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The Influence of Global Inflation on Emerging Market Economies' Inflation*

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Abstract: We calculate global inflation as the first principal component of inflation in a sample of emerging market and advanced economies and find that it may account for an important fraction of headline and core inflation variance across countries. We then show that global inflation is correlated with international commodity price variation, the global economic cycle, and financial volatility, but that a large fraction of its variance is unaccounted for by these factors. Finally, we augment standard inflation forecasting models for ten emerging market economies with global inflation and find that doing so improves forecasting performance for headline inflation. We argue that this predictive potential stems from its correlation with commodity prices, output gap and global financial volatility, but also from the additional information that this variable contains regarding other inflation determinants worldwide.
Keywords: Inflation; Principal Components; Forecasting and Prediction Methods.
JEL Classification: E31; C38; C53.

Resumen: Se calcula el factor global de inflación como el primer componente principal de las series de inflación de una muestra de economías de mercados emergentes y avanzados y se encuentra que este factor puede explicar una proporción importante de la varianza de la inflación general y subyacente de la muestra de países. Se ilustra que la inflación global está correlacionada con la variación de los precios internacionales de las materias primas, el ciclo económico mundial y la volatilidad financiera, pero que una gran proporción de su varianza no se explica por estos factores. Finalmente, se incluye la inflación global en modelos estándar de pronóstico de inflación de diez economías emergentes y se muestra que ello mejora su rendimiento para la inflación general. Se argumenta que este potencial predictivo es consecuencia de la correlación del factor global con variables globales observables, aunque también de información adicional que esta variable contiene respecto a otros determinantes de la inflación mundial.
Palabras Clave: Inflación, componentes principales, pronósticos y métodos de predicción

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1 Introduction

There is wide evidence that inflation across countries is highly correlated and that this synchronization has strengthened in recent decades. Inflation synchronization has been widely explored in the literature but has mainly focused on advanced economies (Ha et al. 2019a). However, existing estimates indicate that inflation synchronization is more pronounced among advanced economies than in emerging market economies (EMEs). In this paper, we emphasize that the influence of global factors on domestic inflation in EMEs is relevant, and we support this statement by showing the predictive ability of the global factor in models of inflation.

We do this in three steps. First, we define global inflation as the first principal component of inflation among a sample of emerging market and advanced economies. Since this factor represents the commonality of inflation variation across countries, it is arguably global. We find that estimated global inflation may account for an important fraction of domestic inflations' variation. Our results indicate that this factor is relevant for both the headline and core measures of inflation, but confirm previous findings in the literature showing that, in general, a larger fraction of headline inflation variation is associated with global factors. Surprisingly, however, we find that global inflation is more relevant for core inflation than for headline inflation for a small subset of countries, among them Mexico, Colombia, Hungary, and Peru, and this result is robust to different methods of computing global inflation. This is relevant because the literature, in general, has highlighted that common factors explain a large share of energy and other commodity prices' variation, but these are generally excluded from the core component of inflation (see, for example, Förster and Tillmann 2014; Parker 2018; Forbes 2019b; Ha et al. 2019a,b). Our finding could be explained, among other factors, by the reliance on the external sector that could play a larger role for the case of EMEs. Indeed, trade may be an important driver of aggregate demand in small open economies, so the relevance of the global economic cycle could be relatively more important for domestic prices of the nontradable sector, that has a relatively higher weight on the core basket of inflation.[1] Other idiosyncratic factors for each country could provide further arguments for the plausibility of this finding.

In the second step, we explore the importance of some global determinants of inflation that could be driving its synchronization globally. There are several plausible explanations. A change in world prices modifies the growth rate of domestic prices to consumers both directly through the import of final goods consumed and indirectly through its effects on production costs. Moreover, if global inflation responds to the world economic cycle, then the former will be higher when global demand is strong, and thus export prices increase, which may alter domestic prices to the extent that producers take them as their reference. Finally, global inflation may be capturing observed or unobserved latent factors that may affect inflation in several countries, such as risk aversion or financial volatility. We estimate the correlation between global inflation and commodity prices, the output gap, and a measure of financial volatility, and we illustrate the composition of global inflation between these variables. Our analysis shows that global inflation correlates with the global economic cycle, international oil prices, and financial volatility. The global output gap and oil price inflation are found to contribute to a larger proportion of headline inflation than of core inflation. This can be rationalized because headline inflation baskets usually include commodities whose prices are determined in the international market, and whose equilibrium prices will increase when aggregate global demand is high or when they exhibit significant negative supply shocks. Importantly, we also find that there is a large fraction of the global inflation variance that is unaccounted for by the observable variables studied, and we interpret this as evidence that global synchronization of inflation goes beyond the international determination of commodity prices, the synchronization of output, and financial volatility.

[1] This factor could be mitigated if the country's exports are very reliant on commodities since world economic growth may increase global demand of commodities, raising their prices, and therefore leading to the appreciation of commodity exporters' currencies and in consequence, disinflationary pressures.

In the third step, we investigate if global inflation is a relevant determinant of inflation in EMEs. We do this by using the case of ten EMEs and augmenting standard inflation forecasting models, namely multiplicative seasonal autoregressive integrated moving average models (SARIMA), with the following predictors: i) global inflation, ii) global output gap, iii) oil price inflation, iv) nonfuel commodities' price inflation, v) exchange rate, vi) VIX index of financial volatility, and vii) the combination of some of these variables. As a benchmark, we use the root mean square error (RMSE) from a univariate model. Then, we compare these models' performance using the pseudo-out-of-sample RMSE ratios, this is, we specify the model and estimate it using data through 2016, then make an *h*-step ahead forecast for horizons of 6, 12, 24, and 36 months (see section 5).

Our results show that global inflation has predictive ability over headline inflation as it achieves a better forecasting performance compared to other covariates in the particular case of the models analyzed in this work. For example, defining each forecast horizon for each country as one case, the model including global headline inflation outperforms our benchmark model (a SARIMA model) in 55% of cases, while the model that instead includes the global output gap outperforms the benchmark model in only 40% of cases. This means an improvement in forecasting performance of about 15%, and importantly the first outperforms the standard benchmark. Our results for headline inflation are confirmed when a different metric is applied and the RMSE of the models including individually a set of global determinants as covariates is compared directly with that of the models including global inflation as the covariate. For the case of core inflation, our results indicate that models augmented with global factors as covariates, including global inflation, underperform the benchmark. Moreover, even comparing global inflation directly with other global variables, we cannot conclude that incorporating the former into the models for this measure may improve forecasts overall for EMEs. Nonetheless, the global inflation factor does have predictive ability for core inflation in some particular countries, suggesting that considering this variable among the set of determinants that are regularly monitored is valuable.

Finally, to address whether global inflation contains information about factors that affect inflation worldwide beyond commodity prices, the global economic cycle, and financial volatility, we calculate the component of global inflation that is orthogonal to these variables. We show that this component is a statistically significant predictor of inflation in our sample of EMEs even after controlling for said variables. These results suggest that the global inflation factor contains valuable information about inflation determinants in EMEs, in addition to that in the observable variables considered. This analysis is important from a policy perspective because it deepens our understanding of the importance of global factors for domestic inflation.

We contribute to the literature in the following ways. First, we emphasize the role of global inflation factors in the case of EMEs for both the headline and core measures of inflation. Second, we assess the relevance of a set of observable variables, traditionally considered important drivers of inflation globally, as determinants of this global inflation factor. Third, our work highlights that the global inflation factor has predictive ability over domestic inflation so the monitoring of the former is relevant to improve the understanding of the inflationary process. Fourth, we evaluate the influence of the global inflation factor on domestic inflation for the case of EMEs in both headline and core inflation and show that there may be gains for the case of the former. Finally, we also show that the predictive ability of global inflation stems not only from the influence of global factors that are traditionally considered, but also from other variables that could potentially be unobservable and could be important determinants of inflation across EMEs.

The value of considering global inflation among the set of relevant inflation determinants is twofold. First, because it is based only on data for inflation that is available in a timely manner, the method proposed is a relatively simple and accessible framework that may be used in policy analysis. Second, the evidence presented in this work, although it is mixed for the case of core inflation, suggests that the global inflation factor is a good predictor of inflation across EMEs. Therefore, our work may open a promising avenue for future research, for example, by incorporating this variable into multivariate or structural models or in real-time forecasting.

The rest of the document is organized as follows. In section 2, we present a brief summary of the literature. In section 3, we describe our data and the estimation of global inflation. In section 4, we evaluate the correlation of estimated global inflation with observable variables that may be driving inflation worldwide. In section 5, we evaluate the performance of models that incorporate global inflation as a predictor of national inflation rates in a sample of EMEs at different time horizons. Finally, in section 6, we conclude.

2 Literature

Our paper is related to three strands of literature. First, it is broadly related to a wide strand of literature that emphasizes the increasing trend of global inflation synchronization due to the convergence of global inflation to lower rates (convergence of trend inflation) and at the cyclical level (inflation gap). In terms of the mechanisms driving the synchronization at the cyclical level, the literature emphasizes the role of global gross domestic product (GDP) synchronization and the importance of global slack for domestic activity (Borio and Filardo 2007; Ayhan Kose et al. 2008; Forbes 2019a; Jašová et al. 2020), the exposure of different countries to similar shocks (Ciccarelli and Mojon 2010; Auer et al. 2017; Ha et al. 2019a; De Soyres and Franco Bedoya 2019; Lane 2020), the synchronization of economic policies in response to similar shocks (Cecchetti et al. 2007; Mumtaz and Surico 2012; Auer et al. 2019; Ha et al. 2019b; Lane 2020), the commonality among determinants of inflation such as money growth and interest rates (Hakkio 2009), a higher persistence of negative inflation rates because of the limited margin of policy to reverse them (Ha et al. 2019b; Lane 2020), and economic openness including trade, financial integration and input-output linkages (Auer et al. 2013; Auer and Mehrotra 2014; Auer et al. 2017, 2019; Ha et al. 2019a; Lane 2020). Economic globalization may have contributed to inflation synchronization at the cyclical level through at least two channels. First, the stronger integration of real production in global value chains and the growth of multinational companies increase the importance of production input imports, and therefore, the relevance of foreign prices in domestic production costs (Rogoff 2003; Melitz and Ottaviano 2008; Auer and Fischer 2010; Auer et al. 2013; Auer and Mehrotra 2014; Auer et al. 2017, 2019; Lane 2020). Second, financial globalization may contribute to inflation comovements through common credit cycles (Lane 2020) or through inflationary shock propagation through the financial channel (Auer et al. 2019). Commodity prices are also an important factor affecting inflation variation across countries since these are determined in the international markets, are more volatile than other products, are usually comoving with other variables that influence inflation (such as world economic growth), and they may have nonlinear effects on inflation as they tend to spillover to other goods (Forbes 2019a,b; Kamber and Wong 2020; Lane 2020).[2] In particular, international prices of food could be a relevant driver of inflation in EMEs (see Holtemöller and Mallick (2016) for the case of India).

There are additional channels, specific for EMEs, that may drive inflation synchronization between these countries. Volatility episodes in the financial sector or episodes of risk aversion that lead to capital reallocation to more advanced economies can trigger depreciation episodes for emerging market currencies. To the extent that these movements are synchronized, inflation rates among these countries could be more correlated (Forbes 2019a). Moreover, foreign shocks could be more important in EMEs than in developed ones because of additional propagation and amplification mechanisms, such as the response of domestic monetary policy to these shocks and other institutional characteristics, including financial frictions and rigidities in the goods and labor markets (Kamber and Wong 2020). Besides, because EMEs are commodity exporters, global commodity price changes are more likely to be translated into

[2] Conversely, Kagraoka (2016) studies the common factors that affect commodities prices, and one of them is found to be associated with the U.S. inflation rate.

aggregate demand shocks in EMEs, which means that the contagion to other domestic prices could be stronger and translated into exchange rate shocks. Nonetheless, it is also possible that on the contrary, inflation among EMEs is less synchronized because they could be more exposed to idiosyncratic shocks and their inflation expectations could be less anchored (Ha et al. 2019b).

In terms of the channels driving the long-run convergence of inflation, the literature has highlighted the following: (i) the success in controlling idiosyncratic volatility by the mitigation of domestic shocks through deep domestic capital markets and effective monetary policy, particularly in advanced economies (Parker 2018), (ii) a long-run decrease in inflation variation as inflation targeting has contributed to the convergence of inflation levels and inflation expectations (Bernanke et al. 1999; Corbo and Schmidt-Hebbel 2002; Orphanides and Williams 2003; Hyvonen 2004; Vega and Winkelried 2005; Arestis et al. 2014; Lane 2020), and (iii) structural changes in the global economy.[3] Economic openness could also affect the convergence of trend inflation by exerting downward pressure on prices through at least two mechanisms: first, the availability of lower-priced products given the participation of countries that are abundant in unskilled labor in international trade; second, through long-run gains in productivity derived from i) the specialization of countries in sectors where they are relatively more efficient, ii) factor mobility between countries that allows the reallocation of production, iii) technological progress induced by knowledge spillovers, and iv) lower markups in response to stronger competition.

The second relevant strand of the literature is a set of papers that use factor models to estimate global inflation and its comovement with domestic inflation.[4] In this strand, estimates about the variation of inflation rates that can be accounted for by the global factor vary widely

[3] For example: (i) population aging may have shifted consumption patterns, (ii) digitization may be leading to a reconfiguration of firm pricing decisions, and (iii) the growing importance of services in economic activity may have affected relative prices (Lane 2020).

[4] Related literature also uses bilateral correlations as a measure of synchronization Wang and Wen (2007); Henriksen et al. (2013).

depending on the sample of countries considered, the period studied, the method used to compute global inflation, and the measure of inflation used. In terms of headline inflation for a group of both emerging and advanced economies, estimates range from 70% in Hakkio (2009) that considers a sample of 36 economies between 1960-2008 and computes global inflation as the first principal component, to 22% found by Ha et al. (2019a) using a Bayesian dynamic factor model for inflation in a group of 99 countries between 1970-2017. Neely and Rapach (2011) use a Bayesian dynamic factor model and find that, in a sample of 64 countries for the period 1950-2009, the global factor explains 35% of annual inflation variability on average. However, estimates of the importance of global factors vary widely between countries. Parker (2018) focuses on a large sample of 223 economies and finds that global inflation accounts for a large share of the variance of national inflation rates in OECD countries, but the importance of the common global factor decreases with income.[5] In terms of different inflation measures, previous findings indicate that measures which include commodity prices are more synchronized. For example, Förster and Tillmann (2014) find that, while around a third of inflation volatility can be accounted by global factors, once inflation excluding food and energy is considered, the importance of the global factor decreases to below 20%. Besides, Karagedikli et al. (2010) find that category-specific factors account for a large part of price comovements of primary commodities-intensive goods in a sample of advanced economies, but that this feature is weaker for other traded goods, reinforcing the relevance of commodity prices as the drivers of global inflation synchronization through contagion to manufactured goods.[6]

[5] See Parker (2018, footnote 3) for his definition of "economies."

[6] A related strand of literature, that is very vast, concerns papers that use factor models to analyze the synchronization of other macroeconomic variables. Some examples include De Lucas Santos et al. (2011) that use the methodology in Stock and Watson (2002a) to identify the countries that share common business cycles, and Chadwick et al. (2015) that examine how exchange rates synchronize for emerging countries. Furthermore, Bagliano and Morana (2009) utilize a factor-augmented VAR model to analyze the comovements between a set of real and nominal macroeconomic variables across a small set of advanced countries, including stock market returns, inflation rates, interest rates, and monetary aggregates.

The third group of papers is the most related to our work, and these explore the forecasting ability of global inflation in domestic inflation rates. Ciccarelli and Mojon (2010) use a static principal component analysis described in Stock and Watson (2002b) and find that global inflation accounts for almost 70% of the variance of inflation (quarterly year-on-year CPI inflation) of 22 OECD countries from 1960Q1 to 2008Q2, and that countries with stronger commitment to price stability are less affected by global inflation. Importantly, deviations of national inflation from global inflation tend to be reverted, which means that national inflation of countries can be better predicted using common worldwide factors of inflation. Concretely, a forecasting model of inflation augmented with global inflation consistently outperforms a standard AR(p) and naive models of inflation. Our work has a similar flavor to theirs since we analyze whether augmenting otherwise standard forecasting models of inflation may improve predictive ability. However, we depart from this work because we include emerging and advanced economies in our sample, because we analyze both headline and core inflation, and because we go one step further into exploring the factors that are determining global inflation and its forecasting ability. More concretely, this is done by isolating fluctuations of global inflation that cannot be accounted for by observable variables, and exploring whether they improve forecasting performance. In a similar spirit, Eickmeier and Pijnenburg (2013) decompose the major determinants of inflation into global components (driven by global shocks or spillovers) and idiosyncratic components. They then include the global components of inflation determinants into a Phillips curve to analyze their effects on domestic inflation. Their findings show that the common component of variations in unit labor costs has a large impact on domestic inflation. Additionally, import price inflation (not driven by oil supply shocks), foreign competition, and global interest rate developments also affect domestic inflation. Our paper differs from this one because we estimate global inflation and assess its predictive ability over domestic inflation in EMEs, rather than the global synchronization of inflation determinants.

3 Global Inflation

In this section we detail the sources of the data used for the analysis and present a concise set of summary statistics. Then we briefly discuss how we calculate global inflation and present the results, both of the time series of global inflation and the calculated factor loadings. To provide a deeper understanding of what we mean by global inflation, we then present two illustrative exercises. First we argue that inflation in advanced economies seems more synchronized with global inflation compared to that in EMEs. Then we present a simple decomposition of Mexican inflation into a global and an idiosyncratic component.

We obtain official consumer price index (CPI) data by country between January 2001 and December 2019 from Haver Analytics. We construct annual inflation rates, also known as year-on-year inflation, as the twelve-month percentage change in the price index for the period January 2002 and December 2019.[7] We classify countries as advanced or emerging market economies according to the IMF classification (International Monetary Fund 2021, table A, 64). Our sample of emerging countries includes Brazil, Chile, China, Colombia, Croatia, Dominican Republic, Hungary, India, Indonesia, Malaysia, Mexico, Peru, Philippines, Poland, Romania, Russia, South Africa, Thailand, and Turkey. The advanced economies included are Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Portugal, Singapore, Slovenia, South Korea, Spain, Sweden, Switzerland, Taiwan, United Kingdom (UK), and the United States (US).

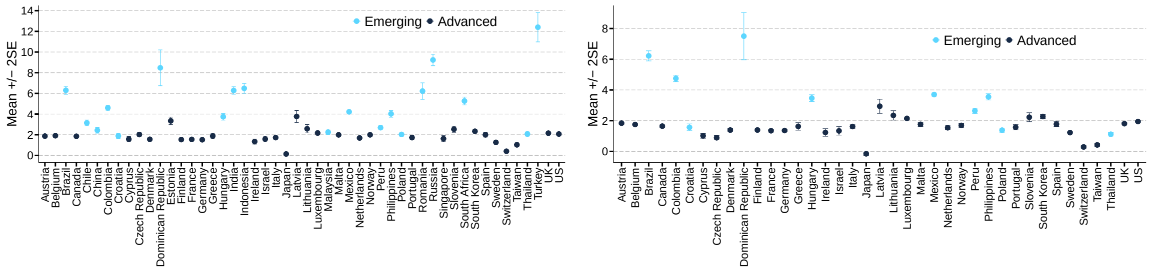
[7] Our sample of inflation rate series spans from 2002 to 2019, intentionally excluding the period of the COVID-19 pandemic. This decision is made to avoid a period of an atypical behavior of inflation driven to a great extent by global shocks, and instead we focus on the argument that even in the absence of dramatic shocks of global nature, global factors play an important role for inflation among EMEs. Extrapolating the results of this work to the period of the pandemic could be sensitive for two reasons. On one hand, during 2022 most countries have observed levels of inflation well above their average levels observed prior to the pandemic. On the other hand, the pandemic has been to a great extent a global shock, so the behavior of inflation has been plausibly dominated by global factors in this period. However, going ahead, the inflationary process may also depend on idiosyncratic factors, so the weight of global inflation could be smaller. This highlights that the role of global factors on inflation may vary over time, so the conclusions in this paper could be different if analyzed in a different time period.

The definition of core inflation is either the official measure of core inflation in each country or an officially reported measure that excludes energy or regulated prices.[8] For the analysis of core inflation, we exclude Singapore since its official measure of core prices includes energy prices. The following countries are not included in the sample for the analysis of core inflation because their measure of core prices did not exist in 2001 or because they do not report core CPI: China, Indonesia, India, Malaysia, Chile, South Africa, Romania, Russia, Turkey, and Estonia. We deepen our analysis for a subsample of ten EMEs, corresponding to those for which we have data for both headline and core inflation for the complete period of study: Brazil, Colombia, Croatia, Dominican Republic, Hungary, Mexico, Peru, Philippines, Poland, and Thailand.

