 reports the results. The second row of each panel records the MSFE outcome when factors are extracted from all the countries taken together (i.e., emerging and developed) as in Section 3.1. The results show that choosing a subset of countries by considering the pairwise inflation spillovers across countries, before construction of the global factors, provides forecast improvement for the Czech Republic, Poland, and Romania. In particular, the forecast gains are primarily obtained for short and medium horizons (h= 1, 2, 3, 4), but not the longer horizons, indicating the importance of using information related to all countries for longer forecast horizons. Moreover, none of the competing models improve on the Section 3.1 strategy for Bulgaria and Hungary.

6. Relative importance of global and local inflation factors: The role of country characteristics

The channels through which local or global shocks are propagated and affect countries' inflation rates are numerous, and their interactions complex. But to shed some light on this question, we seek to uncover some of the country characteristics that tend to increase the relative importance of global over domestic factors. We collect a candidate set of explanatory variables, consisting of time-varying country-specific variables, that might explain the (not-necessarily mutually exclusive) channels which influence domestic consumer prices, either directly or indirectly.

We calculate the time-varying relative importance of global over domestic factors for each country as follows. We relate a country's headline inflation rate to domestic and global factors using a time-varying

[28] Auer et al. (2019) analyze the synchronization of producer price inflation (PPI) across a large set of countries. They find a considerable global co-movement in PPI, similar to the findings for CPI in the previous studies (Neely and Rapach, 2011b; Mumtaz et al., 2011; Auer and Mehrotra, 2014; Bäurle et al., 2021). Akin to these studies, Ciccarelli and García (2015) examine the spillover of inflation expectations in the Euro area, US and UK.

coefficient linear regression model:

$$y_t = \mu + \mathcal{L}^p y_t + \alpha_t F_t^{LocalMACRO} + \gamma_t F_t^{LocalCPI} + \beta_t F_t^{GlobalCPI} + \varepsilon_t \tag{21}$$

where the dependent variable, regressors, and error term are defined as in Specification - 6; but now the coefficients are time varying. We estimate the model parameters by augmenting the local polynomial kernel estimator with OLS, which is proposed by Muller (1998).[29] In particular, the Nadaraya-Watson estimator is used, which fits a constant at each interval defined by the bandwidth. The appropriate value of the bandwidth parameter is selected by leave-one-out cross-validation, and the Epanechnikov kernel function used.

The time-varying relative importance of the domestic and global factors in affecting the local headline inflation rates is measured by the relative global factor (RGF), as suggested by (Bianchi and Civelli, 2015; Auer et al., 2017; Łyziak, 2019).

$$\text{Relative Global Factor}_{\,i,t} = RGF_{i,t} = \beta_{i,t} - \gamma_{i,t}$$

where $\beta_{i,t}$ and $\gamma_{i,t}$ denotes the time varying coefficients measuring the extent to which global and domestic factor affect local headline inflation in EM European country i at time t.

We now turn to investigating the relationship between the country characteristics and the strength of relative global factor on domestic inflation. We consider a wide variety of explanatory variables: (1) Current account balance to GDP; (2) Budget Balance to GDP; (3) Government debt to GDP; (4) Household consumption to GDP; (5) Unemployment rate; (6) FX reserves to GDP; (7) Uncertainty; (8) Real GDP growth; (9) 5-years Credit Default Swap (CDS); (10) Real effective exchange rate (REER); (11) Exports to GDP; (12) Imports to GDP. The online supplementary appendix presents detail on these variables and data sources.

To examine the ability of country characteristic to explain the sensitivity to relative global inflation factor, we estimate the following panel fixed effect regression of the form:

$$\text{RGF}_{\,i,t} = \alpha_i + \Gamma X_{i,t} + e_{i,t} \tag{22}$$

where dependent variable is the quarterly average value of the relative global factor and $X_{i,t}$ includes the explanatory variables mentioned above. To abstract from time-invariant cross-country differences, we include the country fixed effects α_i.

[29] We implement the model using the tvReg R package written by Casas and Fernandez-Casal (2019).

Table 9 presents the panel regression results. Column 1 of Table 9 suggests that the relative importance of the global factor is positively associated with current account balance and government debt. As suggested by Kılınç et al. (2016), higher current account deficits may result in larger currency depreciation in emerging market countries, amplifying the relationship between domestic inflationary pressures and current account deficits. Similarly, a higher level of government debt may create greater dependency on external funding, making a country more open to global shocks, since fiscal fragilities and high debt burdens may restrict a central bank's ability to use counter-cyclical monetary policy. Neely and Rapach (2011a) also point out that a greater government debt leads to a greater reliance on monetization to finance fiscal needs.

The significant coefficients of the exports and imports variable indicate that the degree of trade openness is key to explaining the transmission of global shocks onto the headline inflation rate. In particular, a growing share of imports from other countries will increase the pass-through of supply chain shortages, energy and raw material prices, onto domestic inflation rates. These results are in line with the recent research suggesting that global production networks play a significant role in the transmission of shocks (Carvalho, 2014; Auer et al., 2017, 2019; Carvalho et al., 2021). We also modify the baseline model by splitting exports and imports into EU and Non-EU. Column 2 of Table 9 shows that imports from the EU are highly significant, but imports from Non-EU countries become insignificant. The reason might be that the EU has a single customs union with a single trade policy and tariff system, and that the EM European countries are more connected to the advanced countries in the EU than to the rest of the world.

Overall, our results suggest a number of plausible propagation channels for global factors on domestic inflation. We surmise that the potency of these channels may have increased in recent years, with policy rates being close to the lower bound of zero, diminishing the effectiveness of countries' monetary policies.

7. Conclusion

We present a comprehensive empirical investigation into the forecasting performance of global factors for European EM countries' national inflation rates. We consider a variety of different models, forecasting schemes, forecast horizons and evaluation techniques, to include in our investigation the breadth of approaches in the literature. Naturally our results do not always give consistent findings across countries, models and horizons, but nevertheless some general patterns emerge.

Our empirical findings based on the outcomes of the forecasting exercises firmly support the contention that 'inflation is a global phenomenon' is true for the European EM countries' national inflation rates, and not just for developed, high-income economies. The support comes from comparing the forecast performance of models with global inflation factors to models with either local macro factors, which we contend generalise Phillips Curve-type models, and to models which may in addition include local inflation factors. Because our models with global inflation factors also include all the information in the models with local macro and inflation factors, we are able to show the incremental effect of 'global inflation'. This is important, because otherwise we might attribute to global inflation predictive ability which stems from domestic factors, recognising that in practice domestic variables will respond to the global situation and it might be difficult to separately disentangle the effects of the two sets of factors on national inflation rates. Our approach shifts the onus to global factors adding something over and above that provided by domestic factors.

We provide some insight as to why global factors are an important determinant of domestic inflation, by considering the country-level characteristics which tend to increase the importance of global factors over domestic. Perhaps not surprisingly the degree of openness of a country is a key determinant, but other factors, such as a high level of government debt also matter, and work in the same direction. Tailoring the global inflation factor to the particular EM country also matters - that is, forming the global factor by extracting a factor on the subset of countries which are closely connected to the EM countries. Nevertheless, for some countries, and for the longer horizons, this way of customising the global factor appears not to matter.

We use factors throughout to condense the information in large sets of variables, both for domestic variables, and for foreign variables, consistent with a large body of literature on factor modelling. Where we depart with some of the literature on 'global inflation' is to calculate the factors in a way that ensures their relevance for the variable being forecast, that is, by PLS rather than PCA. We show that this has noticeable effects on our results. While our main set of results use linear factor forecasting models, we also establish that our findings are robust to factor-selection methods that enforce sparsity, as well as a machine-learning method that allows for a non-linear relationship between national inflation rates and the sets of factors. The latter serves to further enhance the forecasting improvements that result from the global inflation factors.

We also consider whether the findings for national headline inflation rates carry over to core inflation, which excludes food and energy, recognising that these elements of the domestic consumption basket will likely be directly influenced by global price movements. While global factors still play an important role in determining European emerging market core inflation rates, local factors are now found to play a more prominent role than they did for headline inflation.

Forecast performance can be evaluated in a number of ways. We compare the models' forecasts at each forecast horizon, using standard tests of equal forecast accuracy, as is often done in the literature. However, the evaluation of forecast paths, or of subsets of forecast paths, would likely be of greater interest to policy makers, as well as being a way of handling the multiple-testing problem that arises from comparing two models at a number of horizons. Generally we find that global factors dominate local factors at the shorter horizons. We also pay particular attention to the horizon at which the factor models lose their edge over the 'long-horizon' or unconditional mean forecast, and show that the factor models generally extend this horizon relative to the benchmark AR model.

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Table 1: Number of variables in each data group across countries

	Bulgaria	Czech R.	Greece	Hungary	Poland	Romania
Macroeconomic variables	84	70	68	65	74	82
Disaggregated price variables	79	89	81	80	89	80
Emerging markets headline CPI	71	71	71	71	71	71
Developed markets headline CPI	27	27	27	27	27	27

Table 2: Point forecast performance: Recursive forecasting - Factors are extracted using the PLS approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.439	0.801	1.082	1.375	1.674	1.974	2.949	3.906
Specification -1	1.141	1.048	0.963	0.826**	0.721***	0.633***	0.560***	0.497***
Specification -2	1.115	0.868***	0.737***	0.620***	0.578***	0.529***	**0.490*****	0.328***
Specification -3	1.009	0.866**	0.729***	0.589***	0.523***	0.506***	0.542**	**0.315*****
Specification -4	1.091	0.875***	0.754***	0.630***	0.594***	0.587***	0.562***	0.451***
Specification -5	1.054	0.944	0.836*	0.631***	0.549***	0.556***	0.624**	0.373***
Specification -6	**0.955**	**0.811*****	**0.690*****	**0.547*****	**0.495*****	**0.503*****	0.503***	0.347***
CZECH REPUBLIC								
AR	0.341	0.492	0.628	0.755	0.863	0.964	1.194	1.463
Specification -1	1.051	1.014	0.973	0.900	0.867	0.804*	0.780*	0.705*
Specification -2	1.035	0.939	0.874*	**0.796****	**0.693*****	**0.601*****	**0.487*****	**0.379*****
Specification -3	1.132	1.058	1.032	0.971	0.871*	0.744**	0.498***	0.430**
Specification -4	1.035	**0.938**	**0.825*****	0.814**	0.869	0.796	0.513***	0.446***
Specification -5	1.128	1.106	1.008	0.921	0.859*	0.736**	0.570***	0.505**
Specification -6	1.113	1.046	1.005	0.980	0.899	0.723***	0.530***	0.404***
GREECE								
AR	0.528	0.687	0.819	0.957	1.144	1.348	2.215	3.135
Specification -1	0.991	0.958	0.943	0.920	0.815	0.692*	0.423**	0.386**
Specification -2	0.908**	**0.807****	**0.759*****	0.721**	0.641**	0.556**	0.270**	0.187**
Specification -3	0.936*	0.869*	0.795***	0.721***	0.591***	**0.482****	0.275**	**0.155****
Specification -4	**0.894*****	0.817**	0.760***	**0.662*****	**0.575*****	0.490**	0.271**	0.188**
Specification -5	0.934**	0.912	0.826**	0.731***	0.645***	0.527**	0.265**	0.174**
Specification -6	0.912**	0.837**	0.789***	0.698***	0.574***	0.485**	**0.238****	0.174**
HUNGARY								
AR	0.463	0.736	0.971	1.235	1.483	1.735	2.480	3.200
Specification -1	1.005	0.990	0.906	0.790	0.736*	0.670*	0.536*	0.481**
Specification -2	1.015	0.933	0.807*	0.740*	0.680*	0.643*	0.402**	0.297**
Specification -3	**0.935**	0.881*	0.814**	0.738**	0.700**	0.633**	0.334**	0.285**
Specification -4	1.025	0.938	0.805*	0.748*	0.715*	0.683*	0.441**	0.328**
Specification -5	1.006	1.007	0.864*	0.754**	0.680**	0.611***	0.395**	0.340**
Specification -6	0.981	**0.870**	**0.776****	**0.705****	**0.638****	**0.573****	**0.332****	**0.266****
POLAND								
AR	0.302	0.486	0.674	0.843	1.015	1.158	1.608	2.082
Specification -1	0.917**	0.894**	0.886**	0.853***	0.786***	0.728***	0.552***	0.525***
Specification -2	0.924	0.866**	0.802***	0.732***	0.659***	0.585***	0.367***	0.314***
Specification -3	0.892*	0.813***	0.751***	0.726***	0.656***	0.504***	0.312***	0.327***
Specification -4	**0.882***	0.854**	0.815**	0.790**	0.732***	0.648**	0.426***	0.366***
Specification -5	0.892*	0.867**	0.819***	0.822**	0.728***	0.534***	0.484***	0.358***
Specification -6	0.887*	**0.798*****	**0.730*****	**0.695*****	**0.614*****	**0.445*****	**0.295*****	**0.268*****
ROMANIA								
AR	0.625	0.935	1.218	1.398	1.565	1.694	2.158	2.687
Specification -1	1.079	1.127	1.103	1.083	1.025	0.987	0.880	0.833*
Specification -2	1.098	1.085	1.045	1.010	0.995	0.958	0.866	0.846
Specification -3	1.072	1.022	**0.928**	0.852*	0.784***	0.727***	0.550***	0.591***
Specification -4	1.141	1.208	1.116	1.051	0.978	0.904	0.719***	0.763**
Specification -5	1.119	1.111	0.986	0.904	0.800**	0.726***	0.624***	0.619***
Specification -6	1.146	1.094	0.953	**0.833****	**0.741*****	**0.710*****	**0.483*****	**0.538*****

The entries are MSFEs, with the Specification types that yields the smallest MSFE are highlighted in bold. The entries in the first row correspond to actual point MSFEs of AR model, while all other entries are relative MSFEs relative to the AR model. Hence, a value smaller than one implies that the corresponding specification type produces more accurate forecasts than those of the AR model. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model, based on the DM forecast accuracy test.

Table 3: Multi-horizon foecast comparison: Rolling forecasting - Factors are extracted using the PLS approach -

	short horizon		medium horizon		long horizon		all horizon	
BULGARIA	uSPA	aSPA	uSPA	aSPA	uSPA	aSPA	uSPA	aSPA
Spec.2 against Spec.1	-1.08	-0.69	0.69**	1.38**	1.74***	2.33***	-1.08	1.60**
Spec.3 against Spec.2	0.55*	1.41**	0.35	0.81*	0.22	0.24	0.22*	0.77*
Spec.4 against Spec.2	-1.08	-0.80	-3.55	-3.11	-2.05	-1.52	-3.55	-2.87
Spec.5 against Spec.4	-0.10	0.80	1.33***	1.73**	0.14	0.28	-0.10	0.96*
Spec.6 against Spec.5	0.73**	0.93**	0.16	0.73*	-0.10	0.69*	-0.10	0.88*
Spec.6 against Spec.2	0.34	1.13**	-0.15	0.13	-0.42	0.06	-0.42	0.36
CZECH REPUBLIC								
Spec.2 against Spec.1	-1.51	-1.20	-0.52	0.20	0.18	0.80*	-1.51	0.10
Spec.3 against Spec.2	1.84***	2.54***	-0.70	0.27	-1.38	-1.30	-1.38	0.49
Spec.4 against Spec.2	0.68**	1.02*	-2.39	-1.67	-1.63	-1.29	-2.39	-1.08
Spec.5 against Spec.4	-0.38	0.49	0.50*	1.40**	-1.31	-1.56	-1.31	0.57
Spec.6 against Spec.5	-0.04	0.26	-3.02	-1.70	1.65***	2.61***	-3.02	0.57
Spec.6 against Spec.2	1.05***	1.65**	-2.70	-1.41	-0.64	-0.03	-2.70	-0.41
GREECE								
Spec.2 against Spec.1	-1.38	-0.98	0.24	0.59	1.73***	1.94**	-1.38	1.12**
Spec.3 against Spec.2	0.60**	1.02*	-2.21	-1.50	-3.88	-3.07	-3.88	-1.99
Spec.4 against Spec.2	-2.03	-1.82	-3.01	-2.15	-2.28	-2.95	-3.01	-2.74
Spec.5 against Spec.4	0.55*	0.76*	-1.17	-0.36	-2.49	-2.63	-2.49	-0.52
Spec.6 against Spec.5	1.44***	2.01**	0.06	0.64	1.24***	2.45***	0.06*	1.97***
Spec.6 against Spec.2	0.09	1.63**	-2.08	-1.56	-1.23	-1.24	-2.08	-1.13
HUNGARY								
Spec.2 against Spec.1	-0.90	0.24	-0.80	-0.81	1.05**	1.21**	-0.90	0.43
Spec.3 against Spec.2	-1.44	-1.04	-0.58	-0.14	-0.76	-0.62	-1.44	-0.78
Spec.4 against Spec.2	-0.09	1.05*	0.49*	1.01*	1.16***	2.28***	-0.09	1.64**
Spec.5 against Spec.4	-2.34	-1.87	-0.32	-0.21	-3.37	-3.33	-3.37	-1.87
Spec.6 against Spec.5	0.14	1.67**	-0.74	-0.55	0.59**	1.96**	-0.74	0.64
Spec.6 against Spec.2	-1.60	-0.55	-0.08	0.26	0.44*	0.59	-1.60	0.27
POLAND								
Spec.2 against Spec.1	-0.68	0.81*	2.57***	3.05***	2.26***	2.54***	-0.68	2.90***
Spec.3 against Spec.2	1.39***	1.69**	-0.86	-0.49	-0.96	-0.18	-0.96	0.05
Spec.4 against Spec.2	0.43**	0.73*	-0.29	0.34	0.63*	1.30**	-0.29	1.67**
Spec.5 against Spec.4	-1.26	-0.03	-2.19	-1.68	-1.20	-1.00	-2.19	-1.52
Spec.6 against Spec.5	0.81***	1.40**	0.31**	1.96**	-0.93	-1.09	-0.93	0.37
Spec.6 against Spec.2	1.37***	1.73**	-0.63	-0.22	-1.10	-0.55	-1.10	-0.02
ROMANIA								
Spec.2 against Spec.1	-1.94	-1.60	-1.90	-1.52	-1.51	-0.90	-1.94	-1.46
Spec.3 against Spec.2	2.54***	3.04***	2.76***	3.13***	0.51**	1.55**	0.51***	3.07***
Spec.4 against Spec.2	1.27***	1.56**	1.36***	1.51**	-2.84	-1.71	-2.84	0.66
Spec.5 against Spec.4	2.38***	2.85***	2.08***	2.82***	-0.28	1.87**	-0.28	2.97***
Spec.6 against Spec.5	-1.73	-0.89	-0.29	-0.19	0.56**	2.71***	-1.73	0.19
Spec.6 against Spec.2	1.79***	3.09***	3.36***	3.84***	-0.26	1.00*	-0.26	3.41***

This table provides the results of uniform superior predictive ability (uSPA) and average superior predictive ability (aSPA) tests for all horizons across the countries. The moving block bootstrap techniques of Kunsch (1989) is used for critical values. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% denotes the significance levels.

