Forecasting Food Price Inflation During Global Crises

Roberto Duncan[*] Patricia Toledo[†]

Current Draft: December 16, 2023
First Draft: December 31, 2022

Abstract

In this paper, we consider the forecasting of domestic food price inflation (DFPI) using global indicators, with emphasis on episodes of macroeconomic turbulence, namely the Global Financial Crisis (GFC) and the COVID-19 pandemic and its subsequent repercussions. Our monthly dataset covers about two decades for more than a hundred economies. We employ dynamic model averaging (DMA) to tackle both model uncertainty and parameter instability and produce pseudo out-of-sample forecasts. Thus, we are able to focus on the forecasting ability of the global predictors of DFPI before and during the global crises. We find evidence that the DMA specification tends to outperform statistical models frequently used in the literature such as random walks, autoregressive models, and time-varying parameter models, especially during global crises. We also identify the most successful predictors during the crises using their posterior probabilities of inclusion. By comparing the distributions of such probabilities, we find that the international food price inflation is the most useful predictor of DFPI for numerous countries during both crises. Other indicators such as domestic CPI inflation as well as the international inflation of agricultural commodities, fertilizers, and other food categories improved their forecasting ability, particularly during the COVID-19 period.

JEL Codes: E31, F47, F62, G01, Q18.
Keywords: Food Prices, International Food Price Inflation, Inflation Forecasting, Dynamic Model Averaging.

[*]Department of Economics, Ohio University. Office: Bentley Annex 349. E-mail: duncanr1@ohio.edu
[†]Corresponding author. Department of Economics, Ohio University. Office: Bentley Annex 345. E-mail: toledot@ohio.edu.
We thank George Kouretas, an anonymous referee, and participants at the 2023 ICMAIF conference for very helpful comments and suggestions. All errors are our responsibility. The views expressed in this paper do not necessarily reflect the views of the institution to which the authors are affiliated. Conflict of Interest: the authors declare that they have no conflict of interest.

1. Introduction

The influence of food prices on household welfare has been well documented in economic research. Higher food prices affect food consumption more in households from low-income countries than in those from high-income economies (Cornelsen et al., 2015).[1] Empirical evidence shows that the affordability of food affects child malnutrition (Arndt et al., 2016; Woldemichael et al., 2022), child mortality rates (Kidane and Woldemichael, 2020), the persistence of poverty in urban areas (Fujii, 2013; Ha et al., 2019), and even the occurrence of social unrest (Bellemere, 2015).[2] Therefore, forecasting food prices constitute a valuable tool in formulating the necessary economic policies to alleviate the adverse effects associated with increasing food prices (Ginn and Pourroy, 2020; Attanasio et al., 2013).[3]

In turn, forecasting domestic food price inflation (DFPI) constitutes a challenging task. As shown in the next section, DFPI displays higher variability than headline CPI inflation, and it is more volatile among middle- and low-income economies compared with their high-income counterparts, especially during crisis periods. On the other hand, in contrast to headline inflation, expectation surveys of DFPI from professional forecasters or other economic agents are usually not available for most economies. In spite of its economic relevance, research on successful methods or models to forecast DFPI during crisis periods has received little attention in the literature.[4]

In this paper, we consider the task of forecasting DFPI across countries with a focus on periods of macroeconomic turbulence. Global recessions usually involve tough times especially for low-income households because they tend to face unemployment and, sometimes, higher costs of living. Our monthly dataset covers more than two decades for 111 advanced, emerging market, and developing economies. Hence, we can perform a forecast evaluation during both the Global Financial Crisis (GFC) and the COVID-19 period and its aftermath, and the corresponding pre-crisis periods.

[1]Within an economy, food consumption in low-income households typically represents a larger share on total expenditures than that among high-income households. According to Capehart and Richardson (2008), US households with incomes in the lowest reported income category spent about 17% of their income on food in 2006, whereas households with incomes greater than $70,000 spent 11% of their income on food.

[2]To be more precise, Arndt et al. (2016) observe a significant reduction in malnutrition rates among children aged 0–59 months during the final quarter of their survey in Mozambique compared to the first three quarters. This decrease coincided with lower inflation rates for basic food items. Woldemichael et al. (2022) find that a one percentage point increase in month-to-month food inflation during pregnancy raised the risk of under-five stunting by 0.95 percent in Ethiopia. Likewise, Kidane and Woldemichael (2020) estimate that a 10 percent inflation in staple food prices during pregnancy reduced the survival rate of Ethiopian children under five by approximately 5.4 percent. Fujii (2013) argues that food inflation in Ethiopia severely and negatively impacted the most impoverished individuals, whether they were part of agricultural households or not. Ha et al. (2019) contend that international food prices reached a historic peak in August 2011, driving an estimated 105 million people into extreme poverty. Lastly, Bellemare (2015) provides evidence of a causal link between food prices and social unrest using international data for the period 1990-2011.

[3]For instance, forecast errors of food prices can have substantial impacts on anti-poverty programs. According to Joutz (1997), a forecasted 1% price increase, as opposed to a 3% price increase for the Food Stamp Program budget, results in a difference of approximately half a billion dollars.

[4]Regarding the forecasting of headline and core inflation during the Global Financial Crisis, a notable exception is Hubrich and Skudelny (2017).

In a globalized world, we expect to see that international drivers play a more prominent role mainly among middle- and low-income small-open economies. Thus, we choose indicators that measure commodity price movements in international markets such as food, grains, energy, and fertilizers. Moreover, we include measures of global supply chain pressures (Benigno et al., 2022), global business cycles (Kilian, 2009), aggregate uncertainty about climate-change related policies (Gavriilidis, 2021), and inflation expectations in the US (University of Michigan), among others.