The choice of the sample of ten emerging countries for which we evaluate predictive ability in section 5 is guided by data availability, namely the countries for which we have data for both headline and core inflation for the complete period of study. These countries are Brazil, Colombia, Croatia, Dominican Republic, Hungary, Mexico, Peru, Philippines, Poland, and Thailand, and we deepen the analysis for this subsample throughout the document.

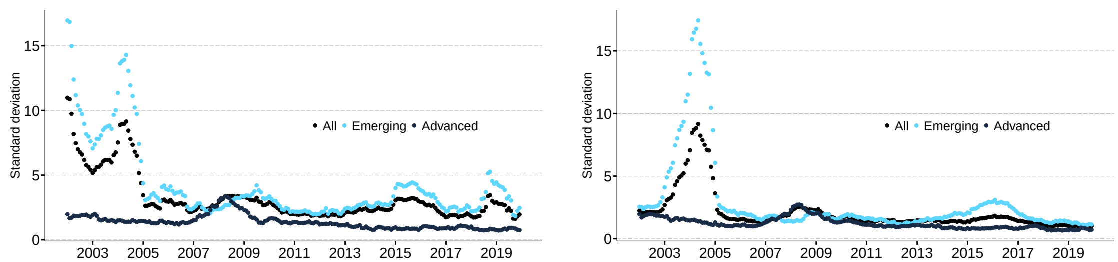
Figure 1 shows the mean plus-minus two standard errors for headline and core inflation rates, computed for each country during the period spanning from January 2002 to December 2019. Figure 1-(a) shows the case of headline inflation for fifty countries. Turkey has the highest mean (12.40%) and Japan, the lowest (0.14%) for headline inflation. Figure 2 shows the standard deviation for headline and core inflation at time t over the total sample and separating between advanced and EMEs. The figure shows that the standard deviation is, on average, larger for headline than for core inflation, and it is also larger for EMEs compared to advanced ones. This is true for all the period except during two short periods of time, the Global

[8] Although naturally representative consumption baskets will differ between countries, using the official measures of core inflation implies that some countries will completely exclude food, while some others (among them Mexico, South Korea, Thailand, Denmark, and Norway) only exclude agricultural products and raw food. In our sample the following countries completely exclude food items from the core measures of inflation: Brazil, China, Colombia, India, Taiwan, South Africa, Russia, Poland, Turkey, Israel, Switzerland, US, UK, Japan, and Canada.



(a) Headline (b) Core

Figure 1: Inflation Mean ± Two Standard Errors for the Period January 2002 to December 2019.
Source: Author's elaboration using data from Haver Analytics and the IMF.



(a) Headline (b) Core

Figure 2: Standard Deviation by Group of Countries for Headline and Core Price Inflation.
Source: Author's elaboration using data from Haver Analytics and the IMF.

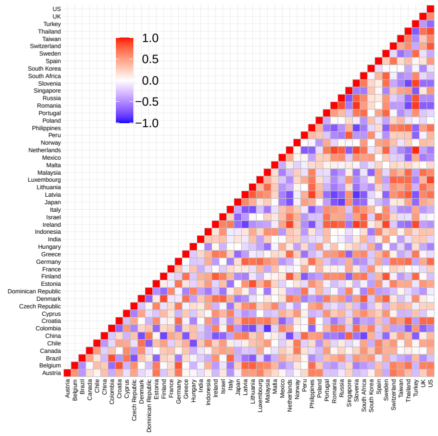
Financial Crisis and between 2012 and 2013, when core inflation's standard deviation is lower in EMEs compared to advanced economies. The figure also shows that the standard deviation decreased over the last twenty years: the observed change was bigger for headline than for core inflation and bigger in emerging market economies than in advanced ones. Appendix A presents additional descriptive statistics. These illustrate that there are clear differences in the behavior of inflation between advanced and emerging market economies: the latter seems to have larger variations. This will be reflected in a lower synchronization of the inflation of this group of countries with global inflation, which is illustrated later in this section.

Figure 3 presents the pairwise correlation of headline and core inflation rates between the countries in our sample for three periods, excluding the Global Financial Crisis. The figure shows that inflation between countries is highly correlated (positive correlations are shown in red in the graphs), particularly for headline inflation (left-hand side). Moreover, this correlation has strengthened during the last two decades for headline inflation (the red tones becoming darker in more recent years shown in the middle and bottom panels). This observation has been previously documented in the literature and it illustrates the increase in global inflation synchronization that motivates the analysis in this document (Ha et al. 2019a). The opposite seems to be true for core inflation (right-hand side).

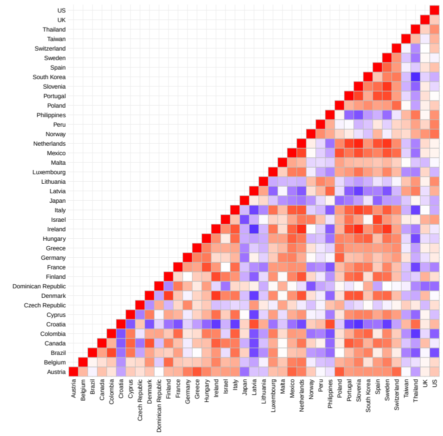
Global inflation is estimated using principal component analysis (PCA). The time series are detrended using the generalized least squares (GLS) method, as in Ng and Perron (2001). As is standard in the literature, data is standardized to have a zero mean and unit variance.[9] We define global headline inflation as the first principal component of standardized headline CPI annual percent variation of all countries in the sample, and global core inflation is defined analogously for the smaller sample. The first principal component for headline inflation (core inflation) explains 39.56% (26.63%) of the total variance, the second 9.53% (12.22%), and the third 9.36% (10.03%). As a robustness check, we compute global inflation using four alternative methods: (i) a static factor model, (ii) a static Bayesian factor model (BFM) with one factor, (iii) a BFM with the incorporation of an endogenous choice of the optimal number of factors, and (iv) a dynamic BFM, (see figure B.1 in appendix B).[10] Results of estimated global inflation, together with standardized inflation for all countries in each measure's sample, are presented in figure 4. The figure shows that between the period 2003-2006 headline inflation was relatively stable and global core inflation decreased. There was a strong increase in global inflation for both measures around the Global Financial Crisis, between 2007 and

[9] Given that inflation rates are standardized, the estimation of global inflation is robust to the inclusion of high volatility inflation series.

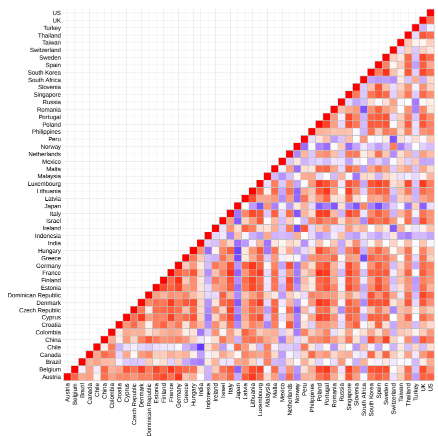
[10] We present the estimator computed using PCA because this model does not make any assumptions about the behavior of the time series used, but results from the five methods computed are similar.



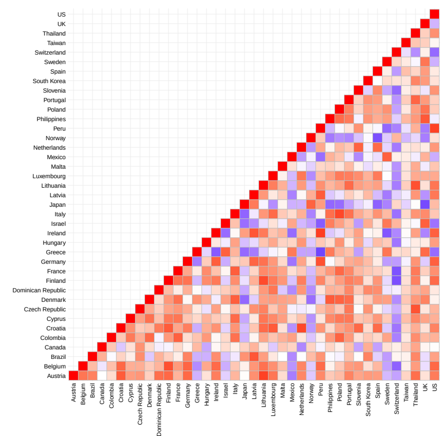
(a) Headline: January 2002 to December 2006



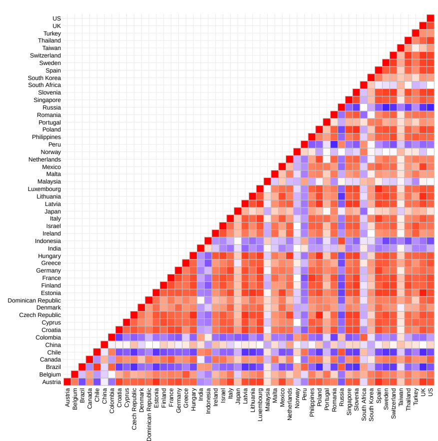
(b) Core: January 2002 to December 2006



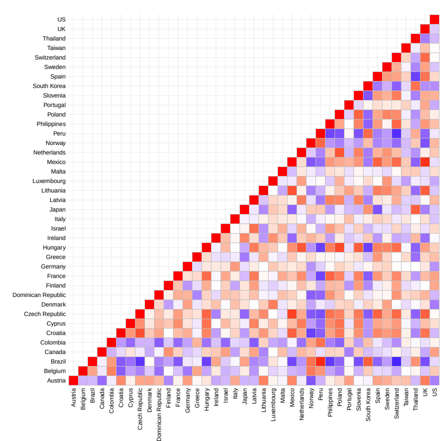
(c) Headline: January 2010 to December 2014



(d) Core: January 2010 to December 2014



(e) Headline: January 2015 to December 2019

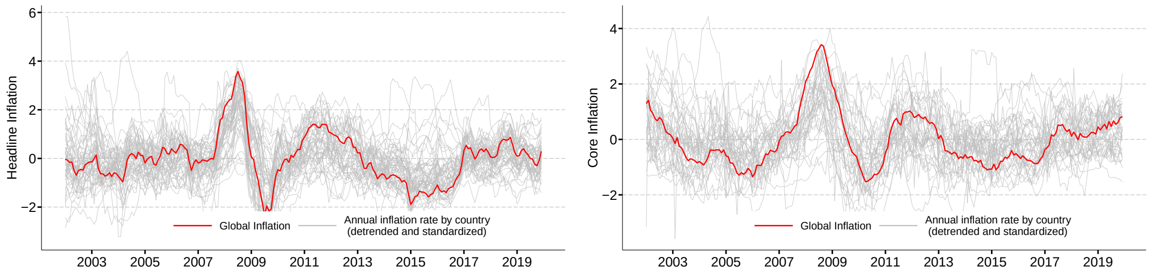


(f) Core: January 2015 to December 2019

Figure 3: Headline and Core Price Inflation Rates Pairwise Correlations.

Notes: Each panel shows the pairwise correlations of headline (left-hand side) and core (right-hand side) inflation in the countries in our sample for three different periods. The top panel shows results for the period January 2002-December 2006, the middle panel for January 2010-December 2014, and the bottom panel for January 2015 to December 2019. The period January 2008-December 2009 is excluded to avoid the Global Financial Crisis. The tone of each square indicates the size of the correlation, where red indicates positive correlations, white no correlation, and blue negative correlation. The darker tones indicate stronger correlation.

Source: Author's elaboration using data from Haver Analytics.



(a) Headline

(b) Core

Figure 4: Inflation Rates and Global Inflation.

Notes: The red line corresponds to global inflation (headline on the left-side panel and core on the right-side panel), which is calculated as the first principal component of inflation in a group of advanced and EMEs. The grey lines show the standardized and detrended annual inflation rates for the countries in the sample for each measure (see section 3 for the details about the sample of countries).
Source: Author's elaboration using data from Haver Analytics.

2008, which began earlier for core inflation, and then there was a sharp decrease during 2009 for both measures. Global inflation increased again between 2010 and 2012, although less sharply than during the crisis, and then decreased until around the year 2015. Global headline inflation increased between 2015 and 2017 and remained relatively stable until 2019. In contrast, global core inflation was more stable between 2015-2017 and then increased until 2019.

Table 1 reports factor loadings for each country.[11] Overall, factor loadings are large, reflecting that global inflation explains an important fraction of inflation variance among countries in the sample.[12] Factor loadings are on average larger for advanced than for emerging market economies, and for headline than for core inflation. There are a few exceptions where the opposite is true, namely that factor loadings for core inflation are larger than those for headline inflation (see the case of Hungary, Mexico, Colombia, Lithuania, Slovenia, Peru and Norway). This last observation is relevant since it contrasts with other work that finds a stronger

[11] Factor loadings reflect the correlation between the global inflation and each country's inflation. More formally, in PCA, the variance of the principal component k is given by the eigenvalue λ_k of the covariance matrix of inflation between all countries. Therefore, the correlation between the principal component k and country m can be calculated as $l_{mk} = \sqrt{\lambda_k}\,\beta_{mk}$, where the factor loading is denoted as l_{mk}, and β_{mk} is the scoring factor of country m in the principal component k.

[12] Given that all series are standardized to have unit variance, the square of the factor loading corresponds to the fraction of inflation variance explained by the principal component for each country in the whole period.

synchronization of headline inflation (Forbes 2019b; Ha et al. 2019b), and with literature that highlights the importance of energy and commodity prices (which are excluded from the core component) as determinants of global inflation.[13] One factor that could be playing a role in the cases of Mexico and Hungary is that their measure of core inflation includes manufactured food items, which will likely move with food commodity prices that affect inflation worldwide. Another relevant factor may be that the external sector is plausibly more important for open EMEs because they rely more on imported goods of both finished manufactured products that are part of the core baskets and production inputs. Moreover, small economies will act as price-takers in the international markets, meaning that their manufacturing export prices may be reacting to global prices and may, in turn, be passed-through to domestic prices. Other idiosyncratic factors for the case of each particular country in the period of study may provide additional explanations for these observations. In the particular case of Mexico, our findings are not as surprising given that gasoline prices—which represent an important fraction of noncore inflation—were administered by the government before 2017.[14] In any case, the large fraction of the variance in core inflation accounted for by global variation is relevant and suggests that the factors that affect inflation globally go beyond the movements in commodity prices.

To further illustrate the stronger synchronization of inflation in advanced economies with the global factor, we calculate the advanced (emerging market) economies headline and core inflation as the first principal component of the corresponding measure of inflation in each group of countries, which we refer to as *advanced (emerging market) economies headline (core) inflation*. We then regress these on the global headline (core) inflation, respectively.

[13] Ha et al. (2019b) find that global demand shocks and oil prices account for around 40% of global inflation variation since 1970.

[14] Results presented in this document are calculated using a long time series spanning from 2002-2019. The estimated global inflation is sensitive to the period studied, and results for each country may be affected by important factors specific to them in this particular period. For example, in a shorter time period beginning in 2017, the calculated factor loading associated with core inflation in Mexico is no longer larger than the one associated with headline inflation (see box 5 in Banco de México 2021).

Table 1: Factor Loadings Associated with Global Inflation.[1]

Country	Headline	Core	Country	Headline	Core
Austria (A)	0.89	0.63	Lithuania (A)	0.77	0.80
Belgium (A)	0.89	0.75	Luxembourg (A)	0.86	0.69
Brazil (E)	-0.32	-0.32	Malaysia (E)	0.51	NA
Canada (A)	0.55	0.01	Malta (A)	0.64	0.53
Chile (E)	0.49	NA	Mexico (E)	0.22	0.56
China (E)	0.64	NA	Netherlands (A)	0.50	0.47
Colombia (E)	-0.01	0.31	Norway (A)	0.14	0.25
Croatia (E)	0.79	0.67	Peru (E)	0.31	0.51
Cyprus (A)	0.81	0.69	Philippines (E)	0.68	0.34
Czech Republic (A)	0.83	0.43	Poland (E)	0.63	0.60
Denmark (A)	0.82	0.75	Portugal (A)	0.65	0.44
Dominican Republic (E)	0.03	-0.14	Romania (E)	0.13	NA
Estonia (A)	0.89	NA	Russia (E)	-0.22	NA
Finland (A)	0.74	0.63	Singapore (A)	0.79	NA
France (A)	0.88	0.66	Slovenia (A)	0.60	0.61
Germany (A)	0.88	0.53	South Africa (E)	0.20	NA
Greece (A)	0.65	0.26	South Korea (A)	0.70	0.60
Hungary (E)	0.51	0.55	Spain (A)	0.86	0.54
India (E)	0.13	NA	Sweden (A)	0.77	0.60
Indonesia (E)	0.17	NA	Switzerland (A)	0.71	0.47
Ireland (A)	0.47	0.35	Taiwan (A)	0.65	0.31
Israel (A)	0.44	0.36	Thailand (E)	0.71	0.27
Italy (A)	0.85	0.74	Turkey (E)	-0.01	NA
Japan (A)	0.29	-0.09	UK (A)	0.74	0.12
Latvia (A)	0.71	0.63	US (A)	0.77	0.40

Source: Author's elaboration using data from Haver Analytics and the IMF.

[1] The table reports the factor loadings of the first principal component for annual headline and core inflation. In the column for core inflation, the term NA indicates that the measure of core prices did not exist in 2001 or that the country did not report core CPI. We did not compute this statistic for Singapore because its official core-prices measure includes energy prices.

[2] (A) denotes advanced economy and (E) denotes emerging market economy.

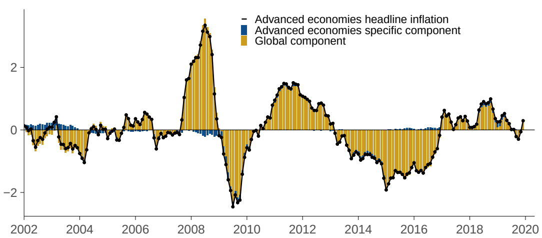
We define the global component of inflation of each group of economies as global inflation multiplied by the coefficient obtained in the regression described, and this is illustrated as the area in gold shown in figure 5. The blue area of the graphs corresponds to the residual of this regression, that we interpret as the component of the common variation of inflation in each group of countries that is specific to that group. The graphs illustrate that the synchronization is, to a great extent, an advanced economies phenomena, since for both measures of inflation, global inflation accounts for almost the totality of advanced economies inflation (panels (a) and (c)). In contrast, the blue area is large for the case of EMEs (panels (b) and (d)). The stronger synchronization of inflation in advanced economies could be explained because they have more input-output linkages, because they tend to observe lower levels and variance of inflation compared to emerging markets, or because inflation expectations are better anchored, so their inflation is less volatile.[15] Moreover, EMEs may be more exposed to idiosyncratic shocks and more vulnerable to exogenous shocks because of weaker macroeconomic stability or weaker anchoring of inflation expectations.[16]

The estimation of global inflation also allows for a decomposition of countries' inflation variance into two elements. The first is the global component, and, for each measure of inflation, is computed by multiplying the estimated global inflation and each country's factor loading reported in table 1. This component may be interpreted as the variance of inflation that is associated with factors that affect inflation globally. The second is the idiosyncratic component computed as the difference between the country's standardized measure of inflation and the estimated global component. We interpret this residual as the contribution of country-specific factors to standardized inflation since it represents the variance in each country's inflation that cannot be accounted for by common inflation variance between countries.

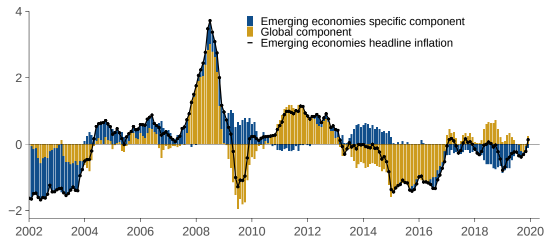
This decomposition allows us to illustrate the relative importance of global inflation and is shown for the case of Mexico in figure 6. As table 1 shows, figure 6 reaffirms that a considerable fraction of Mexican core inflation seems to be associated with global factors (the area of the blue bars representing the global component of standardized inflation is relatively large), but, on average, headline inflation in Mexico was less synchronized with inflation in

[15] A natural concern is that 27 out of 31 advanced economies in our sample are in the Euro Zone, which means that the estimate of the global inflation may be capturing the inflation in this area that is likely to be more correlated given the use of a common currency. Calculating global inflation using the aggregate inflation of the countries in this group instead of each of them individually gives very similar results (the Pearson correlation of the global inflation series calculated with each sample is 0.98 for headline and 0.91 for core inflation). This indicates that global inflation is indeed capturing the common variance of inflation worldwide rather than over representing inflation in the Euro Zone.

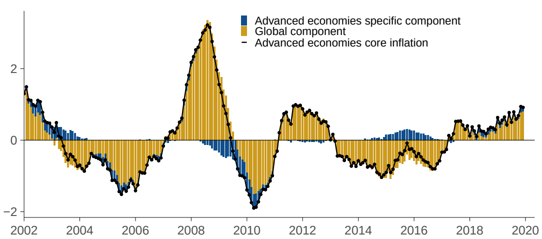
[16] For example, the movements in exchange rates may be playing an important role since capital flows may respond to shocks that affect inflation worldwide. For instance, in the event of a global deceleration, capital may be reallocated to advanced economies, appreciating their currencies relative to those in EMEs, and therefore counteracting the disinflationary global pressures of a weaker economic activity for the case of EMEs.