Table 4: Core Inflation: Recursive forecasting - Factors are extracted using the PLS approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.311	0.498	0.639	0.770	0.874	1.016	1.490	2.110
Specification -1	1.042	0.976	0.916	0.861**	0.814***	0.735***	0.527***	0.377***
Specification -2	1.013	**0.888***	0.820**	0.731***	0.697***	0.640***	0.476***	0.341***
Specification -3	1.052	0.906	**0.786*****	**0.694*****	0.660***	0.600***	0.403***	0.369***
Specification -4	1.045	0.944	0.882	0.807***	0.791***	0.694***	0.504***	0.404***
Specification -5	1.091	0.962	0.862***	0.771***	0.749***	0.662***	0.488***	0.532***
Specification -6	1.060	0.982	0.873	0.734**	**0.647*****	**0.578*****	**0.403*****	**0.322*****
CZECH REPUBLIC								
AR	0.219	0.330	0.404	0.468	0.517	0.562	0.644	0.729
Specification -1	1.349	1.377	1.169	1.010	0.887	0.799**	0.735**	0.686**
Specification -2	1.088	1.075	1.027	0.942	0.834**	**0.708*****	**0.534*****	0.427***
Specification -3	1.186	1.205	1.123	1.118	1.049	0.928	0.647***	0.438***
Specification -4	1.171	1.127	**0.951**	**0.828****	**0.759*****	0.784***	0.673**	0.502***
Specification -5	1.237	1.279	1.174	1.216	1.158	0.979	0.746**	0.638***
Specification -6	1.189	1.254	1.153	1.126	0.980	0.888	0.653***	**0.385*****
GREECE								
AR	0.596	0.726	0.821	0.850	0.977	1.066	1.680	2.187
Specification -1	0.855**	0.764**	0.699**	0.710**	0.652***	0.547***	0.355***	0.255***
Specification -2	**0.730*****	**0.595*****	**0.521*****	0.559***	**0.533*****	**0.484*****	0.324***	0.223***
Specification -3	0.761***	0.648**	0.558***	0.580***	0.594***	0.510***	0.340***	0.210***
Specification -4	0.732**	0.619**	0.555***	**0.553*****	0.567***	0.512***	0.325***	0.225***
Specification -5	0.780***	0.670**	0.579***	0.602***	0.677***	0.568***	0.327***	0.222***
Specification -6	0.761***	0.631**	0.550***	0.582***	0.659***	0.514***	**0.308*****	**0.209*****
HUNGARY								
AR	0.275	0.414	0.505	0.618	0.722	0.819	1.205	1.569
Specification -1	1.084	1.137	1.064	0.970	0.915	0.918	0.637***	0.545***
Specification -2	1.190	1.088	0.898	0.761*	0.774*	0.750*	0.453***	0.407***
Specification -3	1.091	0.999	0.886	0.835	0.793	0.712**	0.451***	**0.336*****
Specification -4	1.170	1.027	0.840	**0.729****	0.814	0.744*	0.531***	0.500***
Specification -5	1.071	**0.971**	**0.837***	0.775**	0.807	0.739**	0.491***	0.470***
Specification -6	1.113	0.977	0.842	0.767*	**0.722****	**0.681****	**0.448*****	0.371***
POLAND								
AR	0.242	0.355	0.445	0.533	0.625	0.696	0.903	1.083
Specification -1	1.022	0.929	0.859***	0.805***	0.739***	0.681***	0.561***	0.499***
Specification -2	0.989	0.865**	0.737***	**0.623*****	**0.559*****	**0.536*****	**0.361*****	**0.379*****
Specification -3	0.993	0.885	0.741***	0.655***	0.585***	0.539***	0.488***	0.422***
Specification -4	**0.966**	**0.855****	0.744***	0.691***	0.666***	0.655***	0.384***	0.454***
Specification -5	1.000	0.922	0.784***	0.722***	0.670***	0.624***	0.481***	0.426***
Specification -6	1.000	0.868*	**0.717*****	0.629***	0.577***	0.552***	0.454***	0.390***
ROMANIA								
AR	0.297	0.405	0.515	0.619	0.716	0.801	1.032	1.282
Specification -1	1.106	1.330	1.386	1.410	1.366	1.285	1.039	0.825*
Specification -2	1.166	1.157	1.072	0.986	0.910	0.796*	0.667***	0.588***
Specification -3	1.179	1.195	1.049	0.843*	0.798*	0.773*	0.646***	0.451***
Specification -4	1.271	1.293	1.117	0.978	0.869	0.717**	0.697***	0.644***
Specification -5	1.208	1.226	**0.966**	0.831*	0.782**	0.756**	0.639***	0.440***
Specification -6	1.227	1.230	1.053	**0.830****	**0.775****	**0.716****	**0.605*****	**0.423*****

See the notes to Table 2.

Table 5: Maximum forecast horizons in months determined by encompassing test

	Bulgaria	Czech	Greece	Hungary	Poland	Romania
A) Recursive Forecasting						
	Bulgaria	Czech	Greece	Hungary	Poland	Romania
AR	6	9	6	6	6	9
Specification -1	12	12	12	12	12	9
Specification -2	12	12	12	12	12	9
Specification -3	12	12	12	12	12	12
Specification -4	12	12	12	12	12	12
Specification -5	12	12	12	12	12	12
Specification -6	12	12	12	12	12	12
B) Rolling Forecasting						
	Bulgaria	Czech	Greece	Hungary	Poland	Romania
AR	6	6	6	6	6	6
Specification -1	9	12	12	12	12	6
Specification -2	12	12	12	12	12	6
Specification -3	12	12	12	12	12	6
Specification -4	12	12	12	12	12	6
Specification -5	12	12	12	12	12	6
Specification -6	12	12	12	12	12	6

Notes: The table shows maximum forecast horizons in months for all forecast horizons determined by the encompassing test.

Table 6: MSFEs based on the use of different dimension-reduction and shrinkage methods - Recursive forecasting

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.439	0.801	1.082	1.375	1.674	1.974	2.949	3.906
MSFE Best w/o shrinkage	**0.955**	**0.811*****	**0.690*****	0.547***	0.495***	0.503***	0.490***	**0.315*****
GPR	0.981	0.851***	0.708***	**0.542*****	**0.492*****	**0.502*****	**0.469*****	0.360***
VBDVS	1.058	0.936*	0.835**	0.735**	0.669**	0.640**	0.500**	0.536**
ENET	0.987	0.814***	0.703***	0.566***	0.525***	0.534***	0.496**	0.401***
LASSO	0.976	0.817***	0.699***	0.567***	0.523***	0.531***	0.497**	0.404***
CZECH REPUBLIC								
AR	0.341	0.492	0.628	0.755	0.863	0.964	1.194	1.463
MSFE Best w/o shrinkage	1.035	0.938	0.825***	0.796**	0.693***	0.601***	0.487***	0.379***
GPR	1.019	1.004	0.851**	**0.756****	**0.644*****	**0.563*****	0.460***	**0.370*****
VBDVS	**0.987**	1.008	0.969	0.930	0.890	0.865	0.754*	0.702*
ENET	1.009	**0.925**	**0.817*****	0.799**	0.687***	0.600***	0.462***	0.413***
LASSO	1.013	0.931	0.831***	0.798**	0.695***	0.604***	**0.459*****	0.413***
GREECE								
AR	0.528	0.687	0.819	0.957	1.144	1.348	2.215	3.135
MSFE Best w/o shrinkage	0.894***	0.807**	**0.759*****	**0.662*****	0.575***	**0.482****	**0.238****	**0.155****
GPR	0.896***	**0.801****	0.763***	0.677***	**0.572*****	0.508**	0.248**	0.158**
VBDVS	0.991	0.852***	0.913**	0.814*	0.688**	0.673**	0.488**	0.430**
ENET	**0.894*****	0.818***	0.773***	0.682***	0.613***	0.518**	0.253**	0.158**
LASSO	0.899***	0.816***	0.772***	0.679***	0.605***	0.509**	0.248**	0.156**
HUNGARY								
AR	0.463	0.736	0.971	1.235	1.483	1.735	2.480	3.200
MSFE Best w/o shrinkage	0.935	**0.870**	**0.776****	0.705**	0.638**	**0.573****	0.332**	**0.266****
GPR	**0.934**	0.880*	0.793**	**0.701****	**0.638****	0.584**	**0.307****	0.275**
VBDVS	1.098	0.962	0.975	0.863	0.826	0.770*	0.564**	0.478**
ENET	0.957	0.884	0.799**	0.722**	0.663**	0.604**	0.350**	0.284**
LASSO	0.950	0.893	0.800**	0.721**	0.664**	0.606**	0.354**	0.285**
POLAND								
AR	0.302	0.486	0.674	0.843	1.015	1.158	1.608	2.082
MSFE Best w/o shrinkage	0.882*	0.798***	0.730***	**0.695*****	0.614***	**0.445*****	0.295***	**0.268*****
GPR	**0.882***	0.877**	0.774***	0.726***	0.624***	0.475***	**0.263*****	0.299***
VBDVS	1.024	0.936	0.933	0.822***	0.849*	0.799**	0.716**	0.543**
ENET	0.890*	**0.791*****	0.738***	0.715***	**0.610*****	0.462***	0.316***	0.322***
LASSO	0.890*	0.809***	**0.724*****	0.718***	0.611***	0.470***	0.313***	0.323***
ROMANIA								
AR	0.625	0.935	1.218	1.398	1.565	1.694	2.158	2.687
MSFE Best w/o shrinkage	1.072	1.022	**0.928**	0.833**	0.741***	0.710***	**0.483*****	**0.538*****
GPR	1.072	**0.997**	0.940	**0.831****	**0.716*****	**0.655*****	0.530***	0.648***
VBDVS	1.060	1.005	0.947*	0.930	0.873**	0.967	0.824	0.939
ENET	1.080	1.033	0.941	0.839***	0.757***	0.737***	0.552***	0.598***
LASSO	1.089	1.045	0.939	0.844***	0.742***	0.735***	0.551***	0.594***

The entries are MSFEs, with the model that gives the smallest MSFE are highlighted in bold. The entries in the first row correspond to actual point MSFEs of AR model, while all other entries are relative MSFEs relative to the AR model. Hence, a value smaller than one implies that the corresponding specification type produces more accurate forecasts than those of the AR model. The entries in the second row of each panel deliver the best-MSFE outcome for a given forecast horizon across all constant parameter Specification types, which are highlighted in bold in Table 2. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model, based on the DM forecast accuracy test.

Table 7: Summary of best-MSFEs models and dimension reduction methods across countries

	Recursive Forecasting							
	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Bulgaria	Spec-6	Spec-6	Spec-6	GPR-6	GPR-6	GPR-6	GPR-2	Spec-3
Czech R.	VBDVS-6	ENET-2	ENET-4	GPR-2	GPR-2	GPR-2	LASSO-3	GPR-6
Greece	ENET-6	GPR-2	Spec-2	Spec-4	GPR-6	Spec-3	Spec-6	Spec-3
Hungary	GPR-3	Spec-6	Spec-6	GPR-6	GPR-6	Spec-6	GPR-6	Spec-6
Poland	GPR-4	ENET-6	LASSO-6	Spec-6	ENET-6	Spec-6	GPR-6	Spec-6
Romania	AR	GPR-3	Spec-3	GPR-6	GPR-6	GPR-3	Spec-6	Spec-6

Notes: Abbreviations; Specification type-1 = "1", Specification type-2 = "2", Specification type-3 = "3", Specification type-4 = "4", Specification type-5 = "5", Specification type-6 = "6". For instance, GPR-6 means that when the Specification-6 is estimated with the GPR model, it yields the lowest MSFE across all TVP models and constant parameter models for a given country.

Table 8: MSFEs based on the use of different global factors based on inflation spillovers - Recursive forecasting

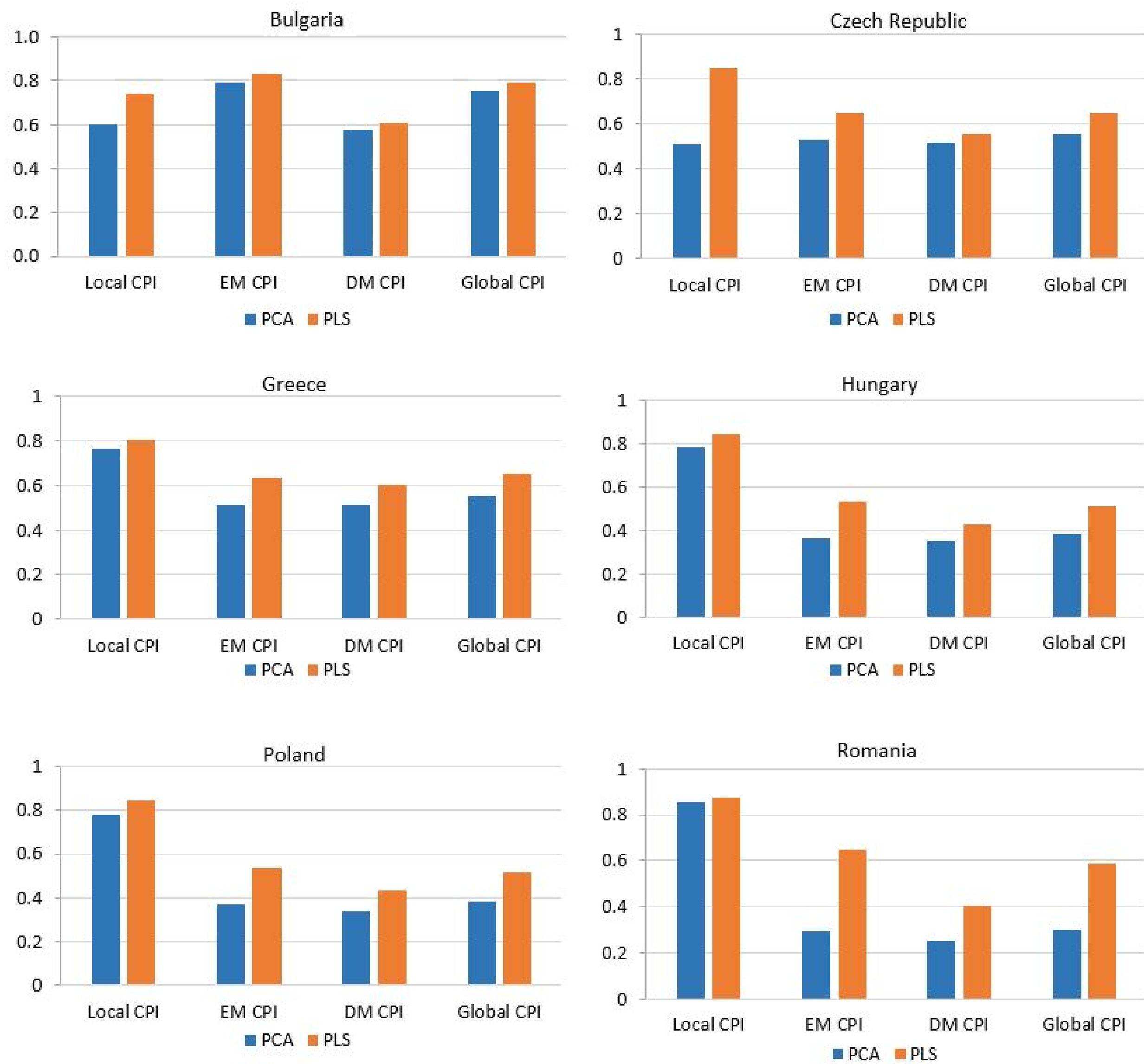
BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.439	0.801	1.082	1.375	1.674	1.974	2.949	3.906
ALL	**0.955**	**0.811*****	**0.690*****	**0.547*****	**0.495*****	**0.503*****	**0.503*****	**0.347*****
Top 10	1.175	0.930*	0.773***	0.743***	0.694***	0.666***	0.688***	0.497***
Top 20	1.156	0.925	0.845***	0.797***	0.715***	0.653***	0.544**	0.445***
Top 30	1.104	0.891***	0.792***	0.696***	0.636***	0.627***	0.614**	0.426***
Top 40	1.113	0.894***	0.798***	0.777**	0.694**	0.623**	0.640**	0.419***
CZECH REPUBLIC								
AR	0.341	0.492	0.628	0.755	0.863	0.964	1.194	1.463
ALL	1.113	1.046	1.005	0.980	0.899	0.723***	0.530***	0.404***
Top 10	1.043	**0.931**	**0.864***	**0.801***	**0.735***	**0.595****	**0.524****	0.440***
Top 20	1.078	1.022	0.914	0.902	0.864	0.685**	0.569**	0.441**
Top 30	1.083	1.034	0.984	0.985	1.010	0.805*	0.603**	**0.354*****
Top 40	1.144	1.091	0.925	0.964	0.984	0.835	0.553**	0.368***
GREECE								
AR	0.528	0.687	0.819	0.957	1.144	1.348	2.215	3.135
ALL	0.912**	0.837**	0.789***	0.698***	0.574***	**0.485****	0.238**	**0.174****
Top 10	0.906**	0.820**	0.781**	0.720**	0.617**	0.513**	0.243**	0.209**
Top 20	0.906**	0.809**	0.767***	0.755**	0.663**	0.602**	**0.233****	0.188**
Top 30	**0.883****	0.809**	0.803***	0.729***	0.630**	0.540**	0.299**	0.191**
Top 40	0.887***	**0.795****	**0.748*****	**0.661*****	**0.572****	0.505**	0.304**	0.185**
HUNGARY								
AR	0.463	0.736	0.971	1.235	1.483	1.735	2.480	3.200
ALL	**0.981**	**0.870**	**0.776****	**0.705****	**0.638****	**0.573****	**0.332****	**0.266****
Top 10	1.052	0.986	0.880	0.810	0.756	0.776	0.440**	0.320**
Top 20	1.074	1.013	0.839*	0.710**	0.685*	0.676*	0.350**	0.298**
Top 30	1.052	0.946	0.871	0.865	0.788	0.745	0.411**	0.315**
Top 40	1.075	0.950	0.845	0.808	0.733*	0.700*	0.437**	0.299**
POLAND								
AR	0.302	0.486	0.674	0.843	1.015	1.158	1.608	2.082
ALL	0.887*	0.798***	0.730***	0.695***	**0.614*****	**0.445*****	**0.295*****	0.268***
Top 10	0.897*	0.869**	0.861*	0.842*	0.750**	0.639**	0.375***	0.334***
Top 20	0.907	0.851**	0.780***	0.723***	0.660***	0.599***	0.390***	**0.268*****
Top 30	0.921	0.875**	0.832**	0.778**	0.695**	0.620***	0.386***	0.343**
Top 40	**0.853****	**0.776*****	**0.709*****	**0.672*****	0.617***	0.507***	0.345***	0.396**
ROMANIA								
AR	0.625	0.935	1.218	1.398	1.565	1.694	2.158	2.687
ALL	1.146	1.094	0.953	0.833**	**0.741*****	**0.710*****	**0.483*****	**0.538*****
Top 10	1.058	1.045	0.943	0.888	0.936	0.955	0.770**	0.745**
Top 20	**0.990**	0.970	0.914	0.884	0.887	0.863*	0.618***	0.686***
Top 30	1.039	**0.966**	**0.897***	**0.823****	0.858**	0.867**	0.654***	0.679***
Top 40	1.084	1.003	0.916	0.850**	0.895**	0.886**	0.691***	0.703**

The entries are MSFEs, with the model that gives the smallest MSFE are highlighted in bold. The entries in the first row correspond to actual point MSFEs of the AR model, while all other entries are relative MSFEs relative to the AR model. Hence, a value smaller than one implies that the corresponding specification type produces more accurate forecasts than the AR model. The entries in the second row of each panel deliver the MSFE outcome for the model where factors are extracted from all the countries taken together, which are reported in Table 2. Top 10, Top 20, Top 30, and Top 40 report the MSFEs results of the Specification - 6 where global factors are estimated considering the Top 10, Top 20, Top 30, and Top 40 countries with the highest inflation shock propagation for a given country, respectively. Based on the DM forecast accuracy test, entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model.