One of our objectives is to determine which of these global indicators can enhance the accuracy of DFPI forecasts. To achieve this, we employ the method of dynamic model averaging (DMA) proposed by Raftery et al. (2010) and extended by Koop and Korobilis (2012) and Catania and Nonejad (2018). This method addresses both model and parameter uncertainty at estimation and enables us to produce pseudo out-of-sample forecasts recursively. Thus, our approach allow us to assess the forecasting ability of global predictors for DFPI before and during the global crises. In particular, through the use of the posterior probability of inclusion as a comparative metric, we can identify the most effective predictors, especially during crisis periods.

We find evidence that the DMA specification outperforms statistical models widely used in the literature. These consider random walks, autoregressive processes, and time-varying parameter models, among others. The gains in predictive accuracy—measured by the root mean square prediction error—are mostly statistically significant. Likewise, we provide evidence that the forecasting performance of the DMA specification improves during global crises—especially the GFC—compared with periods of economic normalcy. By comparing the distributions of the posterior probabilities of inclusion, we find that the international food price inflation is the most useful predictor of DFPI for numerous countries during both crises. Furthermore, domestic CPI inflation as well as the international inflation of agricultural commodities, fertilizers, and other food improved their forecasting ability, particularly during the COVID-19 period.

Related literature. To our knowledge, there is a notable scarcity of research dedicated to forecasting DFPI, especially during periods of global turbulence across economies. The existing literature has primarily focused on predicting domestic prices or their percent changes for some specific food items within individual countries, often without distinguishing between normalcy and crisis periods. For instance, Joutz (1997) conducts a qualitative assessment of forecasts of various US retail prices, as produced by different institutions. These institutions use various forecasting models and techniques, including the Delphi approach as well as structural and ARIMA models. The article reports annual forecasts at the food item level for the years 1997-1998. Meanwhile, Moser et al. (2007) use factor models, VARs, ARIMA, and forecast combinations to forecast CPI and its subindices, including both processed and unprocessed food for the Austrian economy. Their findings indicate that the factor model shows the highest predictive accuracy for unprocessed food, whereas the forecast combination of the factor and VAR models provides the highest predictive accuracy for processed food. Gómez et al. (2012) employ disaggregated data for food products in Colombia, applying flexible least squares methods and forecast combinations. They evaluate the relative performance of their preferred methods against the random walk model. Macias et al. (2022) undertake a real-time nowcasting exercise with simple univariate approaches and an extensive dataset of online prices of food and non-alcoholic beverages in Poland. Their hypothesis is that incorporating online prices can effectively improve DFPI nowcasts. Their competing models include different versions of the random walk model and seasonal ARMA models, as well as forecast combinations and judgmental forecasts. They conclude that that online prices can significantly improve nowcasts of food inflation. More recently, Barkan et al (2023) propose hierarchical recurrent neural networks to forecast disaggregated inflation components of the US CPI (including food components) using information from higher levels in the CPI hierarchy. We share with some of these studies the aim of capturing parameter instabilities and combining forecasts.

Our research is related to an extensive literature dedicated to identifying the best forecasting models for headline (CPI) inflation. While we do not attempt to provide an exhaustive summary of this strand of literature, we will selectively discuss a few relevant contributions.[5] Among such studies, the work by Hubrich and Skudelny (2017) aligns most closely with our research objectives. They undertake an exploration of forecast combinations as a means to address the limitations of individual models in predicting inflation, with a specific emphasis on the (headline or core) Harmonized Index of Consumer Prices (HICP) during the GFC. Their approach suggests the use of performance-based forecast combination with a greater weighting on recent forecast performance. They investigate the pre-GFC and post-GFC periods and find that performance-based weighting outperforms simple averaging. It is important to note, however, some key distinctions with respect to our research. First, our primary focus is on domestic food inflation across a diverse set of economies, as opposed to the HICP inflation within a specific economy, such as the Eurozone. More importantly, instead of working with a forecast combination of a small number of models, DMA contemporaneously exploits a weighted average of a large number of models and addresses parameter instability in a simple fashion. These methodological features are critical to our study's contribution.

In a similar vein, our paper relates to the strand of the DMA forecasting literature where headline inflation is the variable of interest. In fact, the seminar work of Koop and Korobilis (2012) provides a prominent example of DMA's application in forecasting US inflation, using the GDP deflator and the Personal Consumption Expenditure (PCE) index. Their array of competing models includes the random walk, autoregressive processes, models with time-varying parameters, and those incorporating stochastic volatility. The main result from their investigation indicates that DMA consistently outperforms other forecasting methods and, crucially, is never much worse than the best-performing alternative. Expanding upon this work, Di Filippo (2015) extends the scope to the Euro Area, incorporating additional predictors into the analysis. Interestingly, the

[5] Interested readers seeking a more comprehensive understanding are encouraged to explore works such as Faust and Wright (2013), which focuses on advanced economies, and Duncan and Martínez-García (2019), which delves into emerging market and developing economies, along with the references therein.

author finds that the importance of predictors of headline inflation such as international food commodity prices, house prices, and oil prices tend to increase when such variables experience large fluctuations. While our research employs the same DMA methodology, it distinguishes itself by focusing on DFPI and its dynamics during crisis periods, offering insights derived from a large and diverse sample of economies. This focus sets our study apart among the applications of the DMA method.

The reminder of the paper proceeds as follows. Section 2 addresses the data and methods. This part includes a brief description of our preferred method (DMA), the competing models, and the forecasting exercise. Section 3 reports the main findings for the full sample and the crises periods as well as the robustness checks. Section 4 concludes with some final remarks.