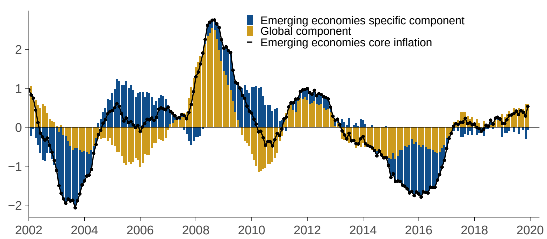
(a) Advanced economies headline inflation



(b) Emerging market economies headline inflation



(c) Advanced economies core inflation



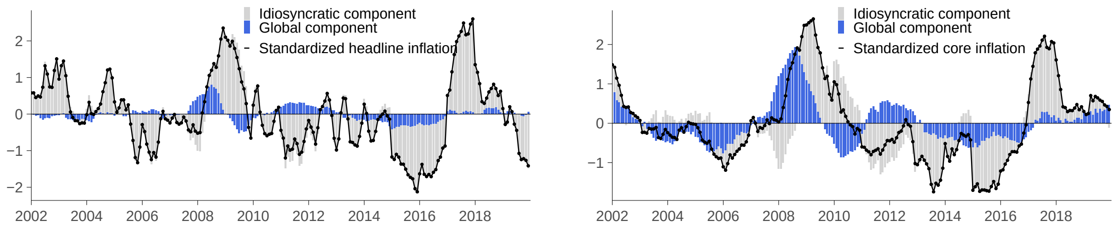
(d) Emerging market economies core inflation

Figure 5: Relevance of Global Inflation for Advanced and Emerging Market Economies Inflation.

Notes: The black line in each graph corresponds to advanced economies or EMEs inflation between January 2002 and December 2019. Advanced (emerging market) economies inflation corresponds to the first principal component of inflation in the group of advanced (emerging market) economies in the sample. The areas in gold represent the contribution of global inflation to each, as measured by the coefficients of global inflation in a regression of advanced (emerging market) economies headline (core) inflation rate, on global headline (core) inflation respectively, multiplied by the value of the latter at each point in time. The blue area represents the residual, that we interpret as the fraction of the common variation among inflation in each group of countries that is uncorrelated with global inflation.
Source: Author's elaboration using data from Haver Analytics and the IMF.

other countries. Another relevant observation is that for the period 2017-2018, the deviations of inflation from its mean were associated with idiosyncratic factors, plausibly reflecting the liberalization of gasoline prices in the country that occurred in that period.

Appendix C shows a similar decomposition of the variation of inflation that is associated with global factors for the sample of EMEs studied in this paper, but including the contribution of the first three principal components. The contribution of each one of these is calculated analogously to that of the first component detailed above. Results illustrate that global headline inflation (as captured by the first principal component) was important in Croatia, Hungary, Philippines, Poland, and Thailand throughout the period studied, whereas global core inflation



(a) Headline (b) Core

Figure 6: Contribution of Global Inflation and Idiosyncratic Factors to Mexico's Price Inflation.

Notes: The black line in each graph corresponds to Mexico's standardized and detrended inflation between January 2002 and December 2019. The blue bars correspond to the contribution of global inflation to standardized inflation, computed as the product of the estimated global factor of each measure of inflation and Mexico's factor loading for the corresponding measure. The grey bars show the difference between standardized inflation and global inflation's contribution, which may be interpreted as the contribution of idiosyncratic factors to standardized inflation.
Source: Author's elaboration using data from Haver Analytics.

seems to have been important in the cases of Mexico, Croatia, Hungary, Poland, and in Peru during the earlier period of the sample. Moreover, global inflation contributed negatively to the average inflation of emerging countries between 2013 and 2017. Another relevant observation is that the contribution of the first principal component is associated with a greater fraction of variation of inflation in most countries studied, but global factors captured by the second and third principal components are also relevant in some countries (for example, Colombia and Peru for the case of headline inflation, and Colombia, Poland, and the Philippines for core inflation). The observation that higher-order principal components capture a relevant additional fraction of variation of inflation indicates that there are several phenomena, not necessarily correlated, that could be driving the global synchronization of inflation (to the extent that different principal components capture different factors).[17]

Note that global inflation will not completely take into account inflation drivers from the economies that were used to construct it (in fact, it is shown that idiosyncratic factors are relevant for the emerging economies studied, and this can be seen in appendix C). Instead, we

[17] In this paper, we focus only on the variation captured by the first principal component to stress our main argument: inflation is influenced by global factors. Incorporating a parsimonious measure of global variation of inflation into forecasting models may improve their performance.

argue that, because inflation in emerging economies is affected by global factors (plausibly strongly given the weaker anchoring of expectations), this simple method may improve our understanding of the determinants of domestic inflation by summarizing a large set of factors in a single principal component. Actually, part of what we find interesting in our results is that, for a subset of emerging economies, global factors seem to explain a larger proportion of core inflation variance than for the case of headline inflation. We argue that this could be because this component may be more vulnerable to global shocks.

4 Determinants of Global Inflation

In this section, we study the factors that may influence prices in the world and illustrate that observable variables that are generally argued to be driving the global synchronization of inflation cannot fully account for the variation in our measure of global inflation. To do this, we estimate the contribution of the global output gap, oil annual price inflation, nonfuel commodities annual price inflation, and VIX financial volatility index to global inflation during the period 2002-2019 by running an OLS regression with global inflation as the dependent variable. Finally, we show the contributions of each factor to inflation in each period together with the unexplained residual.

We use information about the global determinants of inflation obtained from different sources. We estimate the global output gap as the cyclical component of the Hodrick-Prescott filter on aggregate real GDP in US dollars in a set of countries.[18] International prices of commodities are obtained from the International Monetary Fund (IMF). Nonfuel commodities include

[18] We obtain quarterly series of real GDP in billion US dollars between 2000 and 2019 from Haver Analytics. We include the following countries: Brazil, Chile, China, Colombia, Czech Republic, Ecuador, Hong Kong, Hungary, India, Indonesia, Israel, South Korea, Malaysia, Mexico, Peru, Philippines, Poland, Romania, Russia, Singapore, South Africa, Taiwan, Thailand, Turkey, US, the European Union, Japan, Australia, Canada, Denmark, Switzerland, the United Kingdom, Norway, New Zealand and Sweden. We define real-world GDP as the sum of GDP in all these countries. To obtain a monthly time series, we assign the quarterly real world GDP to the second month in the corresponding quarter, and we interpolate data in the missing months. The global output gap corresponds to the cyclical component of a Hodrick–Prescott filter of this monthly time series, using a smoothing parameter of 129,600, following Ravn and Uhlig (2002).

precious metals, food and beverages, and industrial inputs commodities.[19] Oil prices are obtained from the Energy Information Administration (EIA), and we use the annual variation of the monthly average price of the Cushing, Oklahoma WTI Spot Price.[20] As a measure of financial volatility, we use the Chicago Board Options Exchange (CBOE) volatility index (VIX) that we obtain from Haver Analytics. The VIX is a real-time index representing the market's expectations for the relative strength of near-term price changes of the S&P 500 index. We use the average monthly value of the VIX index. We obtain global manufacturing Purchasing Managers' Index (PMI) output index and input prices index from Markit. These measures consist on diffusion indices that summarize whether output and input prices are expanding or contracting according to purchasing managers. These variables are included as proxies for global supply of manufactured goods (output index) and global manufacturing production costs (input prices indices). A higher output index will signal strong supply, whereas higher input prices can signal a negative supply shock.

All variables included in the OLS regression of global inflation on its determinants are standardized to have zero mean and unit variance in the estimation period. The regression does not include a constant term. The results of the estimation are in table 2. These are broadly consistent with the literature. The global output gap, oil price inflation, and financial volatility positively correlate with the headline and core global inflation. The former two observations could be related since the demand pressures associated with the economic cycle could pressure commodity prices that are determined in the international market and reflected in headline inflation.

The positive association between global inflation and financial volatility could be related to several factors. On the one hand, episodes of elevated volatility may be associated with

[19] "Primary Commodity Prices," International Monetary Fund, accessed May 2, 2021, `https://www.imf.org/en/Research/commodity-prices`. Individual series of industrial inputs and food and beverages exist and are used in section 5, but in this section, we focus on the aggregate of nonfuels.

[20] "Petroleum and Other Liquids Spot Prices," Energy Information Administration, accessed August 3, 2021, `https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm`.

geopolitical tensions that may have adverse impacts on global supply and, therefore, translate into inflationary pressures (see, for example, Bouoiyour et al. 2019; Chien-Chiang et al. 2021; Smales 2021) for volatility in oil markets, and Qin et al. (2020); Bouras et al. (2019) for volatility in financial markets). Volatility is also correlated with heightened uncertainty and with volatility in stock markets and exchange rates (Liu and Zhang 2015; Bartsch 2019; Noria and Bush 2019), and these have been argued to impact prices positively through at least four mechanisms.[21] First, uncertainty may impact inflation in emerging markets because it is associated with episodes of exchange rate depreciation that pressure inflation (Redl 2018). Second, there is a high and positive correlation between uncertainty and oil price shocks that have inflationary effects across countries (Kumar et al. 2021). Third, policy-related uncertainty may raise inflationary expectations that are correlated with inflation itself (Istrefi and Piloiu 2014). Fourth, it is plausible that an upward nominal pricing bias mechanism is operating if an uncertainty shock induces firms to set high prices as an insurance mechanism against nominal rigidities that could force them to maintain the chosen price for a long period (Born and Pfeifer 2014; Redl 2018). This upward pricing bias channel may be particularly important during periods of high volatility since the latter increases dispersion in the future marginal costs inducing asymmetries in the profit function that make it more costly for firms to set the price too low relative to their competitors rather than too high (Fernández-Villaverde et al. 2015).[22]

The positive correlation of the VIX index with global inflation could also be due to the association of volatility and the global financial cycle (see table 2). The global comovement of risky asset prices, credit growth, and capital flows is correlated with risk aversion, and influenced by the US monetary policy (Bruno and Shin 2015; Miranda-Agrippino and Rey

[21] Uncertainty can in theory also impact prices negatively through, for example, inducing a region of inaction for firms, discouraging investment and hiring of workers, and therefore a slowdown of economic activity and a fall in prices (Bloom 2009).

[22] Fernández-Villaverde et al. (2015) find that prices in the US fall following a fiscal volatility shock, although they provide arguments for why volatility may rise markups, which are related to nominal rigidities and specifically to the upward pricing bias channel.

2020b). Therefore, the correlation between global inflation and volatility could be rationalized if the VIX index partly reflects the movements in the US monetary policy to the extent that an increase in volatility is associated with a tightening of the US monetary policy in response to high inflation. Another mechanism that may be driving this positive correlation is that liquidity-constrained firms may be pressured to increase prices during episodes of financial distress in order to maintain or increase cash flows and avoid the need for external finance (Gilchrist et al. 2017).

A surprising result is that core inflation negatively correlates with nonfuel commodities' price inflation.[23] Our preferred interpretation is that these prices may positively influence core inflation with a lag since they include industrial inputs and food and beverages, which are used to produce manufactured goods and services, and it could take some time for these costs to be reflected in consumer prices. Moreover, it may also take some time for the state of the tradeable sector to spill over to the nontradable sector and impact core inflation. Another plausible explanation for this result would be that for a large set of countries, core inflation excludes food items, which implies that a group of commodities considered in this index does not play a role. However, this latter hypothesis is inconsistent with the results of an alternative estimation that incorporates food and beverages separately from industrial inputs commodities, suggesting that the negative coefficient associated with nonfuel commodities' inflation is a consequence of industrial inputs commodities, while the coefficient associated with food and beverages is positive and statistically significant.[24]

To illustrate the relative importance of the different determinants of global inflation, in figure 7, we plot standardized global inflation together with the estimated contributions of these determinants. Said contributions to global inflation are calculated as the product of the coefficient in the regressions presented in table 2 associated with each variable and the

[23] The estimation for the global headline inflation excludes nonfuel commodities inflation. We present the preferred model according to the Akaike information criterion.

[24] This alternative estimation is not presented in this document for space considerations but is available upon request.

Table 2: Global Inflation, International Commodity Prices, Output Gap, Financial Volatility, Manufacturing Output, and Manufacturing Input Prices.[1]

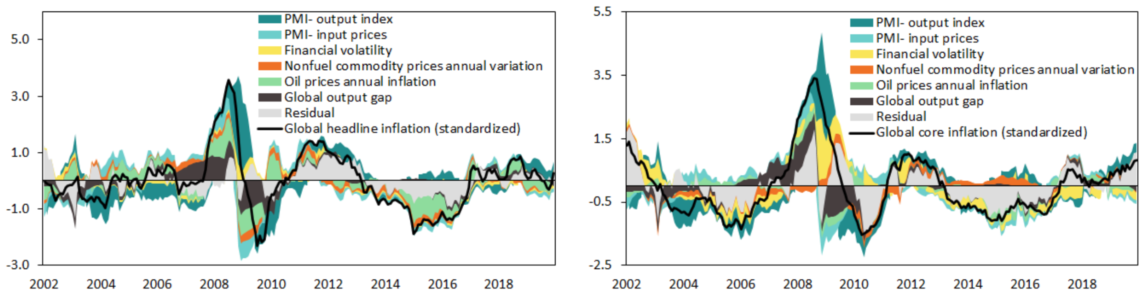
Variable	Global Headline Inflation (1)	Global Core Inflation (2)
Global output gap	0.329***	0.325***
	(0.046)	(0.061)
Oil prices annual variation	0.397***	0.139**
	(0.053)	(0.069)
Nonfuel commodity prices annual variation	0.146***	-0.148**
	(0.056)	(0.073)
Financial volatility	0.112**	0.373***
	(0.049)	(0.064)
Global manufacturing PMI output index	-0.581**	-0.500***
	(0.058)	(0.076)
Global manufacturing PMI input prices index	0.218***	0.173*
	(0.071)	(0.093)
Observations	216	216
R-squared	0.758	0.565

Source: Author's elaboration using data from Haver Analytics, the Energy Information Administration, and the IMF.

[1] The table reports the correlation between global inflation and the global output gap, oil prices annual variation, nonfuel commodity prices annual variation, financial volatility, global manufacturing PMI output index, and global manufacturing PMI input prices index as measured by the coefficients of an OLS regression of global inflation as the dependent variable. The global output gap is measured as the cyclical component of the Hodrick-Prescott filter on aggregate GDP of the countries in the sample. All series are standardized. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

standardized value of each variable at each point in time. The figure shows that the global output gap and oil price inflation are relatively more important for headline inflation than core inflation, which is consistent with the fact that fuels are excluded from core baskets. In contrast, volatility is relatively more important for core inflation, suggesting that uncertainty may be relatively more relevant for determining the prices of manufactured merchandise and services. An important observation is that a considerable fraction of global inflation cannot be accounted for by the variables included in this model (the grey area in the graphs that illustrates the residuals of the regression). Hence, additional variables may be generally overlooked but may be important drivers of inflation across countries.[25] In section 5, we will inquire about this hypothesis more deeply by exploring whether this residual has predictive ability over inflation in EMEs, controlling for the observable variables presented above.

[25] Some examples of these could be the international prices of manufactured goods, supply shocks, and global risk aversion.



(a) Headline (b) Core

Figure 7: Global Inflation, Financial Volatility, Commodity Prices, and Output Gap.

Notes: The black line in each graph corresponds to global inflation between January 2002 and December 2019. The coloured areas represent the contribution of oil and nonfuel commodities' annual price inflation, global output gap, financial volatility, global manufacturing PMI output index, and global manufacturing PMI input prices index to global inflation as measured by the statistically significant coefficients of a regression of global inflation on these variables (shown in table 2) multiplied by the value of these series at each point in time. The grey area represents the residual of the said regression, that we interpret as the fraction of global inflation that cannot be explained by the observable variables included.
Source: Author's elaboration using data from Haver Analytics, the Energy Information Administration, and the IMF.

5 Global Inflation as a Predictor of National Inflation Rates

This section aims to evaluate whether global inflation has predictive ability. To do this, we focus on the sample of the ten EMEs studied, and we compare the forecasting performance of a SARIMA model that incorporates global inflation as covariate with the performance of models that include other determinants of worldwide inflation as covariates.[26] We use two different measures of forecasting performance: 1) the ratio of the RMSE of the augmented models relative to that of a univariate model (our benchmark) and 2) the ratio of the RMSE of forecasting models that include global inflation as covariate and those that include other global determinants of inflation as covariates. We evaluate performance for horizons of 6, 12, 24, and 36 months. In a third step, we perform a simple exercise to analyze whether global inflation contains information that may be affecting inflation in EMEs beyond the information captured by observable determinants analyzed in this work. This is done by estimating the variation of global inflation orthogonal to observables variation and then augmenting the benchmark model with this residual as a covariate. We argue that a statistically significant

[26] The countries included in the sample are Brazil, Colombia, Croatia, Dominican Republic, Hungary, Mexico, Peru, Philippines, Poland, and Thailand. See section 3 for details on sample selection.

coefficient indicates that global inflation contains relevant information for inflation in the countries studied and provided by the observables studied. Apart from being a simple tool for summarizing information of a large set of observable factors, it contains information about a wider set of variables that influence inflation in EMEs and that could be unobservable.

The benchmark model used for the first exercise is a multiplicative seasonal autoregressive integrated moving average model (SARIMA) model given by

$$\Phi_P(B^s)\phi(B) \bigtriangledown_s^D \bigtriangledown^d \pi_t = \delta + \Theta_Q(B^s)\theta(B)w_t \,, \tag{1}$$

where π_t denotes a standardized inflation rate and w_t a white noise. The general model is also denoted as ARIMA$(p, d, q) \times (P, D, Q)_s$. The ordinary autoregressive and moving average components are represented by polynomials $\phi(B)$ and $\theta(B)$ of orders p and q, respectively; the seasonal autoregressive and moving average components are represented by $\Phi_P(B^s)$ and $\Theta_Q(B^s)$ of orders P and Q; and ordinary and seasonal difference components represented by $\bigtriangledown^d = (1 - B)^d$ and $\bigtriangledown_s^D = (1 - B)^D$ where d and D are the differencing and seasonal differencing parameters. Finally, we select the best model using the small-sample corrected AIC criteria (AICc).

The augmented models include additional explanatory variables. We use the concept of regression with SARIMA error to estimate SARIMAX models that are specified as[27]

$$\pi_t = \boldsymbol{\beta}\mathbf{x}_t + u_t \tag{2a}$$

$$\Phi_P(B^s)\phi(B) \bigtriangledown_s^D \bigtriangledown^d u_t = \delta + \Theta_Q(B^s)\theta(B)w_t \,, \tag{2b}$$

[27] The specification (2) nests many simpler specifications such as ARIMAX, ARMAX, ARX, MAX. Using (1) for the benchmark and (2) for the augmented model. SARIMAX models allow for differencing data by seasonal frequency, yet also by nonseasonal differencing (Hyndman and Athanasopoulos 2018). This tool is desirable for our detrended data for which the unit-root hypothesis is nonrejected for some countries (see tables A.3 and A.4 in appendix A) and the presence of seasonalities depicted in figure 8.

where $\boldsymbol{\beta}$ is a vector of dimension $1 \times n$, $\mathbf{x}_t$ is of dimension $n \times 1$, and n indicates the number of explanatory variables. Again, we select the best model using the small-sample corrected AIC criteria (AICc). The explanatory variables that are included are normalized to have zero mean and unit variance in all cases, and these are included individually in some specifications, and in combination with others for other specifications. The set of explanatory variables considered are:

(a) Global inflation estimated using principal components (see section 3 for details). Figure 4 illustrates the time series of global headline and core inflation.

(b) Natural logarithm of the exchange rate (LER) in each country.[28] The exchange rate is defined as the local currency versus the United States Dollar. Monthly data for EMEs' exchange rates are obtained from Haver Analytics.

(c) Global output gap (OG), defined as the difference between actual and potential global output expressed as a percent of potential global output. See details in section 4.

(d) Oil prices' annual variation (OilP).

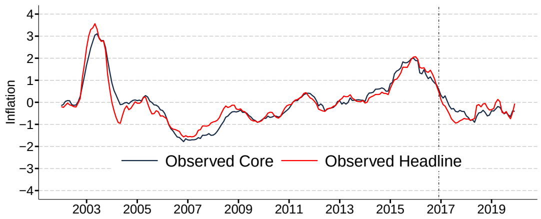
(e) Nonfuel commodity prices' annual variation (COMP).

(f) Food and beverages commodity prices' annual variation (FBCP).

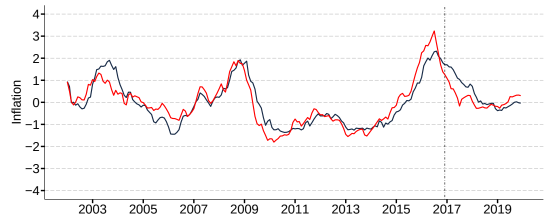
(g) Industrial inputs commodity prices' annual variation (IICP).

(h) Financial volatility (VIX). It refers to the monthly average of daily values of the CBOE volatility index, VIX. See details in section 4.