Table 9: Determinants of relative importance of global factor - Panel regression results

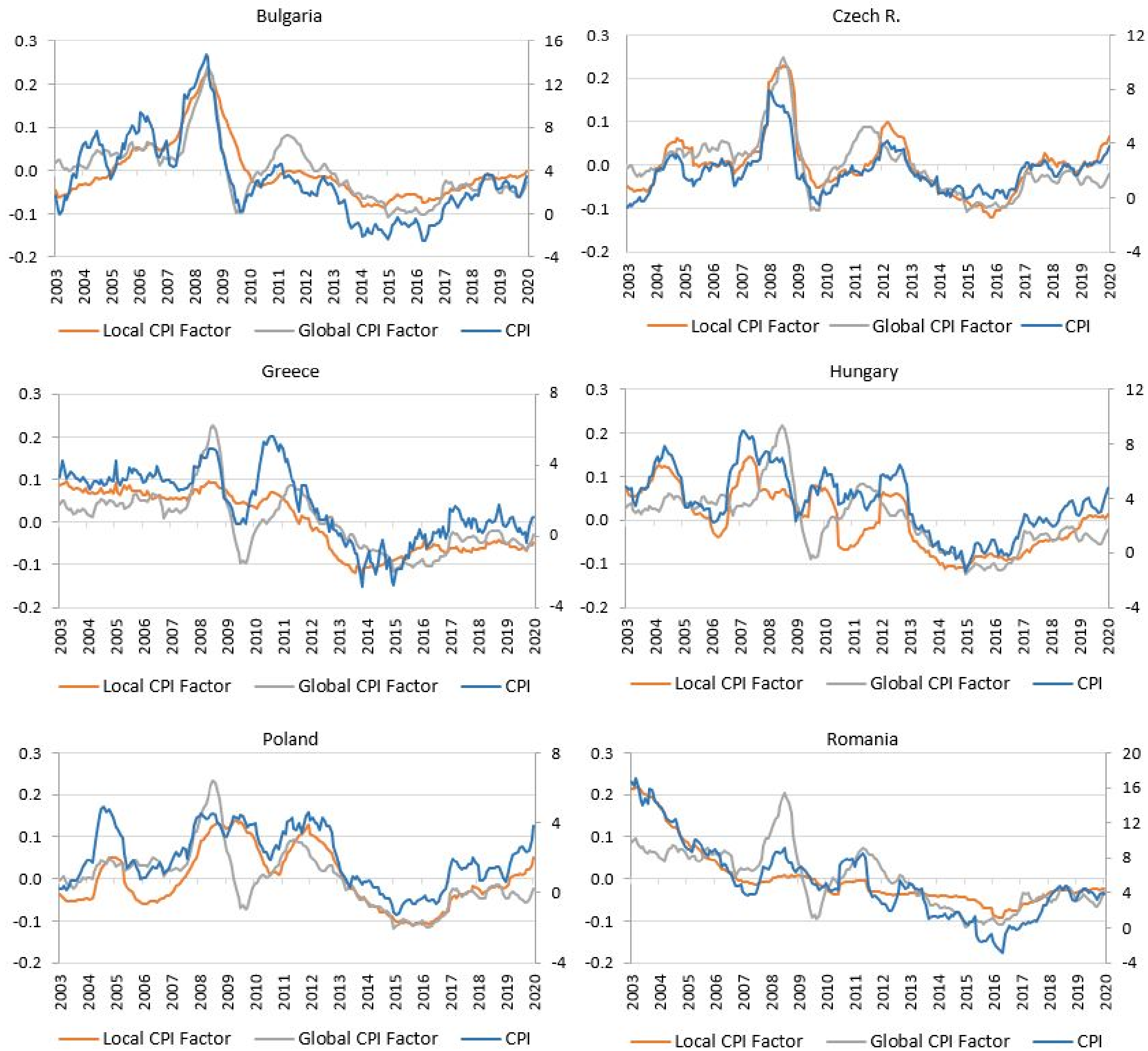
VARIABLES	(1) RGF	(2) RGF
Current Account Balance	0.611***	0.648***
	(0.192)	(0.217)
Budget Balance	0.145	0.150
	(0.211)	(0.210)
Government Debt	0.168***	0.167***
	(0.0419)	(0.0410)
Households Cons.	0.282	0.288
	(0.345)	(0.348)
Unemployment Rate	-0.987***	-0.911***
	(0.239)	(0.230)
FX Reserves	0.0546	0.0607
	(0.0504)	(0.0505)
Uncertainty	-0.515	-2.622
	(9.250)	(9.371)
Real GDP Growth	0.157	0.184
	(0.186)	(0.189)
CDS	-0.00169	0.000358
	(0.0298)	(0.0299)
REER	0.0451	0.0617
	(0.0597)	(0.0628)
Exports	-0.636**	
	(0.249)	
Imports	0.451*	
	(0.262)	
Exports Non EU		-1.142*
		(0.622)
Imports Non EU		0.504
		(0.378)
Exports EU		-0.653***
		(0.248)
Imports EU		0.560**
		(0.275)
Constant	-9.511	-13.48
	(19.87)	(20.62)
Observations	369	369
Adjusted R^2	0.431	0.430
F-stat prob.	0.00	0.00

Figure 1: Share of inflation variance explained by the first common factor of each dataset: PCA vs PLS



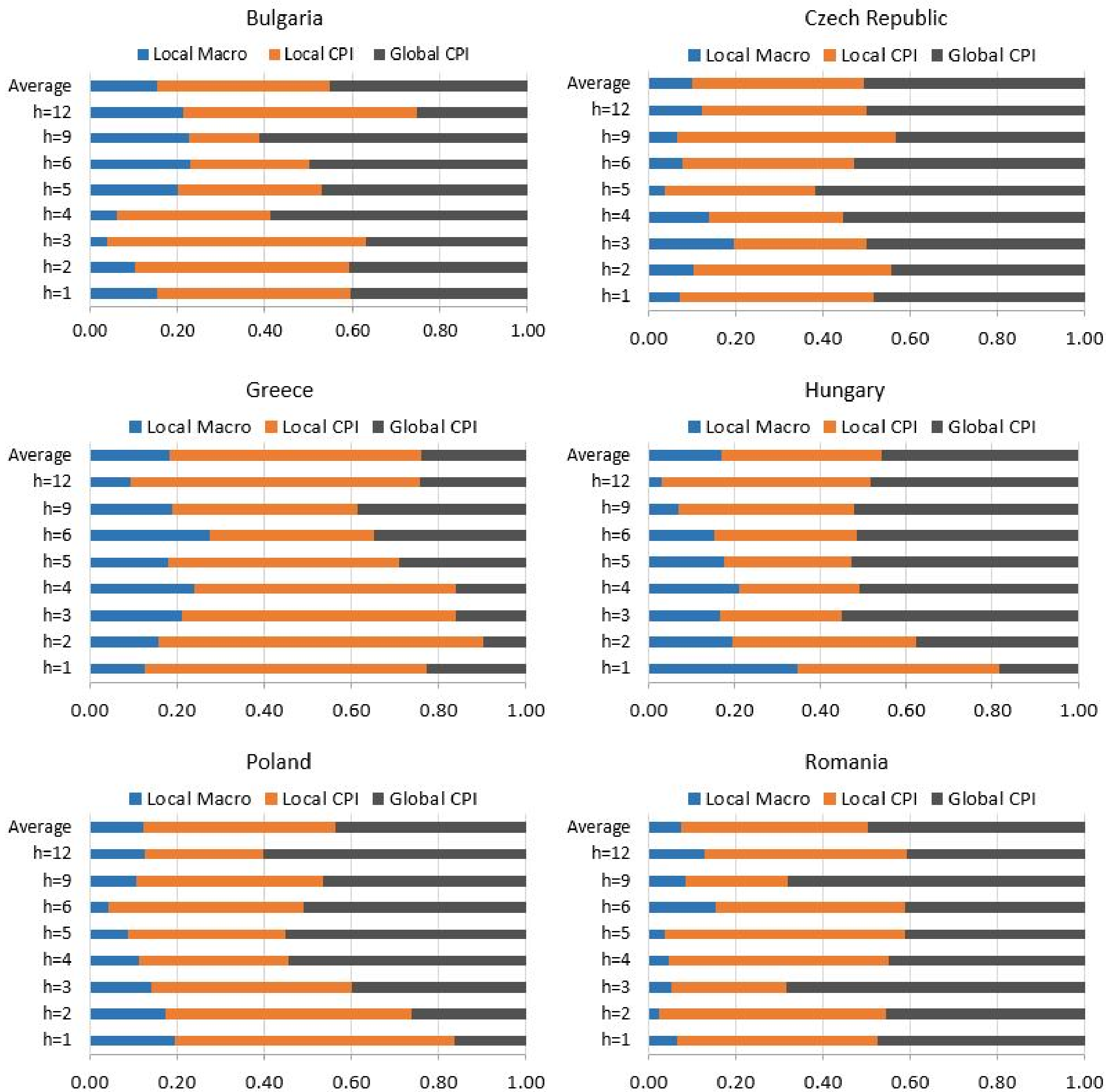
Notes: This figure shows the percentage of variance explained in headline inflation rates of EM European countries by the first common factor of each data groups where factors are obtained from using the PLS and PCA factor extraction methods.

Figure 2: Co-movement of actual inflation rates with local and global CPI factor estimated using the PLS approach.



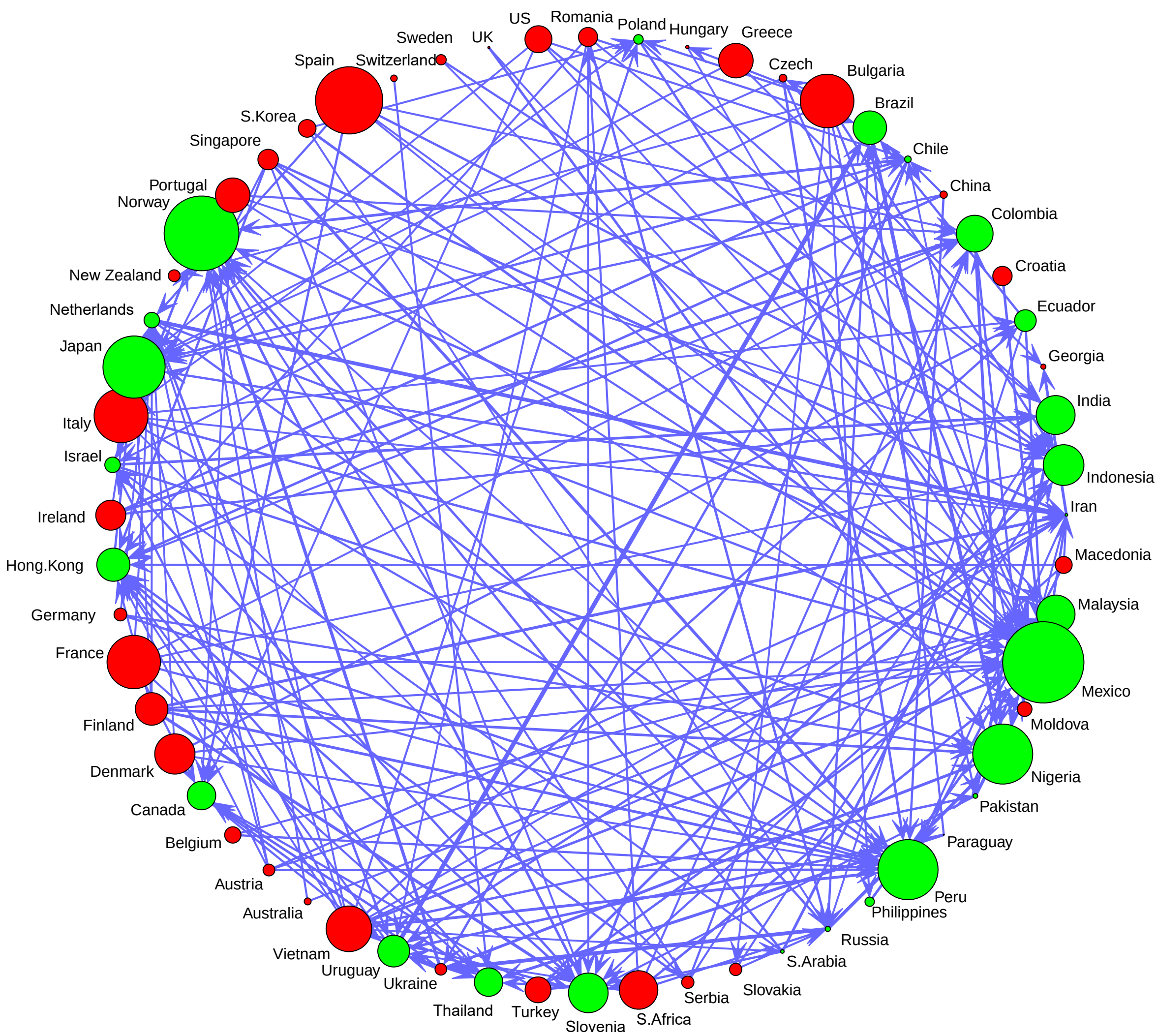
Notes: This figure plots the actual inflation rates along with local and global inflation factors where the factors are calculated as the first common component of the PLS approach utilizing the disaggregated CPI and all country-level headline inflation rate data.

Figure 3: The importance of global and local factor groups for the GPR method.



Notes: The sub-graphs plot the importance of each factor group for the GPR method for all horizons across the countries. The values in the graphs are normalized to sum one. h is the forecasting horizon.

Figure 4: Network analysis of inflation spillovers across countries



Notes: Each edge between two nodes demonstrates the net pairwise inflation spillovers between countries, and the arrow's direction indicates which country transmits the shocks to another country. The thickness of the edge between countries represents the strength of the spillovers between countries. Each node's size denotes the overall magnitude of net total directional spillovers. The red (green) node indicates whether a country is a net transmitter (receiver) of the shocks within the system. For better visualization, we report the pairwise spillovers greater than 0.05. Moreover, we run the model with 60 countries due to the need for a high-power computer.

Online Supplementary Appendix

Table A1: Share of inflation variance explained by each individual factor: PLS vs PCA

	PLS					PCA				
Bulgaria	1^{st} factor	2^{nd} factor	3^{rd} factor	4^{th} factor	$Total$	1^{st} factor	2^{nd} factor	3^{rd} factor	4^{th} factor	$Total$
Local Macro	0.69	0.09	0.08	0.03	0.89	0.09	0.59	0.03	0.02	0.73
Local CPI	0.74	0.21	0.03	0.01	0.99	0.60	0.30	0.01	0.00	0.92
EM CPI	0.83	0.10	0.02	0.01	0.97	0.79	0.01	0.03	0.01	0.84
DM CPI	0.61	0.17	0.09	0.02	0.89	0.57	0.00	0.06	0.01	0.65
Global CPI	0.79	0.14	0.02	0.02	0.98	0.75	0.01	0.00	0.00	0.77
Czech Republic										
Local Macro	0.58	0.12	0.09	0.05	0.85	0.00	0.09	0.09	0.16	0.34
Local CPI	0.85	0.08	0.04	0.02	0.98	0.51	0.32	0.00	0.00	0.84
EM CPI	0.65	0.21	0.07	0.03	0.96	0.53	0.11	0.03	0.01	0.67
DM CPI	0.55	0.17	0.09	0.02	0.83	0.52	0.01	0.05	0.02	0.59
Global CPI	0.65	0.21	0.07	0.03	0.95	0.55	0.09	0.04	0.01	0.69
Greece										
Local Macro	0.84	0.08	0.01	0.01	0.94	0.00	0.73	0.04	0.10	0.87
Local CPI	0.81	0.14	0.02	0.01	0.98	0.77	0.10	0.00	0.02	0.89
EM CPI	0.63	0.20	0.09	0.03	0.95	0.52	0.11	0.08	0.00	0.70
DM CPI	0.60	0.24	0.03	0.01	0.88	0.52	0.00	0.28	0.02	0.82
Global CPI	0.65	0.20	0.08	0.02	0.95	0.55	0.12	0.00	0.05	0.72
Hungary										
Local Macro	0.63	0.10	0.06	0.04	0.83	0.02	0.23	0.36	0.04	0.66
Local CPI	0.84	0.09	0.04	0.00	0.98	0.78	0.00	0.06	0.01	0.85
EM CPI	0.53	0.32	0.07	0.03	0.94	0.36	0.04	0.26	0.01	0.67
DM CPI	0.43	0.24	0.09	0.03	0.79	0.35	0.01	0.19	0.05	0.60
Global CPI	0.52	0.33	0.07	0.03	0.94	0.39	0.06	0.06	0.14	0.65
Poland										
Local Macro	0.55	0.24	0.06	0.05	0.90	0.01	0.00	0.01	0.64	0.66
Local CPI	0.84	0.10	0.03	0.01	0.99	0.78	0.00	0.07	0.04	0.90
EM CPI	0.54	0.33	0.06	0.03	0.95	0.37	0.03	0.19	0.14	0.73
DM CPI	0.43	0.27	0.08	0.03	0.82	0.34	0.11	0.10	0.08	0.63
Global CPI	0.52	0.34	0.05	0.04	0.95	0.38	0.03	0.03	0.29	0.73
Romania										
Local Macro	0.56	0.25	0.08	0.04	0.92	0.07	0.00	0.36	0.19	0.63
Local CPI	0.87	0.10	0.01	0.00	0.99	0.85	0.04	0.05	0.01	0.96
EM CPI	0.64	0.29	0.03	0.02	0.98	0.29	0.52	0.06	0.05	0.92
DM CPI	0.40	0.39	0.09	0.02	0.90	0.25	0.06	0.37	0.02	0.70
Global CPI	0.59	0.33	0.04	0.02	0.98	0.30	0.47	0.00	0.12	0.90

Table A2: Share of variance in each data groups explained by each individual factor: PLS vs PCA

	PLS					PCA				
Bulgaria	1^{st} factor	2^{nd} factor	3^{rd} factor	4^{th} factor	$Total$	1^{st} factor	2^{nd} factor	3^{rd} factor	4^{th} factor	$Total$
Local Macro	0.22	0.26	0.06	0.05	0.58	0.32	0.17	0.08	0.05	0.61
Local CPI	0.41	0.10	0.04	0.05	0.60	0.42	0.10	0.07	0.06	0.64
EM CPI	0.38	0.07	0.07	0.06	0.58	0.38	0.11	0.08	0.06	0.63
DM CPI	0.56	0.07	0.04	0.04	0.71	0.56	0.10	0.08	0.06	0.80
Global CPI	0.41	0.06	0.08	0.04	0.58	0.41	0.10	0.07	0.06	0.64
Czech Republic										
Local Macro	0.11	0.25	0.18	0.07	0.60	0.36	0.14	0.09	0.07	0.65
Local CPI	0.18	0.13	0.06	0.04	0.40	0.20	0.13	0.10	0.07	0.49
EM CPI	0.37	0.10	0.07	0.05	0.58	0.38	0.11	0.08	0.06	0.63
DM CPI	0.56	0.07	0.04	0.07	0.74	0.56	0.10	0.08	0.06	0.80
Global CPI	0.40	0.09	0.06	0.05	0.60	0.41	0.10	0.07	0.06	0.64
Greece										
Local Macro	0.17	0.09	0.24	0.06	0.56	0.27	0.18	0.08	0.06	0.59
Local CPI	0.47	0.06	0.04	0.03	0.59	0.47	0.06	0.06	0.05	0.63
EM CPI	0.37	0.10	0.06	0.06	0.59	0.38	0.11	0.08	0.06	0.63
DM CPI	0.56	0.09	0.04	0.06	0.74	0.56	0.10	0.08	0.06	0.80
Global CPI	0.40	0.09	0.05	0.05	0.59	0.41	0.10	0.07	0.06	0.64
Hungary										
Local Macro	0.18	0.26	0.16	0.06	0.66	0.34	0.18	0.11	0.05	0.68
Local CPI	0.29	0.08	0.05	0.10	0.52	0.29	0.13	0.10	0.06	0.57
EM CPI	0.37	0.09	0.07	0.07	0.59	0.38	0.11	0.08	0.06	0.63
DM CPI	0.55	0.08	0.04	0.06	0.74	0.56	0.10	0.08	0.06	0.80
Global CPI	0.40	0.08	0.07	0.05	0.60	0.41	0.10	0.07	0.06	0.64
Poland										
Local Macro	0.18	0.24	0.06	0.05	0.53	0.36	0.13	0.09	0.06	0.64
Local CPI	0.32	0.08	0.04	0.06	0.50	0.33	0.10	0.09	0.07	0.58
EM CPI	0.37	0.09	0.08	0.06	0.59	0.38	0.11	0.08	0.06	0.63
DM CPI	0.55	0.09	0.05	0.05	0.75	0.56	0.10	0.08	0.06	0.80
Global CPI	0.40	0.07	0.07	0.05	0.59	0.41	0.10	0.07	0.06	0.64
Romania										
Local Macro	0.24	0.19	0.06	0.05	0.54	0.34	0.14	0.10	0.08	0.67
Local CPI	0.66	0.06	0.04	0.03	0.79	0.66	0.07	0.05	0.04	0.81
EM CPI	0.34	0.15	0.06	0.04	0.59	0.38	0.11	0.08	0.06	0.63
DM CPI	0.54	0.10	0.04	0.07	0.75	0.56	0.10	0.08	0.06	0.80
Global CPI	0.38	0.13	0.06	0.03	0.59	0.41	0.10	0.07	0.06	0.64