2. Data and Methods

2.1. Data

Our sample consists of monthly series for 43 high-income and 68 middle- and low-income economies. We list all of them in Appendix A.1. This sample includes sovereign countries and non-independent territories, and the data spans from January 2001 (2001M1) to June 2022 (2022M6). For every economy, we calculate the DFPI rate as the year-over-year change in the logged domestic food price index. The source is the Food and Agriculture Organization (FAO) database.

Table 1 displays summary statistics of DFPI across groups of economies and four distinct sub-periods. Two of them correspond to recent global crises: the Global Financial Crisis (spanning from January 2008 to December 2009) and the COVID-19 pandemic and its aftermath (from March 2020 to June 2022).[6] In addition, we incorporate the corresponding pre-crisis periods—specifically, January 2006 to December 2007 and November 2017 to February 2020. For consistency in the analysis, we set the pre-crisis periods to match the same duration as the crisis periods.

[6]Despite institutions like the National Bureau of Economic Research dating the COVID-19 pandemic recession in the US economy from February to April of 2020, we extend our analysis through June of 2022, which is the last available month in our dataset. This extension considers the subsequent inflationary episode during the post-pandemic times, which can be attributed to various global factors, including the initial pandemic shock, the subsequent fiscal and monetary policy responses across countries, and the Russian invasion of Ukraine.

Table 1: **Descriptive Statistics—Domestic Food Price Inflation**

Group/statistic	**Pre-GFC**	**GFC**	**Pre-COVID-19**	**COVID-19**	**Full Sample**
High-income economies					
Mean	4.20	5.59	2.09	3.68	3.04
Median	2.89	4.65	1.71	2.59	2.21
Std. Dev.	4.39	6.32	2.37	4.13	4.44
Middle-/Low-income economies					
Mean	7.46	11.53	3.80	7.91	7.38
Median	6.82	10.25	2.86	5.65	5.35
Std. Dev.	5.66	10.78	5.83	8.78	10.64
All economies					
Mean	6.20	9.22	3.14	6.27	5.70
Median	5.08	7.25	2.25	4.34	3.83
Std. Dev.	5.44	9.75	4.87	7.62	9.02

Notes: GFC denotes the Global Financial Crisis period (2008M1-2009M12), COVID-19 refers to the COVID-19 pandemic and its aftermath episode (2020M3-2022M6). Two corresponding pre-crisis periods are considered: 2006M1-2007M12 and 2017M11-2020M2. Our sample comprises 43 high-income economies and 68 middle- and low-income economies. The full sample spans from 2001M1 to 2022M6. The DFPI series is sourced from the FAO's database.

Several observations merit attention. First, the variability of DFPI measured by its standard deviation is larger during crisis periods than is over the pre-crisis periods. Furthermore, the variability of DFPI is significantly higher within the category of middle- and low-income economies when contrasted with high-income economies.

Table 2 shows the summary statistics of our predictors. Thus, the information displayed in Table 1 (lower panel, last column) and Table 2 (first row) leads to a third observation. Across all economies throughout the entire period of analysis, the variability of the DFPI rate is greater than that of the CPI inflation rate. Taken together, these observations suggest that, in principle, forecasting DFPI seems to be a more complex task than forecasting CPI inflation, particularly in middle- and low-income economies during crisis periods.

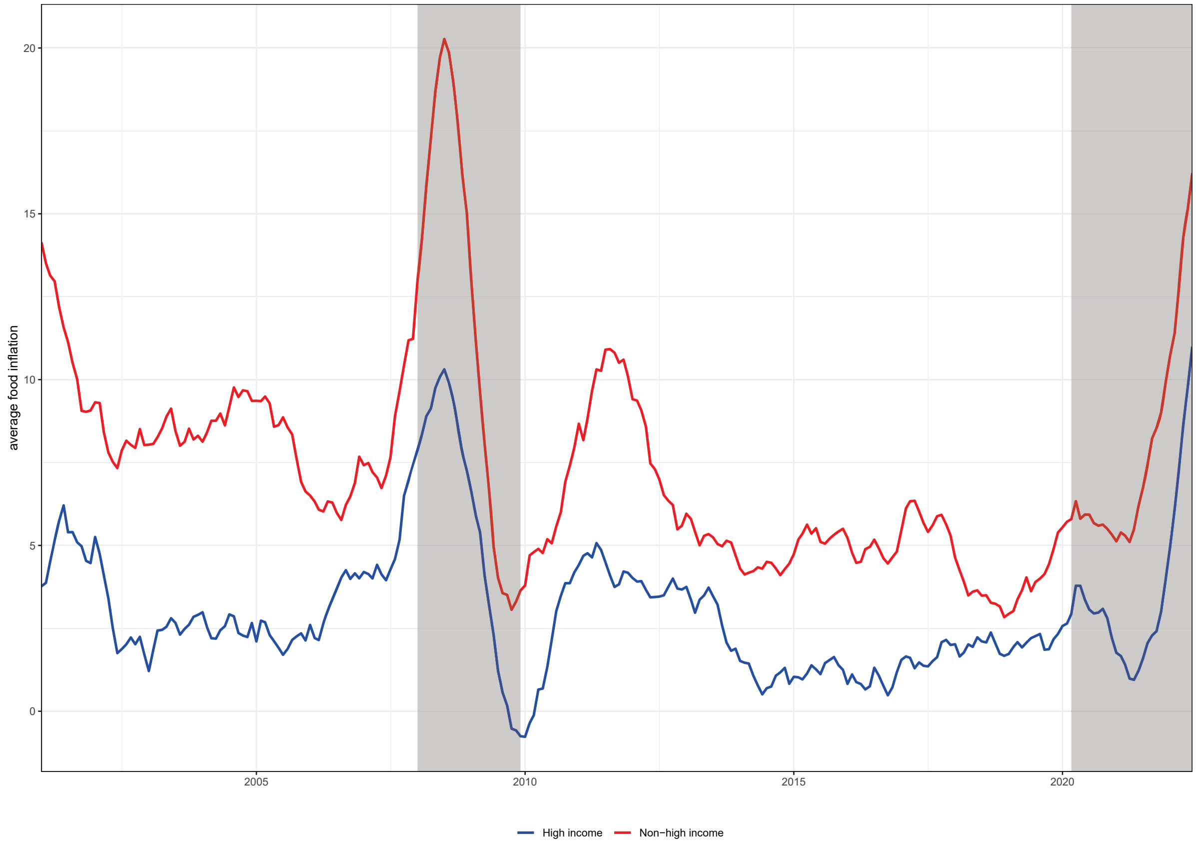
Table 2: **Descriptive Statistics—Predictors**