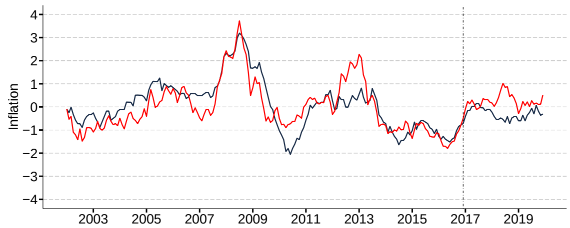
[28] Although the exchange rate is not a global determinant of inflation but rather a domestic variable, we decide to include it in the analysis for two reasons. First, it is a relevant determinant of inflation in open EMEs. Information about it is available daily, and it can be easily incorporated into forecasting models in real-time. Second, although exchange rates respond to idiosyncratic factors, these are arguably also affected by global factors, including the global economic cycle, volatility, and risk aversion. Consequently, exchange rates in EMEs may be partly determined by global factors.



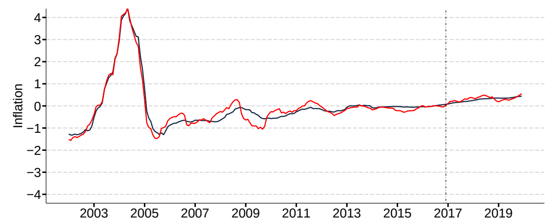
(a) Brazil



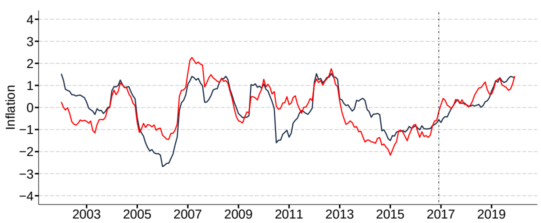
(b) Colombia



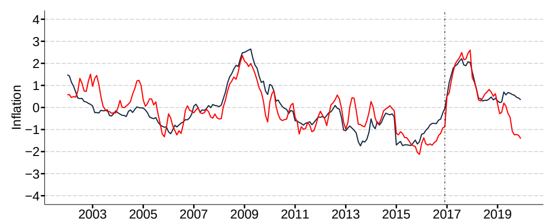
(c) Croatia



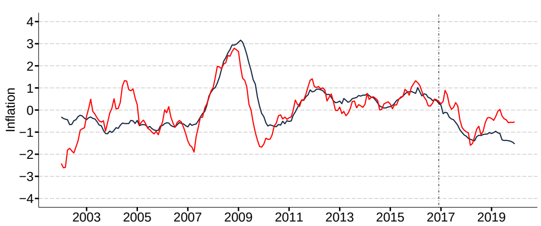
(d) Dominican Republic



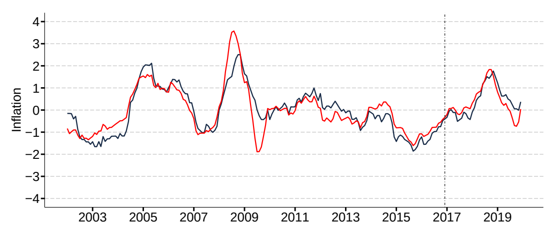
(e) Hungary



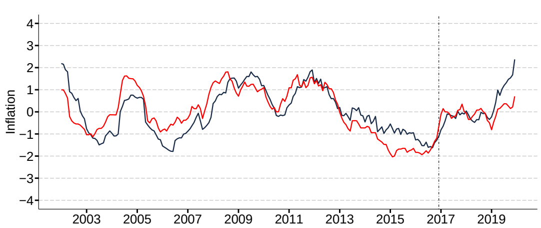
(f) Mexico



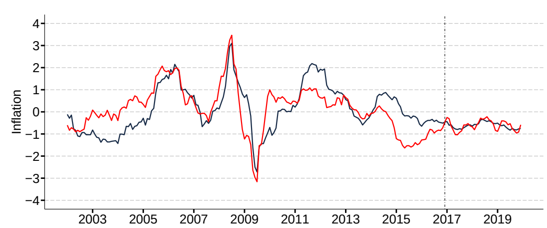
(g) Peru



(h) Philippines



(i) Poland



(j) Thailand

Figure 8: Observed Headline and Observed Core Price Inflation for Selected Emerging Market Economies.

Notes: The inflation rates have been standardized to have zero mean and unit variance. Blue lines indicate core price inflation and red lines indicate headline price inflation. The vertical line indicates in December 2016 the cutoff between the training data (January 2002 to December 2016) and the test data (January 2017 to December 2019).
Source: Author's elaboration using data from Haver Analytics.

To evaluate the predictive performance of each model, we first separate the period from January 2002 to December 2019 into two sub-periods: i) the *training data* period, including 180 observations from January 2002 to December 2016 and ii) the *test data* period, including 36 observations from January 2017 to December 2019. The model parameters are estimated using the training data period only, and predictions are performed for the test data period using the data available up to December 2016 to forecast inflation at different horizons over the test data period.[29] At each period in time, information that would be available up to such time is considered in the forecast. This points to an additional reason why using nonstructural univariate forecasting models is appealing from a policy perspective. These are simple and rely on data available for policy makers in a timely manner.[30] Figure 8 shows headline (red lines) and core (blue lines) inflation rates normalized to have zero mean and unit variance for the ten countries in our sample and the period of study. We show the cutoff between the training data period and the test data period using a vertical line in panels (a) to (j) of the figure.

Guided by recent literature, the first measure of forecasting performance used is the RMSE ratio of augmented SARIMAX models relative to the univariate SARIMA (our benchmark).[31] A value greater than one indicates that the SARIMA model has a better performance. Tables 3 and 4 show the detailed results for the ratio of the RMSE of each model relative to that of the

[29] Since the test data period includes 36 months, this means that the evaluation of the forecasting performance in each horizon is evaluated over the number of observations of that horizon (for example, the six-month horizon forecast is evaluated over six observations and the 36 month forecast over 36 observations). This type of forecasting experiment is known as pseudo-out-of-sample (POOS).

[30] For some forecasting horizons, a univariate framework might be outperformed by multivariate, semi-structural or structural modelling approaches. However, the advantage of using a univariate framework augmented with global inflation is that it is an accessible approach to forecast inflation that relies on data published at a regular frequency and generally faster than other variables required in a multivariate framework.

[31] Literature suggests several methods for model assessment. The most common approach is to rank forecasting models according to an associated loss function, that is typically given by the *mean absolute error* (MAE), or the *root-mean squared error* (RMSE) (Ghysels and Marcellino 2018; Hyndman and Athanasopoulos 2018). These measures have been used in recent literature to compare inflation forecasting models in, for example, Hassler and Pohle (2021, tables 4 and 5), Zhang et al. (2020, table 2), Ciccarelli and Mojon (2010, figure 4), among others. Comparisons using the MAE or RMSE are deterministic, that is, these evaluate whether the MAE or the RMSE is larger for one model than for other, but not whether their difference is statistically significant. Statistical tests for the hypothesis that two forecasts are equivalent, in the sense that the difference in the associated loss is not statistically different from zero, have been proposed by Granger and Newbold (1986) (this test is known as the Morgan-Granger-Newbold test) and by Diebold and Mariano (1995), for example. We do not use the former because it requires stronger assumptions on the forecast errors (zero mean, normally distributed, and uncorrelated). We do not use the latter because it is not a suitable test for POOS experiments (Diebold 2015).

univariate SARIMA for headline and core inflation, respectively. This comparison is presented for each of the ten countries in the sample and each forecasting horizon in 6, 12, 24, and 36 months to evaluate the performance over 40 cases in total.[32] The tables also report success rates, which we define as the fraction of cases where the SARIMAX model, which includes the covariate in each panel, improves the forecast relative to the benchmark model (using the RMSE ratios as an indicator of success).

Eight augmented SARIMA models are compared against the univariate SARIMA model for forecasting headline and core inflation. These eight models, following equation (2), consists of an autoregressive component of domestic inflation augmented with each of the eight variables described above, that is, each of the eight models uses domestic inflation and one of the following variables: global inflation, natural logarithm of the exchange rate (local currency versus de United States dollar), global output gap, oil prices' annual variation, food and beverages commodity prices', industrial inputs commodity prices, and financial volatility as inputs. Then, once the models are tested, the RMSE of each one of the eight is divided by the RMSE of the benchmark SARIMA.

Results in table 3 indicate that global inflation is relevant for forecasting inflation for the case of the headline measure since the latter ranks as the "best" covariate, measured by its success rate. Indeed, the table shows that the model including global inflation as covariate outperforms the benchmark headline inflation model in 55.00% of the cases, and is the only model among the ones analyzed that outperforms the SARIMA benchmark. The model that includes global output gap outperforms the benchmark model in only 40% of cases. The model that ranks second using this criterion is the one including food and beverages commodity prices' annual variation as covariate, since it outperforms the benchmark in 50.00% of cases. The potential of global inflation to improve forecasting performance, in the models analyzed, for the case of core inflation is weaker, as is shown in table 4. Noticeably, none of the covariates studied

[32] We refer to each country and each forecast horizon as one case.

in this work, when included individually in SARIMAX models, improve the performance relative to a SARIMA benchmark. Although global inflation also ranks as the best covariate using the measure detailed above, it underperforms the benchmark since its success rate is only 47.50%.

We perform additional exercises by combining different groups of variables, including pairing global inflation and global output gap together with log-exchange rate, oil prices' annual variation, financial volatility, and commodity prices' annual variation in the models.[33] Table 5 summarizes the results of all the augmented models evaluated by reporting their success rates.[34] We find that for headline inflation, the SARIMAX model including global inflation still ranks as the best, even comparing it to models with several covariates. Models including the combination of global inflation together with some other covariates do have a similar performance: with the log exchange rate, oil price commodities annual variation, and financial volatility. This suggests that global inflation is a good tool to summarize a wide set of worldwide inflation determinants. For core inflation, the model including global inflation together with the log exchange rate ranks as the best model compared to the rest, and it outperforms the SARIMA benchmark, since its success rate is 57.50%. This is reasonable given the importance of variations in the exchange rate for inflation in EMEs.

[33] We choose to combine in pairs global inflation and global output gap to emphasize the point that the former can improve the forecasts relative to a measure of global economic activity, which is commonly used for inflation forecasting, for example, in Phillips curves models.

[34] Table 5 presents the results for a larger set of models than those presented in tables 3 and 4, including combinations of covariates. The detailed results of these additional models are not presented in the document for space considerations but are available upon request.

Table 3: Headline Price Inflation. Root Mean Square Error Ratios with SARIMA Benchmark.[1]

Country	Global inflation				Global output gap				Log exchange rate			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	1.68	1.63	1.21	1.09	1.66	1.55	1.13	1.03	1.68	1.62	1.22	1.10
Colombia	1.82	3.15	4.84	4.30	1.76	2.95	4.51	4.08	1.83	3.13	4.74	4.25
Croatia	0.37	0.31	0.28	0.31	1.28	0.79	0.59	0.56	1.24	0.80	0.60	0.56
Dominican Republic	4.20	2.04	0.87	0.86	4.85	2.33	1.06	0.90	5.18	2.36	1.05	0.89
Hungary	0.29	0.29	0.62	0.79	0.61	0.72	0.74	0.67	0.50	0.56	1.06	0.97
Mexico	1.06	1.05	1.04	1.04	1.10	1.10	1.12	1.12	1.08	1.07	1.07	1.07
Peru	0.87	0.73	0.88	0.84	0.91	0.80	0.93	0.89	0.92	0.74	0.86	0.83
Philippines	0.91	0.76	0.92	0.91	1.74	1.42	1.08	1.07	1.68	1.27	1.04	1.03
Poland	0.19	0.32	0.62	0.78	0.36	0.43	0.60	0.75	0.37	0.42	0.64	0.74
Thailand	1.79	1.99	1.70	1.78	1.23	1.41	1.11	1.24	0.98	0.93	0.69	0.71
Success rate[3]	55.00%				40.00%				47.50%			

Country	Oil prices a.v.[2]				Nonfuel comm. prices a.v				Food and bev. comm. prices a.v.			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	1.91	1.79	1.33	1.23	1.78	1.69	1.27	1.15	1.72	1.65	1.23	1.11
Colombia	2.04	3.40	4.97	4.52	1.93	3.27	4.92	4.43	1.97	3.35	5.02	4.54
Croatia	1.54	1.09	0.73	0.73	1.42	0.97	0.71	0.67	1.28	0.88	0.66	0.62
Dominican Republic	7.50	3.13	1.25	1.12	5.61	2.54	1.14	0.97	4.68	2.22	1.02	0.87
Hungary	0.36	0.37	0.81	0.81	0.49	0.65	1.13	0.99	0.47	0.46	0.82	0.75
Mexico	1.08	1.06	1.06	1.06	1.08	1.06	1.06	1.06	1.09	1.08	1.08	1.09
Peru	0.92	0.74	0.87	0.85	0.84	0.81	0.95	0.94	0.89	0.78	0.92	0.90
Philippines	1.67	1.32	1.05	1.05	1.95	1.57	1.12	1.12	1.83	1.50	1.10	1.10
Poland	0.38	0.60	0.64	0.88	0.33	0.53	0.65	0.79	0.33	0.52	0.64	0.79
Thailand	0.66	0.61	0.44	0.55	0.75	0.71	0.64	0.73	0.96	0.93	0.71	0.80
Success rate[3]	45.00%				47.50%				50.00%			

Country	Industr. inputs comm. pric. a.v.				Financial volatility			
	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	1.82	1.72	1.30	1.19	1.72	1.65	1.23	1.12
Colombia	1.87	3.18	4.81	4.32	1.83	3.13	4.73	4.25
Croatia	1.38	0.93	0.69	0.65	1.30	0.87	0.64	0.60
Dominican Republic	7.77	3.26	1.42	1.23	4.33	2.15	0.98	0.84
Hungary	0.43	0.41	0.85	0.79	0.50	0.48	0.79	0.73
Mexico	1.07	1.06	1.06	1.06	1.08	1.07	1.06	1.06
Peru	0.84	0.81	0.95	0.94	0.92	0.73	0.86	0.84
Philippines	1.92	1.53	1.12	1.11	1.70	1.29	1.05	1.05
Poland	0.36	0.53	0.63	0.80	0.36	0.48	0.61	0.75
Thailand	0.88	0.88	0.67	0.69	1.12	1.17	0.86	1.01
Success rate[3]	47.50%				45.00%			

Source: Author's elaboration using data from Haver Analytics, the Energy Information Administration, and the IMF.

[1] Eight models are compared to a univariate SARIMA model for forecasting headline inflation in each country. We fit eight SARIMAX models with the global inflation, global output gap, log exchange rate, oil prices' annual variation, commodity prices' annual variation (nonfuel and food and beverages), industrial inputs commodity prices' annual variation, and financial volatility as predictors. The table shows RMSE ratios at four forecasting horizons: 6, 12, 24, and 36 months. Values greater than one indicate that the univariate model performs better than the multivariate model. The cases where each SARIMAX model outperforms the univariate model are highlighted in grey. Due to the rounding, the numbers reported in the table may indicate a value of 1.00 even if the ratio is smaller.

[2] Annual variation is denoted by a.v.

[3] Success rate refers to the fraction of cases when forecasting using a SARIMAX model outperforms a univariate model.

To test the robustness of the claim that global inflation improves forecasting performance of simple SARIMA models, we seek a more direct comparison of models that include global inflation as a covariate against other models that incorporate other global inflation determinants traditionally considered. Specifically, we compare SARIMAX models that include as covariates the global output gap, log exchange rate, different commodity prices' annual variation and financial volatility, versus two additional benchmark models: i) SARIMAX including global inflation as a covariate, and ii) SARIMAX including global inflation and the logarithm of the exchange rate as covariates for each country. We choose to compare the models including global inflation paired with the exchange rate because of the relevance of the latter for EMEs. We again use the RMSE to evaluate the performance of the models, but now the benchmark model is the SARIMAX including global inflation. Detailed results are in appendix D, and the summary of the results is presented in tables 6 and 7. Specifically, the tables report success rates for each model, where now the success rate is defined as the fraction of cases where the SARIMAX model that includes the covariates indicated in each row has a smaller RMSE than the SARIMAX model including global inflation (either alone, in table 6, or together with the exchange rate, in table 7).

Table 6 shows that for headline inflation, the SARIMAX model including global inflation performs better than SARIMAX models including each one of the covariables considered. For core inflation, the SARIMAX model including global inflation is either outperformed or performs similar to all of the SARIMAX models considered. The observation that including global inflation as covariate performs equivalently that the model including the exchange rate is important, since inflation in EMEs is generally thought to be closely related to the latter. This result highlights the importance of global determinants of inflation, as summarized by global inflation, for inflation in the EMEs in the sample.

Table 7, on the other hand, shows a comparison between different models including two covariates, and indicates that for headline inflation, the model including global inflation and

Table 4: Core Price Inflation. Root Mean Square Error Ratios with SARIMA Benchmark.[1]

Country	Global inflation				Global output gap				Log exchange rate			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	6.05	8.54	1.46	1.12	6.07	8.40	1.43	1.10	6.21	8.76	1.48	1.14
Colombia	0.50	0.91	2.11	3.02	0.28	0.50	1.58	2.39	0.33	0.66	1.82	2.58
Croatia	0.81	0.54	0.85	1.00	1.62	1.39	1.24	1.19	1.60	1.41	1.26	1.19
Dominican Republic	1.01	0.58	0.41	0.44	0.50	0.30	0.30	0.33	0.70	0.40	0.34	0.36
Hungary	1.70	1.21	1.41	0.83	1.63	2.95	3.10	1.38	1.69	3.09	3.38	1.43
Mexico	0.99	0.94	0.89	0.83	1.07	1.06	1.02	0.97	1.00	0.97	0.92	0.87
Peru	2.54	1.59	1.16	1.06	2.20	1.41	1.07	0.97	2.01	1.35	1.05	0.95
Philippines	0.67	0.38	1.11	1.12	0.48	0.34	1.01	1.01	0.47	0.34	1.02	1.01
Poland	1.26	1.38	1.13	0.89	2.61	3.31	2.53	1.30	2.48	3.15	2.40	1.27
Thailand	1.00	0.87	0.75	0.82	0.79	0.68	0.59	0.59	0.74	0.58	0.48	0.52
Success rate[3]	47.50%				35.00%				42.50%			

Country	Oil prices a.v.[2]				Nonfuel comm. prices a.v				Food and bev. comm. prices a.v.			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	6.66	9.24	1.53	1.19	6.58	9.21	1.55	1.19	6.30	8.90	1.50	1.15
Colombia	0.35	0.68	1.85	2.63	0.34	0.68	1.85	2.62	0.37	0.71	1.90	2.69
Croatia	1.56	1.39	1.24	1.16	1.54	1.36	1.22	1.15	1.58	1.40	1.25	1.17
Dominican Republic	0.99	0.50	0.37	0.41	0.63	0.37	0.33	0.35	0.51	0.29	0.29	0.31
Hungary	1.67	3.36	3.62	1.41	1.65	3.30	3.47	1.39	1.48	3.07	3.21	1.34
Mexico	1.05	1.02	0.97	0.92	1.00	0.97	0.92	0.87	1.04	1.01	0.97	0.91
Peru	2.35	1.49	1.11	1.01	2.43	1.53	1.15	1.03	2.35	1.50	1.13	1.02
Philippines	0.62	0.36	1.11	1.12	0.48	0.33	1.03	1.03	0.48	0.33	1.02	1.01
Poland	2.72	3.53	2.67	1.34	2.62	3.37	2.58	1.30	2.63	3.38	2.59	1.30
Thailand	0.72	0.56	0.46	0.50	0.56	0.40	0.34	0.35	0.61	0.43	0.36	0.36
Success rate[3]	35.00%				37.50%				35.00%			

Country	Industr. inputs comm. pric. a.v.				Financial volatility			
	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	6.79	9.42	1.59	1.23	6.21	8.76	1.49	1.14
Colombia	0.32	0.65	1.81	2.56	0.34	0.67	1.85	2.62
Croatia	1.61	1.44	1.29	1.22	1.64	1.48	1.33	1.26
Dominican Republic	0.92	0.49	0.40	0.42	0.69	0.41	0.33	0.35
Hungary	2.13	3.82	4.14	1.54	1.87	3.55	3.81	1.46
Mexico	1.02	0.99	0.93	0.88	1.04	1.01	0.96	0.91
Peru	2.43	1.52	1.15	1.04	2.23	1.43	1.09	0.98
Philippines	0.48	0.31	1.04	1.05	0.47	0.34	1.01	1.00
Poland	2.64	3.40	2.61	1.31	2.51	3.26	2.50	1.28
Thailand	0.65	0.50	0.40	0.42	0.78	0.60	0.52	0.56
Success rate[3]	37.50%				37.50%			

Source: Author's elaboration using data from Haver Analytics, the Energy Information Administration, and the IMF.