Table A3: Point forecast performance: Recursive forecasting - Euro area sovereign debt crisis

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.502	0.898	1.205	1.594	1.996	2.378	3.547	4.675
Specification -1	**0.987**	0.902	**0.692*****	0.639***	0.516***	0.411***	0.696***	0.673***
Specification -2	1.310	0.920*	0.779***	0.717***	0.633***	0.433***	0.580***	0.259***
Specification -3	1.334	**0.819***	0.782**	0.651***	0.466***	0.314***	0.499***	**0.170*****
Specification -4	1.845	1.182	0.915	0.585***	0.512***	0.466***	0.569***	0.196***
Specification -5	1.606	0.950	0.896**	0.583***	**0.435*****	**0.268*****	0.767*	0.354***
Specification -6	1.426	0.856**	0.738***	**0.567*****	0.443***	0.318***	**0.465*****	0.179***
CZECH REPUBLIC								
AR	0.345	0.484	0.656	0.716	0.801	0.963	1.111	1.123
Specification -1	1.282	1.448	1.180	1.069	**0.887****	**0.602****	0.613**	0.816
Specification -2	1.332	1.368	1.254	1.278	1.051	0.670	0.476***	0.511***
Specification -3	1.684	1.933	1.790	1.730	1.220	0.828	0.730***	0.664***
Specification -4	1.686	1.960	1.399	1.132	0.954	0.910	0.464***	**0.453*****
Specification -5	1.898	1.920	1.560	1.368	1.228	0.909	**0.293*****	0.464***
Specification -6	1.791	2.068	1.779	1.722	1.265	0.839	0.614***	0.534***
GREECE								
AR	0.629	0.876	1.022	1.137	1.150	1.164	1.060	1.308
Specification -1	1.071	1.011	0.929	0.893**	1.045	1.068	1.059	0.874*
Specification -2	0.954	0.839**	0.853***	0.786***	0.856**	1.016	0.849**	0.545***
Specification -3	0.992	1.051	**0.798*****	**0.702*****	**0.571*****	0.546***	0.458***	0.389***
Specification -4	**0.930**	**0.799*****	0.927	0.824***	0.681***	0.546***	0.764	0.463***
Specification -5	1.004	0.924	0.808*	0.830*	0.656***	**0.475*****	0.395***	**0.335*****
Specification -6	0.967	0.900	0.989	1.002	0.855	0.807*	**0.276*****	0.346***
HUNGARY								
AR	0.493	0.747	0.883	0.975	1.078	1.189	1.514	1.581
Specification -1	**0.840**	**0.842***	**0.861***	1.035	1.012	1.189	1.123	0.992
Specification -2	1.568	1.508	1.272	1.127	1.055	0.916**	0.572***	**0.339*****
Specification -3	1.202	1.151	1.071	1.038	0.947	**0.799*****	0.507***	0.508***
Specification -4	1.580	1.528	1.187	0.995	1.119	1.126	0.511***	0.554**
Specification -5	1.361	1.290	1.108	**0.875***	**0.923**	0.967	**0.509*****	0.713**
Specification -6	1.544	1.512	1.089	1.008	1.024	1.027	0.525***	0.635***
POLAND								
AR	0.485	0.616	0.685	0.674	0.971	1.040	1.144	1.105
Specification -1	0.838***	**0.721*****	0.705***	0.674***	0.670***	0.631***	0.535***	0.835***
Specification -2	0.799***	0.899	0.742*	0.498***	**0.376*****	**0.274*****	0.479***	0.742***
Specification -3	**0.796*****	0.942	0.760*	0.602***	0.467***	0.383***	0.441***	**0.492*****
Specification -4	0.800***	0.922	0.662***	**0.436*****	0.444***	0.461***	0.425***	0.992
Specification -5	0.829***	0.982	**0.621*****	0.571***	0.518***	0.380***	**0.373*****	0.965
Specification -6	0.814***	0.958	0.736**	0.542***	0.462***	0.387***	0.405***	0.515***
ROMANIA								
AR	0.892	1.525	2.040	2.403	2.667	2.917	3.517	3.488
Specification -1	1.105	1.102	1.098	1.057	1.035	1.003	0.808*	0.673***
Specification -2	0.924	0.706***	0.602***	0.561***	0.622***	0.645***	0.710*	0.804*
Specification -3	**0.847****	**0.641****	**0.478*****	**0.377*****	**0.443*****	**0.525*****	0.784**	0.460***
Specification -4	0.987	0.901	0.810*	0.752**	0.721***	0.692***	0.632**	0.660***
Specification -5	0.884*	0.740*	0.586**	0.530***	0.481***	0.542***	**0.623****	**0.287*****
Specification -6	0.931	0.672***	0.525***	0.414***	0.489***	0.603***	0.737**	0.297***

The entries are MSFEs, with the Specification types that yields the smallest MSFE are highlighted in bold. The entries in the first row correspond to actual point MSFEs of AR model, while all other entries are relative MSFEs relative to the AR model. Hence, a value smaller than one implies that the corresponding specification type produces more accurate forecasts than those of the AR model. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model, based on the DM forecast accuracy test

Table A4: Headline Inflation - Commodity Augmented: Recursive forecasting - Factors are extracted using the PLS approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.439	0.801	1.082	1.375	1.674	1.974	2.949	3.906
$LocalMACRO + LocalCPI + Commodity$	1.038	0.839***	0.728***	0.607***	0.554***	0.523***	**0.495*****	0.360***
$Specification - 6$	**0.955*****	0.811***	0.690***	0.547***	0.495***	0.503***	0.503***	**0.347*****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	0.977	**0.806*****	**0.680*****	**0.539*****	**0.492*****	**0.494*****	0.518***	0.377***
CZECH REPUBLIC								
AR	0.341	0.492	0.628	0.755	0.863	0.964	1.194	1.463
$LocalMACRO + LocalCPI + Commodity$	1.105	1.017	**0.952***	**0.861*****	**0.745*****	**0.626*****	**0.493*****	0.397***
$Specification - 6$	1.113	1.046	1.005	0.980	0.899	0.723***	0.530***	0.404***
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.130	1.099	1.054	1.017	0.935	0.738**	0.537***	**0.378*****
GREECE								
AR	0.528	0.687	0.819	0.957	1.144	1.348	2.215	3.135
$LocalMACRO + LocalCPI + Commodity$	0.916**	**0.820****	**0.772****	0.727**	0.645**	0.577**	0.276**	0.203**
$Specification - 6$	**0.912****	0.837**	0.789***	**0.698*****	**0.574*****	**0.485****	**0.238****	**0.174****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	0.929*	0.839**	0.795***	0.711***	0.599***	0.490**	0.260**	0.181**
HUNGARY								
AR	0.463	0.736	0.971	1.235	1.483	1.735	2.480	3.200
$LocalMACRO + LocalCPI + Commodity$	1.018	0.949	0.822	0.775*	0.718*	0.673*	0.440**	0.296**
$Specification - 6$	**0.981**	**0.870**	**0.776****	**0.705****	**0.638****	**0.573****	**0.332****	**0.266****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.008	0.901	0.801**	0.722**	0.656**	0.582**	0.370**	0.267**
POLAND								
AR	0.302	0.486	0.674	0.843	1.015	1.158	1.608	2.082
$LocalMACRO + LocalCPI + Commodity$	0.937	0.876**	0.802***	0.727***	0.648***	0.579***	0.362***	0.312***
$Specification - 6$	**0.887****	**0.798*****	0.730***	**0.695*****	**0.614*****	**0.445*****	0.295***	**0.268*****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	0.905*	0.806***	**0.727*****	0.696***	0.615***	0.454***	**0.294*****	0.269***
ROMANIA								
AR	0.625	0.935	1.218	1.398	1.565	1.694	2.158	2.687
$LocalMACRO + LocalCPI + Commodity$	1.098	1.116	1.089	1.066	1.020	0.974	0.882	0.878
$Specification - 6$	1.146	1.094	**0.953**	**0.833*****	**0.741*****	**0.710*****	**0.483*****	**0.538*****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.157	1.143	1.015	0.898*	0.774***	0.743***	0.515***	0.559***

The entries are MSFEs, with the Specification types that yields the smallest MSFE are highlighted in bold. The entries in the first row correspond to actual point MSFEs of AR model, while all other entries are relative MSFEs relative to the AR model. Hence, a value smaller than one implies that the corresponding specification type produces more accurate forecasts than those of the AR model. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model, based on the DM forecast accuracy test.

Table A5: Headline Inflation - Commodity Augmented: Rolling forecasting - Factors are extracted using the PLS approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.429	0.770	1.015	1.257	1.489	1.719	2.576	3.585
$LocalMACRO + LocalCPI + Commodity$	1.088	0.983	0.871***	0.695***	0.620***	0.597***	**0.612****	0.443***
$Specification - 6$	1.117	0.938	0.731***	**0.628*****	**0.582*****	**0.596*****	0.675*	**0.424*****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.083	**0.930**	**0.716*****	0.652***	0.600***	0.617***	0.720*	0.432***
CZECH REPUBLIC								
AR	0.348	0.497	0.638	0.770	0.875	0.981	1.252	1.586
$LocalMACRO + LocalCPI + Commodity$	1.088	1.023	0.984	0.921	**0.791***	**0.675*****	**0.515*****	**0.395*****
$Specification - 6$	1.157	1.063	**0.954**	**0.861***	0.846**	0.835*	0.603***	0.407***
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.148	1.075	0.996	0.907	0.892	0.887	0.616***	0.406***
GREECE								
AR	0.523	0.680	0.809	0.939	1.125	1.334	2.204	3.107
$LocalMACRO + LocalCPI + Commodity$	**0.936**	0.896	0.842*	0.786**	0.691**	0.629**	0.308**	**0.236****
$Specification - 6$	0.944	**0.873**	**0.815*****	**0.748*****	**0.659****	**0.506****	0.321**	0.255**
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	0.957	0.893	0.830**	0.753***	0.681**	0.538**	**0.299****	0.270**
HUNGARY								
AR	0.473	0.745	0.976	1.220	1.434	1.656	2.280	2.916
$LocalMACRO + LocalCPI + Commodity$	1.080	1.013	0.935	0.955	0.936	0.822	0.474*	**0.346****
$Specification - 6$	1.011	**0.913**	0.839*	**0.820**	**0.738***	0.636*	**0.366****	0.363**
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.037	0.919	**0.808***	0.824	0.756	**0.630***	0.490*	0.356**
POLAND								
AR	0.308	0.508	0.705	0.881	1.063	1.202	1.586	2.023
$LocalMACRO + LocalCPI + Commodity$	0.864**	0.866**	0.834**	0.746**	0.723***	0.642***	0.431***	0.403***
$Specification - 6$	**0.856****	**0.813*****	**0.787*****	**0.736*****	**0.640*****	**0.497*****	**0.409*****	**0.336*****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	0.869**	0.836***	0.815**	0.738***	0.677***	0.510***	0.424***	0.345***
ROMANIA								
AR	0.636	0.966	1.307	1.540	1.780	2.010	2.895	3.900
$LocalMACRO + LocalCPI + Commodity$	1.155	1.273	1.260	1.196	1.082	0.986	0.848	0.617**
$Specification - 6$	1.160	1.135	0.914	**0.730*****	**0.617*****	0.634***	**0.708***	**0.460*****
$LocalMACRO + LocalCPI + GlobalCPI + Commodity$	1.164	1.144	**0.903**	0.753***	0.631***	**0.620*****	0.720*	0.474***

The entries are MSFEs, with the Specification types that yields the smallest MSFE are highlighted in bold. The entries in the first row correspond to actual point MSFEs of AR model, while all other entries are relative MSFEs relative to the AR model. Hence, a value smaller than one implies that the corresponding specification type produces more accurate forecasts than those of the AR model. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model, based on the DM forecast accuracy test.

Table A6: Giacomini and White (2006) test results for PLS approach in a recursive window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.06	0.35	0.45	0.03	0.01	0.01	0.02	0.02
Specification - 2	0.36	0.00	0.00	0.00	0.00	0.01	0.01	0.01
Specification - 3	0.89	0.06	0.01	0.00	0.00	0.01	0.04	0.01
Specification - 4	0.21	0.00	0.00	0.00	0.01	0.01	0.02	0.01
Specification - 5	0.53	0.60	0.19	0.01	0.01	0.01	0.09	0.01
Specification - 6	0.35	0.01	0.00	0.00	0.00	0.01	0.02	0.01
CZECH REPUBLIC								
Specification - 1	0.31	0.85	0.74	0.35	0.22	0.11	0.15	0.16
Specification - 2	0.69	0.57	0.18	0.06	0.01	0.01	0.02	0.02
Specification - 3	0.09	0.56	0.80	0.70	0.16	0.06	0.01	0.03
Specification - 4	0.64	0.47	0.01	0.07	0.44	0.27	0.02	0.02
Specification - 5	0.08	0.23	0.98	0.42	0.19	0.05	0.03	0.05
Specification - 6	0.26	0.65	1.00	0.79	0.38	0.03	0.01	0.03
GREECE								
Specification - 1	0.83	0.61	0.59	0.51	0.24	0.15	0.07	0.05
Specification - 2	0.04	0.04	0.01	0.03	0.04	0.06	0.04	0.04
Specification - 3	0.19	0.14	0.02	0.02	0.03	0.04	0.04	0.04
Specification - 4	0.01	0.04	0.01	0.01	0.02	0.04	0.04	0.04
Specification - 5	0.10	0.31	0.05	0.01	0.01	0.03	0.05	0.04
Specification - 6	0.05	0.08	0.01	0.01	0.02	0.04	0.04	0.04
HUNGARY								
Specification - 1	0.99	0.89	0.50	0.23	0.20	0.16	0.13	0.09
Specification - 2	0.95	0.59	0.20	0.15	0.14	0.15	0.08	0.05
Specification - 3	0.60	0.20	0.08	0.07	0.07	0.05	0.05	0.05
Specification - 4	0.87	0.55	0.14	0.12	0.16	0.18	0.09	0.05
Specification - 5	0.99	0.94	0.17	0.06	0.04	0.03	0.07	0.06
Specification - 6	0.85	0.22	0.05	0.06	0.06	0.05	0.05	0.04
POLAND								
Specification - 1	0.05	0.08	0.04	0.01	0.00	0.00	0.00	0.01
Specification - 2	0.34	0.05	0.00	0.00	0.01	0.01	0.00	0.01
Specification - 3	0.20	0.01	0.00	0.00	0.00	0.00	0.00	0.01
Specification - 4	0.12	0.04	0.03	0.04	0.03	0.03	0.01	0.02
Specification - 5	0.20	0.05	0.02	0.03	0.01	0.00	0.02	0.02
Specification - 6	0.13	0.00	0.00	0.00	0.00	0.00	0.00	0.01
ROMANIA								
Specification - 1	0.04	0.02	0.03	0.07	0.72	0.84	0.28	0.17
Specification - 2	0.09	0.32	0.64	0.92	0.93	0.63	0.34	0.29
Specification - 3	0.17	0.80	0.38	0.11	0.01	0.00	0.00	0.00
Specification - 4	0.01	0.01	0.09	0.36	0.73	0.24	0.01	0.04
Specification - 5	0.10	0.18	0.83	0.28	0.06	0.01	0.00	0.00
Specification - 6	0.02	0.30	0.57	0.04	0.00	0.00	0.00	0.00

This table reports p-values based on Giacomini and White (2006) forecast accuracy test results where factor extracting using the PLS-approach. Point forecasts are obtained from recursive window forecasting exercise.

Table A7: Giacomini and White (2006) test results for PLS approach in a rolling window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.14	0.35	0.87	0.07	0.02	0.02	0.04	0.05
Specification - 2	0.16	0.70	0.18	0.00	0.00	0.00	0.05	0.01
Specification - 3	0.25	0.21	0.00	0.01	0.01	0.01	0.16	0.02
Specification - 4	0.18	0.60	0.39	0.00	0.00	0.00	0.09	0.01
Specification - 5	0.02	0.26	0.66	0.05	0.12	0.03	0.34	0.04
Specification - 6	0.22	0.34	0.00	0.00	0.00	0.00	0.12	0.02
CZECH REPUBLIC								
Specification - 1	0.46	0.80	0.54	0.39	0.24	0.23	0.20	0.11
Specification - 2	0.62	0.91	0.79	0.61	0.11	0.02	0.01	0.02
Specification - 3	0.08	0.48	0.93	0.59	0.09	0.04	0.01	0.02
Specification - 4	0.32	0.94	0.36	0.18	0.62	0.31	0.01	0.05
Specification - 5	0.03	0.39	0.93	0.31	0.09	0.08	0.04	0.07
Specification - 6	0.08	0.59	0.67	0.18	0.09	0.14	0.01	0.02
GREECE								
Specification - 1	0.90	0.90	0.92	0.88	0.42	0.25	0.06	0.05
Specification - 2	0.11	0.15	0.09	0.06	0.04	0.07	0.03	0.04
Specification - 3	0.53	0.37	0.16	0.11	0.10	0.08	0.04	0.05
Specification - 4	0.01	0.16	0.02	0.01	0.02	0.04	0.04	0.04
Specification - 5	0.32	0.45	0.05	0.04	0.05	0.05	0.04	0.05
Specification - 6	0.27	0.22	0.03	0.02	0.03	0.04	0.04	0.04
HUNGARY								
Specification - 1	0.93	0.96	0.76	0.38	0.31	0.22	0.17	0.16
Specification - 2	0.71	0.89	0.63	0.62	0.59	0.38	0.09	0.08
Specification - 3	0.74	0.75	0.49	0.66	0.47	0.31	0.09	0.14
Specification - 4	0.66	0.99	0.49	0.31	0.36	0.16	0.08	0.09
Specification - 5	0.72	0.57	0.58	0.56	0.21	0.06	0.08	0.09
Specification - 6	0.92	0.36	0.17	0.24	0.20	0.15	0.07	0.09
POLAND								
Specification - 1	0.27	0.17	0.04	0.02	0.00	0.00	0.00	0.01
Specification - 2	0.03	0.03	0.03	0.01	0.02	0.03	0.00	0.01
Specification - 3	0.05	0.01	0.20	0.17	0.00	0.01	0.00	0.02
Specification - 4	0.10	0.13	0.05	0.01	0.00	0.01	0.02	0.03
Specification - 5	0.07	0.01	0.01	0.00	0.00	0.01	0.04	0.04
Specification - 6	0.04	0.01	0.01	0.00	0.00	0.00	0.00	0.02
ROMANIA								
Specification - 1	0.02	0.02	0.09	0.46	0.87	0.47	0.05	0.02
Specification - 2	0.09	0.14	0.15	0.22	0.66	0.83	0.24	0.01
Specification - 3	0.13	0.91	0.22	0.05	0.03	0.01	0.04	0.00
Specification - 4	0.06	0.03	0.50	0.71	0.26	0.15	0.14	0.03
Specification - 5	0.27	0.54	0.45	0.24	0.20	0.01	0.09	0.00
Specification - 6	0.00	0.18	0.42	0.00	0.00	0.00	0.14	0.00

This table reports p-values based on Giacomini and White (2006) forecast accuracy test results where factor extracting using the PLS-approach. Point forecasts are obtained from rolling window forecasting exercise.