Predictor	Mean	Median	Std. Dev.
CPI Inflation (Headline, %)	2.48	1.98	2.95
Global commodity price indices			
Agriculture (international price index, %Δ)	4.15	2.05	13.10
Food (international price index, %Δ)	4.97	3.48	15.38
Other Food (international price index, %Δ)	4.04	2.36	10.79
Grains (international price index, %Δ)	5.03	4.83	19.59
Energy (international price index, %Δ)	5.52	7.69	35.85
Fertilizers Prices (international price index, %Δ)	7.65	3.49	33.98
Global indices of economic activity/uncertainty/expectations			
Global Supply Chain Pressures (index)	0.04	-0.23	1.04
Global Economic Activity (Kilian index)	9.78	-2.46	72.49
Climate Policy Uncertainty (US, index)	116.38	100.80	61.03
Expected inflation (US, %)	3.04	2.90	0.72
CRB (international index, %Δ)	1.55	2.27	22.15

Notes: Headline CPI inflation is obtained from the IMF's IFS. International price indices (energy, agriculture, food, grains, fertilizers, other food) are from the World Bank's database. The Global Supply Chain Pressure Index (GSCPI) is proposed by Benigno et al. (2022). The Kilian (2009) index measures global real economic activity in industrial commodity markets. The Climate Policy Uncertainty index is developed by Gavriilidis (2021). The expected inflation rate (the median expected price change next 12 months) come from the Surveys of Consumers conducted by the University of Michigan. The CRB index is a commodity futures price index (19 commodities).

Figure 1 shows the average DFPI rates calculated across middle- and low-income economies (red line) and across high-income economies (blue line). The graph also includes two shaded areas, one for the GFC and the other for the COVID-19 pandemic crisis. One notable difference is that the average DFPI increased at the beginning or even before the start of the GFC, while in the case of the COVID-19 pandemic crisis, the average DFPI initially fell at the onset and rose months later. Put differently, global crises, sooner or later, are accompanied with sharp rises in average DFPI in both groups of countries.

Figure 1: Average Domestic Food Price Inflation Rates in Middle- and Low-Income and High-Income Economies



Notes: Shaded areas indicate the GFC period (2008M1-2009M12) and the COVID-19 pandemic crisis and its aftermath (2020M3-2022M6).

In addition to CPI inflation, Table 2 provides descriptive statistics for other predictor variables that we use for DFPI forecasting. We can divide these variables in two distinct groups, namely, global commodity price indices and global indices that measure economic activity, aggregate uncertainty, and inflation expectations. Appendix A.2 reports the sources of DFPI rates and its predictors.[7]

Perhaps not surprisingly, the variability of the percent change in any of the international price indices is greater than that of the DFPI rate (see Tables 1 and 2). These indices seek to capture the

[7]In the group of global price indices, note that the World Bank's food price index is different from DFPI indices. The former is a composite that includes subindices like oils and meals, grains, and other food commodities traded in international markets, while the latter is a component of the domestic consumer price index that generally covers a wider set of food items.

impact of world prices of both imported final goods and production inputs (energy, certain grains, and fertilizers) as cost push factors on DFPI rates.[8]

We also take into account proxy indicators of global economic factors that aim to gauge economic activity, uncertainty, and expectations at worldwide level. For example, the Global Supply Chain Pressure Index (GSCPI) recently developed by Benigno et al. (2022) aims to capture supply chain disruptions in the global economy that characterized, especially, the COVID-19 pandemic times. The index proposed by Kilian (2009) seeks to assess monthly variation in the global economic cycle and can be viewed as a world pull factor on DFPI. The Climate Policy Uncertainty index developed by Gavriilidis (2021) includes information about US climate policy and climate-change related events. As a proxy of the expected inflation rate in advanced economies, we include the median expected price change next 12 months from the Surveys of Consumers conducted by the University of Michigan. Finally, the Commodity Research Bureau (CRB) index is incorporated to approximate possibly anticipated fluctuations in commodity prices.

