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How local is the local inflation factor? Evidence from emerging European countries[☆]

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A R T I C L E   I N F O

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A B S T R A C T

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 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 that tend to increase the importance of global factors for domestic inflation.

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. 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. Even for developed countries, the importance of the 'globalization of inflation', and its implications for the conduct of domestic monetary policy, has been contested. In this paper, we address the relevance of the globalization-of-inflation phenomenon for emerging market (EM) economies, analyzing a number of emerging European economies.

There are a number of reasons for focusing on less developed countries. Firstly, less advanced countries typically experience more variable inflation rates, putting a premium on the accurate modeling and forecasting of inflation in those countries, both for the conduct of policy by monetary authorities and 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, that only affect the inflation gap). Hence, for the conduct of monetary

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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.

As for developed economies, there does not appear to be a clear consensus on the importance of global factors for domestic inflation rates for EM economies. (We review a number of the studies in Section 2.) There are a number of issues that might affect the findings, and we seek to provide a detailed examination of some of these. 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 with 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,[1] 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.

As part of the choice of forecasting model, it may be important to allow for non-linearities. At least for the U.S., evidence has accumulated against the traditional Phillips curve, with the 'missing disinflation' in the U.S. 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 (2020)). McLeay and Tenreyro (2019) argue that the actions of monetary authorities will diminish the observed responsiveness of prices to slack, leading to a flattening of the Phillips curve. Atkeson and Ohanian (2001) had earlier found that a simple average of the four quarterly inflation 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 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, Mishkin, and Sufi (2019)). We consider whether our findings change when we allow for non-linearities.

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 'globalization of inflation' phenomenon is sometimes understood to go 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.[2] 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.

Looking ahead: in our baseline linear models (described in Section 4), we find that global factors play an important role in determining European EM national headline inflation rates, in addition to the explanatory power provided by local, domestic factors; thus inflation is a global phenomenon for the European EM countries', just as it has found to be for advanced economies (see Section 5). 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 baseline findings are shown to be robust to other modeling approaches. They carry over to factor-selection methods that enforce sparsity, as well as to a machine-learning method that allows for a non-linear relationship between national inflation rates and the sets of factors. These results serve as a robustness check, and they extend the analysis over a range of models that are becoming increasingly popular in the literature. The additional

[1] A case in point is the study by Gillitzer and McCarthy (2019), who show 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 below, in the main text) does not favor 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)).

[2] See e.g., Ball and Mazumder (2020), who argue that large relative price changes may also occur in industries other than food and energy, and suggest measuring inflation using the weighted median of price changes across industries (proposed as a measure of core inflation by Bryan and Cecchetti (1993)).

methods are described in Section 6.1, and the results in Section 6.2. We consider a number of methods of evaluating forecast performance – we look at path forecasts and the horizon of predictability – 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 EM economies. In Section 7 we consider 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. Section 8 casts light on the country-level characteristics that make a country's inflation rate more responsive to global inflation. That is, we explore the potential propagation channels of global factors on domestic inflation rates for emerging markets.

2. Literature review

Before presenting our approach and results, we briefly review some of the literature on the relative importance of global factors and domestic factors (including a country's monetary policy), as determinants of countries' inflation rates, for both developed and developing countries. Ciccarelli and Mojon (2010) argue that the international character of economic fluctuations is not new (see, e.g., Kose, Otrok, and Whiteman (2003)), but suggest 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*.[3] 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. However, the importance of the 'globalization of inflation' for the effectiveness of domestic monetary policy has been disputed,[4] as has the appropriate way of modeling and forecasting inflation.

One reason for suspecting that global factors might have been more important is the literature on international interconnectedness, as measured by global value chains; see e.g., Auer, Borio, and Filardo (2017). Greater international interconnectedness might result in an increase in the importance of 'global slack' (relative to domestic conditions) in determining national inflation rates. Kabukçuoğlu and Martínez-García (2018) find that modeling 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, Becker, Bratsiotis, and Osborn (2017, p.2) suggest that '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 favor of the globalization of inflation is also equivocal. Duncan and Martínez-García (2019) consider a range of models for 14 EM 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, Moessner, and Takáts (2019) find a diminished role for global inflation in determining EM 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 EM economies. Hałka and Szafranek (2016) find that 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 the output gap for European emerging countries' inflation rates, although core CPI was less affected than food and energy.

3. Data

We collected a large set of macroeconomic indicators on the Central and Eastern European countries: Bulgaria, Czech Republic, Greece, Hungary, Poland, and Romania (hereinafter referred to as EM European countries). We selected EM European countries which have made the largest strides in terms of globalization in recent years.[5] The dataset 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: the European Commission economic sentiment index, Market PMI survey, etc. To capture the

[3] That said, it has long been recognized 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).

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

[5] See Gygli, Haelg, and Sturm (2019).

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

potential vulnerability of EM European countries to external factors, we also considered the current account balance and export and import value indices. The macroeconomic indicators were downloaded from Bloomberg.

In addition to the macroeconomic indicators, we employ a large dataset of disaggregated harmonized indices of consumer prices (HICP), up to the 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', 'dental services', etc. The number of HICP components ranges from 73 to 89 indices across countries, since not all items are not available for all countries.[6] The disaggregated price data were obtained from the Eurostat database.

To construct a proxy for global inflation, we collected 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 was based on data availability: earlier-period high-quality data were not available for some countries we would have otherwise included. The country-level headline consumer price indices were taken from the IMF database.

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.

4. Methodology

4.1. 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 & Mojon, 2010; Mumtaz, Simonelli, & Surico, 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, Poncela, and Rodríguez (2015), Groen and Kapetanios (2016), PLS estimates the latent factors by maximizing the covariance 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, Hastie, et al. (2001). For each dataset X, the algorithm standardizes each predictor variable 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 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 pth PLS direction $\widehat{\gamma}_p$ solves the following optimization problem:

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

where M denotes the sample covariance matrix of the x_j. The condition $\alpha' M \widehat{\gamma}_k = 0$ 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 factors that summarize 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

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

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

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 developed 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 the inflation rates of all countries), the 'EM inflation factor' (EMCPI, constructed using only inflation rates of emerging countries), and the 'developed market inflation factor' (DMCPI, constructed using only inflation rates of developed countries).