Table A8: Giacomini and White (2006) test results for PCA approach in a recursive window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.66	0.81	0.72	0.66	0.60	0.61	0.54	0.56
Specification - 2	0.04	0.10	0.09	0.14	0.13	0.15	0.68	0.46
Specification - 3	0.06	0.14	0.10	0.13	0.12	0.15	0.50	0.98
Specification - 4	0.13	0.23	0.25	0.14	0.06	0.04	0.28	0.84
Specification - 5	0.17	0.74	0.42	0.40	0.04	0.01	0.27	0.49
Specification - 6	0.00	0.03	0.01	0.02	0.04	0.06	0.28	0.66
CZECH REPUBLIC								
Specification - 1	0.92	0.28	0.28	0.40	0.41	0.40	0.17	0.06
Specification - 2	0.03	0.18	0.33	0.22	0.18	0.08	0.01	0.06
Specification - 3	0.00	0.27	0.52	0.71	0.30	0.14	0.00	0.00
Specification - 4	0.00	0.01	0.01	0.03	0.04	0.05	0.05	0.09
Specification - 5	0.00	0.00	0.01	0.02	0.02	0.04	0.08	0.19
Specification - 6	0.01	0.16	0.26	0.47	0.33	0.25	0.07	0.08
GREECE								
Specification - 1	0.39	0.71	0.71	0.88	0.98	0.97	0.93	0.96
Specification - 2	0.73	0.95	0.82	0.72	0.55	0.54	0.45	0.46
Specification - 3	0.27	0.58	0.42	0.44	0.67	0.61	0.16	0.12
Specification - 4	0.69	0.76	0.88	0.87	0.38	0.37	0.26	0.12
Specification - 5	0.30	0.29	0.38	0.42	0.43	0.79	0.19	0.14
Specification - 6	0.17	0.31	0.16	0.18	0.36	0.79	0.19	0.12
HUNGARY								
Specification - 1	0.50	0.50	0.62	0.74	0.73	0.72	0.77	0.72
Specification - 2	0.31	0.38	0.52	0.81	0.85	0.81	0.86	0.34
Specification - 3	0.15	0.34	0.13	0.35	0.28	0.23	0.79	0.31
Specification - 4	0.23	0.36	0.58	0.93	0.93	0.88	0.70	0.42
Specification - 5	0.28	0.47	0.31	0.64	0.42	0.30	0.57	0.29
Specification - 6	0.42	0.86	0.60	0.87	0.95	0.98	0.39	0.24
POLAND								
Specification - 1	0.02	0.06	0.08	0.12	0.10	0.08	0.63	0.26
Specification - 2	0.07	0.11	0.22	0.49	0.52	0.55	0.95	0.36
Specification - 3	0.79	0.60	0.58	0.80	0.70	0.61	0.34	0.76
Specification - 4	0.73	0.78	0.76	0.51	0.47	0.52	0.61	0.75
Specification - 5	0.73	0.60	0.59	0.37	0.41	0.77	0.46	0.58
Specification - 6	0.96	0.85	0.81	0.58	0.73	0.75	0.53	0.66
ROMANIA								
Specification - 1	0.45	0.35	0.43	0.40	0.29	0.24	0.07	0.01
Specification - 2	0.09	0.05	0.08	0.07	0.06	0.05	0.07	0.06
Specification - 3	0.32	0.04	0.04	0.03	0.03	0.03	0.02	0.02
Specification - 4	0.01	0.00	0.01	0.01	0.02	0.04	0.07	0.03
Specification - 5	0.07	0.00	0.01	0.00	0.01	0.01	0.02	0.01
Specification - 6	0.08	0.00	0.01	0.00	0.01	0.01	0.01	0.01

This table reports p-values based on Giacomini and White (2006) forecast accuracy test results where factor extracting using the PCA-approach. Point forecasts are obtained from recursive window forecasting exercise.

Table A9: Giacomini and White (2006) test results for PCA approach in a rolling window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.14	0.32	0.29	0.44	0.46	0.47	0.45	0.32
Specification - 2	0.12	0.11	0.10	0.08	0.06	0.04	0.02	0.08
Specification - 3	0.23	0.03	0.00	0.00	0.00	0.00	0.00	0.32
Specification - 4	0.04	0.08	0.11	0.02	0.03	0.05	0.12	0.47
Specification - 5	0.20	0.07	0.00	0.00	0.00	0.01	0.01	0.10
Specification - 6	0.16	0.03	0.01	0.00	0.00	0.00	0.01	0.62
CZECH REPUBLIC								
Specification - 1	0.99	0.77	0.59	0.61	0.40	0.30	0.40	0.76
Specification - 2	0.04	0.15	0.25	0.09	0.17	0.09	0.00	0.03
Specification - 3	0.00	0.00	0.00	0.11	0.28	0.08	0.09	0.02
Specification - 4	0.06	0.22	0.16	0.11	0.14	0.16	0.11	0.26
Specification - 5	0.00	0.02	0.03	0.02	0.10	0.07	0.31	0.53
Specification - 6	0.02	0.06	0.07	0.10	0.18	0.16	0.31	0.06
GREECE								
Specification - 1	0.53	0.21	0.31	0.44	0.64	0.69	0.52	0.68
Specification - 2	0.18	0.22	0.38	0.45	0.69	0.98	0.64	0.55
Specification - 3	0.01	0.06	0.04	0.08	0.07	0.04	0.18	0.14
Specification - 4	0.07	0.03	0.09	0.14	0.49	0.92	0.34	0.12
Specification - 5	0.00	0.02	0.03	0.09	0.09	0.01	0.54	0.20
Specification - 6	0.02	0.02	0.02	0.04	0.05	0.11	0.23	0.13
HUNGARY								
Specification - 1	0.43	0.55	0.73	0.47	0.44	0.44	0.55	0.26
Specification - 2	0.22	0.22	0.18	0.28	0.39	0.62	0.96	0.97
Specification - 3	0.05	0.12	0.01	0.04	0.09	0.13	0.29	0.26
Specification - 4	0.16	0.18	0.22	0.23	0.17	0.13	0.64	0.65
Specification - 5	0.09	0.13	0.01	0.00	0.04	0.04	0.65	0.45
Specification - 6	0.08	0.09	0.01	0.05	0.12	0.14	0.53	0.64
POLAND								
Specification - 1	0.40	0.51	0.47	0.65	0.60	0.58	0.68	0.34
Specification - 2	0.74	0.30	0.14	0.07	0.09	0.12	0.07	0.01
Specification - 3	0.87	0.68	0.26	0.08	0.10	0.38	0.86	0.53
Specification - 4	0.32	0.29	0.53	0.28	0.22	0.33	0.17	0.27
Specification - 5	0.98	0.47	0.19	0.07	0.13	0.61	0.64	0.40
Specification - 6	0.61	0.65	0.25	0.02	0.03	0.10	0.58	0.11
ROMANIA								
Specification - 1	0.14	0.12	0.18	0.20	0.07	0.05	0.02	0.01
Specification - 2	0.04	0.00	0.00	0.00	0.00	0.00	0.09	0.10
Specification - 3	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.49
Specification - 4	0.01	0.00	0.00	0.01	0.01	0.09	0.74	0.98
Specification - 5	0.02	0.01	0.01	0.00	0.00	0.03	0.88	0.63
Specification - 6	0.00	0.00	0.00	0.00	0.01	0.02	0.10	0.40

This table reports p-values based on Giacomini and White (2006) forecast accuracy test results where factor extracting using the PCA-approach. Point forecasts are obtained from rolling window forecasting exercise.

Table A10: Harvey et al. (1997) test results for PLS approach in a recursive window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.95	0.79	0.26	0.03	0.02	0.01	0.03	0.02
Specification - 2	0.78	0.00	0.00	0.00	0.01	0.01	0.02	0.01
Specification - 3	0.55	0.05	0.02	0.01	0.01	0.01	0.04	0.01
Specification - 4	0.86	0.00	0.00	0.01	0.01	0.02	0.03	0.01
Specification - 5	0.71	0.33	0.13	0.01	0.01	0.02	0.07	0.02
Specification - 6	0.21	0.01	0.01	0.00	0.01	0.01	0.03	0.01
CZECH REPUBLIC								
Specification - 1	0.81	0.57	0.39	0.21	0.15	0.09	0.11	0.12
Specification - 2	0.64	0.31	0.12	0.06	0.01	0.01	0.02	0.02
Specification - 3	0.93	0.69	0.59	0.37	0.11	0.05	0.02	0.03
Specification - 4	0.66	0.27	0.01	0.06	0.25	0.17	0.03	0.03
Specification - 5	0.93	0.85	0.51	0.24	0.13	0.05	0.03	0.05
Specification - 6	0.84	0.65	0.50	0.41	0.23	0.03	0.02	0.03
GREECE								
Specification - 1	0.43	0.33	0.32	0.29	0.16	0.11	0.06	0.05
Specification - 2	0.04	0.04	0.02	0.03	0.04	0.06	0.04	0.04
Specification - 3	0.13	0.10	0.02	0.02	0.03	0.04	0.04	0.04
Specification - 4	0.01	0.04	0.02	0.01	0.02	0.04	0.04	0.04
Specification - 5	0.07	0.19	0.05	0.02	0.01	0.03	0.04	0.04
Specification - 6	0.05	0.06	0.02	0.01	0.02	0.04	0.04	0.04
HUNGARY								
Specification - 1	0.49	0.45	0.28	0.15	0.13	0.11	0.10	0.08
Specification - 2	0.52	0.32	0.13	0.10	0.10	0.11	0.07	0.05
Specification - 3	0.33	0.14	0.07	0.06	0.06	0.05	0.05	0.05
Specification - 4	0.56	0.30	0.10	0.09	0.11	0.12	0.08	0.05
Specification - 5	0.50	0.53	0.12	0.05	0.04	0.03	0.06	0.06
Specification - 6	0.44	0.15	0.05	0.05	0.05	0.05	0.05	0.04
POLAND								
Specification - 1	0.05	0.07	0.04	0.02	0.00	0.00	0.01	0.02
Specification - 2	0.20	0.04	0.00	0.00	0.01	0.01	0.01	0.02
Specification - 3	0.14	0.01	0.00	0.00	0.00	0.00	0.01	0.02
Specification - 4	0.09	0.04	0.03	0.04	0.03	0.03	0.02	0.03
Specification - 5	0.13	0.04	0.02	0.03	0.01	0.01	0.03	0.02
Specification - 6	0.10	0.01	0.00	0.01	0.01	0.00	0.01	0.02
ROMANIA								
Specification - 1	0.04	0.02	0.03	0.07	0.72	0.84	0.28	0.17
Specification - 2	0.09	0.32	0.64	0.92	0.93	0.63	0.34	0.29
Specification - 3	0.17	0.80	0.38	0.11	0.01	0.00	0.00	0.00
Specification - 4	0.01	0.01	0.09	0.36	0.73	0.24	0.01	0.04
Specification - 5	0.10	0.18	0.83	0.28	0.06	0.01	0.00	0.00
Specification - 6	0.02	0.30	0.57	0.04	0.00	0.00	0.00	0.00

This table reports p-values based on Harvey et al. (1997) forecast accuracy test results where factor extracting using the PLS-approach. Point forecasts are obtained from recursive window forecasting exercise.

Table A11: Harvey et al. (1997) test results for PLS approach in a rolling window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.90	0.79	0.44	0.06	0.02	0.02	0.04	0.05
Specification - 2	0.89	0.63	0.12	0.00	0.00	0.00	0.05	0.02
Specification - 3	0.84	0.14	0.01	0.01	0.01	0.01	0.12	0.03
Specification - 4	0.88	0.68	0.23	0.01	0.00	0.01	0.07	0.02
Specification - 5	0.98	0.84	0.35	0.04	0.09	0.03	0.21	0.04
Specification - 6	0.85	0.21	0.01	0.00	0.00	0.01	0.09	0.02
CZECH REPUBLIC								
Specification - 1	0.74	0.59	0.30	0.23	0.16	0.15	0.14	0.09
Specification - 2	0.66	0.46	0.41	0.33	0.08	0.02	0.02	0.02
Specification - 3	0.93	0.73	0.53	0.32	0.07	0.04	0.01	0.02
Specification - 4	0.81	0.48	0.21	0.12	0.34	0.19	0.01	0.05
Specification - 5	0.97	0.77	0.47	0.19	0.07	0.06	0.04	0.06
Specification - 6	0.93	0.68	0.36	0.12	0.08	0.10	0.02	0.03
GREECE								
Specification - 1	0.54	0.54	0.54	0.45	0.24	0.16	0.06	0.05
Specification - 2	0.08	0.11	0.07	0.05	0.04	0.06	0.04	0.04
Specification - 3	0.29	0.22	0.11	0.08	0.08	0.07	0.04	0.05
Specification - 4	0.01	0.11	0.02	0.01	0.02	0.04	0.04	0.04
Specification - 5	0.19	0.26	0.04	0.04	0.05	0.05	0.04	0.05
Specification - 6	0.17	0.14	0.03	0.03	0.03	0.04	0.04	0.04
HUNGARY								
Specification - 1	0.53	0.48	0.39	0.22	0.19	0.15	0.12	0.11
Specification - 2	0.62	0.45	0.34	0.33	0.32	0.23	0.08	0.07
Specification - 3	0.61	0.39	0.27	0.35	0.27	0.19	0.08	0.10
Specification - 4	0.65	0.50	0.27	0.19	0.21	0.12	0.07	0.08
Specification - 5	0.62	0.69	0.32	0.31	0.14	0.06	0.07	0.08
Specification - 6	0.53	0.21	0.12	0.16	0.13	0.11	0.06	0.07
POLAND								
Specification - 1	0.98	0.98	0.93	0.74	0.44	0.27	0.05	0.03
Specification - 2	0.93	0.90	0.89	0.85	0.65	0.43	0.16	0.02
Specification - 3	0.91	0.54	0.14	0.05	0.03	0.01	0.04	0.01
Specification - 4	0.95	0.97	0.72	0.37	0.17	0.11	0.11	0.04
Specification - 5	0.83	0.70	0.26	0.16	0.13	0.02	0.07	0.00
Specification - 6	0.99	0.88	0.24	0.01	0.00	0.01	0.10	0.01
ROMANIA								
Specification - 1	0.04	0.02	0.03	0.07	0.72	0.84	0.28	0.17
Specification - 2	0.09	0.32	0.64	0.92	0.93	0.63	0.34	0.29
Specification - 3	0.17	0.80	0.38	0.11	0.01	0.00	0.00	0.00
Specification - 4	0.01	0.01	0.09	0.36	0.73	0.24	0.01	0.04
Specification - 5	0.10	0.18	0.83	0.28	0.06	0.01	0.00	0.00
Specification - 6	0.02	0.30	0.57	0.04	0.00	0.00	0.00	0.00

This table reports p-values based on Harvey et al. (1997) forecast accuracy test results where factor extracting using the PLS-approach. Point forecasts are obtained from rolling window forecasting exercise.

Table A12: Harvey et al. (1997) test results for PCA approach in a recursive window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.65	0.58	0.62	0.65	0.67	0.67	0.70	0.69
Specification - 2	0.96	0.92	0.93	0.90	0.90	0.89	0.64	0.26
Specification - 3	0.95	0.90	0.92	0.91	0.91	0.89	0.72	0.51
Specification - 4	0.90	0.85	0.84	0.90	0.95	0.96	0.82	0.57
Specification - 5	0.88	0.61	0.76	0.77	0.96	0.99	0.83	0.72
Specification - 6	0.99	0.97	0.99	0.97	0.96	0.95	0.82	0.35
CZECH REPUBLIC								
Specification - 1	0.54	0.17	0.17	0.23	0.24	0.24	0.88	0.95
Specification - 2	0.97	0.88	0.80	0.86	0.88	0.94	0.98	0.94
Specification - 3	1.00	0.83	0.71	0.63	0.81	0.90	0.99	1.00
Specification - 4	1.00	0.98	0.98	0.97	0.96	0.95	0.95	0.93
Specification - 5	1.00	1.00	0.99	0.98	0.98	0.96	0.93	0.87
Specification - 6	0.99	0.89	0.84	0.73	0.80	0.84	0.94	0.93
GREECE								
Specification - 1	0.77	0.63	0.63	0.55	0.49	0.49	0.53	0.52
Specification - 2	0.62	0.48	0.42	0.38	0.30	0.30	0.26	0.27
Specification - 3	0.83	0.69	0.76	0.75	0.64	0.33	0.11	0.09
Specification - 4	0.64	0.61	0.55	0.44	0.22	0.22	0.17	0.09
Specification - 5	0.82	0.82	0.78	0.76	0.75	0.59	0.13	0.10
Specification - 6	0.88	0.81	0.89	0.88	0.78	0.41	0.13	0.10
HUNGARY								
Specification - 1	0.72	0.72	0.67	0.61	0.62	0.62	0.60	0.62
Specification - 2	0.81	0.78	0.71	0.58	0.57	0.58	0.56	0.79
Specification - 3	0.90	0.80	0.90	0.79	0.82	0.85	0.41	0.19
Specification - 4	0.85	0.78	0.68	0.53	0.47	0.45	0.37	0.24
Specification - 5	0.83	0.74	0.81	0.65	0.76	0.82	0.31	0.18
Specification - 6	0.76	0.56	0.68	0.44	0.52	0.51	0.23	0.16
POLAND								
Specification - 1	0.02	0.05	0.06	0.09	0.08	0.06	0.34	0.83
Specification - 2	0.06	0.08	0.14	0.28	0.29	0.30	0.48	0.78
Specification - 3	0.41	0.32	0.32	0.41	0.37	0.33	0.21	0.40
Specification - 4	0.62	0.60	0.61	0.71	0.73	0.71	0.67	0.39
Specification - 5	0.62	0.68	0.68	0.78	0.76	0.60	0.74	0.68
Specification - 6	0.48	0.57	0.58	0.68	0.62	0.61	0.29	0.35
ROMANIA								
Specification - 1	0.75	0.79	0.75	0.77	0.82	0.84	0.94	0.98
Specification - 2	0.93	0.95	0.93	0.94	0.95	0.95	0.94	0.94
Specification - 3	0.80	0.96	0.96	0.97	0.97	0.97	0.97	0.98
Specification - 4	0.99	0.99	0.98	0.98	0.98	0.96	0.94	0.96
Specification - 5	0.94	0.99	0.99	0.99	0.99	0.99	0.98	0.99
Specification - 6	0.93	0.99	0.99	0.99	0.99	0.99	0.99	0.99

This table reports p-values based on Harvey et al. (1997) forecast accuracy test results where factor extracting using the PCA-approach. Point forecasts are obtained from recursive window forecasting exercise.