The selection of predictors draws inspiration not only from the literature on inflation forecasting, including both DFPI and headline CPI rates, but also from the strand of literature that examines their main covariates or determinants. For instance, a substantial body of research emphasizes agricultural commodity prices (Irz et al., 2013; Kuhns et al., 2015; Peersman, 2022) and energy prices (Baek and Koo, 2010; Baines, 2014) as major drivers of domestic food prices. With the recent surge in inflation in the US and other advanced economies, some scholars have underscored the significance of global supply chain pressures (Di Giovanni et al., 2022). In a comprehensive survey, Castelnuovo (2019) concludes that the response of inflation to uncertainty shocks remains ambiguous in both theory and empirical evidence. Depending on its nature and the state of the economy, among other factors, uncertainty shocks may propagate akin to aggregate demand or aggregate supply shocks. Lastly, there exists an extensive strand of literature establishing the theoretical and empirical links between expected inflation and realized inflation (for a comprehensive review, see Binder and Kamdar, 2022).

It is worth noting that we are unable to include variables related to domestic economic activity, aggregate uncertainty, and inflation expectations at the country level because they are largely unavailable at a monthly frequency for a large sample like ours. Instead, headline CPI inflation might partially capture some of the inflationary pressures stemming from domestic sources such as demand shocks and changes in fiscal and monetary policies.

[8] Peersman (2022) finds that international food price shocks have an impact on food retail prices through the food production chain in the Euro Area. There is a group of articles that regard the price of energy as a covariate or determinant of domestic food prices (e.g., Baek and Koo, 2010; Baines, 2014).

2.2. Methods and models

2.2.1. Dynamic model averaging

In a forecasting exercise like ours, one can argue that a combination of predictors can provide a useful forecast of DFPI. Moreover, one may consider different sets of predictors suggested by economic theory with time-varying coefficients (their marginal effects), which may capture structural changes in different periods.

One methodology to address this general case is dynamic model averaging (DMA). This method was originally proposed by Raftery et al. (2010) in an industrial application. Later, DMA was adapted for inflation forecasting by Koop and Korobilis (2012). The idea is to capture both model uncertainty and parameter uncertainty in a parsimonious fashion. This seems an appropriate option in our case because we have potentially many exogenous variables (including several global indicators and lags of the dependent variable) and a large sample of economies. In addition, parameter instabilities are usually present during episodes of macroeconomic turbulence.

In this section, we adopt a state-space specification and follow mainly the notation proposed by Koop and Korobilis (2012) and Catania and Nonejad (2018).[9] Let π_t denote the DFPI rate. Consider a set of K models that can have a vector of potentially different predictors $x_t^{(k)}$ with $k = 1, 2, ..., K$. Then, we can represent the k^{th} dynamic linear model—our null specification (M_0)—as

$$\pi_t = x_t^{(k)}\theta_t^{(k)} + \epsilon_t^{(k)}, \qquad \epsilon_t^{(k)} \sim N\left(0, V_t^{(k)}\right) \tag{1}$$

$$\theta_t^{(k)} = \theta_{t-1}^{(k)} + \eta_t^{(k)}, \qquad \eta_t^{(k)} \sim N\left(0, W_t^{(k)}\right) \tag{2}$$

where $\theta_t^{(k)}$ is the vector of (stochastic) parameters for the model with k regressors, $V_t^{(k)}$ and $W_t^{(k)}$ are the corresponding conditional variances of the error terms $\epsilon_t^{(k)}$ and $\eta_t^{(k)}$, and these satisfy that $E[\epsilon_t^{(k)}\eta_t^{(k)}] = 0$. Note that all these elements of the system are allowed to vary over time.[10]

Raftery et al. (2010) suggests an approximation within a Bayesian approach to obtain a computationally efficient and feasible estimation. Leaving some technical details aside, this approximation entails the choice of three parameters, $0 < \delta \leq 1$, $0 < \beta \leq 1$, and $0 < \alpha \leq 1$ that are known as forgetting factors. The first two govern the motion of $W_t^{(k)}$ and $V_t^{(k)}$ over time. For example, if $\delta = 1$, then $W_t^{(k)} = 0$ and, thus, $\theta_t^{(k)} = \theta_{t-1}^{(k)}$. That is, there is no time variation in the coefficients and we go back to the standard model with constant slopes. On the other hand, if δ is close to zero, then we induce (extremely) large time variations in the vector of slopes. Similarly, when $\beta = 1$, then $V_t^{(k)} = V^{(k)}$ and we recover the constant-variance model. Values of this parameter

[9] For additional technical details and the multiple applications of DMA in macroeconomics forecasting, see Nonejad (2021).

[10] The terminology "dynamic model averaging", as described by Koop and Korobilis (2012), refers to the state-space system that includes different models at each period, with the models being averaged using conditional probabilities. Furthermore, the marginal effects of the predictors have the potential to vary over time.

close to zero imply (extremely) large observational volatility. In turn, the parameter α generates time variation in the full model set (Catania and Nonejad, 2018; Nonejad, 2021). Values of this parameter closer to zero induce (extremely) fast switches among models. Thus, practitioners tend to pick values close to one for all those parameters. Based on simulations, Catania and Nonejad (2018) suggest fixing δ close to 1 if the practitioner chooses $\beta < 1$.

As in Catania and Nonejad (2018), we assume $\beta = 0.96$ and $\alpha = 0.99$ and fix a grid such that $\delta \in \{0.90, 0.91, ..., 1\}$. For the vector of predictors, we include an intercept, six lags of DFPI, the domestic (headline) CPI inflation, the 12-month change in the log of each international price index (agriculture commodities, food, other food, grains, energy, fertilizers, CRB), the GSCPI, the Kilian index, the CPU index, and the expected inflation rate as defined in subsection 2.1. Since we have $K = 18$ predictors, we consider a total of $2^{18} - 1 = 262143$ possible combinations at each point in time for a given value of δ, while contemporaneously allowing that their coefficients evolve over time.[11] If we consider the values of the grid of δ, we have $(2^{18} - 1)(11) = 2883573$ possible model combinations including averaging over δ.