4.2. 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 scheme and an 84-month fixed-length rolling window forecasting scheme to generate forecasts from the different specifications. We design a set of models that allow 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 LocalMACRO factor). That is, we are not so 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 constructing 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. Or, for example, the LocalCPI factor may partly reflect global developments. 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 with the interpretation. Hence, the forecasting exercise consists of the following models:[8]

- **Specification 1**: Local macro factor model *(+LocalMACRO)*
  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \varepsilon_{t+h}$
- **Specification 2**: Local inflation factor model *(+LocalCPI)*
  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \varepsilon_{t+h}$
- **Specification 3**: EM inflation factor model *(+emCPI)*
  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \theta' F_t^{EMCPI} + \varepsilon_{t+h}$
- **Specification 4**: Developed market inflation factor model *(+dmCPI)*
  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \theta' F_t^{DMCPI} + \varepsilon_{t+h}$
- **Specification 5**: Augmented inflation factor model *(+em_dmCPI)*
  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \theta' F_t^{EMCPI} + \delta' F_t^{DMCPI} + \varepsilon_{t+h}$
- **Specification 6**: Global inflation factor model *(+GlobalCPI)*
  $y_{t+h} = \mu + \mathcal{L}^p y_t + \beta' F_t^{LocalMACRO} + \vartheta' F_t^{LocalCPI} + \theta' F_t^{GlobalCPI} + \varepsilon_{t+h}$

where y_t, alternatively, denotes the year-over-year inflation rates of European emerging countries, L^p is shorthand for a lag polynomial of order p, and F_t^j for j = [LocalMACRO, LocalCPI, EMCPI, DMCPI, GlobalCPI] represents the estimated country-specific common factors described in Section 4.1.[9] The lag length p of the AR component of each specification type is selected based on the SIC. While Specifications 1 and 2 enable us to assess the importance of local inflation and macro factors in addition to lags of the inflation rate and constant, Specifications 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-, and 12-step-ahead forecasts. Furthermore, we compare forecast accuracy using the mean squared forecast error (MSFE).

In addition to these models, we examine the usefulness of various time-varying parameter and shrinkage models in Section 6. 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.

4.3. Forecast evaluation

Our baseline forecasting results consist of the standard approach of comparing models' forecasts for a particular horizon, and of testing the null of equal predictive ability, for that *specific* horizon, popularized by the Diebold and Mariano (1995) test (DM). Various extensions have been proposed, such as the Giacomini and White (2006) tests of *conditional* predictive ability, which remain applicable

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

[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.

when the forecasts come from nested models (as do the tests of Clark and West (2007)).

However, we also consider the evaluation of forecast performance based on the forecast path. A forecast user (e.g., a central banker) may be 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 & 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 sidestep 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).

Hence, we utilize the multi-horizon superior predictive ability (SPA) test of Quaedvlieg (2021), and we report results for the DM and related tests. 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 squared error loss, the models' loss differentials are given by:

$$\boldsymbol{d}_{ij,t} \equiv \boldsymbol{L}_{i,t} - \boldsymbol{L}_{j,t}, \tag{2}$$

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 $\boldsymbol{\mu}_{ij} \equiv \lim_{T\to\infty} \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{\mu}_{ij,t}$.[10] We test the following hypothesis of equal predictive performance at a single horizon h, corresponding to a standard DM test:

$$H^{\mathrm{DM}} : \mu^h_{ij} = 0 \tag{3}$$

$$t^h_{\mathrm{DM},ij} = \frac{\sqrt{T}\bar{d}^h_{ij}}{\hat{\omega}^h_{ij}} \tag{4}$$

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 hth 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 model j at some specific horizons, while 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 tests: the 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 $\mu^{(\mathrm{Uniform})}_{ij} = \min_h \mu^h_{ij}$ for the uSPA and $\mu^{(\mathrm{Avg})}_{ij} = w'\mu_{ij} = \sum_{h=1}^{H} w_h \mu^h_{ij}$ 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:

$$H_{0,\mathrm{uSPA}} : \mu^{(\mathrm{Unif})}_{ij} \leq 0 \tag{5}$$

$$t_{\mathrm{uSPA},ij} = \min_h \frac{\sqrt{T}\bar{d}^h_{ij}}{\hat{\omega}^h_{ij}} \tag{6}$$

against the one-sided alternative that $\mu^{(\mathrm{Uniform})}_{ij} > 0$ using the t_{uSPA} test statistic, which is the minimum of DM test statistics defined in Eq. (4). Similarly, the associated null for the aSPA test can be written as:

$$H_{0,\mathrm{ASPA}} : \mu^{(\mathrm{Avg})}_{ij} \leq 0 \tag{7}$$

$$t_{\mathrm{aSPA},ij} = \frac{\sqrt{T}\bar{d}_{ij}}{\hat{\zeta}_{ij}} \tag{8}$$

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

5. Results

5.1. Do global inflation factors drive local inflation rates?

Fig. 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 Fig. 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 & Mojon, 2010; Mumtaz et al., 2011; Parker, 2018). Fig. 1 shows that although the local CPI factor estimated based on disaggregated CPI data 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 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 the global CPI and EM CPI factors are slightly higher than the local CPI factor.