[1] Eight models are compared to a univariate SARIMA model for forecasting core inflation in each country. We fit eight SARIMAX models with the global inflation, global output gap, log exchange rate, oil prices' annual variation, commodity prices' annual variation (nonfuel and food and beverages), industrial inputs commodity prices' annual variation, and financial volatility as predictors. The table shows RMSE ratios at four forecasting horizons: 6, 12, 24, and 36 months. Values greater than one indicate that the univariate model performs better than the multivariate model. The cases where each SARIMAX model outperforms the univariate model are highlighted in grey. Due to the rounding, the numbers reported in the table may indicate a value of 1.00 even if the ratio is smaller.

[2] Annual variation is denoted by a.v.

[3] Success rate refers to the fraction of cases when forecasting using a SARIMAX model outperforms a univariate model.

Table 5: Success Rates (%) Summary for SARIMA Benchmark.[1]

	Headline	Core
Global inflation	55.00	47.50
Global output gap	40.00	35.00
Log exchange rate	47.50	42.50
Oil prices a.v.	45.00	35.00
Nonfuel commodity prices	47.50	37.50
Commodity prices a.v. (food and beverages)	50.00	35.00
Commodity prices a.v. (industrial inputs)	47.50	37.50
Financial volatility	45.00	37.50
Global inflation and log exchange rate	55.00	57.50
Global inflation and oil prices a.v.	55.00	52.50
Global inflation and nonfuel commodity prices a.v.	52.50	47.50
Global inflation, commodities (F&B) prices a.v., and commodities (II) prices a.v.	47.50	50.00
Global inflation and financial volatility	55.00	52.50
Global output gap and log exchange rate	45.00	35.00
Global output gap and oil prices a.v.	42.50	35.00
Global output gap and nonfuel commodity prices a.v.	50.00	35.00
Global output gap, commodity (F&B) prices a.v., and commodity (II) prices a.v.	47.50	30.00
Global output gap and financial volatility	40.00	40.00
Global output gap, oil prices a.v., nonfuel comm. prices a.v, financial volatility	47.50	32.50
Global output gap, log exch. rate, oil prices a.v., nonfuel comm. prices a.v, finan. volat.	47.50	32.50

Source: Author's elaboration using data from Haver Analytics, the Energy Information Administration, and the IMF.

[1] Success rate is defined as the fraction of cases where the RMSE of a SARIMAX model including the covariates specified in each row is smaller than the RMSE of a SARIMA model used as benchmark. The total number of cases is 40 in headline and 40 in core inflation: four forecasting horizons for each of the ten EMEs. Annual variation is denoted by a.v.

the logarithm of the exchange rate has a better forecasting performance using the metric specified in this exercise. For core inflation, our benchmark including global inflation and the log of the exchange rate as covariate is outperformed by the model including the global output gap together with the log exchange rate and by the model including global output gap and financial volatility, which actually achieves the best performance under this metric for the case of core inflation. The results showing that the models that incorporate financial volatility as covariate have a performance that is comparable to including the exchange rate as covariate are important because they could be suggesting that this variable captures to some extent global financial factors that may affect exchange rates of a group of EMEs. Summarizing, the results reported in tables 6 and 7 confirm the result that incorporating global inflation into SARIMA forecasting models of headline inflation in EMEs may improve their performance, since the result found above holds using as criterion the comparison of the RMSE of these models relative to the SARIMAX including global inflation. For the case of core inflation, evidence is again mixed but consistent with previous results. Individually, some other global determinants seem to perform better than global inflation. However, the SARIMAX model including the combination of exchange rate and global inflation outperforms the SARIMAX models including a combination of other covariates.[35] Detailed results used to construct these tables are in appendix D. In these tables, we can again observe the pattern described above for the case of core inflation. Although global inflation does not outperform other covariates uniformly, there are some particular countries where improvements are observed, highlighting the global inflation factor's forecasting potential (see the case of Croatia, Mexico, and Poland in table D.2).

Table 6: Success Rates (%) Summary for SARIMAX with Global Inflation as Benchmark.[1]

Covariable	Headline	Core
Global output gap	37.50	60.00
Log exchange rate	25.00	50.00
Oil prices a.v.	12.50	50.00
Financial volatility	32.50	50.00
Nonfuel commodity prices a.v.	12.50	52.50
Commodity prices a.v. (food and beverages, FB)	12.50	52.50
Commodity prices a.v. (industrial inputs, II)	17.50	50.00

Source: Author's elaboration using data from Haver Analytics, the Energy Information Administration, and the IMF.

[1] Success rate is defined as the fraction of cases where the RMSE of a SARIMAX model including the covariates specified in each row is smaller than the RMSE of a SARIMAX model that includes global inflation as covariate. The total number of cases is 40 in headline and 40 in core inflation: four forecasting horizons for each of the ten EMEs. Annual variation is denoted by a.v. See tables with detailed results in appendix D. Details of some specifications summarized in this table are omitted due to space considerations but are available from the authors upon request.

[35] Results of the estimation are sensitive to idiosyncratic variation of countries in the test period. Therefore, although global inflation seems to be more correlated with core inflation than with headline inflation for some EMEs in the sample (see table 1), the forecasting performance of headline global inflation seems to be stronger, and this could be because this measure is relatively less affected by idiosyncratic variation in the test period beginning in 2017. For example, as appendix C illustrates, variation of core inflation was mainly driven by idiosyncratic factors during the test period in the case of Colombia, Mexico, and Peru.

Table 7: Success Rates (%) Summary for SARIMAX with Global Inflation and Log-Exchange Rate Benchmark.[1]

Covariables	Headline	Core
Global inflation and oil prices a.v.	42.50	25.00
Global inflation and nonfuel commodity prices a.v.	47.50	40.00
Global inflation and financial volatility	17.50	30.00
Global output gap and log exchange rate	37.50	52.50
Global output gap and oil prices a.v.	15.00	40.00
Global output gap and nonfuel commodity prices a.v.	32.50	37.50
Global output gap and financial volatility	37.50	55.00

Source: Author's elaboration using data from Haver Analytics, the Energy Information Administration, and the IMF.

[1] Success rate is defined as the fraction of cases where the RMSE of a SARIMAX model including the covariates specified in each row is smaller than the RMSE of a SARIMAX model that includes global inflation and the logarithm of the exchange rate as covariate. The total number of cases is 40 in headline and 40 in core inflation: four forecasting horizons for each of the ten EMEs. Annual variation is denoted by a.v. See tables with detailed results in appendix D. Details of some specifications summarized in this table are omitted due to space considerations but are available from the authors upon request.

The forecasting performance of global inflation for the case of headline inflation could be partly explained by noncore inflation, which is affected by similar factors in both advanced and emerging market economies, concretely by commodity prices. In contrast, the better performance of the global output gap compared to global core inflation shown in table 6 could be related to the fact that the synchronization of inflation is mainly an advanced-economies phenomenon (see section 3), and to the importance of different determinants of inflation for each group of countries. Indeed, the factors influencing core inflation in advanced economies may be relatively less important for EMEs compared to the global economic cycle. For example, small EMEs like the ones analyzed in this work may be more vulnerable to the global economic cycle because of the disproportionate importance of imported manufactured production inputs or because the domestic economic cycle may respond stronger to global demand because EMEs tend to rely more on commodity exports, which will respond more strongly to global activity.

The aim of the exercises presented is to stress that, since global factors influence inflation, a variable that captures the common movements of inflation across economies has predictive ability over inflation. We propose to build this variable by using the first principal component of inflation of a set of countries. This is not to say that the subsequent principal components do not contain additional information that could further improve performance. Indeed, because the second and third principal components explain each around 10% of the variation of inflation across countries (see section 3), these also have predictive ability over domestic inflation among EMEs.

This is shown in appendix D, where we compare the SARIMAX model that contains the first principal component with models that add the second and the third principal components, using the two metrics described above. The results suggest that, using both metrics, models including subsequent principal components improve the performance of the core inflation forecasts analyzed in this work. However, evidence is mixed for the case of headline inflation. The second and third principal components improve forecasting performance of the models studied for the case of headline inflation under the metric of direct comparison of RMSE between SARIMAX models, but not when comparing their RMSE against the SARIMA benchmark. The results suggest that common global inflation variation may be related to different phenomena that, because they are not necessarily correlated, may be associated with different principal components (for example prices of inputs, manufactured goods, wages, the global economic cycle, and volatility or uncertainty). Although our results suggest that forecasting performance is improved by incorporating additional principal components as covariates, the main takeaway of this work is that, because the variation of inflation of open EMEs is influenced by global factors, a variable that summarizes the global comovement of prices has predictive ability over domestic inflation. We emphasize that the improvement can be achieved in a parsimonious way by just incorporating the first principal component, although subsequent principal components can be good candidates to include as additional covariates in more complicated models.

To conclude this section, we now focus on the model with just the first principal component and deepen the analysis by exploring the reasons that make it a relevant covariate to consider.

The results presented so far in this section show that global inflation has predictive ability over domestic inflation. However, this could stem from the fact that this variable summarizes a wide set of information contained in observable variables that are generally monitored or from the fact that it contains relevant information about the worldwide determinants of inflation, in addition to that provided by said indicators. Given the importance of the residual shown in figure 7, we argue that the latter is true. To illustrate this more formally, we extract the component of global inflation that is orthogonal to the observable variables studied, the global output gap, commodities' inflation, financial volatility, and the PMI indices by estimating the residuals of the regression presented in table 2, denoted $\hat{\varepsilon}_t$.

We call this time series the "residual global inflation." We then compute the SARIMAX model with the covariates global output gap (OG_t), commodity prices' annual variation (COMP_t), oil prices' annual variation (OilP_t), financial volatility (VIX_t), and residual global inflation ($\hat{\varepsilon}_t$). A statistically significant coefficient of $\hat{\varepsilon}_t$ in the described model (that would indicate predictive ability of residual global inflation on EMEs' inflation) would suggest that, indeed, global inflation contains additional information that could be related to other variables that are not considered. In contrast, lack of predictive ability of $\hat{\varepsilon}_t$ would indicate that the improvement in forecasting performance, once global inflation is included in the models, stems from the fact that this variable summarizes the impact that the set of observable variables considered in this paper have on domestic inflation.

Table 8 presents the coefficient and standard errors of residual global inflation in the specification described. The table shows that residual global inflation has statistically significant predictive ability over inflation for both headline and core inflation rates (most coefficients are positive and statistically significant columns A and C in table 8). We therefore conclude that the reasons behind global inflation synchronization go beyond the synchronization in the economic cycle, the prices of commodities, and financial volatility. This is relevant because it shows that the mechanisms underpinning common movements of inflation are deeper. In terms of this paper, it also means that the predictive ability of global inflation is not only consequence of its ability to summarize this set of variables, but that it contains information about the direction of changes of variables that affect world inflation, but that go beyond these set of variables.

Some of these factors could be related to the variation in manufactured goods prices that is uncorrelated with commodity prices and supply constraints, for example stress in global manufacturing networks or adverse weather conditions. Moreover, residual global inflation could also be capturing unobserved factors that are relevant for inflation worldwide, such as consumer sentiment or global financial conditions to the extent that the VIX is not fully capturing the comovement of global financial variables.[36] To explore this possibility, we add to the regression two additional covariates that will act as proxies for the global supply of manufactured goods: the global manufacturing PMI input prices index (PMI_t^{IP}), and the global manufacturing PMI output index (PMI_t^{OI}). The results of this exercise are shown in columns B and D of table 8). Once we do this, the predictive ability is lost for several countries, although not for all. This shows that the predictive ability of global inflation does stem, to some extent, from its ability to summarize the information about a wide set of global inflation determinants, but also because it could contain information about some others that could be unobservable. We consider this variable a very strong tool because it is a simple way to incorporate a lot of information, that relies on data that is published regularly and is generally available before many other indicators.[37]

[36] While it has been argued that the global financial cycle reflects market volatility and risk aversion (see Miranda-Agrippino and Rey (2020b)), recent work has found that, in fact, the responsiveness of capital flows and global lending to risk (measured by the VIX index) has declined (Miranda-Agrippino and Rey (2020a).

[37] An additional advantage is that inflation forecasts are also available, meaning that it would be easy to extend the horizon of forecasts, but that is left for future work.

Table 8: Residual Global Inflation as Predictor of Inflation in Emerging Market Economies.[1]

Country	Headline Inflation		Core Inflation	
	Without PMI controls (A)	With PMI controls (B)	Without PMI controls (C)	With PMI controls (D)
Brazil	0.071	0.020	-0.030	0.0528
	(0.056)	(0.031)	(0.0658)	(0.031)
Colombia	0.182^{**}	0.024	0.291^{***}	0.096^{*}
	(0.074)	(0.042)	(0.086)	(0.050)
Croatia	0.827^{***}	0.396^{***}	0.507^{***}	0.046
	(0.097)	(0.083)	(0.092)	(0.044)
Dominican Republic	0.184^{***}	0.015	-0.047	-0.086
	(0.059)	(0.033)	(0.070)	(0.038)
Hungary	0.462^{***}	0.243^{***}	0.613^{***}	0.0281^{***}
	(0.111)	(0.075)	(0.118)	(0.094)
Mexico	0.257^{**}	0.036	0.280^{***}	0.040
	(0.103)	(0.068)	(0.089)	(0.058)
Peru	0.185^{*}	-0.002	0.115^{*}	0.004
	(0.103)	(0.046)	(0.066)	(0.035)
Philippines	0.283^{***}	0.061	0.188	-0.019
	(0.083)	(0.053)	(0.118)	(0.063)
Poland	0.487^{***}	0.199^{***}	0.438^{***}	0.141^{*}
	(0.076)	(0.052)	(0.107)	(0.072)
Thailand	0.683^{***}	0.262^{***}	0.215^{*}	0.000
	(0.097)	(0.082)	(0.120)	(0.083)

Source: Author's elaboration using data from Haver Analytics, the Energy Information Administration, and the IMF.

[1] We perform a regression analysis using the models

$$\hat{\pi}_t^G = \beta_1 \mathrm{OG}_t + \beta_2 \mathrm{CP}_t + \beta_3 \mathrm{OilP}_t + \beta_4 \mathrm{VIX}_t + \eta_t \ ,$$

and

$$\hat{\pi}_t^G = \beta_1 \mathrm{OG}_t + \beta_2 \mathrm{CP}_t + \beta_3 \mathrm{OilP}_t + \beta_4 \mathrm{VIX}_t + \beta_5 \mathrm{PMI}_t^{\mathrm{IP}} + \beta_6 \mathrm{PMI}_t^{\mathrm{OI}} + \varepsilon_t \ ,$$

and obtain the residuals: $\hat{\eta}_t$ and $\hat{\varepsilon}_t$, that we denote residual global inflation. In the model $\hat{\pi}_t^G$ denotes the global inflation estimated as discussed in section 3, OG_t is the global output gap, COMP_t the nonfuel commodity prices' annual variation, OilP_t the oil prices' annual variation, VIX_t the financial volatility, $\mathrm{PMI}_t^{\mathrm{IP}}$ the global manufacturing PMI input prices index, and $\mathrm{PMI}_t^{\mathrm{OI}}$ the global manufacturing PMI output index. The table shows, for each country in our sample, the coefficient and standard error of residual global inflation in a SARIMAX model with covariates OG_t, CP_t, OilP_t, VIX_t, and $\hat{\eta}_t$ in columns (A) and (C) and a SARIMAX model with covariates OG_t, CP_t, OilP_t, VIX_t, and $\hat{\varepsilon}_t$ in columns (B) and (D). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6 Conclusion

This paper studies the global synchronization of inflation to understand how much inflation in different countries is affected by global factors. We estimate global inflation as the first principal headline and core inflation component in a set of countries. We show that it correlates with the global output gap, commodity price inflation, financial volatility, and some measures of the global supply. These observations suggest that factors affecting global economic activity and commodity prices may influence inflation across countries. We also show that global inflation has predictive ability over headline inflation. We argue that this improvement stems from the fact that global inflation effectively summarizes observable variables but that it may also contain additional information from unobservable variables or from other relevant inflation determinants.

This work focuses on the period 2002-2019. The quantitative results shown cannot be directly extrapolated to different periods, because the relevance of global factors on domestic inflation may vary over time. Nonetheless, this paper is useful because it underscores that global inflation is a relevant determinant of inflation, but it also more generally presents a simple framework within reach of policy makers that may help dimension the magnitude of the importance of domestic inflation's global component for any particular period of time that is of interest for the researcher. Moreover, by showing that the global factor of inflation proposed has a strong predictive ability on inflation among EMEs, the document shows that this is a relevant determinant of inflation, whose monitoring may complement the analysis and provide a more nuanced understanding of this phenomenon, nurturing informed policy-making. Having said this, promising avenues of research include a deeper exploration of how global inflation can be included in structural or multivariate models, and how it can be incorporated into real-time forecasting.

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A Additional Descriptive Statistics

Table A.1: Headline Price Inflation Rates Summary Statistics, January 2002 to December 2019.

Country	min	max	mean	median	SD	ACF (1st lag)	ACF (5th lag)	Classification
Austria	-0.33	3.99	1.87	1.80	0.84	0.95	0.62	Advanced
Belgium	-1.66	5.90	1.91	1.84	1.18	0.94	0.57	Advanced
Brazil	2.46	17.24	6.30	5.90	2.84	0.98	0.74	Emerging
Canada	-0.95	4.68	1.85	1.88	0.85	0.87	0.36	Advanced
Chile	-2.29	9.85	3.15	2.81	2.04	0.97	0.68	Emerging
China	-1.79	8.81	2.43	2.10	2.01	0.95	0.65	Emerging
Colombia	1.76	8.96	4.60	4.36	1.76	0.98	0.81	Emerging
Croatia	-1.86	8.31	1.89	1.69	1.81	0.96	0.76	Emerging
Cyprus	-2.61	6.42	1.57	1.70	1.85	0.94	0.68	Advanced
Czech Republic	-0.52	7.64	2.02	1.94	1.56	0.95	0.65	Advanced
Denmark	-0.10	4.39	1.56	1.45	0.92	0.96	0.73	Advanced
Dominican Republic	-1.56	65.10	8.47	4.36	12.72	0.98	0.77	Emerging
Estonia	-2.15	11.58	3.34	3.53	2.69	0.97	0.76	Advanced
Finland	-0.70	4.96	1.53	1.30	1.12	0.95	0.77	Advanced
France	-0.77	4.05	1.55	1.66	0.91	0.96	0.66	Advanced
Germany	-0.54	3.38	1.52	1.58	0.80	0.92	0.63	Advanced
Greece	-2.73	5.61	1.87	2.16	1.98	0.97	0.85	Advanced
Hungary	-1.45	9.05	3.74	3.72	2.36	0.97	0.81	Emerging
India	1.46	13.36	6.28	5.50	2.65	0.96	0.81	Emerging
Indonesia	2.41	18.40	6.49	6.16	3.49	0.94	0.62	Emerging
Ireland	-2.90	5.37	1.34	1.19	1.80	0.97	0.83	Advanced
Israel	-2.74	6.94	1.58	1.30	2.03	0.97	0.68	Advanced
Italy	-0.60	4.24	1.72	1.88	1.13	0.97	0.79	Advanced
Japan	-2.40	3.42	0.14	-0.10	1.00	0.96	0.69	Advanced
Latvia	-4.35	17.70	3.77	2.84	4.21	0.99	0.86	Advanced
Lithuania	-1.89	12.67	2.58	2.49	2.96	0.98	0.84	Advanced
Luxembourg	-1.41	5.82	2.17	2.25	1.42	0.94	0.62	Advanced
Malaysia	-2.48	8.52	2.25	2.09	1.56	0.92	0.38	Emerging
Malta	-0.95	5.87	1.99	1.81	1.23	0.90	0.52	Advanced
Mexico	2.13	6.77	4.22	4.13	0.98	0.94	0.60	Emerging
Netherlands	-0.64	4.80	1.69	1.63	1.05	0.94	0.71	Advanced
Norway	-1.83	5.41	1.99	1.95	1.11	0.89	0.34	Advanced
Peru	-1.11	6.75	2.68	2.74	1.45	0.95	0.61	Emerging
Philippines	-0.37	12.34	4.02	3.58	2.40	0.97	0.63	Emerging
Poland	-1.34	5.03	2.03	1.96	1.66	0.97	0.78	Emerging
Portugal	-1.70	4.13	1.72	1.94	1.41	0.96	0.75	Advanced
Romania	-3.48	28.44	6.22	4.95	5.86	0.96	0.81	Emerging
Russia	2.20	18.96	9.23	9.00	4.08	0.97	0.77	Emerging
Singapore	-1.57	7.57	1.62	0.73	2.14	0.96	0.77	Advanced
Slovenia	-1.15	8.42	2.53	2.21	2.14	0.95	0.79	Advanced
South Africa	-1.99	13.02	5.26	5.31	2.77	0.98	0.74	Emerging
South Korea	-0.43	5.90	2.34	2.28	1.24	0.95	0.75	Advanced
Spain	-1.44	5.32	2.00	2.29	1.61	0.97	0.74	Advanced
Sweden	-1.55	4.37	1.26	1.35	1.15	0.95	0.68	Advanced
Switzerland	-1.44	3.07	0.40	0.46	0.89	0.95	0.64	Advanced
Taiwan	-2.34	5.80	1.03	0.94	1.36	0.80	0.40	Advanced
Thailand	-4.40	9.16	2.07	1.94	2.05	0.95	0.57	Emerging
Turkey	3.99	73.20	12.40	9.10	10.43	0.91	0.59	Emerging
UK	-0.12	5.21	2.15	2.09	1.11	0.97	0.75	Advanced
US	-2.10	5.60	2.07	2.04	1.26	0.93	0.49	Advanced

Source: Author's elaboration using data from Haver Analytics and the IMF.