Table A13: Harvey et al. (1997) test results for PCA approach in a rolling window

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	0.90	0.81	0.82	0.75	0.74	0.73	0.74	0.80
Specification - 2	0.91	0.92	0.92	0.94	0.95	0.96	0.98	0.93
Specification - 3	0.85	0.97	1.00	1.00	1.00	1.00	0.99	0.80
Specification - 4	0.96	0.93	0.92	0.97	0.97	0.95	0.91	0.73
Specification - 5	0.87	0.94	0.99	1.00	1.00	0.99	0.98	0.92
Specification - 6	0.89	0.97	0.99	1.00	1.00	0.99	0.99	0.66
CZECH REPUBLIC								
Specification - 1	0.50	0.40	0.32	0.33	0.24	0.19	0.23	0.60
Specification - 2	0.96	0.89	0.84	0.93	0.88	0.92	0.99	0.97
Specification - 3	1.00	0.99	0.99	0.91	0.82	0.93	0.93	0.97
Specification - 4	0.95	0.85	0.89	0.92	0.90	0.89	0.92	0.83
Specification - 5	1.00	0.98	0.97	0.97	0.92	0.94	0.81	0.71
Specification - 6	0.98	0.95	0.94	0.92	0.87	0.89	0.81	0.94
GREECE								
Specification - 1	0.71	0.86	0.81	0.75	0.66	0.64	0.71	0.64
Specification - 2	0.88	0.86	0.77	0.75	0.64	0.51	0.34	0.31
Specification - 3	0.98	0.95	0.96	0.94	0.94	0.96	0.12	0.10
Specification - 4	0.94	0.97	0.93	0.90	0.73	0.54	0.21	0.09
Specification - 5	0.99	0.97	0.97	0.93	0.93	0.98	0.30	0.14
Specification - 6	0.98	0.98	0.98	0.96	0.96	0.91	0.15	0.10
HUNGARY								
Specification - 1	0.75	0.70	0.62	0.73	0.75	0.75	0.69	0.83
Specification - 2	0.86	0.85	0.88	0.83	0.77	0.67	0.48	0.49
Specification - 3	0.96	0.91	0.99	0.96	0.93	0.90	0.82	0.17
Specification - 4	0.89	0.88	0.85	0.85	0.88	0.90	0.66	0.35
Specification - 5	0.93	0.90	0.99	1.00	0.96	0.96	0.35	0.26
Specification - 6	0.93	0.93	0.98	0.96	0.91	0.90	0.70	0.34
POLAND								
Specification - 1	0.23	0.28	0.26	0.35	0.32	0.32	0.64	0.79
Specification - 2	0.61	0.82	0.90	0.94	0.93	0.91	0.94	0.99
Specification - 3	0.44	0.64	0.83	0.93	0.92	0.78	0.44	0.70
Specification - 4	0.80	0.82	0.70	0.83	0.85	0.80	0.88	0.83
Specification - 5	0.49	0.73	0.87	0.94	0.90	0.67	0.66	0.76
Specification - 6	0.33	0.65	0.84	0.98	0.97	0.92	0.68	0.91
ROMANIA								
Specification - 1	0.90	0.91	0.88	0.87	0.94	0.95	0.98	0.99
Specification - 2	0.96	1.00	1.00	1.00	1.00	0.99	0.93	0.92
Specification - 3	1.00	1.00	1.00	1.00	1.00	1.00	0.94	0.72
Specification - 4	0.99	1.00	1.00	0.99	0.98	0.93	0.61	0.49
Specification - 5	0.98	0.98	0.99	1.00	0.99	0.97	0.55	0.34
Specification - 6	1.00	1.00	1.00	1.00	0.99	0.98	0.92	0.76

This table reports p-values based on Harvey et al. (1997) forecast accuracy test results where factor extracting using the PCA-approach. Point forecasts are obtained from rolling window forecasting exercise.

Table A14: Point forecast performance: Rolling forecasting - Factors are extracted using the PLS approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.429	0.770	1.015	1.257	1.489	1.719	2.576	3.585
Specification -1	1.150	1.063	0.990	0.883**	0.815***	0.771***	**0.605****	0.567**
Specification -2	1.197	1.031	0.917*	0.705***	0.645***	0.620***	0.637**	0.419***
Specification -3	1.071	**0.911**	0.732***	0.686***	0.649***	0.601***	0.709*	**0.395*****
Specification -4	1.157	1.064	0.939	0.726***	0.632***	0.631***	0.680**	0.491***
Specification -5	1.203	1.114	0.944	0.731**	0.762*	0.706**	0.809	0.443**
Specification -6	1.117	0.938	**0.731*****	**0.628*****	**0.582*****	**0.596*****	0.675*	0.424***
CZECH REPUBLIC								
AR	0.348	0.497	0.638	0.770	0.875	0.981	1.252	1.586
Specification -1	1.051	1.023	0.947	0.910	0.882	0.847	0.783*	0.696**
Specification -2	1.049	**0.984**	0.961	0.919	**0.780****	**0.667*****	0.511***	**0.385*****
Specification -3	1.169	1.091	1.011	0.931	0.837**	0.745**	0.557***	0.399***
Specification -4	1.076	0.993	**0.917**	0.863*	0.931	0.860	**0.505*****	0.529**
Specification -5	1.255	1.086	0.990	0.889	0.829**	0.791**	0.629**	0.549**
Specification -6	1.157	1.063	0.954	**0.861***	0.846**	0.835*	0.603***	0.407***
GREECE								
AR	0.523	0.680	0.809	0.939	1.125	1.334	2.204	3.107
Specification -1	1.010	1.014	1.013	0.982	0.878	0.756	0.433**	0.406**
Specification -2	0.919**	0.857*	0.832**	0.765**	0.647**	0.563**	0.299**	**0.207****
Specification -3	0.967	0.918	0.874*	0.805**	0.707**	0.586**	0.324**	0.208**
Specification -4	**0.903*****	**0.854***	**0.776*****	**0.674*****	**0.587*****	**0.489****	**0.287****	0.223**
Specification -5	0.960	0.933	0.831**	0.766**	0.735**	0.618**	0.318**	0.229**
Specification -6	0.944	0.873	0.815***	0.748***	0.659**	0.506**	0.321**	0.255**
HUNGARY								
AR	0.473	0.745	0.976	1.220	1.434	1.656	2.280	2.916
Specification -1	1.006	0.995	0.959	0.839	0.776	0.693	0.582*	0.573*
Specification -2	1.052	0.981	0.927	0.908	0.880	0.790	0.427**	**0.360****
Specification -3	1.038	0.974	0.923	0.933	0.869	0.793	0.430**	0.456*
Specification -4	1.060	0.999	0.906	0.841	0.806	0.662*	0.391**	0.378**
Specification -5	1.047	1.049	0.952	0.923	0.791*	**0.619****	0.417**	0.384**
Specification -6	1.011	**0.913**	**0.839***	**0.820**	**0.738***	0.636	**0.366****	0.363**
POLAND								
AR	0.308	0.508	0.705	0.881	1.063	1.202	1.586	2.023
Specification -1	0.951	0.923*	0.889**	0.850***	0.790***	0.735***	0.581***	0.603***
Specification -2	0.858***	0.863**	0.828***	0.739***	0.683***	0.629***	0.438***	0.385***
Specification -3	0.859**	0.828***	0.904*	0.900*	0.753***	0.631***	**0.362*****	0.416***
Specification -4	0.876**	0.885**	0.811**	**0.721*****	0.672***	0.629***	0.450***	0.430**
Specification -5	0.880**	0.840***	**0.779*****	0.797***	0.713***	0.625***	0.548**	0.432**
Specification -6	**0.856****	**0.813*****	0.787***	0.736***	**0.640*****	**0.497*****	0.409***	**0.336*****
ROMANIA								
AR	0.636	0.966	1.307	1.540	1.780	2.010	2.895	3.900
Specification -1	1.094	1.144	1.098	1.042	0.989	0.938	0.775***	0.720***
Specification -2	1.138	1.241	1.225	1.145	1.046	0.971	0.812	0.588***
Specification -3	1.077	1.009	**0.874**	0.818**	0.754**	0.712***	**0.695****	0.496***
Specification -4	1.140	1.225	1.072	0.961	0.867	0.794*	0.736*	0.654**
Specification -5	1.074	1.050	0.920	0.868	0.832*	0.718***	0.713**	0.553***
Specification -6	1.160	1.135	0.914	**0.730*****	**0.617*****	**0.634*****	0.708*	**0.460*****

See notes to Table A5.

Table A15: Point forecast performance: Recursive forecasting - Factors are extracted using the PCA approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.439	0.801	1.082	1.375	1.674	1.974	2.949	3.906
Specification -1	1.021	1.019	1.044	1.069	1.094	1.107	1.145	1.135
Specification -2	1.140	1.141	1.173	1.196	1.223	1.209	1.036	**0.919**
Specification -3	1.108	1.110	1.126	1.166	1.203	1.220	1.072	1.008
Specification -4	1.132	1.162	1.224	1.252	1.322	1.358	1.151	1.036
Specification -5	1.067	1.020	1.094	1.078	1.158	1.206	1.094	1.080
Specification -6	1.143	1.159	1.179	1.210	1.276	1.337	1.125	0.954
CZECH REPUBLIC								
AR	0.341	0.492	0.628	0.755	0.863	0.964	1.194	1.463
Specification -1	**0.997**	**0.954**	**0.954**	**0.968**	**0.964**	**0.964**	1.123	1.285
Specification -2	1.067	1.062	1.066	1.092	1.122	1.172	1.482	1.573
Specification -3	1.101	1.056	1.055	1.053	1.186	1.330	1.463	1.453
Specification -4	1.117	1.191	1.278	1.438	1.562	1.612	1.593	1.536
Specification -5	1.158	1.233	1.369	1.401	1.451	1.368	1.435	1.322
Specification -6	1.138	1.106	1.097	1.093	1.169	1.259	1.391	1.350
GREECE								
AR	0.528	0.687	0.819	0.957	1.144	1.348	2.215	3.135
Specification -1	1.018	1.017	1.029	1.017	0.999	0.995	1.010	1.009
Specification -2	1.012	**0.996**	**0.977**	**0.951**	0.918	0.901	0.866	0.875
Specification -3	1.042	1.054	1.103	1.121	1.049	0.944	0.602*	0.578*
Specification -4	1.014	1.027	1.019	0.977	**0.885**	**0.865**	0.807	0.701*
Specification -5	1.072	1.147	1.154	1.186	1.133	1.029	0.637*	0.594*
Specification -6	1.064	1.112	1.185	1.226	1.116	0.962	**0.599***	**0.547***
HUNGARY								
AR	0.463	0.736	0.971	1.235	1.483	1.735	2.480	3.200
Specification -1	1.038	1.049	1.057	1.042	1.053	1.071	1.054	1.049
Specification -2	1.068	1.068	1.075	1.031	1.030	1.043	1.029	1.083
Specification -3	1.077	1.049	1.124	1.113	1.180	1.202	0.963	0.796
Specification -4	1.099	1.079	1.069	1.010	**0.984**	**0.969**	0.907	0.823
Specification -5	1.064	1.055	1.079	1.043	1.108	1.158	0.894	0.765
Specification -6	1.046	1.010	1.034	**0.988**	1.005	1.005	**0.836**	**0.726**
POLAND								
AR	0.302	0.486	0.674	0.843	1.015	1.158	1.608	2.082
Specification -1	**0.917*****	**0.877****	**0.858****	**0.862***	**0.851****	**0.853****	0.979	1.101
Specification -2	0.930**	0.906*	0.896	0.917	0.909	0.903	0.986	1.151
Specification -3	0.976	0.956	0.955	0.975	0.956	0.930	**0.779**	0.935
Specification -4	1.012	1.030	1.045	1.104	1.129	1.124	1.148	0.920
Specification -5	1.026	1.039	1.053	1.103	1.108	1.045	1.203	1.124
Specification -6	0.997	1.024	1.030	1.060	1.039	1.039	0.857	**0.908**
ROMANIA								
AR	0.625	0.935	1.218	1.398	1.565	1.694	2.158	2.687
Specification -1	1.015	1.023	1.030	1.053	1.105	1.145	1.221	1.287
Specification -2	1.056	1.119	1.152	1.219	1.294	1.350	1.502	1.632
Specification -3	1.054	1.204	1.331	1.478	1.601	1.732	1.825	1.825
Specification -4	1.116	1.243	1.248	1.359	1.406	1.463	1.560	1.798
Specification -5	1.068	1.217	1.301	1.419	1.471	1.552	1.630	1.679
Specification -6	1.064	1.198	1.279	1.425	1.551	1.691	1.830	1.964

See the notes to Table 2.

Table A16: Point forecast performance: Rolling forecasting - Factors are extracted using the PCA approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.429	0.770	1.015	1.257	1.489	1.719	2.576	3.585
Specification -1	1.050	1.041	1.081	1.099	1.133	1.164	1.190	1.244
Specification -2	1.117	1.192	1.211	1.358	1.507	1.642	1.430	1.248
Specification -3	1.140	1.316	1.372	1.473	1.548	1.543	1.457	1.146
Specification -4	1.119	1.108	1.097	1.169	1.305	1.385	1.234	1.102
Specification -5	1.125	1.178	1.277	1.329	1.392	1.393	1.433	1.246
Specification -6	1.210	1.375	1.411	1.448	1.509	1.505	1.326	1.064
CZECH REPUBLIC								
AR	0.348	0.497	0.638	0.770	0.875	0.981	1.252	1.586
Specification -1	0.999	**0.982**	**0.959**	**0.951**	**0.908**	**0.886**	**0.906**	1.035
Specification -2	1.096	1.103	1.106	1.208	1.220	1.284	1.415	1.388
Specification -3	1.285	1.321	1.229	1.203	1.185	1.375	1.404	1.351
Specification -4	1.101	1.091	1.182	1.366	1.411	1.460	1.391	1.220
Specification -5	1.251	1.304	1.426	1.509	1.344	1.257	1.309	1.163
Specification -6	1.270	1.377	1.377	1.358	1.253	1.308	1.239	1.253
GREECE								
AR	0.523	0.680	0.809	0.939	1.125	1.334	2.204	3.107
Specification -1	1.024	1.076	1.105	1.110	1.071	1.064	1.082	1.062
Specification -2	1.067	1.133	1.145	1.137	1.061	1.003	0.927	0.911
Specification -3	1.150	1.171	1.266	1.309	1.231	1.147	**0.664***	**0.588***
Specification -4	1.122	1.279	1.245	1.219	1.091	1.017	0.811	0.691*
Specification -5	1.207	1.318	1.363	1.362	1.273	1.215	0.840	0.673*
Specification -6	1.154	1.244	1.378	1.426	1.295	1.146	0.682	0.630*
HUNGARY								
AR	0.473	0.745	0.976	1.220	1.434	1.656	2.280	2.916
Specification -1	1.043	1.033	1.027	1.062	1.087	1.093	1.075	1.110
Specification -2	1.087	1.091	1.105	1.100	1.099	1.061	0.993	0.997
Specification -3	1.116	1.126	1.241	1.264	1.351	1.308	1.107	**0.835**
Specification -4	1.129	1.120	1.128	1.143	1.192	1.205	1.105	0.906
Specification -5	1.125	1.152	1.248	1.245	1.245	1.251	**0.937**	0.851
Specification -6	1.124	1.171	1.276	1.271	1.289	1.244	1.075	0.911
POLAND								
AR	0.308	0.508	0.705	0.881	1.063	1.202	1.586	2.023
Specification -1	0.956	**0.955**	**0.947**	**0.965**	**0.953**	**0.948**	1.048	1.123
Specification -2	1.017	1.069	1.128	1.245	1.300	1.277	1.339	1.398
Specification -3	0.984	1.036	1.145	1.239	1.210	1.099	**0.968**	1.104
Specification -4	1.080	1.091	1.055	1.091	1.125	1.129	1.276	1.179
Specification -5	0.995	1.053	1.169	1.254	1.159	1.068	1.105	1.162
Specification -6	**0.948**	1.030	1.107	1.246	1.279	1.215	1.106	1.231
ROMANIA								
AR	0.636	0.966	1.307	1.540	1.780	2.010	2.895	3.900
Specification -1	1.043	1.078	1.084	1.096	1.167	1.215	1.264	1.230
Specification -2	1.122	1.254	1.274	1.292	1.329	1.346	1.235	1.227
Specification -3	1.104	1.216	1.267	1.410	1.494	1.488	1.157	1.048
Specification -4	1.141	1.310	1.292	1.347	1.302	1.217	1.057	0.997
Specification -5	1.115	1.256	1.346	1.480	1.470	1.405	1.026	**0.928**
Specification -6	1.111	1.255	1.273	1.447	1.473	1.452	1.138	1.101

See notes to Table A5.

Table A17: Multi-horizon foecast comparison: Rolling forecasting - Factors are extracted using the PCA approach -

	short horizon		medium horizon		long horizon		all horizon	
BULGARIA	uSPA	aSPA	uSPA	aSPA	uSPA	aSPA	uSPA	aSPA
Spec.2 against Spec.1	-1.07	-1.02	-0.98	-0.75	0.74**	1.50**	-1.07	0.21
Spec.3 against Spec.2	-0.10	0.10	0.80**	0.87*	-0.93	-0.94	-0.93	-0.14
Spec.4 against Spec.2	0.76**	0.95*	0.47	0.85*	0.03	0.28	0.03	0.63
Spec.5 against Spec.4	-1.11	-0.40	1.93***	2.33***	-0.85	-0.34	-1.11	0.92*
Spec.6 against Spec.5	-2.50	-2.19	-2.86	-2.73	-0.89	-0.61	-2.86	-1.73
Spec.6 against Spec.2	-1.75	-1.58	-0.53	-0.14	-0.68	-0.61	-1.75	-0.63
CZECH REPUBLIC								
Spec.2 against Spec.1	-2.02	-1.91	-2.24	-2.12	-2.26	-1.53	-2.26	-2.05
Spec.3 against Spec.2	-0.31	-0.17	0.04	0.13	-0.94	-0.83	-0.94	-0.41
Spec.4 against Spec.2	-0.60	-0.48	-1.49	-1.32	-0.40	-0.10	-1.49	-0.70
Spec.5 against Spec.4	-0.16	0.29	1.10***	1.69**	-0.57	-0.18	-0.57	1.58**
Spec.6 against Spec.5	-0.29	-0.11	0.09	0.16	-0.91	-0.53	-0.91	-0.20
Spec.6 against Spec.2	-0.20	-0.13	0.14	0.23	-1.20	-0.79	-1.20	-0.23
GREECE								
Spec.2 against Spec.1	1.45***	1.55**	1.28***	1.34**	2.05***	2.91***	1.28***	2.14**
Spec.3 against Spec.2	-0.18	1.62**	0.25	0.58	0.33	0.40	-0.18	0.75
Spec.4 against Spec.2	-1.36	-0.28	-2.56	-2.16	-1.17	-0.86	-2.56	-1.39
Spec.5 against Spec.4	0.63*	1.43**	1.85***	2.14**	2.65***	3.15***	0.63***	2.98***
Spec.6 against Spec.5	-1.79	-1.32	-0.23	0.13	-0.96	-0.98	-1.79	-0.64
Spec.6 against Spec.2	-2.52	-0.07	0.12	0.38	0.75*	0.97*	-2.52	0.60
HUNGARY								
Spec.2 against Spec.1	0.86**	1.14**	0.53	0.57	1.36**	2.03**	0.53**	1.48**
Spec.3 against Spec.2	-0.42	-0.05	-0.64	-0.27	-4.22	-3.31	-4.22	-2.04
Spec.4 against Spec.2	-2.92	-1.53	-0.42	-0.21	0.03	0.04	-2.92	-0.28
Spec.5 against Spec.4	-0.02	0.16	0.94**	1.10**	0.12	0.35	-0.02	0.74*
Spec.6 against Spec.5	0.23	0.59	-1.60	-1.27	-3.26	-2.62	-3.26	-1.91
Spec.6 against Spec.2	-0.63	-0.35	-0.64	-0.23	-4.02	-3.17	-4.02	-2.29
POLAND								
Spec.2 against Spec.1	-0.75	-0.20	-0.56	-0.42	0.36	0.73*	-0.75	0.12
Spec.3 against Spec.2	1.71***	3.33***	1.58***	1.84**	1.13***	1.31**	1.13***	2.03***
Spec.4 against Spec.2	-1.12	-0.55	0.21	0.29	-0.76	-0.72	-1.12	-0.43
Spec.5 against Spec.4	1.30***	2.91***	1.21***	2.23***	2.15***	3.11***	1.21***	3.58***
Spec.6 against Spec.5	-0.20	0.45	-0.67	-0.51	-3.17	-2.46	-3.17	-1.73
Spec.6 against Spec.2	0.56**	2.88***	0.48*	0.87*	-1.29	-0.79	-1.29	0.44
ROMANIA								
Spec.2 against Spec.1	-1.65	-1.53	-1.30	-0.88	1.87***	2.42***	-1.65	0.60
Spec.3 against Spec.2	1.41**	2.10**	1.18***	1.98***	-1.94	-1.60	-1.94	1.01*
Spec.4 against Spec.2	1.74***	1.94**	0.96**	1.33**	-0.09	0.06	-0.09	0.92*
Spec.5 against Spec.4	-0.76	-0.04	0.88**	0.98**	-0.82	-0.24	-0.82	0.47
Spec.6 against Spec.5	0.26	0.58	-0.62	0.09	-0.93	-0.78	-0.93	-0.26
Spec.6 against Spec.2	1.60***	2.28**	1.38***	2.20***	-1.45	-1.16	-1.45	1.39**