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

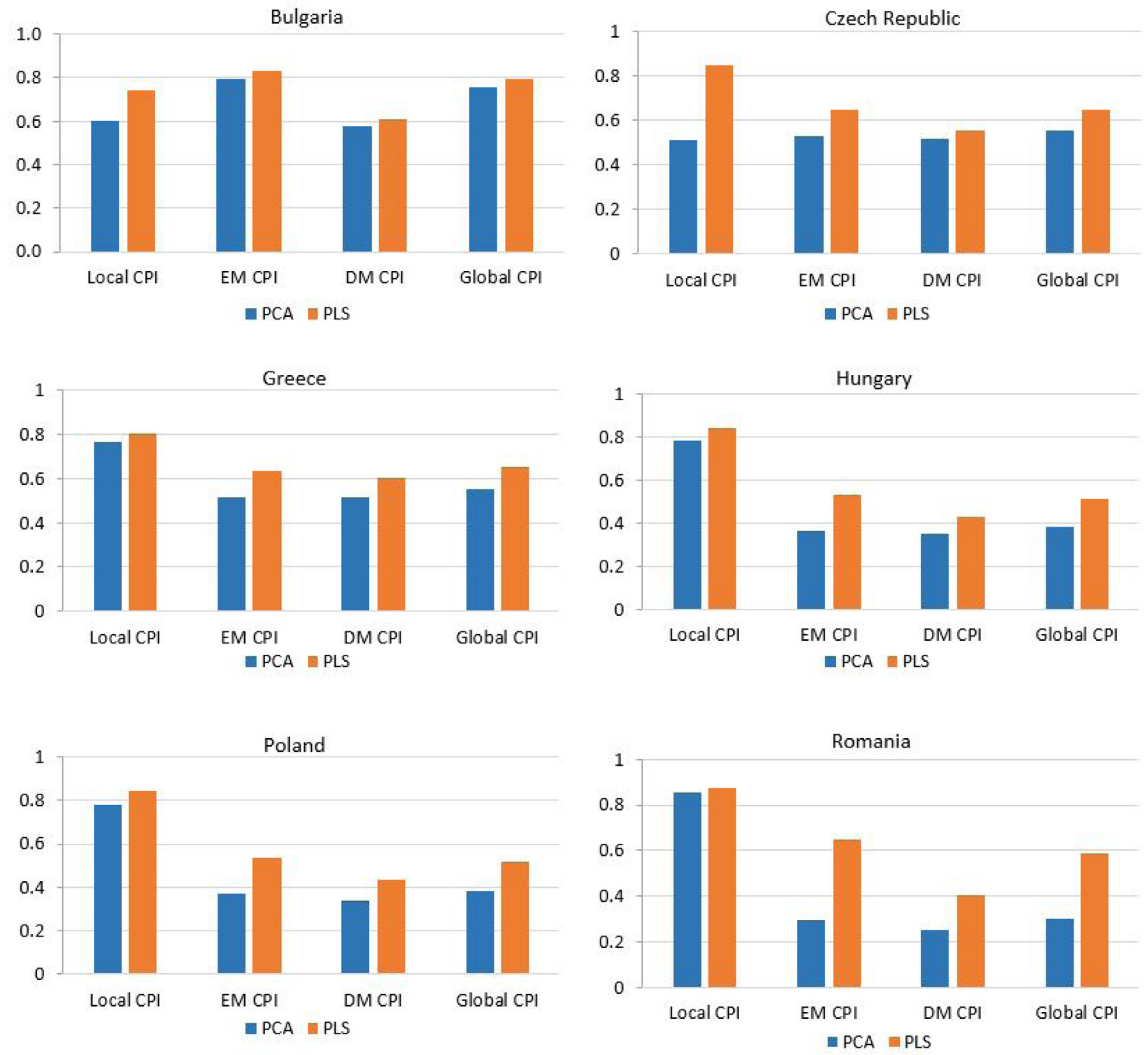

Fig. 1. Share of inflation variance explained by the first common factor of each dataset: PCA vs. PLS.
Notes: This figure shows the percentage of variance explained in headline inflation rates of EM European countries by the first common factor of each data group where factors are obtained using the PLS and PCA factor extraction methods.

In terms of how 'global' is global, we note the higher level of the variance explained by the (PLS-based) EMCPI factor compared to the DMCPI factor, that we observe in all countries.[11] Some of the recent literature would appear to suggest that our European Union member countries might be more affected by developed-market 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 & Shim, 2014). This results in an increase in the convergence of EM 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 dynamics, which yields interesting nuances.

[11] Unsurprisingly, while the first factors of EMCPI and DMCPI 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).