Table A.2: Core Price Inflation Rates Summary Statistics, January 2002 to December 2019.

Country	min	max	mean	median	SD	ACF (1st lag)	ACF (5th lag)	Classification
Austria	0.80	3.23	1.84	1.79	0.50	0.93	0.64	Advanced
Belgium	0.75	3.06	1.75	1.67	0.41	0.88	0.61	Advanced
Brazil	2.69	14.49	6.22	5.79	2.42	0.99	0.83	Emerging
Canada	0.52	3.98	1.64	1.55	0.58	0.92	0.67	Advanced
Colombia	2.67	8.35	4.75	4.55	1.53	0.98	0.84	Emerging
Croatia	-1.77	6.75	1.57	1.40	1.62	0.97	0.80	Emerging
Cyprus	-1.17	4.37	1.02	0.79	1.16	0.93	0.72	Advanced
Czech Republic	-1.53	3.19	0.89	0.78	1.01	0.95	0.61	Advanced
Denmark	0.00	3.75	1.39	1.29	0.79	0.95	0.75	Advanced
Dominican Republic	0.29	58.13	7.50	3.97	11.29	0.99	0.81	Emerging
Finland	-0.64	3.82	1.39	1.25	0.93	0.97	0.82	Advanced
France	0.21	2.69	1.35	1.25	0.62	0.97	0.81	Advanced
Germany	0.43	2.49	1.36	1.32	0.43	0.82	0.51	Advanced
Greece	-3.23	4.78	1.63	1.74	1.77	0.97	0.89	Advanced
Hungary	0.52	7.02	3.47	3.38	1.62	0.96	0.70	Emerging
Ireland	-3.30	5.69	1.23	0.97	1.79	0.97	0.84	Advanced
Israel	-3.27	7.49	1.34	0.91	2.00	0.97	0.69	Advanced
Italy	0.20	3.30	1.62	1.67	0.82	0.96	0.85	Advanced
Japan	-1.70	2.27	-0.15	-0.30	0.77	0.96	0.81	Advanced
Latvia	-3.35	13.97	2.94	1.88	3.38	0.99	0.88	Advanced
Lithuania	-0.91	10.36	2.34	1.86	2.23	0.98	0.81	Advanced
Luxembourg	0.80	3.41	2.15	2.27	0.56	0.94	0.78	Advanced
Malta	-0.29	4.93	1.76	1.62	0.97	0.87	0.42	Advanced
Mexico	2.30	5.64	3.70	3.68	0.74	0.97	0.78	Emerging
Netherlands	0.01	4.62	1.54	1.26	0.92	0.94	0.71	Advanced
Norway	-0.36	4.00	1.69	1.52	0.88	0.95	0.80	Advanced
Peru	0.59	5.77	2.64	2.56	1.26	0.99	0.87	Emerging
Philippines	0.47	7.24	3.55	3.30	1.49	0.97	0.76	Emerging
Poland	-0.47	3.95	1.38	1.11	0.99	0.95	0.72	Emerging
Portugal	-0.65	4.92	1.57	1.48	1.24	0.94	0.78	Advanced
Slovenia	-0.23	8.97	2.22	1.41	2.14	0.96	0.82	Advanced
South Korea	0.59	5.61	2.27	2.08	0.96	0.96	0.75	Advanced
Spain	-0.25	4.21	1.77	1.48	1.16	0.98	0.86	Advanced
Sweden	-0.08	2.78	1.22	1.16	0.63	0.94	0.74	Advanced
Switzerland	-1.21	1.88	0.29	0.37	0.61	0.97	0.82	Advanced
Taiwan	-2.26	2.40	0.42	0.49	0.70	0.37	0.34	Advanced
Thailand	-1.16	3.71	1.12	0.87	0.84	0.96	0.66	Emerging
UK	0.76	3.63	1.80	1.68	0.62	0.94	0.77	Advanced
US	0.61	2.93	1.94	2.00	0.43	0.96	0.68	Advanced

Source: Author's elaboration using data from Haver Analytics and the IMF.

Table A.3: Unit Root Tests on Headline Price Inflation.

Country	ADF test[2]					
	2002M1-2016M12			2002M1-2019M12		
	Sequential $t-$test	SIC	MAIC	Sequential $t-$test	SIC	MAIC
Austria	-2.03** (12)	-2.03** (12)	-2.03** (12)	-2.80*** (13)	-2.49** (12)	-2.49** (12)
Belgium	-1.48 (12)	-1.48 (12)	-1.48 (12)	-1.64 (12)	-1.64 (12)	-1.64 (12)
Brazil	-2.48** (13)	-2.48** (13)	-2.48** (13)	-3.04*** (13)	-3.04*** (13)	-3.04*** (13)
Canada	-3.08*** (12)	-4.52*** (1)	-3.08*** (12)	-3.26*** (12)	-4.65*** (1)	-3.26*** (12)
Chile	-2.23** (12)	-2.23** (12)	-2.23** (12)	-2.47** (12)	-2.47** (12)	-2.47** (12)
China	-1.04 (12)	-1.04 (12)	-1.04 (12)	-1.01 (14)	-0.87 (12)	-0.87 (12)
Colombia	-1.50 (13)	-1.74* (1)	-1.50 (13)	-1.80* (13)	-1.93* (1)	-1.80* (13)
Croatia	-2.06** (12)	-2.06** (12)	-2.06** (12)	-2.20** (12)	-2.20** (12)	-2.20** (12)
Cyprus	-1.62 (12)	-1.62 (12)	-1.62 (12)	-2.01** (14)	-1.59 (12)	-1.59 (12)
Czech Republic	-1.26 (12)	-1.26 (12)	-1.26 (12)	-1.52 (12)	-1.52 (12)	-1.52 (12)
Denmark	-1.82* (12)	-2.29** (1)	-1.82* (12)	-2.24** (12)	-2.75*** (1)	-2.24** (12)
Dominican Republic	-1.43 (13)	-1.43 (13)	-1.43 (13)	-1.28 (13)	-1.28 (13)	-1.28 (13)
Estonia	-1.66 (12)	-1.66 (12)	-1.66 (12)	-2.07** (12)	-2.07** (12)	-2.07** (12)
Finland	-1.31 (12)	-1.25 (1)	-1.31 (12)	-1.32 (12)	-1.32 (12)	-1.32 (12)
France	-1.91* (12)	-2.56** (1)	-1.91* (12)	-2.03** (12)	-2.80*** (1)	-2.03** (12)
Germany	-2.46** (12)	-2.17** (1)	-2.09** (13)	-2.49** (12)	-2.89*** (2)	-2.27** (13)
Greece	-1.49 (12)	-1.80* (1)	-1.49 (12)	-1.81* (14)	-2.03* (1)	-1.54 (12)
Hungary	-2.12** (12)	-2.27** (1)	-2.12** (12)	-2.06** (12)	-2.37** (1)	-2.06** (12)
India	-1.14 (13)	-1.97* (1)	-1.14 (13)	-1.36 (13)	-2.31** (1)	-1.23 (14)
Indonesia	-1.23 (12)	-2.15** (1)	-1.23 (12)	-1.32 (12)	-2.22** (1)	-1.32 (12)
Ireland	-1.30 (12)	-0.99 (1)	-1.30 (12)	-1.42 (12)	-1.42 (12)	-1.42 (12)
Israel	-2.10** (13)	-3.47*** (6)	-1.74* (12)	-2.41** (13)	-2.41** (13)	-2.02** (12)
Italy	-1.61 (12)	-1.61 (12)	-1.61 (12)	-1.67* (12)	-1.67* (12)	-1.67* (12)
Japan	-2.10** (12)	-2.10** (12)	-2.10** (12)	-2.38** (12)	-2.38** (12)	-2.38** (12)
Latvia	-1.45 (13)	-2.88*** (4)	-1.45 (13)	-1.65 (13)	-1.65 (13)	-1.65 (13)
Lithuania	-2.00** (12)	-1.92* (1)	-2.00** (12)	-2.22** (12)	-2.03** (1)	-2.22** (12)
Luxembourg	-1.73* (12)	-1.73* (12)	-1.73* (12)	-1.60 (12)	-1.60 (12)	-1.60 (12)
Malaysia	-2.12** (13)	-3.29*** (1)	-1.75* (12)	-2.37** (13)	-3.52*** (1)	-2.02** (12)
Malta	-1.26 (12)	-1.26 (12)	-1.26 (12)	-1.33 (12)	-1.33 (12)	-1.33 (12)
Mexico	-1.48 (13)	-1.08 (12)	-1.08 (12)	-2.44** (13)	-3.03*** (1)	-2.13** (12)
Netherlands	-0.65 (12)	-0.64 (1)	-0.65 (12)	-0.97 (12)	-1.01 (1)	-0.97 (12)
Norway	-3.55*** (13)	-3.55*** (13)	-2.81*** (12)	-3.91*** (13)	-3.91*** (13)	-3.29*** (12)
Peru	-0.61 (13)	-1.10 (1)	-0.61 (13)	-0.80 (14)	-0.93 (13)	-0.80 (14)
Philippines	-1.81* (13)	-2.84*** (1)	-1.81* (13)	-1.61 (13)	-3.03*** (1)	-1.61 (13)
Poland	-1.66* (13)	-1.70 (1)	-1.66* (13)	-1.83* (13)	-2.00* (1)	-1.83* (13)
Portugal	-2.47** (13)	-2.17** (1)	-2.19** (12)	-2.52** (12)	-2.52** (12)	-2.52** (12)
Romania	0.42 (12)	0.42 (12)	0.42 (12)	-0.32 (12)	-0.32 (12)	-0.31 (14)
Russia	-1.26 (13)	-1.26 (13)	-1.26 (13)	-1.25 (13)	-1.25 (13)	-1.08 (14)
Singapore	-0.92 (13)	-1.08 (12)	-0.92 (13)	-0.96 (13)	-1.12 (12)	-0.96 (13)
Slovenia	-0.73 (12)	-0.78 (2)	-0.73 (12)	-0.99 (12)	-1.02 (2)	-0.99 (12)
South Africa	-2.04** (13)	-2.04** (13)	-1.78* (12)	-2.44** (13)	-2.44** (13)	-2.14** (12)
South Korea	-1.57 (13)	-1.36 (12)	-1.57 (13)	-1.72* (13)	-1.72* (13)	-1.72* (13)
Spain	-1.89* (12)	-2.83*** (1)	-1.89* (12)	-2.25** (13)	-3.10*** (1)	-1.81* (12)
Sweden	-1.43 (12)	-1.43 (12)	-1.43 (12)	-1.50 (12)	-1.50 (12)	-1.50 (12)
Switzerland	-2.14** (12)	-3.03*** (2)	-1.87* (13)	-1.97** (12)	-3.00*** (2)	-1.70* (13)
Taiwan	-1.06 (12)	-1.77* (1)	-1.06 (12)	-1.10 (12)	-1.10 (12)	-1.10 (12)
Thailand	-1.50 (13)	-2.52** (1)	-1.29 (12)	-1.63 (13)	-2.78*** (1)	-1.44 (12)
Turkey	0.43 (13)	0.60 (1)	0.47 (2)	0.23 (13)	0.32 (1)	0.17 (14)
UK	-1.28 (13)	-1.81* (1)	-1.08 (12)	-1.65 (13)	-2.34** (2)	-1.45 (12)
US	-1.57 (13)	-1.39 (12)	-1.39 (12)	-1.68* (13)	-1.49 (12)	-1.49 (12)

Source: Author's elaboration using data from Haver Analytics.

1 The stars ***, **, and * denote a statistical significant at the 1%, 5%, and 10% level, respectively.

2 It corresponds to the DF-GLS statistic with the number of lags selected using the t sequential test (Ng and Perron 1995), the Schwartz criteria, and the MAIC criteria (Ng and Perron 2001, 1521). The null hypothesis is that the process is $I(1)$. We applied each test to GLS detrended data using the model with a constant.

Table A.4: Unit Root Tests on Core Price Inflation.[1]

Country	ADF test[2]					
	2002M1-2016M12			2002M1-2019M12		
	Sequential $t-$test	SIC	MAIC	Sequential $t-$test	SIC	MAIC
Austria	-1.84* (12)	-1.98* (1)	-1.84* (12)	-2.20** (12)	-2.20** (12)	-2.20** (12)
Belgium	-0.88 (12)	-1.23 (1)	-0.75 (13)	-0.83 (12)	-1.13 (1)	-0.83 (12)
Brazil	-2.45** (13)	-3.91*** (3)	-2.45** (13)	-2.91*** (13)	-4.18*** (3)	-2.91*** (13)
Canada	-4.09*** (12)	-4.73*** (1)	-3.95*** (13)	-4.10*** (12)	-4.72*** (1)	-4.10*** (12)
Colombia	-1.28 (12)	-1.90* (3)	-1.28 (12)	-1.52 (12)	-2.07** (3)	-1.52 (12)
Croatia	-2.01** (13)	-1.75* (12)	-1.75* (12)	-1.90* (12)	-1.90* (12)	-1.90* (12)
Cyprus	-1.63 (12)	-2.82*** (1)	-1.63 (12)	-1.57 (12)	-1.57 (12)	-1.57 (12)
CzechRepublic	-1.44 (12)	-2.23** (1)	-1.44 (12)	-1.58 (12)	-1.58 (12)	-1.58 (12)
Denmark	-1.57 (12)	-1.57 (12)	-1.57 (12)	-2.22** (14)	-1.84* (12)	-1.84* (12)
DominicanRepublic	-1.69* (13)	-3.09*** (5)	-1.69* (13)	-1.57 (13)	-1.57 (13)	-1.57 (13)
Finland	-0.82 (12)	-0.92 (1)	-0.82 (12)	-0.80 (12)	-0.88 (1)	-0.80 (12)
France	-2.03** (12)	-2.03* (1)	-2.03** (12)	-1.92* (14)	-1.90* (1)	-1.61 (13)
Germany	-1.96* (12)	-2.05* (1)	-1.72* (13)	-2.03** (12)	-2.20** (1)	-1.70* (14)
Greece	-1.69* (12)	-2.01* (1)	-1.69* (12)	-1.45 (12)	-1.85* (1)	-1.45 (12)
Hungary	-1.16 (13)	-1.55 (1)	-1.16 (13)	-1.64 (14)	-1.75* (1)	-1.64 (14)
Ireland	-1.15 (13)	-0.99 (12)	-1.15 (13)	-1.34 (13)	-1.16 (12)	-1.34 (13)
Israel	-0.96 (13)	-0.73 (12)	-0.96 (13)	-0.97 (13)	-0.79 (12)	-0.97 (13)
Italy	-2.20** (13)	-2.62*** (1)	-2.20** (13)	-2.38** (13)	-2.79*** (12)	-2.38** (13)
Japan	-1.97* (12)	-1.92* (1)	-1.97* (12)	-2.17** (12)	-2.17** (12)	-2.17** (12)
Latvia	-1.93* (13)	-2.23** (4)	-1.68* (12)	-1.82* (12)	-2.27** (4)	-1.82* (12)
Lithuania	-1.94* (12)	-2.00* (2)	-1.94* (12)	-1.97* (12)	-2.12** (2)	-1.97* (12)
Luxembourg	-0.92 (12)	-0.92 (12)	-0.92 (12)	-1.30 (14)	-1.14 (12)	-1.14 (12)
Malta	-1.28 (12)	-1.28 (12)	-1.28 (12)	-1.32 (12)	-1.32 (12)	-1.32 (12)
Mexico	-0.68 (12)	-0.68 (12)	-0.68 (12)	-1.08 (12)	-1.08 (12)	-1.08 (12)
Netherlands	0.03 (12)	0.11 (1)	0.03 (12)	-0.28 (14)	-0.41 (12)	-0.41 (12)
Norway	-2.60*** (12)	-1.78* (1)	-2.25** (13)	-2.28** (13)	-2.00* (1)	-2.10** (14)
Peru	-1.52 (12)	-3.22*** (3)	-1.52 (12)	-2.01** (14)	-3.11*** (3)	-1.42 (12)
Philippines	-2.14** (13)	-2.41** (1)	-1.75* (12)	-2.66*** (14)	-2.63*** (1)	-2.19** (13)
Poland	-0.63 (12)	-0.79 (1)	-0.63 (12)	-1.19 (12)	-1.19 (12)	-1.19 (12)
Portugal	-1.49 (12)	-1.62 (1)	-1.49 (12)	-1.77* (12)	-1.83* (1)	-1.77* (12)
Slovenia	-0.98 (12)	-0.46 (1)	-0.98 (12)	-1.14 (12)	-0.70 (1)	-1.14 (12)
SouthKorea	-2.14** (13)	-1.85* (12)	-1.85* (12)	-2.08** (12)	-2.08** (12)	-2.08** (12)
Spain	-1.90* (12)	-2.26** (1)	-1.90* (12)	-2.08** (13)	-2.24** (1)	-1.81* (12)
Sweden	-1.03 (12)	-1.05 (1)	-1.03 (12)	-1.17 (12)	-1.40 (1)	-1.17 (12)
Switzerland	-1.48 (13)	-1.66 (1)	-1.48 (13)	-2.24** (14)	-2.44** (3)	-1.86* (13)
Taiwan	-0.33 (13)	-0.33 (13)	-0.33 (13)	-0.42 (13)	-0.42 (13)	-0.42 (13)
Thailand	-1.99** (12)	-2.80*** (1)	-1.99** (12)	-2.08** (12)	-2.08** (12)	-2.08** (12)
UK	-1.16 (12)	-1.70 (1)	-1.16 (12)	-1.52 (12)	-1.88* (1)	-1.52 (12)
US	-1.19 (12)	-1.68 (1)	-1.19 (12)	-1.29 (12)	-1.83* (1)	-1.29 (12)

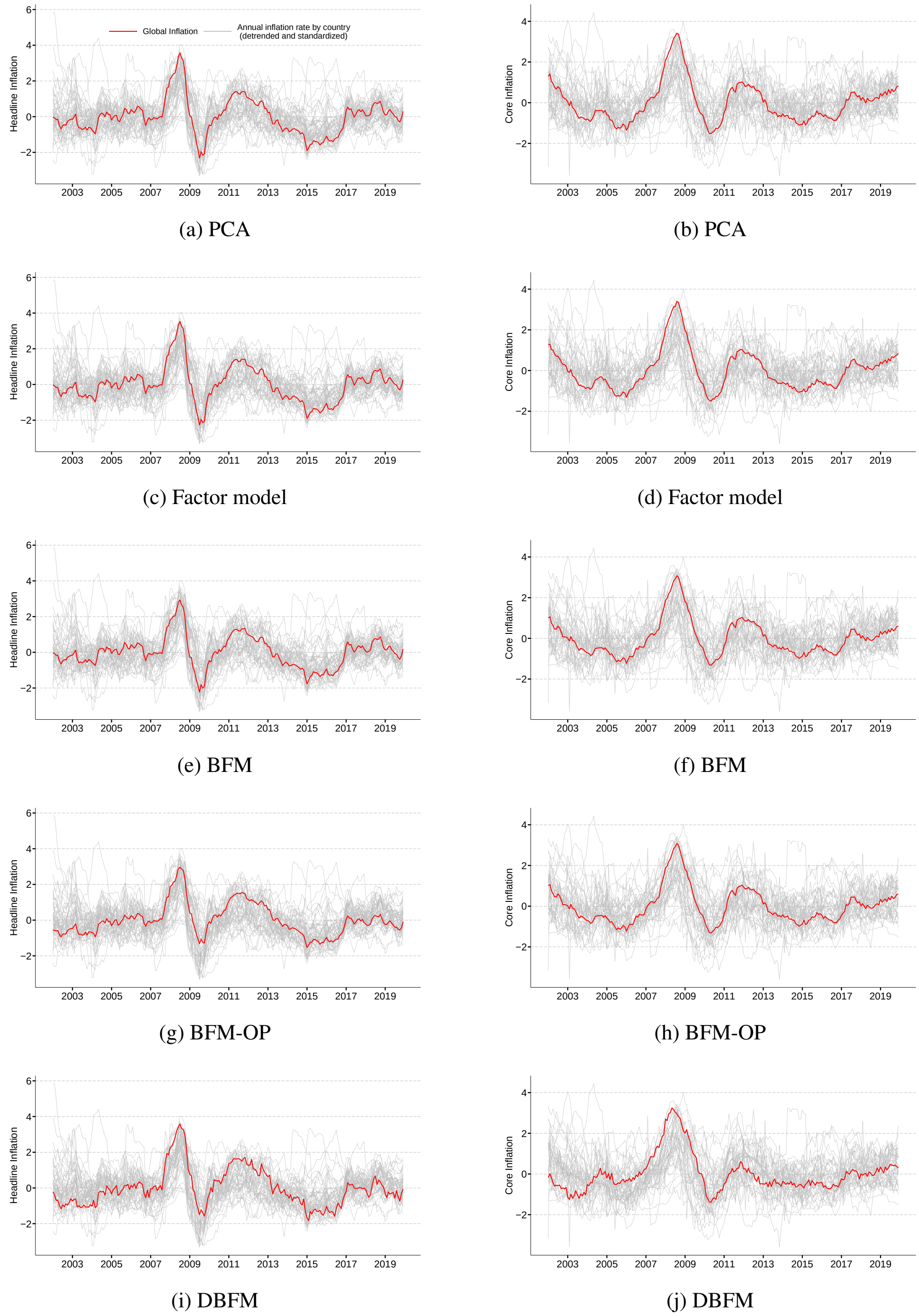
Source: Author's elaboration using data from Haver Analytics.