Table A18: Mincer-Zarnowitz regressions for recursive forecasting exercise where factors are extracted using the PLS

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	12.21***	14.10***	17.67***	16.66***	17.88***	23.55***	32.34***	41.83***
Specification - 2	5.54*	2.31	1.10	1.33	5.94**	7.81**	10.25***	23.66***
Specification - 3	1.75	1.04	0.09	0.32	1.78	10.81***	26.66***	16.87***
Specification - 4	5.12*	3.80	4.73*	19.57***	27.43***	33.42***	19.48***	42.62***
Specification - 5	5.35*	2.11	0.17	0.49	4.80*	26.72***	26.05***	13.71***
Specification - 6	1.33	1.57	0.38	0.27	2.86	10.54***	26.25***	29.42***
CZECH REPUBLIC								
Specification - 1	0.64	1.19	1.42	2.30	2.74	4.06	14.03***	12.73***
Specification - 2	0.76	1.15	0.47	0.83	0.19	1.94	0.11	1.76
Specification - 3	2.25	1.66	0.70	1.01	5.43*	6.12**	1.95	5.13*
Specification - 4	0.03	1.63	0.32	4.67*	9.99***	8.14**	1.97	10.35***
Specification - 5	2.76	5.38*	2.92	1.31	0.38	1.75	19.37***	20.27***
Specification - 6	2.19	1.25	0.36	0.24	3.07	4.98*	1.99	3.83
GREECE								
Specification - 1	13.99***	23.09***	26.53***	48.10***	69.92***	101.82***	39.39***	31.97***
Specification - 2	3.78	8.18**	9.72***	16.18***	39.58***	50.29***	18.97***	29.22***
Specification - 3	6.20**	10.52***	8.35**	7.52**	12.40***	15.06***	12.22***	10.20***
Specification - 4	4.83*	6.64**	7.02**	7.89**	24.16***	36.14***	43.01***	29.96***
Specification - 5	7.78**	9.88***	8.05**	6.30**	10.08***	19.04***	27.16***	16.84***
Specification - 6	5.07*	6.42**	5.19*	4.91*	11.90***	22.87***	10.89***	17.37***
HUNGARY								
Specification - 1	2.55	0.77	0.76	0.49	1.93	4.57*	19.82***	23.46***
Specification - 2	4.70*	1.84	1.59	2.95	2.52	2.04	6.93**	19.58***
Specification - 3	5.31*	3.43	4.35	5.74*	14.12***	16.87***	12.54***	4.08
Specification - 4	5.72*	2.54	2.07	2.17	2.16	2.98	20.50***	40.31***
Specification - 5	4.93*	6.24**	8.62**	10.24***	12.33***	6.19**	32.77***	25.33***
Specification - 6	7.75**	4.57*	2.96	2.21	5.27*	7.47**	8.60***	3.37
POLAND								
Specification - 1	1.33	3.39	5.15*	5.85**	6.40**	6.90**	6.11**	6.65**
Specification - 2	7.16**	7.76**	8.31**	6.78**	7.48**	11.43***	1.91	2.13
Specification - 3	2.36	4.43	2.17	1.38	2.32	0.27	0.12	8.89***
Specification - 4	6.87**	2.01	0.40	0.88	5.50*	19.23***	19.97***	7.32**
Specification - 5	5.29*	2.57	0.77	0.07	0.93	4.65*	52.96***	5.00*
Specification - 6	4.24	3.51	1.05	0.27	1.21	1.28	1.40	8.76***
ROMANIA								
Specification - 1	1.61	3.32	4.34	5.42*	6.53**	6.67**	5.51*	13.89***
Specification - 2	6.94**	9.20***	11.69***	15.69***	18.38***	17.08***	9.10***	27.06***
Specification - 3	3.40	4.41	4.38	6.43**	7.93**	9.85***	3.13	7.06**
Specification - 4	7.72**	10.85***	11.68***	14.03***	14.51***	9.54***	10.04***	26.81***
Specification - 5	3.72	8.12**	11.35***	14.63***	13.86***	14.91***	18.47***	21.95***
Specification - 6	3.68	3.41	2.63	2.78	3.14	3.49	7.90**	5.86**

Notes: This table presents the p-values and chi-square test statistics with two degrees of freedom for Mincer-Zarnowitz efficiency test. Entries marked with an asterisk(s) (*** 1% level; ** 5% level; * 10% level) imply that competing model forecasts are not efficient compared to those of AR model.

Table A19: Mincer-Zarnowitz regressions for rolling forecasting exercise where factors are extracted using the PLS

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	12.81***	10.52***	9.33***	8.12**	10.35***	20.07***	7.81**	13.87***
Specification - 2	18.83***	26.43***	23.77***	9.10***	4.64*	5.29*	9.24***	3.53
Specification - 3	6.27**	2.86	0.72	2.00	1.60	9.53***	46.90***	2.92
Specification - 4	10.86***	15.47***	15.58***	13.63***	9.20***	14.52***	23.63***	14.91***
Specification - 5	8.32**	4.25	1.26	0.33	1.44	29.35***	50.59***	4.22
Specification - 6	7.00**	2.83	0.24	0.65	0.25	6.96**	59.98***	7.86**
CZECH REPUBLIC								
Specification - 1	1.18	1.73	1.88	2.12	1.13	1.73	12.54***	14.53***
Specification - 2	3.35	2.54	0.54	1.59	1.36	0.39	1.53	1.74
Specification - 3	4.23	2.65	1.36	3.22	8.28**	8.08**	0.31	1.15
Specification - 4	7.49**	6.68**	4.30	10.06***	20.91***	12.32***	0.24	7.03**
Specification - 5	9.54***	7.36**	3.01	9.40***	4.89*	6.72**	15.44***	17.62***
Specification - 6	3.58	1.44	0.16	0.89	6.06**	6.77**	5.16*	1.35
GREECE								
Specification - 1	14.24***	26.61***	30.60***	50.20***	78.60***	123.85***	33.57***	36.42***
Specification - 2	3.70	8.24**	7.79**	9.48***	17.67***	30.91***	15.83***	43.64***
Specification - 3	2.01	4.76*	5.70*	10.01***	20.61***	26.08***	19.16***	25.56***
Specification - 4	6.21**	8.61***	7.49**	6.76**	18.24***	32.02***	23.64***	27.17***
Specification - 5	2.79	3.84	1.33	2.62	15.50***	19.96***	28.90***	18.39***
Specification - 6	1.72	1.19	0.80	3.92	16.68***	18.68***	17.99***	50.46***
HUNGARY								
Specification - 1	2.87	2.87	2.73	2.75	6.25**	8.13**	23.31***	27.18***
Specification - 2	2.38	3.48	11.66***	14.11***	9.92***	8.60***	2.72	2.04
Specification - 3	3.66	6.64**	10.90***	24.20***	15.60***	14.58***	13.25***	7.22**
Specification - 4	0.68	3.01	10.13***	9.92***	6.42**	5.38*	7.50**	20.23***
Specification - 5	4.80*	12.59***	12.32***	26.09***	10.84***	2.92	13.16***	15.12***
Specification - 6	2.65	2.07	8.37***	16.40***	10.66***	7.27**	13.70***	8.15**
POLAND								
Specification - 1	1.15	2.07	3.35	4.98*	6.76**	8.42***	8.48***	13.16***
Specification - 2	4.82*	13.76***	24.83***	25.86***	20.29***	13.34***	4.36	6.11**
Specification - 3	2.58	7.70**	15.02***	17.44***	15.04***	8.98***	0.14	5.73*
Specification - 4	2.91	5.66*	11.58***	6.47**	7.52**	12.31***	43.04***	27.61***
Specification - 5	5.52**	5.36*	7.65**	6.28**	3.38	7.40**	109.18***	9.26***
Specification - 6	1.01	2.73	6.49**	7.05**	6.84**	3.45	4.43	13.57***
ROMANIA								
Specification - 1	8.53***	11.16***	18.01***	25.55***	46.03***	58.02***	52.02***	48.17***
Specification - 2	17.18***	21.55***	35.29***	54.99***	63.37***	59.15***	83.60***	45.16***
Specification - 3	4.70*	6.43**	9.41***	30.39***	23.00***	16.15***	38.50***	27.84***
Specification - 4	13.61***	18.78***	22.26***	32.60***	47.95***	32.54***	66.83***	70.91***
Specification - 5	11.01***	22.22***	24.09***	38.80***	40.36***	22.36***	60.90***	26.62***
Specification - 6	5.12*	3.21	2.28	16.26***	4.71*	6.85**	47.33***	31.47***

See notes to Table A18.

Table A20: Mincer-Zarnowitz regressions for recursive forecasting exercise where factors are extracted using the PCA

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	8.31**	12.01***	17.36***	22.07***	26.46***	32.18***	117.43***	542.19***
Specification - 2	19.37***	23.03***	29.75***	36.98***	47.48***	65.77***	88.47***	111.84***
Specification - 3	18.30***	31.89***	40.82***	50.61***	62.59***	78.46***	93.77***	327.32***
Specification - 4	8.84***	11.30***	20.84***	56.49***	95.50***	135.97***	110.49***	266.19***
Specification - 5	1.88	7.21**	21.53***	49.98***	120.49***	193.55***	160.38***	195.90***
Specification - 6	30.76***	49.41***	66.49***	103.16***	122.76***	149.57***	119.28***	143.41***
CZECH REPUBLIC								
Specification - 1	1.11	1.66	3.09	6.07**	8.12**	10.55***	20.41***	136.39***
Specification - 2	2.51	4.78*	7.25**	15.22***	22.34***	31.17***	47.32***	340.31***
Specification - 3	4.20	4.92	9.18***	21.18***	49.37***	92.24***	102.71***	100.65***
Specification - 4	6.86**	17.41***	28.70***	46.86***	70.89***	91.29***	102.27***	461.52***
Specification - 5	8.31**	7.37**	11.76***	18.33***	33.70***	50.18***	105.44***	111.60***
Specification - 6	1.68	1.66	4.62*	17.88***	42.34***	79.10***	128.73***	133.47***
GREECE								
Specification - 1	4.16	5.91**	7.52**	15.33***	25.60***	50.33***	143.75***	264.27***
Specification - 2	0.23	0.25	0.67	1.10	6.34**	27.24***	155.90***	270.34***
Specification - 3	0.24	0.48	0.11	4.23	12.47***	23.00***	39.91***	77.21***
Specification - 4	1.28	1.25	6.02**	11.01***	18.52***	52.69***	226.36***	197.66***
Specification - 5	0.12	0.04	1.34	7.70**	21.23***	43.29***	79.32***	113.79***
Specification - 6	0.18	1.02	5.02*	17.14***	29.06***	47.63***	54.62***	83.94***
HUNGARY								
Specification - 1	1.35	5.63**	10.66***	17.45***	24.81***	32.75***	43.54***	76.69***
Specification - 2	0.49	0.77	2.30	5.56**	10.82***	18.57***	39.84***	322.46***
Specification - 3	9.04***	10.29***	14.98***	12.41***	15.48***	20.78***	26.61***	47.80***
Specification - 4	0.98	0.09	0.37	2.35	5.28*	11.36***	40.53***	109.45***
Specification - 5	5.04*	3.45	3.12	3.21	9.98***	20.44***	46.15***	101.02***
Specification - 6	5.30*	4.87*	9.28 ***	9.18***	13.62***	19.00***	16.60***	33.68***
POLAND								
Specification - 1	0.79	0.27	0.28	0.87	2.09	4.78*	23.05***	94.02***
Specification - 2	4.31	6.95**	13.50***	17.21***	24.66***	30.26***	44.38***	133.30***
Specification - 3	2.16	3.68	15.67***	29.05***	48.70***	55.30***	42.26***	87.22***
Specification - 4	13.39***	22.41***	36.66***	42.08***	58.12***	68.21***	95.44***	107.86***
Specification - 5	2.21	7.14**	17.72***	27.51***	53.13***	68.81***	163.02***	163.02
Specification - 6	3.90	2.36	5.45*	10.22***	20.98***	29.94***	45.72***	127.56***
ROMANIA								
Specification - 1	1.53	4.06	7.20**	10.98***	16.00***	22.54***	71.43***	160.00***
Specification - 2	3.88	7.22**	10.14***	16.32***	26.05***	41.60***	108.30***	159.73***
Specification - 3	3.03	3.68	8.54***	20.14***	44.70***	76.99***	147.05***	203.31***
Specification - 4	5.58*	9.83***	13.86***	23.92***	41.35***	51.79***	84.11***	259.10***
Specification - 5	2.12	2.85	5.34*	14.78***	33.85***	56.60***	102.60***	197.00***
Specification - 6	3.72	4.80*	8.21**	17.11***	41.50***	81.52***	151.63***	244.71***

See notes to Table A18.

Table A21: Mincer-Zarnowitz regressions for rolling forecasting exercise where factors are extracted using the PCA

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
Specification - 1	2.03	2.43	3.50	11.24***	24.93***	37.07***	75.98***	324.45***
Specification - 2	16.49***	30.24***	34.20***	57.70***	96.75***	159.12***	187.02***	207.17***
Specification - 3	13.35***	31.09***	49.00***	100.16***	134.48***	167.31***	229.51***	433.34***
Specification - 4	5.35*	12.36***	19.01***	38.81***	62.22***	89.96***	107.26***	179.47***
Specification - 5	2.24	8.74***	24.09***	57.15***	132.74***	225.23***	224.73***	254.56***
Specification - 6	8.61***	16.95***	24.42***	53.85***	101.35***	151.75***	170.13***	270.25***
CZECH REPUBLIC								
Specification - 1	0.96	1.79	2.89	2.73	2.65	3.82	8.58***	60.36***
Specification - 2	10.31***	12.49***	19.86***	36.69***	41.28***	51.98***	62.32***	382.43***
Specification - 3	3.27	4.89*	7.78**	14.10***	21.90***	73.11***	102.01***	127.88***
Specification - 4	5.27*	12.26***	28.26***	51.15***	72.43***	87.41***	101.61***	185.82***
Specification - 5	13.23***	10.42***	23.74***	42.89***	33.40***	39.95***	113.55***	111.80***
Specification - 6	0.57	2.08	11.49***	23.09***	25.26***	55.06***	73.95***	88.50***
GREECE								
Specification - 1	1.57	5.41*	6.69**	12.24***	20.07***	44.35***	160.43***	299.14***
Specification - 2	0.52	0.40	1.04	3.76	11.74***	42.36***	119.73***	281.01***
Specification - 3	1.21	1.87	6.61**	19.82***	47.26***	70.35***	74.03***	84.04***
Specification - 4	0.85	4.20	8.76***	19.00***	30.35***	68.29***	129.17***	205.20***
Specification - 5	4.09	12.51***	18.28***	32.09***	57.99***	88.15***	193.23***	353.65***
Specification - 6	2.57	4.08	15.21***	44.70***	73.77***	98.24***	93.72***	99.56***
HUNGARY								
Specification - 1	6.69**	15.01***	18.55***	26.65***	33.49***	44.23***	43.99***	55.48***
Specification - 2	3.92	5.30*	7.05**	10.32***	16.98***	22.28***	28.25***	119.67***
Specification - 3	1.43	3.84	10.01***	17.25***	23.91***	24.28***	42.56***	37.03***
Specification - 4	7.78**	5.71*	6.93**	6.16**	13.44***	27.32***	76.13***	90.96***
Specification - 5	6.36**	7.83**	15.56***	22.29***	29.10***	37.00***	46.74***	100.29***
Specification - 6	4.91*	4.45	7.77**	11.59***	17.64***	22.32***	45.89***	71.07***
POLAND								
Specification - 1	3.07	2.69	3.91	9.70***	15.17***	21.40***	44.20***	92.61***
Specification - 2	2.16	7.14**	13.41***	16.33***	26.34***	38.13***	114.09***	233.45***
Specification - 3	2.39	14.66***	38.49***	37.42***	37.34***	38.66***	49.44***	114.66***
Specification - 4	4.02	11.25***	19.11***	14.54***	19.25***	28.70***	99.44***	130.38***
Specification - 5	3.86	18.37***	39.22***	25.94***	17.37***	21.65***	87.79***	119.27***
Specification - 6	6.54**	12.00***	20.72***	20.28***	28.91***	41.12***	79.62***	206.83***
ROMANIA								
Specification - 1	6.46**	9.91***	19.88***	32.79***	62.63***	93.47***	189.59***	215.47***
Specification - 2	8.84***	18.44***	32.96***	49.93***	76.52***	110.50***	176.48***	216.22***
Specification - 3	2.10	6.28**	13.36***	45.29***	77.38***	97.01***	151.52***	167.11***
Specification - 4	6.51**	18.82***	33.83***	56.34***	82.77***	77.36***	139.43***	159.02***
Specification - 5	3.26	8.18***	19.06***	52.20***	58.29***	58.22***	129.51***	172.54***
Specification - 6	4.34	12.13***	23.60***	59.81***	77.25***	98.14***	135.97***	148.13***

See notes to Table A18.