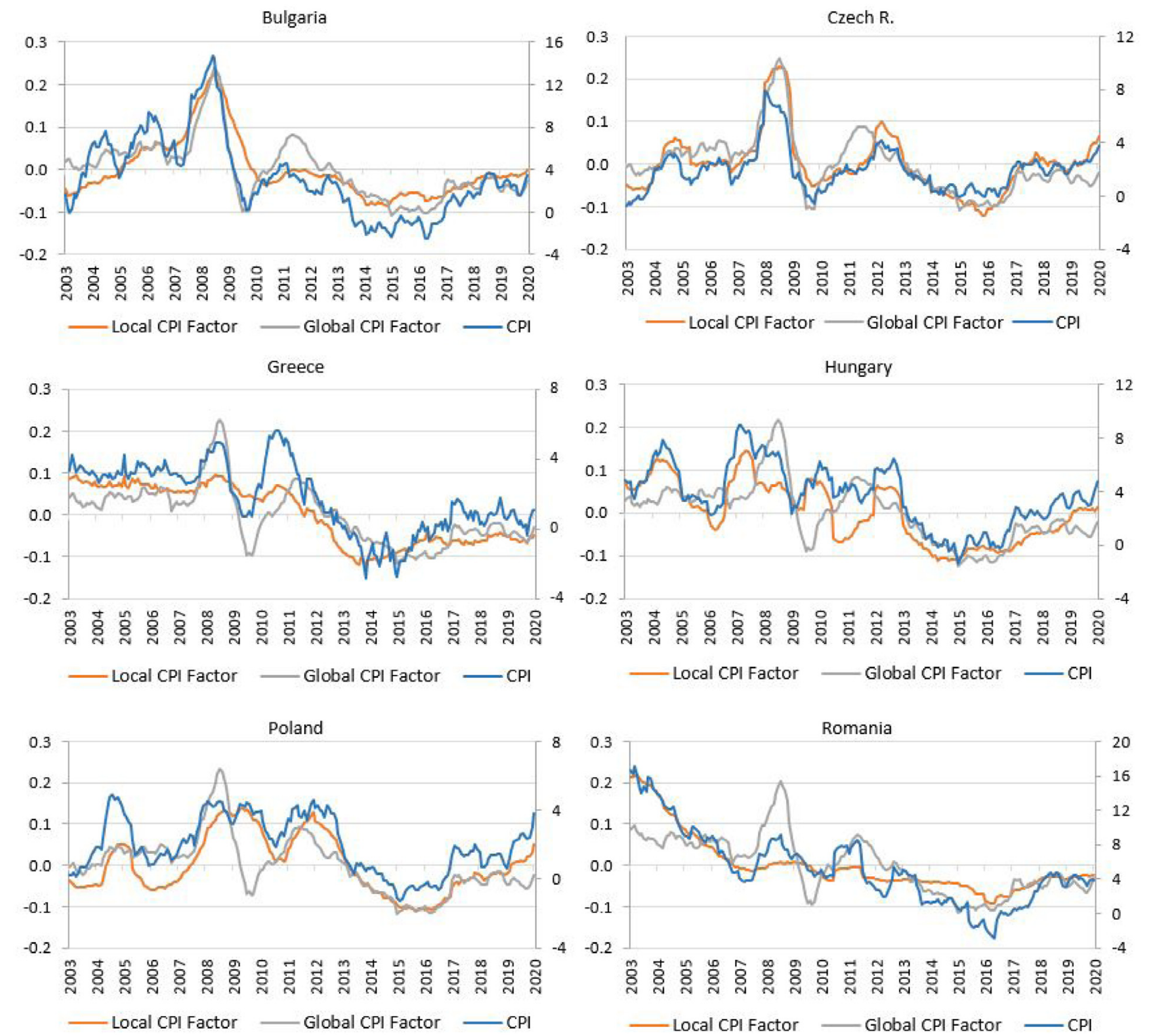

Fig. 2. Co-movement of actual inflation rates with local and global CPI factor estimated using the PLS approach.
Notes: This figure plots the actual inflation rates along with local and global inflation factors where the factors are calculated as the first common component of the PLS approach utilizing the disaggregated CPI and all country-level headline inflation rate data.

Fig. 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 and 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, leading to an increase in the prevalence of global price shocks in domestic inflation dynamics after 2018. As shown in Fig. 2, the inflation rates became more interconnected to both global and local CPI factors after 2018, and they started to move in a highly synchronized manner, especially in Bulgaria, Czech Republic, Greece, and Romania.[12]

[12] Figures A1–A2 of the appendix provide the plots of local and global CPI factors over the sample period, where factors are obtained 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.

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

	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 9	h = 12
BULGARIA								
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 yield the smallest MSFE highlighted in bold. The entries in the first row correspond to actual point MSFEs of the AR model, while all other entries are 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 asterisks (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model, based on the DM forecast accuracy test. Specification types: Specification 1: +LocalMACRO; Specification 2: +LocalCPI; Specification 3: +emCPI; Specification 4: +dmCPI; Specification 5: +em_dmCPI; Specification 6: +GlobalCPI.

5.2. 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 4.2, 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, where we set the number of factors to four for each dataset.[13] For the PLS approach, the first four factors of each dataset explain more than 82% of the variation in inflation rates for each country. The shares of variance explained by each individual factor are given in Tables A1–A2 of the supplementary appendix. The entries in Table 2 lower than unity indicate a better forecast performance than the AR benchmark. We produce a sequence of eight h-step-ahead forecasts for each month, i.e., $h = 1, 2, 3, 4, 5, 6, 9$, and 12. To make the 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 seven out of the eight forecast horizons for Hungary and Poland. The forecast gains are also increasing in the horizon, and a reduction of over 70% in the MSFE relative to the benchmark is achieved when $h = 12$, for both countries. Specification 6 (+GlobalCPI) achieves reductions in the 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 the 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 one of the eight cases.

Second, recall that we have eight forecast horizons and six countries, such that there are 48 comparisons in total. 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 that exploits international information consistently outperforms the AR model. It is also worth remarking that Specifications 3–6 (which include at least one international factor, namely, EMCPI, DMCPI, and GlobalCPI) are the best in three quarters (40 out of 48). Hence, Specifications 1 and 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.[14]

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 indicate that Specification 6 (+GlobalCPI) remains superior to the other models when these are augmented with commodity prices, for both the 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.[15]

Third, the plethora of rejections of the DM test in Table 2 (note that entries that are marked with *, **, or ***, imply the rejection of the null hypothesis of equal predictive accuracy) confirm 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.[16] For a detailed discussion of the distribution of the test statistics and power of the DM test in cases of both parameter estimation uncertainty and nested models, see (Clark & McCracken, 2012; Clements & Harvey, 2010; Clements & Hendry, 2005; Corradi & Swanson, 2007; McCracken, 2000). 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.[17] 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.[18]

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

14 As a robustness check, we examined the models performances during the euro area sovereign debt crisis (May 2010 to May 2012). Table A3 of the appendix shows that global factors play a significant role in driving local inflation rates, since Specifications 3–6 attain the top rank in 33 out of 48 cases.

15 When we undertake pairwise comparisons of Specification 6 with a model which replaces global inflation factors with the commodity price index, we find that 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.

16 Harvey, Leybourne, and Newbold (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 present the equality of the mean squared forecast error test of Harvey et al. (1997). Again, the findings are similar to those for the DM test.

17 As a robustness check, we repeated the same forecasting exercise using 60- and 72-month rolling schemes. Similar results were found, albeit with slightly higher MSFEs.

18 Tables A15–A16 summarize the results for the same forecasting exercise, but where 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 the forecast performance of the competing models compared to the AR model. In particular, none of the competing models improves 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

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

	Short horizon		Medium horizon		Long horizon		All horizon	
	uSPA	aSPA	uSPA	aSPA	uSPA	aSPA	uSPA	aSPA
BULGARIA								
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) are used for critical values. Asterisks (*** 1% level; ** 5% level; * 10%) denote the significance levels. Specification types: Spec.1: +LocalMACRO; Spec.2: +LocalCPI; Spec.3: +emCPI; Spec.4: +dmCPI; Spec.5: +em_dmCPI; Spec.6: +GlobalCPI.

The pairwise comparison of competing models using the 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 for 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 these 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 $h = 1, 2$, and 3 for a short horizon, $h = 4, 5$, and 6 for a medium horizon, and $h = 9$ and 12 for a long horizon. This allows us to reap some of the

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.

benefits of path evaluation, while tailoring the paths such that we can determine whether the contribution of the added factors depends on the horizon.