2.2.2. Competing models

We confront our null specification (M_0) with a variety of competitors. The set of competing forecasting models or methods is the following:

- M_1: Driftless random walk (RW). In this case, $\pi_{t+h} = \pi_t$, for any forecast horizon $h > 0$.
- M_2: Autoregressive (AR(p)) model with fixed parameters (AR), with p lags.
- M_3: Time-varying parameter (TVP) model, which is an AR(p) process where each parameter evolves as a unit-root process with a time-varying variance.
- M_4: The *kitchen sink* approach (KS). This specification contains six lags of the dependent variable and all the predictors discussed above, which are always included. We set $\beta = 1$, $\alpha = 0.99$, and fix a grid for $\delta \in \{0.90, 0.91, ..., 1\}$.
- M_5: Dynamic model selection (DMS). This is similar to the DMA specification but selects the model with the highest posterior probability at each period and use it to forecast. We also assume $\beta = 0.96$ and $\alpha = 0.99$.

Most of these benchmark models are suggested by the strands of literature reviewed in section 1. These include studies focused on inflation forecasting for both advanced and developing economies

[11]The smallest possible model considered is the only-intercept model. The prior for the coefficients at $t = 0$ is a multivariate Gaussian with zero mean vector and variance-covariance matrix equal to $100\mathbf{I}_{19}$, where $\mathbf{I}$ is the identity matrix. Further details can be found in Catania and Nonejad (2018).

(see Faust and Wright, 2013; Hubrich and Skudelny, 2017; Mandalinci, 2017; Duncan and Martínez-García, 2019), as well as those centered on DFPI forecasting (Moser et al., 2007; Gómez et al., 2012; Macias et al., 2022), and the DMA literature (Koop and Korobilis, 2012; Nonejad, 2021).

For instance, among the various versions of the random walk (RW) model, we include the driftless RW as our first competing model, which serves as a popular benchmark in the literature (e.g., Faust and Wright, 2013). We also examine the well-known variant proposed by Atkeson and Ohanian (2001) as a robustness check. Our second model takes the form of an AR process. This type of competing model finds widespread use in other studies focused on food price forecasting (Moser et al., 2007; Gómez et al., 2012; Macias et al., 2022). While the RW model assumes the presence of a unit root, AR models typically provide a stationary alternative. The third model combines an autoregressive process with time-varying parameters. This feature has proven to be especially useful in inflation forecasting, particularly among emerging and developing economies (Mandalinci, 2017). Our fourth model (KS) extends the autoregressive process to include all the predictors used in the null model. This model is commonly referred to as the "kitchen sink" approach in the DMA literature (Catania and Nonejad, 2018). Since both M_4 and the DMA specification consider the same predictors, this aspect allows us to evaluate the advantages of DMA in terms of model selection. Finally, the fifth specification considers dynamic model selection (Koop and Korobilis, 2012; Nonejad, 2021). In contrast to DMA that weights models, DMS will choose a single model. The objective is to assess the different alternatives of model selection.

We opt to use up to six lags in most of our models, following the approach in Hubrich and Skudelny (2017). We refrain to extend the maximum number of lags beyond six, as this value at a monthly frequency corresponds to the inclusion of two lags at a quarterly frequency. The latter is a standard value established in the literature on inflation forecasting (see, e.g., Faust and Wright, 2013; Duncan and Martínez-García, 2019; Duncan and Martínez-García, 2023). The rationale behind this decision rests on the potential drawbacks associated with introducing irrelevant lags and large noise due to parameter estimation. This can deteriorate the forecasting power of some competing models like the autoregressive model with fixed parameters.[12] This scenario could artificially favor our DMA specification, which can automatically drop useless predictors that the autoregressive process is forced to keep. As we discuss below, on average, the AR(1) slightly outperforms the AR(6) process. That said, we also investigate the performance of an AR(6) and an AR(p) with optimal lag selection in the section of robustness checks.

[12] Interestingly, Dufour (1984) shows that any AR(p) models with fixed parameters can produce unbiased forecasts even if the order of the estimated model is lower than the actual one. This result holds exactly when the parameters are estimated by OLS in finite samples.

2.2.3. Forecast evaluation

We use the direct method to produce pseudo out-of-sample forecasts. Ing (2003) concludes that the RMSPE of the direct approach is not greater than that of the iterated approach if the model is misspecified. In general, direct forecasts are more robust to model misspecification (Ing, 2003).[13]

We employ recursive estimation windows to calculate pseudo out-of-sample forecasts at various horizons, namely 1, 6, and 12 months. The prediction error is determined by taking the difference between the actual and predicted values. The initial training sample period spans from January 2001 to June 2004. For instance, the first forecast with a horizon of 1 month is generated in July 2004, while the final forecast is made in June 2022.[14]

To evaluate the forecasting performance, first, we compute the root mean squared prediction error (RMSPE) for each economy, specification, and forecast horizon. Then, we construct the relative RMSPE, also known as Theil's U statistic, which is the ratio of the RMSPE of the DMA specification to the RMSPE of each competing model. Values less than one imply that the DMA specification outperforms the alternative models or methods in terms of lower RMSPE.

To assess the statistical significance of the difference of the relative RMSPE from one, we use a one-sided Diebold-Mariano-West (DMW) test (Diebold and Mariano, 1995; West, 1996) for non-nested models. To account for small sample sizes, we adjust the test statistic using the approach proposed by Harvey et al. (1997). The test statistics are calculated using Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors.