Table A22: Core Inflation: Rolling forecasting - Factors are extracted using the PLS approach -

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.312	0.498	0.657	0.795	0.908	1.057	1.511	2.159
Specification -1	1.022	0.969	0.887**	0.799***	0.745***	0.677***	0.526***	**0.375*****
Specification -2	1.029	0.924*	0.850**	**0.743*****	**0.690*****	0.612***	0.517***	0.382***
Specification -3	1.096	0.951	0.830**	0.748***	0.703***	**0.584*****	**0.462*****	0.468***
Specification -4	1.098	0.995	0.997	0.970	0.891	0.693***	0.495***	0.454***
Specification -5	1.179	1.018	0.920	0.888	0.878	0.741***	0.588***	0.555***
Specification -6	1.042	**0.898**	**0.825****	0.750***	0.691***	0.595***	0.464***	0.402***
CZECH REPUBLIC								
AR	0.224	0.340	0.425	0.499	0.565	0.627	0.775	0.893
Specification -1	1.339	1.332	1.075	**0.929**	**0.802*****	**0.702*****	0.619***	0.615***
Specification -2	1.187	1.181	1.106	1.069	0.895	0.751***	**0.613*****	**0.422*****
Specification -3	1.165	1.163	1.209	1.261	1.093	0.990	0.686**	0.470***
Specification -4	1.181	1.154	1.038	1.012	0.859**	0.842*	0.651**	0.569***
Specification -5	1.151	1.158	1.248	1.296	1.212	1.033	0.744*	0.598***
Specification -6	1.185	1.226	1.219	1.194	0.971	0.951	0.682**	0.511***
GREECE								
AR	0.594	0.729	0.829	0.869	1.001	1.107	1.741	2.261
Specification -1	0.884**	0.811	0.748**	0.713**	0.646***	0.541***	0.343***	**0.252*****
Specification -2	**0.765*****	**0.622****	**0.580*****	0.557***	**0.551*****	**0.471*****	**0.301*****	0.257***
Specification -3	0.829***	0.706**	0.651**	0.524***	0.567***	0.546***	0.389***	0.261***
Specification -4	0.803***	0.668**	0.631***	**0.514*****	0.599***	0.541***	0.344***	0.299***
Specification -5	0.858**	0.747*	0.679**	0.602***	0.644***	0.660**	0.348***	0.286***
Specification -6	0.813***	0.689**	0.615***	0.529***	0.639***	0.606***	0.321***	0.304***
HUNGARY								
AR	0.274	0.413	0.506	0.616	0.709	0.794	1.116	1.433
Specification -1	1.190	1.166	1.073	0.994	0.943	0.869	0.630**	0.538***
Specification -2	1.240	**0.994**	0.859	0.820	0.952	0.827	**0.549****	0.443***
Specification -3	1.194	1.060	0.891	0.843*	0.940	0.770	0.632**	0.366***
Specification -4	1.161	1.065	0.884	0.876	0.967	0.679**	0.635**	0.554***
Specification -5	1.191	1.072	0.936	0.826**	0.941	0.714*	0.823	0.415***
Specification -6	1.176	1.072	**0.852***	**0.809*****	**0.871**	**0.651****	0.569**	**0.355*****
POLAND								
AR	0.256	0.387	0.495	0.595	0.688	0.755	0.939	1.096
Specification -1	1.041	0.990	0.840**	0.777***	0.732***	0.683***	0.599***	0.545***
Specification -2	0.919	0.844***	**0.664*****	**0.568*****	**0.494*****	**0.517*****	0.438***	**0.426*****
Specification -3	0.866**	0.817***	0.708***	0.625***	0.564***	0.582***	0.591***	0.470***
Specification -4	0.920	0.879**	0.724***	0.609***	0.536***	0.597***	**0.428*****	0.426***
Specification -5	0.899**	0.868**	0.789***	0.669***	0.605***	0.707***	0.562***	0.501***
Specification -6	**0.836*****	**0.790*****	0.736***	0.628***	0.547***	0.570***	0.502***	0.430***
ROMANIA								
AR	0.321	0.467	0.640	0.824	0.973	1.096	1.386	1.595
Specification -1	1.128	1.192	1.153	1.141	1.118	1.078	1.013	0.837*
Specification -2	1.092	1.120	1.032	1.025	0.997	0.910	**0.759****	0.643***
Specification -3	1.188	1.190	1.031	0.889	0.994	1.130	0.849	0.504***
Specification -4	1.083	1.077	1.065	1.013	0.937	**0.834**	1.015	1.020
Specification -5	1.172	1.152	**0.941**	**0.768****	**0.893**	0.953	0.856	0.545***
Specification -6	1.276	1.268	0.963	0.825**	0.924	1.021	0.761*	**0.495*****

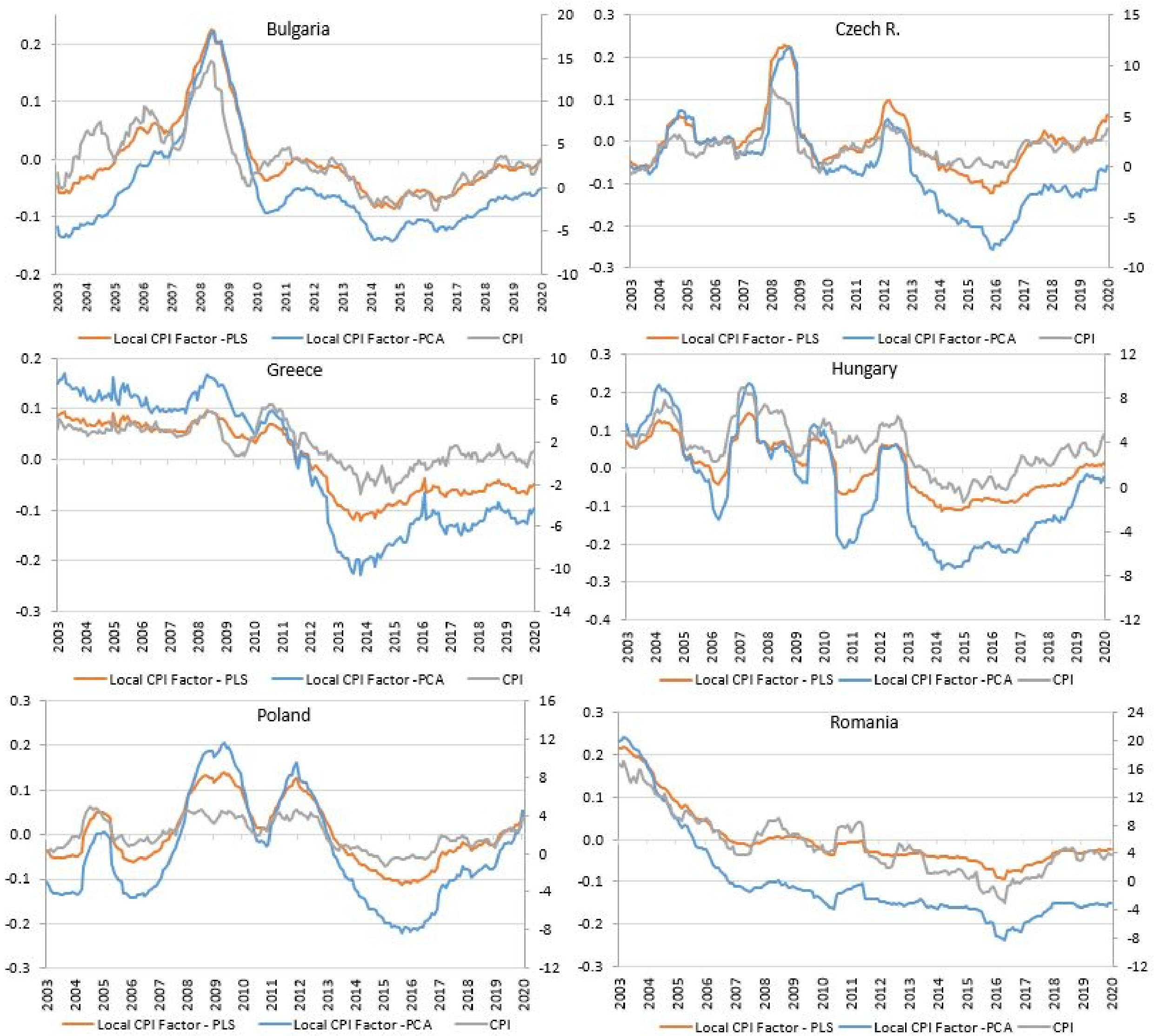
See notes to Table A5.

Table A23: MSFEs based on the use of different dimension-reduction and shrinkage methods - Rolling forecasting

BULGARIA	h=1	h=2	h=3	h=4	h=5	h=6	h=9	h=12
AR	0.429	0.770	1.015	1.257	1.489	1.719	2.576	3.585
MSFE Best w/o shrinkage	1.071	**0.911**	0.731***	0.628***	**0.582*****	0.596***	0.605**	**0.395*****
GPR	1.050	0.954	**0.714*****	**0.604*****	0.590***	**0.585*****	**0.564****	0.447**
VBDVS	1.057	0.951	0.765***	0.840***	0.755***	0.725***	0.608***	0.550***
ENET	5.068	2.779	1.954	1.355	0.972	0.904	0.622**	0.406***
LASSO	5.029	2.796	1.924	1.350	0.973	0.886	0.630**	0.397***
CZECH REPUBLIC								
AR	0.348	0.497	0.638	0.770	0.875	0.981	1.252	1.586
MSFE Best w/o shrinkage	1.049	**0.984**	0.917	0.861*	0.780**	0.667***	0.505***	**0.385*****
GPR	1.041	1.014	**0.914**	**0.813****	**0.731****	**0.603*****	**0.478*****	0.398***
VBDVS	**0.963**	0.992	0.989	0.899	0.881	0.791**	0.784*	0.686*
ENET	1.376	1.113	1.030	0.946	0.837**	0.757**	0.597**	0.453***
LASSO	1.390	1.110	1.054	0.951	0.851**	0.763**	0.596**	0.456**
GREECE								
AR	0.523	0.680	0.809	0.939	1.125	1.334	2.204	3.107
MSFE Best w/o shrinkage	0.903***	0.854*	0.776***	**0.674*****	**0.587*****	**0.489****	0.287**	0.207**
GPR	**0.902*****	**0.841****	**0.773*****	0.681***	0.608***	0.512**	**0.265****	**0.199****
VBDVS	1.007	0.901**	0.911**	0.845*	0.747**	0.709*	0.477**	0.416**
ENET	1.891	1.295	1.227	1.219	1.064	0.830	0.356**	0.273**
LASSO	1.850	1.285	1.206	1.251	1.087	0.848	0.371**	0.277**
HUNGARY								
AR	0.473	0.745	0.976	1.220	1.434	1.656	2.280	2.916
MSFE Best w/o shrinkage	1.006	0.913	**0.839***	0.820	0.738*	**0.619****	0.366**	0.360**
GPR	**0.964**	**0.909**	0.846*	**0.793***	**0.722***	0.623**	**0.345****	**0.359****
VBDVS	1.089	0.954	0.952	0.893	0.862	0.792*	0.560**	0.507**
ENET	1.811	1.070	1.501	1.222	1.044	0.896	0.690	0.409**
LASSO	1.787	1.080	1.502	1.228	1.052	0.905	0.693	0.407**
POLAND								
AR	0.308	0.508	0.705	0.881	1.063	1.202	1.586	2.023
MSFE Best w/o shrinkage	**0.856****	**0.813*****	**0.779*****	**0.721*****	0.640***	0.497***	0.362***	0.336***
GPR	0.867**	0.857**	0.781***	0.744***	**0.633*****	**0.496*****	**0.358*****	**0.319*****
VBDVS	0.997	0.897**	0.907**	0.819***	0.757***	0.726***	0.818*	0.524**
ENET	1.739	1.135	1.174	1.015	0.892	0.755**	0.591**	0.447***
LASSO	1.741	1.150	1.156	1.012	0.904	0.751**	0.601**	0.445***
ROMANIA								
AR	0.636	0.966	1.307	1.540	1.780	2.010	2.895	3.900
MSFE Best w/o shrinkage	1.074	1.009	0.874	0.730***	**0.617*****	0.634***	0.695**	**0.460*****
GPR	1.074	**0.988**	**0.859****	**0.805****	0.733***	**0.595*****	0.679**	0.517***
VBDVS	1.025	1.008	0.888***	0.906*	0.843**	0.823*	**0.596*****	0.686**
ENET	3.332	2.115	1.508	1.083	0.852*	0.861	0.759	0.562***
LASSO	3.282	2.139	1.528	1.104	0.834*	0.872	0.778	0.561***

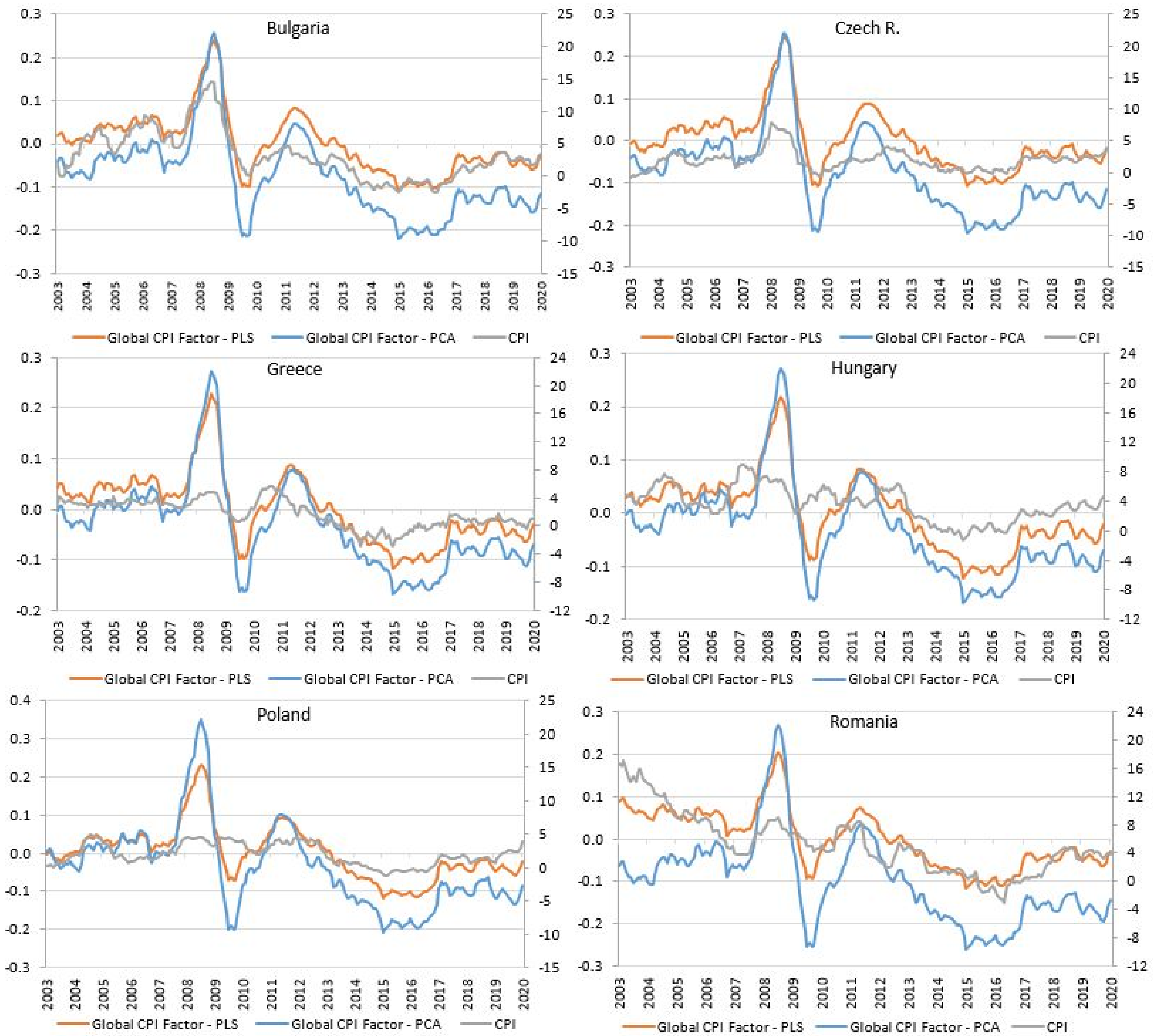
See notes to Table 6.

Figure A1: Time series evolution of Local CPI factors along with headline inflation rates



Notes: This figure shows the time series plots of first Local CPI factors along with headline inflation rate of corresponding EM European country, where factors are obtained from using the PLS and PCA factor extraction methods.

Figure A2: Time series evolution of Global CPI factors along with headline inflation rates



Notes: This figure shows the time series plots of first Global CPI factors along with headline inflation rate of corresponding EM European country, where factors are obtained from using the PLS and PCA factor extraction methods.

TVP-VAR-Based Dynamic Connectedness Approach

To construct inflation connectedness measures, we run the following TVP-VAR model:

$$x_t = D_t x_{t-1} + u_t \qquad e_t, \sim N(0, S_t) \tag{23}$$

$$vec(D_t) = vec(D_{t-1}) + v_t, \qquad u_t \sim N(0, R_t) \tag{24}$$

where x_t, x_{t-1} and e_t are $k \times 1$ dimensional vector and D_t and S_t are $k \times k$ dimensional matrices. $vec(D_t)$ and u_t are $k^2 \times 1$ dimensional vectors whereas R_t is a $k^2 \times k^2$ dimensional matrix.[30] Then, we first transform the TVP-VAR to its vector moving average (VMA) representation using the following equation: $x_t = \sum_{i=1}^{p} D_{it} x_{t-i} + e_t = \sum_{j=0}^{\infty} A_{jt} e_{t-j}$. Secondly, we compute the H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD). Hence, $\tilde{\phi}^g_{ij,t}(H)$ represents the influence country j inflation rate has on the inflation rate of country i with regard to its forecast error variance share which can be defined as:

$$\phi^g_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} (\iota'_i A_t S_t \iota_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\iota_i A_t S_t A'_t \iota_i)}, \qquad \tilde{\phi}^g_{ij,t}(H) = \frac{\phi^g_{ij,t}(H)}{\sum_{j=1}^{k} \phi^g_{ij,t}(H)}$$

where $\sum_{j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = k$, and ι_i corresponds to a selection vector with unity on the ith position and zero otherwise. Then, we compute the total connectedness index (TCI) through the use of the GFEVD as follows:

$$TO_{jt} = \sum_{i=1, i\neq j}^{k} \tilde{\phi}^g_{ij,t}(H) \tag{25}$$

$$FROM_{jt} = \sum_{i=1, i\neq j}^{k} \tilde{\phi}^g_{ji,t}(H) \tag{26}$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{27}$$

$$TCI_t = k^{-1} \sum_{j=1}^{k} TO_{jt} \equiv k^{-1} \sum_{j=1}^{k} FROM_{jt}. \tag{28}$$

$$NPDC_{ij,t} = \tilde{\phi}_{ij,t}(H) - \tilde{\phi}_{ji,t}(H) \tag{29}$$

where $\tilde{\phi}^g_{ij,t}(H)$ represents the impact a shock in inflation rate of country j has on the country i 's inflation. Eq. (25) illustrates the aggregated impact a shock in a country inflation rate j has on all *other* countries inflation rates which is defined as *total directional connectedness to others*. Eq. (26) indicates the aggregated influence all *other* countries have on country j (*total directional connectedness from others*). Eq. (27) subtracts the impact of country j has on others from the influences of *others* have on country j, resulting in the *net total directional connectedness* which

[30]The optimal 1-lag length is selected by the Bayesian information criterion (BIC).

provides information whether a country is a net transmitter or a net receiver of shocks. Country j is a net transmitter (*receiver*) of inflation shocks - and hence driving (*driven by*) the network - when the impact of a country j has on others is larger (*smaller*) than the influence all others have on country j, $NET_{jt} > 0$ ($NET_{jt} < 0$). Eq. (28) shows the TCI_t that is the average impact one country has on all $others$. Higher values of this measure implies a higher interconnectedness of the network, suggesting that a inflation shock in one country will influence other countries. Finally, Eq. (29) defines *net pairwise directional connectedness* ($NPDC_{ij,t}$) which indicates whether a shock to country j inflation is driving country i domestic inflation rate or vice versa.

Table A24: Variables definitions and data sources - Panel regression

Variables	Definition	Source
Current Account Balance	Current Account Balance / GDP	Bloomberg
Budget Balance	Budget Balance / GDP	Bloomberg
Government Debt	Goverment Debt / GDP	Bloomberg
Households Cons.	Household consumption /GDP	Bloomberg
Unemployment Rate	Unemployment rate	Bloomberg
Real GDP Growth	Real GDP Growth year over year	Bloomberg
CDS	5-Year Credit Default Swaps	Bloomberg
Exports	Total exports / GDP	Bloomberg
Imports	Total imports / GDP	Bloomberg
Uncertainty	Country specific uncertainty Index	St Louis FRED
REER	Real effective exchange rate	BIS
FX Reserves	FX Reserve / GDP	IMF

Notes: Uncertainty index determines uncertainty using the frequency of the selfsame word in the quarterly Economist Intelligence Unit country reports. Real effective exchange rates are calculated as weighted averages of bilateral exchange rates adjusted by relative consumer prices.