An inspection of Table 3 leads to several clear-cut conclusions.[19] Firstly, we find strong evidence in favor of Specification 3 (+emCPI) being superior to Specification 2 (+LocalCPI) 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. Draghi described the inflation outlook as 'less sanguine' for the euro area, due to the external weakness in demand, and also highlighted the risks to EM economies emanating from weakness in China.[20] Secondly, the aSPA test, combining all horizons, is positive and statistically significant, suggesting that Specification 4 outperforms Specification 2 in Hungary and Poland. Finally, although there are limited episodes that favor the addition of 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 shorter horizons.[21] 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).

5.3. 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, where 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) that include at least one global factor, these models have the best 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 EM core inflation rates, local factors now play a more prominent role in driving price changes (relative to headline inflation rates).[22]

Drilling down a little deeper, comparing Specifications 3 and 4 (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 depreciation (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.

6. Robustness checks

In this section, we report on a number of additional analyses. These serve as robustness checks, and also extend our analysis. Section 6.1 extends the range of models to include various time-varying parameter and shrinkage models. These models are designed to be flexible enough to capture some forms of structural change and parameter non-constancies (Korobilis, 2019). We investigate the potential for time-varying parameter models to improve on the linear factor models, because although more complicated models offer greater flexibility and adaptability,

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

[20] Access to full details of the press conference is available at https://www.ecb.europa.eu/press/pressconf/2015/html/is151022.en.html.

[21] 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 $h = 1, 2, 3, 4$, and 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 test 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.

[22] In Table A22 of the supplementary appendix, we report the results for the 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, Specifications 1 and 2 are 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.

Table 4
Core inflation: Recursive forecasting – Factors are extracted using the PLS approach.

	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 9	h = 12
BULGARIA								
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.

this may not result in improved forecast performance out-of-sample. The results for these models are discussed in Section 6.2. Of interest is whether the key finding for linear models – that global factors are an important determinant of EM inflation rates – remains the case when we extend the set of models.

Lastly, in Section 6.3 we consider an alternative way of evaluating forecast performance. Specifically, we calculate how far ahead the models (based on the different sets of information) are able to outperform the simple benchmark model. This supplements the forecast comparisons reported in Section 5.

6.1. *Additional models: Time-varying parameters and shrinkage*

6.1.1. *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 the 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:

$$y_t = x_t\beta_t + \varepsilon_t \\ \beta_t = \beta_{t-1} + \eta_t \quad (9)$$

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, and 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 $W_t = \mathrm{diag}\left(w_{1,t}, \ldots, w_{p,t}\right)$ is a $p \times p$ diagonal matrix. This approach is implemented with a dynamic variable selection (DVS) prior of the form:

$$\begin{aligned} \beta_{j,t} \mid \gamma_{j,t}, \tau_{j,t}^2 &\sim \left(1-\gamma_{j,t}\right) N\left(0, c \times \tau_{j,t}^2\right) + \gamma_{j,t} N\left(0, \tau_{j,t}^2\right) \\ \gamma_{j,t} \mid \pi_t &\sim \text{Bernoulli}\left(\pi_{0,t}\right) \\ \frac{1}{\tau_{j,t}^2} &\sim \text{Gamma}\left(g_0, h_0\right) \\ \pi_{0,t} &\sim \text{Beta}(1, 1) \end{aligned} \quad (10)$$

where the subscripts (j, t) represent the jth 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 the 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:

$$q^\star\left(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t}\right) = \underset{q\left(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t}\right)}{\arg\max} \int q\left(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t}\right) \times \log\left(\frac{q\left(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t}\right)}{p\left(\boldsymbol{\beta}_t, \boldsymbol{w}_t \mid \boldsymbol{y}_{1:t}\right)}\right) \quad (11)$$

where subscripts $(1:t)$ indicate observations of a state variable from period 1 up to period t.[23]

6.1.2. Gaussian process regression (GPR)

Gaussian process regression is a machine learning method based on non-parametric kernel-based probabilistic models. 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

$$y = x^T\beta + \varepsilon, \qquad y = f(\mathbf{x}) + \varepsilon \quad (12)$$

where $\varepsilon \sim N\left(0, \sigma^2\right)$, 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, 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 the 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 suggested by Rasmussen and Williams (2006), we utilize the commonly used covariance function, which is called squared exponential kernel:

$$k\left(x, x'\right) = \sigma_f^2 \exp\left(-\frac{1}{2\ell^2}\left\|x - x'\right\|^2\right) \quad (13)$$

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

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

$$\phi(x)^T\beta + f(x) \quad (14)$$

where $f(x) \sim GP\left(0, k\left(x, x'\right)\right)$, indicating that $f(x)$ are from zero mean GP with $k\left(x, x'\right)$. Then, $\phi(x)$ denotes 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, GPR projects the inputs into high-dimensional space using the set of basis functions and then estimates the linear model in this high-dimensional space rather than directly on the inputs themselves. Thus, this model represents a GPR model, and the response y can be defined as:

$$P\left(y_i \mid f\left(x_i\right), x_i\right) \sim N\left(y_i \mid \phi\left(x_i\right)^T\beta + f\left(x_i\right), \sigma^2\right) \quad (15)$$

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

$$P(f \mid X) \sim N(f \mid 0, K(X, X)) \quad (16)$$

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

6.1.3. Least absolute shrinkage operator (LASSO)

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

$$\hat{\beta}^{lasso} = \min_{\beta} \quad \|Y - X\beta\|_2 + \lambda\sum_{j=1}^{N}|\beta_j|, \quad (17)$$

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

6.1.4. 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 LASSO and ridge estimators, known as the elastic net estimator (ENET). The

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

ENET estimator is represented as follows:

$$\hat{\beta}^{EN} = \min_{\beta} \quad \|Y - X\beta\|_2 + \lambda_1 \sum_{j=1}^{N} |\beta_j| + \lambda_2 \sum_{j=1}^{N} {\beta_j}^2, \tag{18}$$

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

6.2. Do these models improve on the linear models?

Do the time-varying parameter and data shrinkage (TVP) models yield improvements in forecast performance? We estimate 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, 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 shows 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 superior forecasting performance to the benchmark AR model. Furthermore, it can be seen that the forecast improvements provided by the TVP models are statistically significant compared to the AR, based on application of the DM test. The accuracy gains from implementing TVP models increase 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 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, Vasconcelos, Veiga, and Zilberman (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.