[1] The stars ***, **, and * denote a statistical significant at the 1%, 5%, and 10% level, respectively.

[2] It corresponds to the DF-GLS statistic with the number of lags selected using the t sequential test (Ng and Perron 1995), the Schwartz criteria, and the MAIC criteria (Ng and Perron 2001, 1521). The null hypothesis is that the process is $I(1)$. We applied each test to GLS detrended data using the model with a constant.

B Robustness: Alternative Methods of Computing Global Inflation

In this appendix we show results of alternative methods of computing the global inflation. We used in total six different methods to estimate the global inflation: i) principal component analysis (PCA), ii) factor analysis (FA), and iii) four Bayesian factor models (BFM). We compute the BFM with three specifications: a) one factor, b) with the number of factors selected using the BIC criteria, c) with the number of factors selected using the BIC criteria and starting the algorithm with the PCA estimator, and d) a dynamic factor model. The BFM a) to c) are based in Freitas and West (2004) and the dynamic factor model in Jackson et al. (2015). We present results for headline inflation. Results for core inflation are omitted for space considerations, but are available upon request.



(a) PCA (b) PCA

(c) Factor model (d) Factor model

(e) BFM (f) BFM

(g) BFM-OP (h) BFM-OP

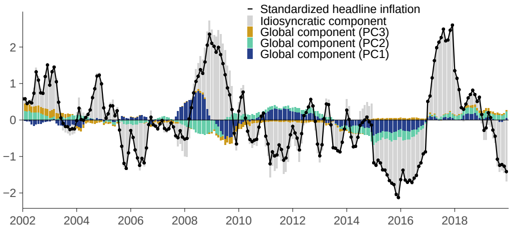
(i) DBFM (j) DBFM

Figure B.1: Factors Estimators for Headline and Core Price Inflation.

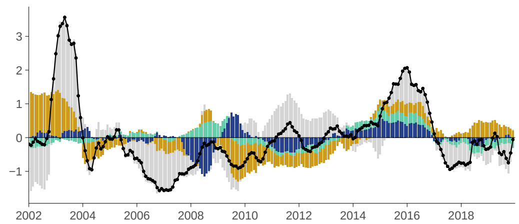
Notes: The red line in each graph corresponds to the common factor estimated by different methods: (a) and (b) Principal component analysis, (c) and (d) Static factor model, (e) and (f) Bayesian static factor model, (g) and (h) Bayesian static factor model with optimal number of factors chosen endogenously, and (i) and (j) Dynamic Bayesian factor model. The grey lines are the standardized and detrended annual inflation rates for all the countries in the sample considered for each measure of inflation. The left-side panel corresponds to calculations for headline inflation, the right-side panel for core.
Source: Author's elaboration using data from Haver Analytics.

C Decomposition of Emerging Market Economies' Inflation between Global and Idiosyncratic Components

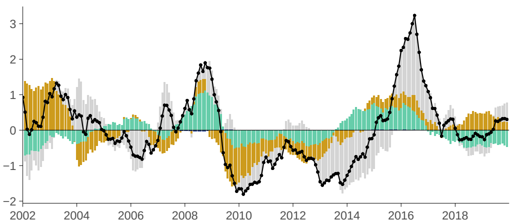
In this section we present the decomposition of headline and core inflation of EMEs into the components that are related to global factors and variation that is idiosyncratic to each country. Variation that is associated with global inflation is computed by multiplying each of the first three principal components with each country's corresponding factor loading. The idiosyncratic component of inflation is defined as the residual, and is computed as the difference between the country's standardized measure of inflation and the estimated contribution of global inflation as captured by the first three principal components.



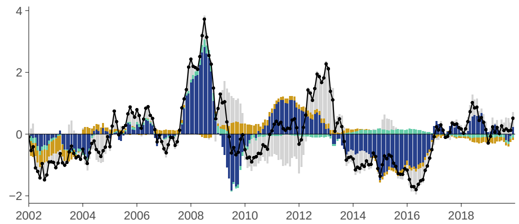
(a) Mexico



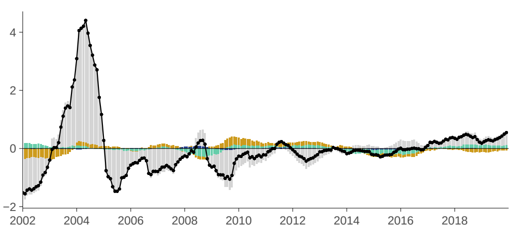
(b) Brazil



(c) Colombia



(d) Croatia



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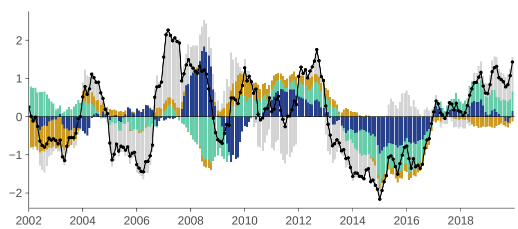
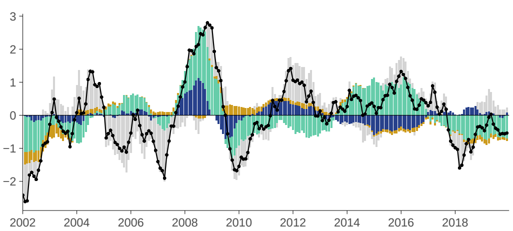


(f) Hungary



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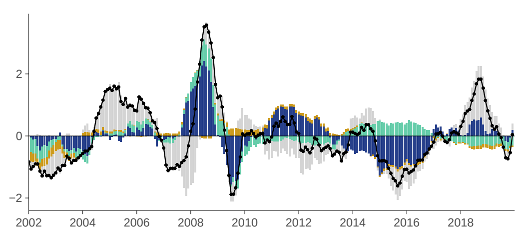

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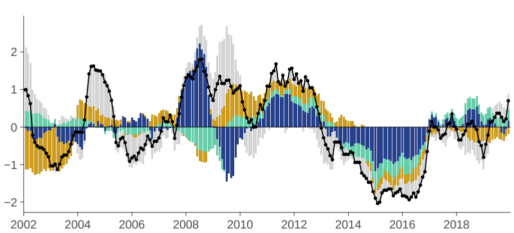
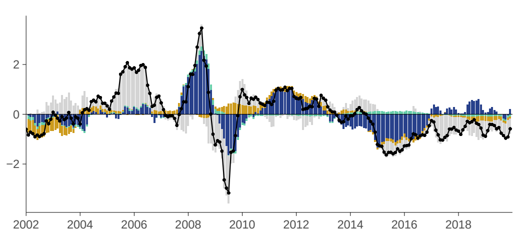


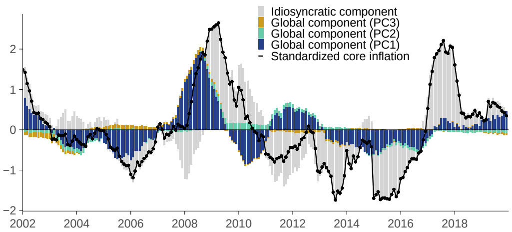
(i) Poland



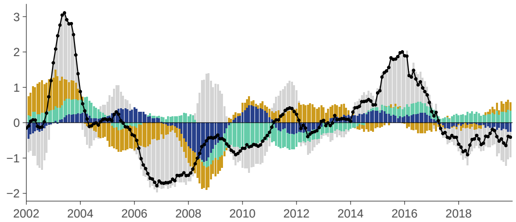
(j) Thailand

Figure C.1: Contribution of Global and Idiosyncratic Factors to Headline Price Inflation.

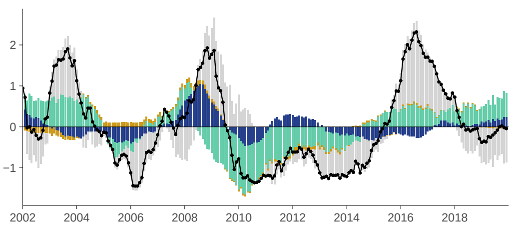
Notes: The black line graphs each country's standardized headline inflation between 2002 and 2019. The blue (green) [khaki] bars correspond to global inflation's first (second) [third] principal component contribution, computed as the product of the estimated global factor of headline inflation with the first (second) [third] principal component and each country's factor loading for headline inflation for the corresponding component. The grey bars correspond to the difference between standardized inflation and the total contribution of global inflation (considering the first three principal components.
Source: Author's elaboration using data from Haver Analytics.



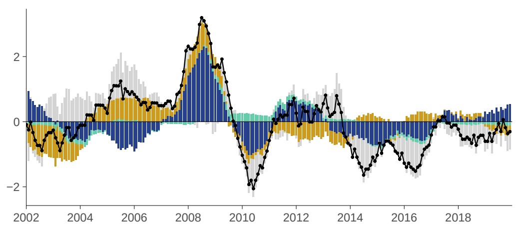
(a) Mexico



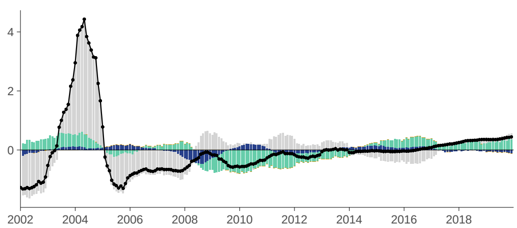
(b) Brazil



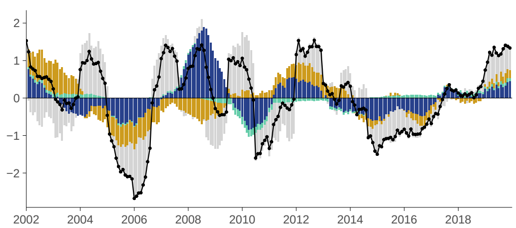
(c) Colombia



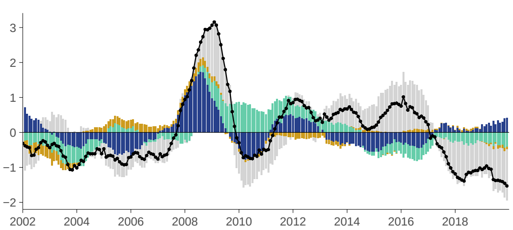
(d) Croatia



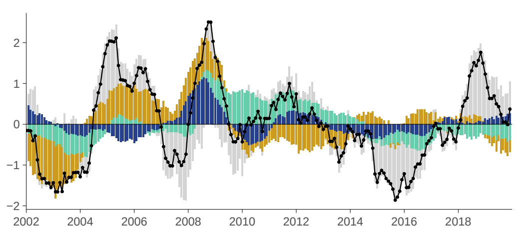
(e) Dominican Republic



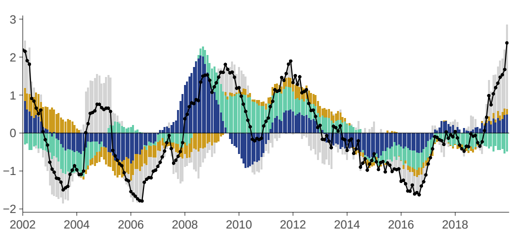
(f) Hungary



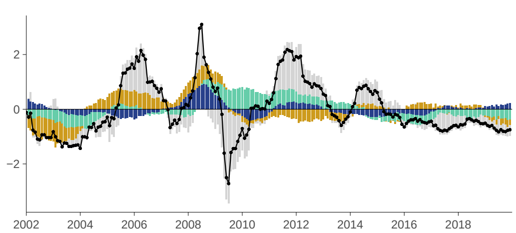
(g) Peru



(h) Philippines



(i) Poland



(j) Thailand

Figure C.2: Contribution of Global and Idiosyncratic Factors to Core Price Inflation.

Notes: The black line graphs each country's standardized core inflation between 2002 and 2019. The blue (green) [khaki] bars correspond to global inflation's first (second) [third] principal component contribution, computed as the product of the estimated global factor of core inflation with the first (second) [third] principal component and each country's factor loading for core inflation for the corresponding component. The grey bars correspond to the difference between standardized inflation and the total contribution of global inflation (considering the first three principal components.
Source: Author's elaboration using data from Haver Analytics.

D Additional Forecasting Results

The tables D.1 and D.2 shows the results comparing SARIMAX models including different covariates versus the SARIMAX model with the first principal component that is used as the benchmark. For headline price inflation, table D.1 shows that the benchmark model outperforms all of the models with other covariates. For core price inflation, table D.2 shows that the benchmark model underperforms relative to four out of seven models, outperforms one model and performs similar to two of them.

Table D.1: Headline Price Inflation. Root Mean Square Error Ratios with SARIMAX Including Global Inflation as Benchmark.[1]

Country	Global output gap				Log exchange rate				Oil prices a.v.[2]				Financial volatility			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	0.99	0.95	0.93	0.95	1.00	1.00	1.00	1.01	1.14	1.10	1.09	1.13	1.02	1.01	1.02	1.02
Colombia	0.97	0.94	0.93	0.95	1.00	0.99	0.98	0.99	1.12	1.08	1.03	1.05	1.01	0.99	0.98	0.99
Croatia	3.42	2.50	2.07	1.82	3.32	2.54	2.12	1.84	4.12	3.46	2.57	2.39	3.48	2.77	2.26	1.95
Dominican Rep.	1.15	1.14	1.22	1.05	1.23	1.15	1.22	1.04	1.78	1.53	1.44	1.31	1.03	1.05	1.13	0.98
Hungary	2.12	2.52	1.19	0.85	1.76	1.96	1.70	1.22	1.27	1.31	1.30	1.02	1.74	1.68	1.27	0.92
Mexico	1.04	1.05	1.07	1.08	1.01	1.02	1.02	1.02	1.01	1.01	1.02	1.02	1.02	1.02	1.02	1.02
Peru	1.05	1.09	1.06	1.06	1.05	1.00	0.98	0.99	1.05	1.01	0.99	1.00	1.06	1.00	0.98	0.99
Philippines	1.91	1.86	1.18	1.17	1.84	1.67	1.13	1.13	1.83	1.74	1.14	1.14	1.86	1.70	1.15	1.15
Poland	1.88	1.33	0.97	0.96	1.92	1.32	1.03	0.95	2.00	1.87	1.03	1.12	1.88	1.48	0.98	0.96
Thailand	0.69	0.71	0.65	0.70	0.55	0.47	0.41	0.40	0.37	0.31	0.26	0.31	0.63	0.59	0.51	0.56
Success rate[3]	37.50%				25.00%				12.50%				32.50%			

Country	Nonfuel comm. prices a.v				Food and bev. comm. prices a.v.				Industr. inputs comm. pric. a.v.			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	1.05	1.04	1.05	1.06	1.02	1.01	1.01	1.02	1.08	1.06	1.07	1.09
Colombia	1.06	1.04	1.02	1.03	1.08	1.06	1.04	1.05	1.02	1.01	0.99	1.00
Croatia	3.79	3.07	2.51	2.20	3.44	2.79	2.33	2.03	3.70	2.97	2.44	2.14
Dominican Rep.	1.34	1.24	1.31	1.13	1.11	1.08	1.17	1.02	1.85	1.60	1.63	1.44
Hungary	1.73	2.28	1.81	1.26	1.66	1.60	1.31	0.95	1.49	1.45	1.36	0.99
Mexico	1.02	1.01	1.02	1.02	1.03	1.03	1.04	1.04	1.01	1.01	1.01	1.01
Peru	0.96	1.10	1.09	1.12	1.01	1.07	1.05	1.07	0.97	1.10	1.09	1.12
Philippines	2.14	2.06	1.22	1.23	2.00	1.97	1.20	1.21	2.10	2.02	1.22	1.22
Poland	1.72	1.65	1.04	1.01	1.71	1.62	1.04	1.01	1.90	1.65	1.02	1.02
Thailand	0.42	0.36	0.38	0.41	0.54	0.47	0.42	0.45	0.49	0.44	0.39	0.39
Success rate[3]	12.50%				12.50%				17.50%			

Source: Author's elaboration using data from Haver Analytics, the Energy Information Administration, and the IMF.

[1] Seven models are compared to a SARIMAX model augmented with global inflation. These consist of SARIMAX models with headline inflation in each country as dependent variable and with the global inflation, log exchange rate, global output gap, oil prices' annual variation, nonfuel commodity prices' annual variation, food and beverages commodity prices' annual variation, industrial inputs commodity prices' annual variation, and financial volatility as predictors. The table shows RMSE ratios at four forecasting horizons: 6, 12, 24, and 36 months. Values greater than one indicate that the SARIMAX model augmented with global inflation performs better than the model augmented with the covariate indicated in each panel. The cases where the SARIMAX model augmented with each covariate outperforms the model that uses global inflation as covariate are highlighted in grey. Due to the rounding, the numbers reported in the table may indicate a value of 1.00 even if the ratio is smaller.

[2] Annual variation is denoted by a.v.

[3] Success rate refers to the fraction of cases when forecasting using a SARIMAX models with the covariate indicated in each panel outperforms the SARIMAX augmented by global inflation.

Table D.2: Core Price Inflation. Root Mean Square Error Ratios with SARIMAX Including Global Inflation as Benchmark.[1]

Country	Global output gap				Log exchange rate				Oil prices a.v.[2]				Financial volatility			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	1.00	0.98	0.98	0.99	1.03	1.03	1.02	1.02	1.10	1.08	1.05	1.06	1.03	1.03	1.02	1.02
Colombia	0.56	0.54	0.75	0.79	0.67	0.72	0.86	0.85	0.70	0.75	0.88	0.87	0.68	0.74	0.88	0.87
Croatia	2.00	2.59	1.46	1.19	1.98	2.62	1.47	1.19	1.94	2.59	1.46	1.16	2.04	2.76	1.56	1.26
Dominican Rep.	0.49	0.52	0.74	0.76	0.69	0.69	0.84	0.82	0.98	0.86	0.91	0.93	0.68	0.70	0.82	0.81
Hungary	0.96	2.43	2.20	1.66	1.00	2.55	2.40	1.72	0.98	2.77	2.57	1.69	1.10	2.92	2.71	1.76
Mexico	1.08	1.13	1.15	1.17	1.01	1.04	1.04	1.04	1.06	1.09	1.09	1.11	1.05	1.08	1.08	1.09
Peru	0.87	0.89	0.92	0.92	0.79	0.85	0.90	0.90	0.93	0.94	0.95	0.95	0.88	0.90	0.94	0.93
Philippines	0.72	0.89	0.91	0.90	0.71	0.89	0.91	0.90	0.93	0.95	0.99	1.00	0.71	0.89	0.90	0.90
Poland	2.07	2.39	2.24	1.45	1.97	2.28	2.12	1.42	2.16	2.55	2.36	1.51	2.00	2.36	2.21	1.44
Thailand	0.79	0.78	0.79	0.72	0.74	0.67	0.64	0.63	0.72	0.65	0.62	0.61	0.78	0.69	0.70	0.68
Success rate[3]	60.00%				50.00%				50.00%				50.00%			

Country	Nonfuel comm. prices a.v				Food and bev. comm. prices a.v.				Industr. inputs comm. pric. a.v.			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	1.09	1.08	1.06	1.07	1.04	1.04	1.03	1.04	1.12	1.10	1.09	1.10
Colombia	0.69	0.74	0.88	0.87	0.74	0.78	0.90	0.89	0.65	0.71	0.86	0.85
Croatia	1.91	2.54	1.43	1.15	1.95	2.60	1.46	1.17	1.99	2.69	1.51	1.21
Dominican Rep.	0.62	0.64	0.80	0.80	0.50	0.51	0.70	0.71	0.91	0.85	0.98	0.95
Hungary	0.97	2.72	2.47	1.67	0.87	2.53	2.28	1.61	1.25	3.15	2.94	1.85
Mexico	1.01	1.04	1.04	1.04	1.05	1.08	1.09	1.10	1.03	1.05	1.05	1.06
Peru	0.96	0.96	0.99	0.98	0.93	0.95	0.97	0.97	0.96	0.96	0.99	0.98
Philippines	0.72	0.85	0.92	0.92	0.71	0.87	0.91	0.91	0.72	0.82	0.94	0.93
Poland	2.08	2.44	2.28	1.46	2.09	2.44	2.29	1.46	2.10	2.46	2.31	1.47
Thailand	0.56	0.46	0.46	0.43	0.61	0.50	0.48	0.44	0.65	0.58	0.54	0.51
Success rate[3]	52.50%				52.50%				50.00%			

Source: Author's elaboration using data from Haver Analytics, the Energy Information Administration, and the IMF.