3. Results

3.1. Main findings

To start, we offer an overview of the forecasting accuracy of our DMA specification. Table 3 displays statistics summarizing the distribution of RMSPEs for each forecast horizon (h). These statistics cover all economies throughout the entire period of analysis. For example, the median RMSPE stands at 1.27 percentage points (p.p.) at the one-month forecast horizon. Considering the substantial standard deviation of DFPI (9 p. p.; as detailed in the last column of Table 1), the predictive accuracy of the DMA model, as measured by the RMSPEs, appears reasonable across different quartiles.[15]

[13] It is worth adding that Marcellino et al. (2006) contend that whether one approach is better than the other remains a largely empirical matter.

[14] We set the length of the burn-in period equal to 24 periods. That is, results from the first two years are discarded.

[15] It is noteworthy that the maximum values at the six-month and twelve-month horizon correspond to the Bahamas and Gabon, respectively.

Table 3: Distribution of RMSPEs of the DMA Specification

	$h = 1$	$h = 6$	$h = 12$
Minimum	0.45	0.75	0.73
First quartile	0.91	1.49	1.49
Second quartile	1.27	2.16	2.44
Third quartile	2.17	3.34	3.55
Maximum	4.89	76.02	48.55

Notes: Each entry reports a statistic for each forecast horizon (h-month ahead forecasts), including all economies during the full period of analysis.

Table 4 reports the median and mean of the average forecast error (AFE) of the DMA specification across the 111 economies of our sample. As can be seen, the median of the AFE ranges between -0.02 and 0.03 p.p. Furthermore, the table shows the number of economies with a p-value greater than 0.05 and 0.1 for the null hypothesis that the AFE is equal to zero. This is a test of unconditional unbiasedness. The p-values are calculated using Newey-West HAC standard errors. We cannot reject the null that the mean bias of the DMA specification is equal to zero for the great majority of the economies in our sample.[16]

Table 4: Average Forecast Error of the DMA Specification

	$h = 1$	$h = 6$	$h = 12$
Median	0.00	0.03	-0.02
Mean	0.00	0.04	0.03
$\#p$-value> 0.05	110	106	107
$\#p$-value> 0.1	107	103	104

Notes: Rows for medians (means) report the median (mean) of the average bias from the DMA specification calculated over all countries. The rows $\#p$-value> 0.05 and $\#p$-value> 0.1 report the number of economies that show a p-value greater than 0.05 and 0.1, respectively, for the null hypothesis of an average bias equal to zero using Newey-West HAC standard errors.

Table 5 shows the median and mean of the ratios of the RMSPEs of our DMA specification (M_0) relative to competing models ($M_1 - M_5$) for each forecast horizon ($h = 1, 6, 12$) using the full sample of economies and periods.

The last column reports the mean across forecast horizons. The table also displays the count of cases (economies) where the relative RMSPE falls below 1, as shown in the row labeled $\# < 1$. This count signifies that our null specification provides superior forecasting ability in predicting DFPI compared with its competitor. The last two rows for each model panel shows the number of cases in which the p-value related to the null hypothesis of equal predictive ability (equal RMSPEs) is below 0.1 and 0.05, respectively.

[16] In the Appendix Table A1, we provide analogous statistics for the competing models.

Table 5: RMSPE of the DMA Specification Relative to Competing Models

	$h = 1$	$h = 6$	$h = 12$	Mean
M_1: RW				
Median	0.96	0.55	0.38	0.63
Mean	0.98	0.94	0.53	0.82
$\# < 1$	84	108	106	99
$\#p$-value< 0.1	40	105	104	83
$\#p$-value< 0.05	28	104	103	78
M_2: AR				
Median	0.95	0.58	0.48	0.67
Mean	0.96	1.00	0.67	0.88
$\# < 1$	87	107	105	100
$\#p$-value< 0.1	50	106	103	86
$\#p$-value< 0.05	36	104	101	80
M_3: TVP				
Median	0.98	0.70	0.63	0.77
Mean	0.99	1.13	0.88	1.00
$\# < 1$	80	106	104	97
$\#p$-value< 0.1	26	104	103	78
$\#p$-value< 0.05	16	97	98	70
M_4: KS				
Median	0.85	0.85	0.86	0.85
Mean	0.84	0.83	0.90	0.85
$\# < 1$	109	110	104	108
$\#p$-value< 0.1	103	90	87	93
$\#p$-value< 0.05	92	76	76	81
M_5: DMS				
Median	0.95	0.92	0.92	0.93
Mean	0.95	0.91	0.93	0.93
$\# < 1$	104	109	106	106
$\#p$-value< 0.1	86	97	93	92
$\#p$-value< 0.05	74	92	84	83

Notes: Rows for medians (means) report the median (mean) ratio of RMSPE from the DMA specification relative to that of the competing forecasting models calculated over all countries. Values less than one imply that DMA has a lower RMSPE than does the competitive benchmark. The row $\# < 1$ reports the number of economies that show relative RMSPE lower than 1 for a particular forecast horizon (h) and model. The rows $\#p$-value< 0.1 and $\#p$-value< 0.05 report the number of economies that show a p-value lower than 0.1 and 0.05, respectively, for the null of equal predictive accuracy measured by the RMSPEs of the DMA and the alternative model. We use the Diebold-Mariano-West statistic modified by the Harvey et al. (1997) adjustment for small samples. AR denotes the AR(1) model, RW is driftless the random walk model, TVP is the AR(6) model with time-varying parameters, KS denotes the "kitchen sink" approach with all the regressors and AR(6) component, DMS stands for dynamic model selection.