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 Cross, Hou, and Poon (2020), Fava and Lopes (2020), Giannone, Lenza, and Primiceri (2018). 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 specifications (in terms of factors) and factor-selection modeling method (constant parameter, TVP, or GPR) that 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. Fig. 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 to one. Fig. 3 reveals that the relative importance of the factor groups varies across country and forecast horizon. For instance, in Hungary, global CPI factors gain importance as the forecast horizon increases, where the relative importance measure reaches 0.58 (for $h = 6$) from the initial level 0.10 (for $h = 1$). On the other hand, local and global factors seem to be equally important across the forecast horizons for the Czech Republic. Despite these differences, overall we find that 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 (+LocalMACRO) is generally not as good as the models with inflation factors (local or global). If we interpret the

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.

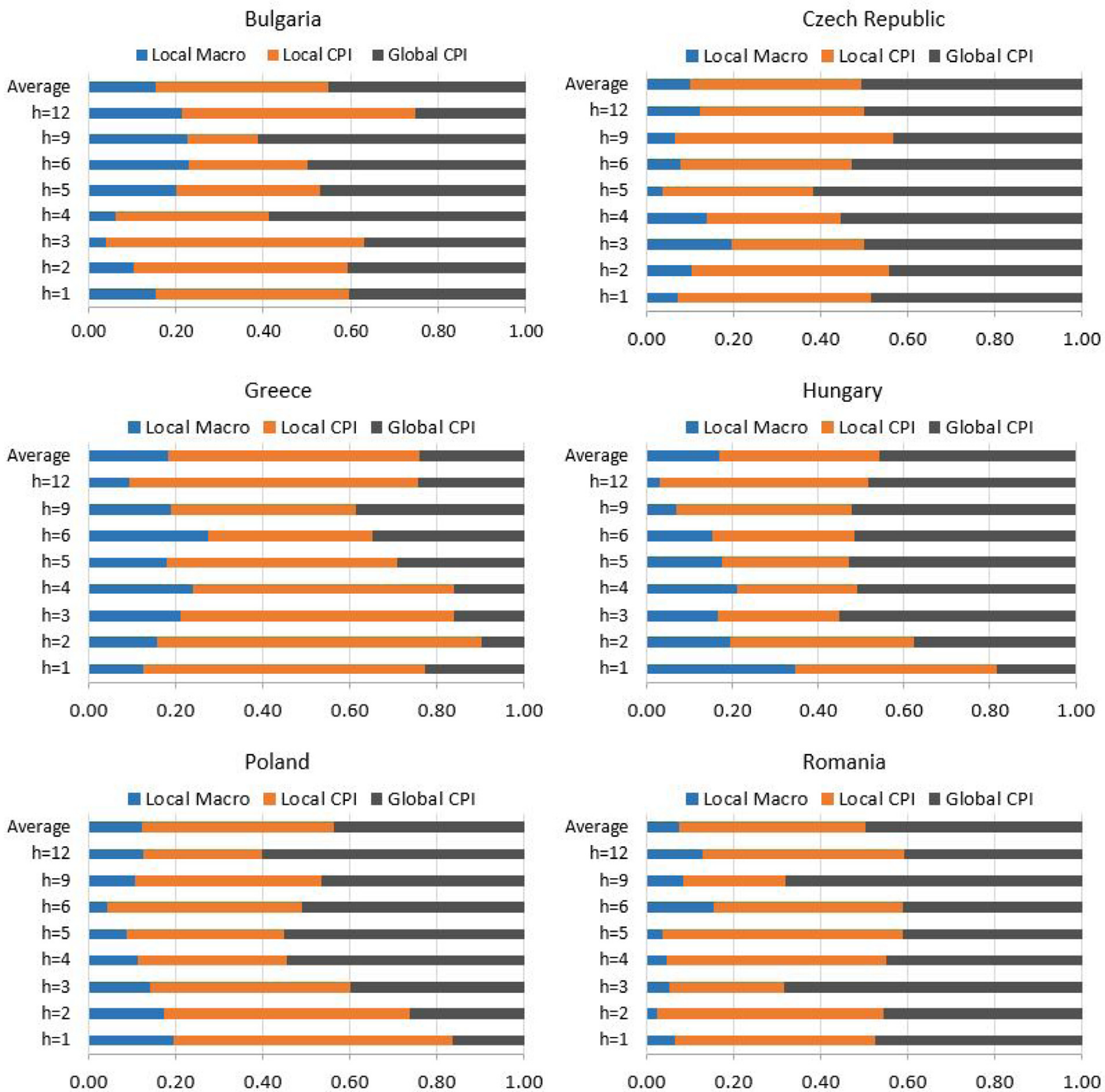

Fig. 3. The importance of global and local factor groups for the GPR method.
Notes: The sub-graphs plot the importance of each factor group for the GPR method for all horizons across the countries. The values in the graphs are normalized to sum to one. h is the forecasting horizon.

model with local macro factors as an approximation[25] to a Phillips curve-type relationship, then our findings favor global inflation explanations of EM national inflation rates.

6.3. Forecast informativeness: How far can we forecast?

In some instances the policymaker 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

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.

to forecast more cyclical or short-acting components such as food.

Following the work of Breitung and Knüppel (2021), 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 the maximum forecast horizon.

As an alternative, we can write the null hypothesis as:

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

which implies that the forecast error using the unconditional mean as the forecast is not correlated with the difference between the two forecasts. 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 $\beta_{1,h} > 0$, where 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).

Table 5 presents the maximum forecast horizons h^*, suggested by the encompassing test, for all our models (for headline inflation), 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. The results demonstrate that the AR model forecasts are not informative beyond nine 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 six months ahead for any country.

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 nine 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 & Martínez-García, 2015). 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.

7. 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 economies 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, Chatziantoniou, and Gabauer (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 Fig. 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 the net total directional connectedness for each country, implying that a larger node 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, and France) to the rest of the world. On the contrary, Japan, Norway, and Mexico are the highest net receivers of 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 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 4.1. The results show

[26] Technical details of the TVP-VAR model and connectedness measures are provided in the 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.