[1] Seven models are compared to a SARIMAX model augmented with global inflation. These consist of SARIMAX models with core inflation in each country as dependent variable and with the global inflation, log exchange rate, global output gap, oil prices' annual variation, nonfuel commodity prices' annual variation, food and beverages commodity prices' annual variation, industrial inputs commodity prices' annual variation, and financial volatility as predictors. The table shows RMSE ratios at four forecasting horizons: 6, 12, 24, and 36 months. Values greater than one indicate that the SARIMAX model augmented with global inflation performs better than the model augmented with the covariate indicated in each panel. The cases where the SARIMAX model augmented with each covariate outperforms the model that uses global inflation as covariate are highlighted in grey. Due to the rounding, the numbers reported in the table may indicate a value of 1.00 even if the ratio is smaller.

[2] Annual variation is denoted by a.v.

[3] Success rate refers to the fraction of cases when forecasting using a SARIMAX models with the covariate indicated in each panel outperforms the SARIMAX augmented by global inflation.

The tables D.3 and D.4 shows the results comparing different SARIMAX models versus SARIMAX model with the first principal component and log exchange rate as benchmark model. For headline price inflation, table D.3 shows that the benchmark model outperforms all of the models estimated. For core price inflation, table D.4 shows that the benchmark model also outperforms all SARIMAX models compared.

Table D.3: Headline Price Inflation. Root Mean Square Error Ratios with SARIMAX Including Global Inflation and Log Exchange Rate as Benchmark.[1]

Country	Global inflation in pairs with other variables											
	& oil prices a.v.[2]				& nonfuel comm. prices a.v.				& financial volatility			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	1.14	1.11	1.10	1.12	1.04	1.04	1.04	1.03	1.02	1.01	1.01	1.01
Colombia	1.21	1.16	1.10	1.12	1.10	1.08	1.07	1.07	1.00	1.00	1.00	1.00
Croatia	0.87	0.96	1.07	1.01	0.50	0.62	0.77	0.81	1.02	1.12	1.07	1.04
Dominican Rep.	1.25	1.18	1.18	1.18	1.10	1.09	1.11	1.12	1.02	1.04	1.03	1.05
Hungary	0.84	1.00	1.08	1.04	2.51	2.71	0.91	0.76	0.90	0.99	1.10	1.03
Mexico	0.98	0.97	0.97	0.97	0.99	0.98	0.98	0.98	1.00	1.00	1.00	1.00
Peru	0.95	1.04	1.04	1.06	0.90	1.11	1.12	1.14	0.99	1.00	1.00	1.01
Philippines	0.89	0.90	1.00	0.99	1.20	1.22	1.06	1.06	1.02	1.03	1.02	1.02
Poland	0.85	0.98	0.89	0.97	0.74	0.98	0.82	0.96	0.79	0.97	0.86	0.97
Thailand	0.96	0.97	1.02	1.03	0.91	0.91	0.88	0.90	1.02	1.06	1.09	1.13
Success rate[3]	42.50%				47.50%				17.50%			

Country	Global output gap in pairs with other variables															
	& log exchange rate				& oil prices a.v.				& nonfuel comm. prices a.v.				& financial volatility			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	0.97	0.94	0.92	0.93	1.10	1.04	1.01	1.04	1.02	0.98	0.96	0.97	0.98	0.95	0.93	0.94
Colombia	0.97	0.94	0.93	0.95	1.08	1.02	0.98	1.01	1.02	0.98	0.97	0.99	0.97	0.94	0.93	0.95
Croatia	3.35	2.56	2.12	1.81	3.90	3.34	2.46	2.27	3.83	3.12	2.51	2.16	3.21	2.50	2.06	1.75
Dominican Rep.	1.38	1.26	1.36	1.17	1.99	1.64	1.57	1.46	1.53	1.42	1.52	1.31	1.20	1.24	1.34	1.15
Hungary	1.67	1.64	1.43	1.10	1.74	2.23	1.68	1.34	1.66	1.64	1.40	1.08	1.68	1.96	1.23	0.91
Mexico	1.02	1.03	1.05	1.05	1.04	1.05	1.07	1.07	1.04	1.05	1.07	1.07	1.04	1.05	1.06	1.07
Peru	0.99	1.06	1.06	1.08	1.04	1.08	1.06	1.07	0.95	1.12	1.11	1.14	1.05	1.09	1.06	1.06
Philippines	1.90	1.87	1.18	1.17	1.99	2.00	1.20	1.20	2.22	2.31	1.28	1.28	1.93	1.91	1.20	1.19
Poland	1.51	1.27	0.90	0.92	1.42	1.49	0.78	1.05	1.29	1.37	0.82	0.95	1.48	1.29	0.84	0.93
Thailand	0.63	0.62	0.54	0.54	0.44	0.43	0.44	0.46	0.52	0.50	0.48	0.52	0.71	0.76	0.72	0.80
Success rate[3]	37.50%				15.00%				32.50%				37.50%			

Source: Author's elaboration using data from Haver Analytics, the Energy Information Administration, and the IMF..

[1] Seven models are compared to a SARIMAX model augmented with global inflation and the logarithm of the exchange rate as covariates and headline inflation in each country as dependent variable. This model is used as the benchmark. The seven models include headline inflation as dependent variable and include global inflation and oil prices a.v., global inflation and nonfuel commodity prices a.v,, global inflation and financial volatility, global output gap and the logarithm of the exchange rate, global output gap and oil prices a.v., global output gap and nonfuel commodity prices a.v., and global output gap and financial volatility as predictors. The table shows RMSE ratios at four forecasting horizons: 6, 12, 24, and 36 months. Values greater than one indicate that the benchmark model performs better than the augmented model with each pair of covariates. The cases where the SARIMAX model augmented with each pair of covariates outperforms the benchmark model are highlighted in grey. Due to the rounding, the numbers reported in the table may indicate a value of 1.00 even if the ratio is smaller.

[2] Annual variation is denoted by a.v. Global inflation is denoted by GI and global output gap by OG.

[3] Success rate refers to the fraction of cases when forecasting using the augmented SARIMAX model with each covariate outperforms the benchmark model.

Table D.4: Core Price Inflation. Root Mean Square Error Ratios with SARIMAX Including Global Inflation and Log Exchange Rate as Benchmark.[1]

Country	Global inflation in pairs with other variables											
	& oil prices a.v.[2]				& nonfuel comm. prices a.v.				& financial volatility			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	1.07	1.05	1.03	1.04	1.06	1.05	1.04	1.05	1.00	1.00	1.00	1.00
Colombia	1.08	1.04	1.02	1.02	1.06	1.04	1.02	1.02	1.05	1.03	1.02	1.02
Croatia	1.06	1.08	1.01	0.96	0.83	0.84	1.19	1.22	1.02	1.02	0.98	0.98
Dominican Republic	1.01	0.96	0.96	0.99	0.92	0.93	0.95	0.96	0.82	0.91	0.92	0.94
Hungary	1.14	1.23	1.12	0.97	1.19	1.22	1.02	0.94	1.12	1.23	1.15	0.98
Mexico	1.01	1.01	1.01	1.01	0.98	0.98	0.98	0.98	1.00	1.00	1.00	1.00
Peru	1.18	1.12	1.07	1.07	1.18	1.12	1.09	1.08	1.12	1.08	1.05	1.05
Philippines	1.00	0.99	1.01	1.01	1.00	0.93	1.04	1.05	1.22	0.98	1.10	1.13
Poland	1.25	1.36	1.33	1.09	1.05	1.12	1.14	1.02	1.09	1.18	1.20	1.03
Thailand	0.91	0.88	0.86	0.84	0.79	0.74	0.67	0.68	0.96	0.91	0.93	0.91
Success rate[3]	25.00%				40.00%				30.00%			

Country	Global output gap in pairs with other variables															
	& log exchange rate				& oil prices a.v.				& nonfuel comm. prices a.v.				& financial volatility			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	1.01	0.99	0.98	0.99	1.08	1.04	1.01	1.03	1.07	1.04	1.02	1.04	1.00	0.98	0.98	0.99
Colombia	0.59	0.56	0.76	0.80	0.63	0.60	0.78	0.82	0.61	0.59	0.78	0.81	0.60	0.58	0.78	0.81
Croatia	2.02	2.60	1.48	1.21	1.96	2.53	1.43	1.16	1.90	2.42	1.38	1.13	2.00	2.58	1.46	1.20
Dominican Republic	0.49	0.45	0.66	0.73	0.80	0.71	0.81	0.87	0.64	0.75	0.89	0.84	0.69	0.79	0.89	0.84
Hungary	1.05	2.86	2.45	1.64	0.94	2.81	2.36	1.56	0.93	2.72	2.22	1.55	1.10	3.04	2.54	1.63
Mexico	1.09	1.14	1.16	1.18	1.05	1.11	1.12	1.14	1.05	1.09	1.10	1.11	1.04	1.10	1.11	1.12
Peru	0.88	0.91	0.94	0.94	1.03	1.00	0.99	0.99	1.06	1.02	1.02	1.01	0.97	0.96	0.97	0.96
Philippines	0.87	0.88	1.00	1.02	1.12	0.92	1.08	1.12	0.87	0.84	1.02	1.04	0.87	0.88	0.99	1.01
Poland	2.14	2.65	2.52	1.46	2.43	3.04	2.87	1.57	2.23	2.78	2.64	1.49	2.13	2.66	2.52	1.46
Thailand	0.69	0.62	0.59	0.56	0.73	0.69	0.69	0.61	0.48	0.37	0.38	0.35	0.79	0.75	0.78	0.70
Success rate[3]	52.50%				40.00%				37.50%				55.00%			

Source: Author's elaboration using data from Haver Analytics, the Energy Information Administration, and the IMF..

[1] Seven models are compared to a SARIMAX model augmented with global inflation and the logarithm of the exchange rate as covariates and core inflation in each country as dependent variable. This model is used as the benchmark. The seven models include core inflation as dependent variable and include global inflation and oil prices a.v., global inflation and nonfuel commodity prices a.v,, global inflation and financial volatility, global output gap and the logarithm of the exchange rate, global output gap and oil prices a.v., global output gap and nonfuel commodity prices a.v., and global output gap and financial volatility as predictors. The table shows RMSE ratios at four forecasting horizons: 6, 12, 24, and 36 months. Values greater than one indicate that the benchmark model performs better than the augmented model with each pair of covariates. The cases where the SARIMAX model augmented with each pair of covariates outperforms the benchmark model are highlighted in grey. Due to the rounding, the numbers reported in the table may indicate a value of 1.00 even if the ratio is smaller.

[2] Annual variation is denoted by a.v. Global inflation is denoted by GI and global output gap by OG.

[3] Success rate refers to the fraction of cases when forecasting using the augmented SARIMAX model with each covariate outperforms the benchmark model.

We show the results of the models that include as covariate the first principal component (model SARIMAX-PCA1), the first and second principal components (model SARIMAX-PCA2), and the first, second, and third principal components (model SARIMAX-PCA3). We remind the reader that the first principal component for headline inflation (core inflation) explains 39.6% (26.6%) of the total variance, the second 9.5% (12.2%), and the third 9.4% (10.0%). For headline price inflation, we can explain 58.5% of the total variance with the first three principal components. For core price inflation, we can explain 48.9% of the total variance with the first three principal components. Table D.5 shows that for headline inflation, when one compares the SARIMAX models with one, two, or three principal components with the SARIMA model, the model SARIMAX-PCA1 yields the highest success rate for forecasting inflation in EMEs. Table D.6 shows that, for core inflation, the SARIMAX-PCA3 model has the highest success rate.

Table D.5: Headline Price Inflation. Root Mean Square Error Ratios with SARIMA Benchmark versus SARIMAX with the First Principal Component, SARIMAX with the First and Second Principal Components, and SARIMAX with the First, Second, and Third Principal Components.[1]

Country	First				First and Second				First, Second, and Third			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	1.68	1.63	1.21	1.09	1.68	1.58	1.15	1.02	1.72	1.56	1.18	1.09
Colombia	1.82	3.15	4.84	4.30	1.74	2.76	3.99	3.42	1.73	2.57	4.27	3.89
Croatia	0.37	0.31	0.28	0.31	0.44	0.39	0.35	0.38	0.40	0.36	0.36	0.40
Dominican Republic	4.20	2.04	0.87	0.86	3.93	1.55	0.59	0.59	3.91	1.53	0.60	0.60
Hungary	0.29	0.29	0.62	0.79	0.73	0.98	0.71	0.47	0.75	1.11	0.77	0.57
Mexico	1.06	1.05	1.04	1.04	1.05	1.04	1.02	1.02	1.05	1.03	1.02	1.02
Peru	0.87	0.73	0.88	0.84	0.92	0.57	0.63	0.57	0.97	0.57	0.61	0.54
Philippines	0.91	0.76	0.92	0.91	1.57	1.62	1.16	1.18	1.18	1.31	1.12	1.15
Poland	0.19	0.32	0.62	0.78	0.26	0.33	0.99	0.89	0.29	0.40	0.95	0.86
Thailand	1.79	1.99	1.70	1.78	1.72	1.85	1.50	1.53	1.74	1.92	1.50	1.49
Success rate[3]	55.00%				45.00%				42.50%			

Source: Author's elaboration using data from Haver Analytics.
[1] The table shows RMSE ratios at four forecasting horizons: 6, 12, 24, and 36 months. Values greater than one indicate that the univariate model performs better than the multivariate model. The cases where the SARIMAX model outperforms the SARIMA model are highlighted in grey. Due to the rounding, the numbers reported in the table may indicate a value of 1.00 even if the ratio is smaller.
[2] Success rate refers to the fraction of cases when forecasting using a SARIMAX model outperforms the SARIMA benchmark.

Table D.6: Core Price Inflation. Root Mean Square Error Ratios with SARIMA Benchmark versus SARIMAX with the First Principal Component, SARIMAX with the First and Second Principal Components, and SARIMAX with the First, Second, and Third Principal Components.[1]

Country	First				First and Second				First, Second, and Third			
	6M	12M	24M	36M	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	6.05	8.54	1.46	1.12	5.69	8.19	1.44	1.10	5.80	8.41	1.46	1.14
Colombia	0.50	0.91	2.11	3.02	0.35	0.79	2.02	2.93	0.34	0.77	2.00	2.87
Croatia	0.81	0.54	0.85	1.00	0.78	0.52	0.84	0.99	0.90	0.62	0.85	0.84
Dominican Republic	1.01	0.58	0.41	0.44	0.99	0.57	0.40	0.44	0.96	0.55	0.40	0.42
Hungary	1.70	1.21	1.41	0.83	1.71	1.22	1.40	0.83	2.30	1.38	1.19	0.59
Mexico	0.99	0.94	0.89	0.83	0.94	0.89	0.84	0.79	0.94	0.89	0.84	0.79
Peru	2.54	1.59	1.16	1.06	2.62	1.62	1.17	1.06	2.62	1.62	1.17	1.07
Philippines	0.67	0.38	1.11	1.12	0.65	0.56	0.98	0.95	0.62	0.46	1.01	1.04
Poland	1.26	1.38	1.13	0.89	1.29	1.44	1.35	0.99	0.81	0.89	0.92	0.78
Thailand	1.00	0.87	0.75	0.82	1.15	1.02	0.87	0.89	1.02	0.86	0.73	0.66
Success rate[3]	47.50%				55.00%				60.00%			

Source: Author's elaboration using data from Haver Analytics.

[1] The table shows RMSE ratios at four forecasting horizons: 6, 12, 24, and 36 months. Values greater than one indicate that the univariate model performs better than the multivariate model. The cases where the SARIMAX model outperforms the SARIMA model are highlighted in grey. Due to the rounding, the numbers reported in the table may indicate a value of 1.00 even if the ratio is smaller.

[2] Success rate refers to the fraction of cases when forecasting using a SARIMAX model outperforms the SARIMA benchmark.

Finally, we show the results comparing the SARIMAX-PCA1 model as benchmark versus the SARIMAX-PCA2 and the SARIMAX-PCA3. Table D.7 shows that the SARIMAX-PCA2 and the SARIMAX-PCA3 models underperform relative to the SARIMAX-PCA1 model under this metric for headline price inflation. Table D.8 shows that the SARIMAX-PCA2 and the SARIMAX-PCA3 models perform better than the SARIMAX-PCA1 model for core price inflation.

Table D.7: Headline Price Inflation. Root Mean Square Error Ratios with SARIMAX with the First Principal Component as Benchmark versus the SARIMAX with the First and Second and SARIMAX with the First, Second, and Third Principal Components.[1]

Country	First and Second				First, Second, and Third			
	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	1.00	0.97	0.95	0.94	1.02	0.96	0.98	1.00
Colombia	0.96	0.88	0.82	0.80	0.95	0.81	0.88	0.90
Croatia	1.17	1.25	1.23	1.24	1.06	1.14	1.26	1.30
Dominican Republic	0.93	0.76	0.68	0.69	0.93	0.75	0.69	0.70
Hungary	2.57	3.43	1.14	0.60	2.64	3.87	1.24	0.72
Mexico	0.99	0.99	0.98	0.98	0.99	0.99	0.98	0.98
Peru	1.06	0.78	0.72	0.68	1.12	0.78	0.69	0.64
Philippines	1.72	2.13	1.27	1.30	1.30	1.72	1.22	1.26
Poland	1.35	1.03	1.60	1.14	1.53	1.24	1.53	1.09
Thailand	0.96	0.93	0.89	0.86	0.98	0.96	0.88	0.84
Success rate[3]	57.50%				55.00%			

Source: Author's elaboration using data from Haver Analytics.

[1] The table shows RMSE ratios at four forecasting horizons: 6, 12, 24, and 36 months. Values greater than one indicate that the SARIMAX model including the first principal component performs better than the model including the variables specified in each panel as covariates. In addition, in grey, we highlighted the cases where the SARIMAX model with the first and second principal components and the SARIMAX model with the first, second, and third principal components outperform the SARIMAX with the first principal component.

[2] Success rate refers to the fraction of cases where using SARIMAX models with the variables specified outperforms the benchmark model, which corresponds to the SARIMAX with the first principal component.

Table D.8: Core Price Inflation. Root Mean Square Error Ratios with SARIMAX with the First Principal Component as Benchmark versus the SARIMAX with the First and Second, SARIMAX with the First, Second, and Third Principal Components.[1]

Country	First and Second				First, Second, and Third			
	6M	12M	24M	36M	6M	12M	24M	36M
Brazil	0.94	0.96	0.99	0.99	0.96	0.98	1.00	1.02
Colombia	0.70	0.86	0.96	0.97	0.68	0.84	0.95	0.95
Croatia	0.97	0.96	0.99	0.99	1.12	1.16	0.99	0.84
Dominican Republic	0.98	0.99	1.00	1.00	0.94	0.94	0.98	0.96
Hungary	1.00	1.01	1.00	0.99	1.35	1.14	0.84	0.71
Mexico	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Peru	1.03	1.02	1.01	1.00	1.03	1.02	1.01	1.01
Philippines	0.98	1.47	0.88	0.85	0.93	1.21	0.91	0.93
Poland	1.02	1.04	1.20	1.11	0.65	0.64	0.82	0.88
Thailand	1.15	1.17	1.15	1.09	1.02	0.99	0.96	0.80
Success rate[3]	55.00%				70.00%			

Source: Author's elaboration using data from Haver Analytics.

[1] The table shows RMSE ratios at four forecasting horizons: 6, 12, 24, and 36 months. Values greater than one indicate that the SARIMAX model including the first principal component performs better than the model including the variables specified in each panel as covariates. In addition, in grey, we highlighted the cases where the SARIMAX model with the first and second principal components and the SARIMAX model with the first, second, and third principal components outperform the SARIMAX with the first principal component.

[2] Success rate refers to the fraction of cases where using SARIMAX models with the variables specified outperforms the benchmark model, which corresponds to the SARIMAX with the first principal component.