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

Table 5
Maximum forecast horizons in months, determined by encompassing test.

(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.

that choosing a subset of countries by considering the pairwise inflation spillovers across countries, before constructing the global factors, provides forecast improvements for the Czech Republic, Poland, and Romania. In particular, the forecast gains are primarily obtained for short and medium horizons ($h = 1$, 2, 3, and 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 improves on Section 4.1 strategy for Bulgaria and Hungary.

8. The role of country characteristics in explaining the importance of the global inflation factors

The channels through which 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-level characteristics that tend to increase the importance of the effects global factors have on local inflation rates. 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 effect of global factors on domestic consumer prices, either directly or indirectly.

To investigate the relationship between the country-level characteristics and the strength of the effect of the global factor on domestic inflation, we consider the following set of variables: (1) Current account balance to GDP (CAB), (2) Budget Balance to GDP (BB), (3) Household consumption to GDP (HCONS), (4) Unemployment rate (UNR), (5) FX reserves to GDP (FXR), (6) Uncertainty (UNC), (7) Real GDP growth (RGDP), (8) 5-year Credit Default Swap (CDS), (9) Real effective exchange rate (REER), (10) Exports to GDP (EXP), and (11) Imports to GDP (IMP).[29] We estimate the following panel regression, allowing for country-specific fixed effects (the α_i) to capture time-invariant cross-country differences:

$$\begin{aligned} y_{i,t} = {} & \alpha_i + \theta F_{it}^{LocalMACRO} + \gamma F_{it}^{LocalCPI} + \beta F_{it}^{GlobalCPI} \\ & + \beta_1 F_{it}^{GlobalCPI} \times CAB_{it} + \beta_2 F_{it}^{GlobalCPI} \times BB_{it} \\ & + \beta_3 F_{it}^{GlobalCPI} \times HCONS_{it} + \beta_4 F_{it}^{GlobalCPI} \\ & \times UNR_{it} + \beta_5 F_{it}^{GlobalCPI} \times FXR_{it} \\ & + \beta_6 F_{it}^{GlobalCPI} \times UNC_{it} + \beta_7 F_{it}^{GlobalCPI} \times RGDP_{it} \\ & + \beta_8 F_{it}^{GlobalCPI} \times CDS_{it} \\ & + \beta_9 F_{it}^{GlobalCPI} \times REER_{it} + \beta_{10} F_{it}^{GlobalCPI} \times EXP_{it} \\ & + \beta_{11} F_{it}^{GlobalCPI} \times IMP_{it} + e_{i,t}. \end{aligned} \tag{21}$$

The dependent variable ($y_{i,t}$) is the quarterly average value of the year-over-year inflation rates of European emerging countries. The country-level characteristics listed above appear as interaction terms with the global factor. This setup allows us to determine whether the effects of the global factor change with the country-level characteristics by simply testing for the significance of the interaction terms.

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 the current account balance and government debt. As suggested by Kılınç, Tunç, and Yörükoğlu (2016), higher current account deficits may result in larger currency depreciation in EM countries, amplifying the relationship between domestic inflationary pressures and current account deficits. Similarly, a higher level of household consumption may create greater dependency on imported goods, making a country more open to global shocks. The significant coefficients of the export and import variables 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

[29] The online supplementary appendix presents details on these variables and data sources.

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

	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 9	h = 12
BULGARIA								
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 highlighted in bold. The entries in the first row correspond to actual point MSFEs of the AR model, while all other entries are 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 asterisks (*** 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-MSFE 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 1 = ‘1’, Specification 2 = ‘2’, Specification 3 = ‘3’, Specification 4 = ‘4’, Specification 5 = ‘5’, Specification 6 = ‘6’. For instance, GPR-6 means that when 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.

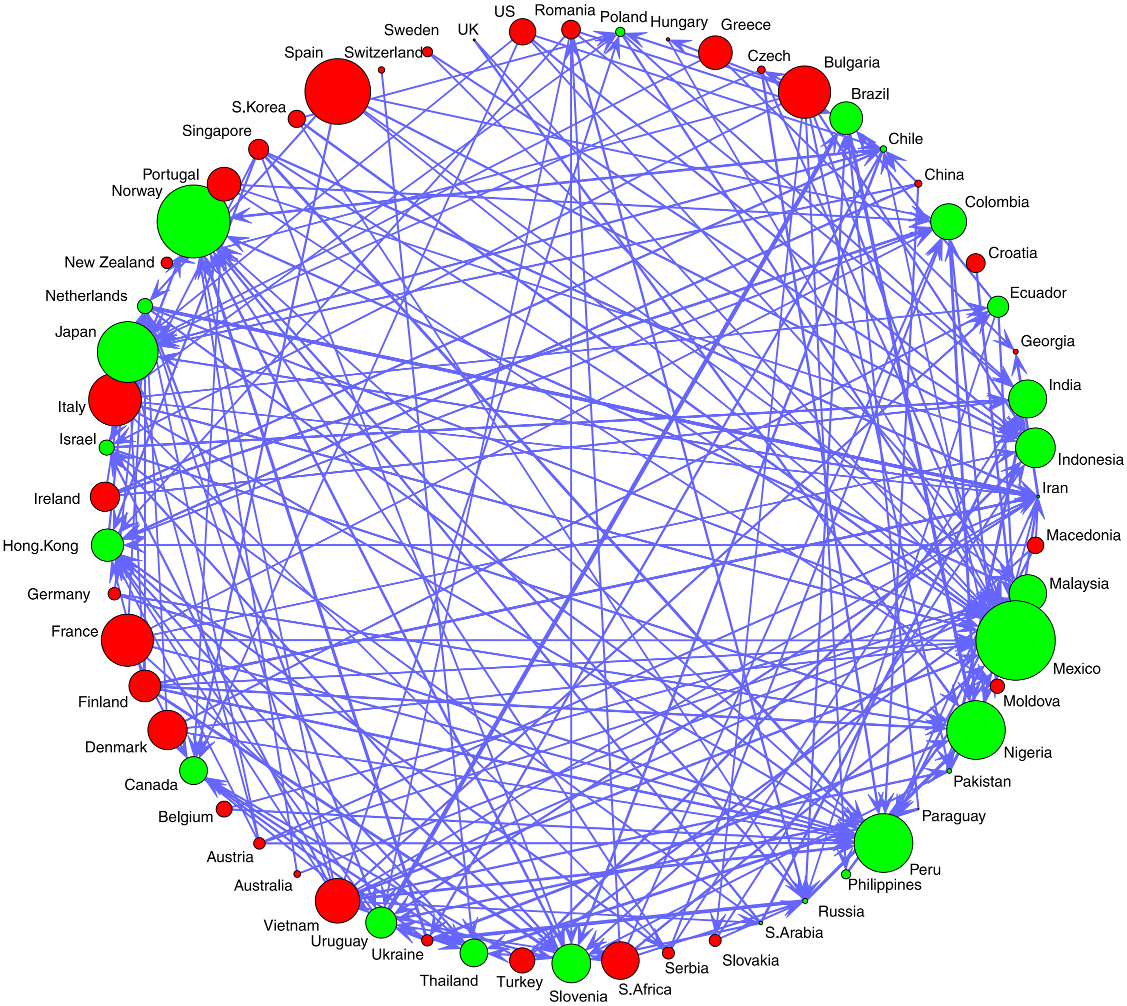

Fig. 4. Network analysis of inflation spillovers across countries.
Notes: Each edge between two nodes demonstrates the net pairwise inflation spillovers between countries, and the arrow's direction indicates which country transmits the shocks to another country. The thickness of the edge between countries 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 a better visualization, we report the pairwise spillovers greater than 0.05. Moreover, we ran the model with 60 countries, due to the need for a high-powered computer.

with recent research suggesting that global production networks play a significant role in the transmission of shocks (Auer et al., 2017, 2019; Carvalho, 2014; Carvalho, Nirei, & Tahbaz-Salehi, 2021). We also modify the baseline model by splitting exports and imports into EU and non-EU countries. 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 the countries' own monetary policies.

9. Conclusion

We presented a comprehensive empirical investigation into the forecasting performance of global factors for European EM countries' national inflation rates. We considered 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 did not always give consistent findings across countries, models, and horizons, but nevertheless some general patterns emerged.

Our empirical findings based on the outcomes of the forecasting exercises firmly support the contention that it is true that 'inflation is a global phenomenon' 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 local

Table 8
MSFEs based on the use of different global factors based on inflation spillovers – Recursive forecasting.

	h = 1	h = 2	h = 3	h = 4	h = 5	h = 6	h = 9	h = 12
BULGARIA								
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 highlighted in bold. The entries in the first row correspond to actual point MSFEs of the AR model, while all other entries are 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 MSFE results of 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 asterisks (*** 1% level; ** 5% level; * 10% level) are significantly superior to the AR model.

macro factors, which we contend generalize 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, recognizing 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 on to global factors adding something over and above that provided by domestic factors.

We provided some insight as to why global factors are an important determinant of domestic inflation, by considering the country-level characteristics that tend to increase the importance of global factors on domestic inflation. Perhaps not surprisingly, the degree of openness of a country is a key determinant, but other factors, such as a higher current account deficits and higher level of household consumption also matter and work in the same

Table 9
Determinants of importance of global factor – Panel regression results.

Variables	(1) $y_{i,t}$	(2) $y_{i,t}$
LocalMACRO	0.133	0.125
	(0.135)	(0.132)
LocalCPI	1.302***	1.261***
	(0.135)	(0.130)
GlobalCPI	1.100***	1.100***
	(0.098)	(0.097)
GlobalCPI × *CAB*	0.729***	0.577**
	(0.204)	(0.223)
GlobalCPI × *BB*	0.0086	−0.056
	(0.091)	(0.091)
GlobalCPI × *HCONS*	0.700***	0.643***
	(0.192)	(0.187)
GlobalCPI × *UNR*	−0.084	−0.012
	(0.128)	(0.130)
GlobalCPI × *FXR*	0.343***	0.103
	(0.104)	(0.114)
GlobalCPI × *UNC*	−0.016	0.035
	(0.068)	(0.067)
GlobalCPI × *RGDP*	0.0311	0.0301
	(0.097)	(0.091)
GlobalCPI × *CDS*	0.005	−0.053
	(0.066)	(0.068)
GlobalCPI × *REER*	−0.127	−0.057
	(0.078)	(0.099)
GlobalCPI × *EXP*	−2.141**	
	(0.843)	
GlobalCPI × *IMP*	2.127***	
	(0.685)	
GlobalCPI × *EXP_EU*		−2.183***
		(0.764)
GlobalCPI × *IMP_EU*		2.147***
		(0.645)
GlobalCPI × *EXP_NonEU*		0.329
		(0.239)
GlobalCPI × *IMP_NonEU*		0.103
		(0.202)
Constant	3.016***	3.018***
	(0.078)	(0.075)
Observations	369	369
F-stat prob.	0.00	0.00
Adjusted R^2	0.848	0.855

Asterisks (*** 1% level; ** 5% level; * 10% level) denote significance levels. Robust standard errors are reported in parentheses. All explanatory variables are used in standardized forms.

direction. Tailoring the global inflation factor to the particular EM country also matters for some countries – that is, forming the global factor by extracting a factor on the subset of countries that are closely connected to the EM countries.

We used 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 modeling. Where we depart from some of the literature on 'global inflation' is by calculating the factors in a way that ensures their relevance for the variable being forecast, that is, by PLS rather than PCA. We showed that this has noticeable effects on our results. While our main set of results used linear factor forecasting models, we also established that our findings are robust to factor-selection methods that enforce sparsity, as well as to a machine-learning method that allows for a non-linear relationship between national inflation rates and the sets of factors. The latter served to further enhance the forecasting improvements that resulted from the global inflation factors.

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

Forecast performance can be evaluated in a number of ways. We compared 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 policymakers, 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 found that global factors dominate local factors at shorter horizons. We also paid particular attention to the horizon at which the factor models lose their edge over the 'long-horizon' or unconditional mean forecast, and we showed that the factor models generally extend this horizon relative to the benchmark AR model.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijforecast.2023.01.008.

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