An examination of the median relative RMSPE reveals consistent values below one for all competing models and horizons. This finding suggests an advantage for the null specification, particularly at longer horizons (6 and 12 months ahead). Put differently, the relative RMSPE tends to decline as the forecast horizon increases. The number of cases with a RMSPE ratio lower than one is mostly above a hundred (out of 111 economies). Most of the gains in lower RMSPE are statistically significant at a 10% significance level. For example, 83 out of 111 economies (around 75%) show, on average, a RMSPE of the null specification statistically lower than that of the RW across all forecast horizons. Notice that the KS (M_4) and the DMS (M_5) specifications own a predictive ability closer to that of our DMA specification, which suggests that the inclusion of the predictors above mentioned (aside from lags of the DFPI) is playing an important role in forecasting DFPI. This observation is consistent with DMA's comparable forecast performance to DMS, as supported by prior studies (see Koop and Korobilis, 2012; Catania and Nonejad, 2018).

3.2. Crisis and pre-crisis periods

3.2.1. Can we forecast DFPI better during the Global Financial Crisis?

How do these metrics perform in both crisis and pre-crisis scenarios? Table 6 shows the summary statistics related to the ratios of the RMSPEs and p-values for two subsamples, namely, the pre-GFC period (2006.1-2007.12) and the GFC episode (2008.1-2009.12).

Table 6: RMSPE of the DMA Specification Relative to Competing Models—Global Financial Crisis

	Pre-GFC period			GFC period		
	$h = 1$	$h = 6$	$h = 12$	$h = 1$	$h = 6$	$h = 12$
M_1: RW						
Median	1.01	0.68	0.51	0.93	0.47	0.34
Mean	1.02	0.72	0.54	0.97	0.80	0.37
$\# < 1$	47	104	105	77	108	109
$\#p$-value< 0.1	10	54	47	30	89	82
$\#p$-value< 0.05	5	30	16	15	73	44
M_2: AR						
Median	0.99	0.73	0.60	0.87	0.50	0.41
Mean	1.00	0.76	0.65	0.92	0.82	0.47
$\# < 1$	60	97	101	88	107	109
$\#p$-value< 0.1	16	48	34	46	93	73
$\#p$-value< 0.05	8	23	20	30	73	35
M_3: TVP						
Median	0.98	0.82	0.70	0.96	0.63	0.56
Mean	1.00	0.82	0.73	1.01	0.99	0.64
$\# < 1$	66	96	98	76	107	106
$\#p$-value< 0.1	20	41	24	27	68	42
$\#p$-value< 0.05	13	14	10	18	39	14
M_4: KS						
Median	0.85	0.87	0.88	0.83	0.85	0.86
Mean	0.85	0.86	0.88	0.85	0.84	0.87
$\# < 1$	98	90	83	103	99	82
$\#p$-value< 0.1	57	23	7	61	35	12
$\#p$-value< 0.05	37	13	2	46	21	3
M_5: DMS						
Median	0.97	0.94	0.94	0.92	0.90	0.94
Mean	0.95	0.93	0.93	0.92	0.93	0.94
$\# < 1$	84	96	92	97	97	91
$\#p$-value< 0.1	30	23	6	54	43	4
$\#p$-value< 0.05	18	9	1	39	19	0

Notes: Rows for medians (means) report the median (mean) ratio of RMSPE from the DMA specification relative to that of the competing forecasting models calculated over all countries for the pre-GFC period (2006.1-07.12) and the GFC episode (2008.1-09.12). Values less than one imply that DMA has a lower RMSPE than does the competitive benchmark. The row $\# < 1$ reports the number of economies that show relative RMSPE lower than 1 for a particular forecast horizon (h) and model. The rows $\#p - value < 0.1$ and $\#p - value < 0.1$ report the number of economies that show a p-value lower than 0.1 and 0.05, respectively, for the null of equal predictive accuracy measured by the RMSPEs of the DMA and the alternative model. We use the Diebold-Mariano-West statistic modified by the Harvey et al. (1997) adjustment for small samples. AR denotes the AR(1) model, RW is driftless the random walk model, TVP is the AR(6) model with time-varying parameters, KS denotes the "kitchen sink" approach with all the regressors and AR(6) component, DMS stands for dynamic model selection.

The main message is that it is possible to obtain relative gains in forecasting DFPI using our null specification (M_0) during the GFC for most of the economies. Looking at the row of the medians, the relative RMSPEs are always below one and usually smaller during the GFC compared with those prior to that crisis. For the number of cases with p-values lower than 10%, a similar pattern in favor of the null model is observed. For some competing models such as the AR process (M_2), the number of statistically significant differences is relatively high in the GFC period (e.g., it is 93 out 111 at the six-month horizon). Once again, the KS (M_4) and the DMS (M_5) specifications, that take into account the same set of predictors used in our null model, constitute the closest competitors. This suggests that the chosen set of predictors contain useful information to forecast DFPI across economies.

3.2.2. Can we forecast DFPI better during the COVID-19 outbreak?

Table 7 displays the statistics concerning the RMSPE ratios and p-values for the pre-COVID-19 period (2017.11-2020.2) and the COVID-19 episode (2020.3-2022.6). Recall that we consider the pandemic and its aftermath, including the Russian invasion to Ukraine and the resulting fluctuations in international oil and gas prices. Hence, the energy price index might play a key role in forecasting DFPI during this period.

Table 7: RMSPE of the DMA Specification Relative to Competing Models—COVID-19 Period

	Pre-COVID-19 period			COVID-19 period		
	$h = 1$	$h = 6$	$h = 12$	$h = 1$	$h = 6$	$h = 12$
M_1: RW						
Median	0.97	0.61	0.38	0.94	0.52	0.37
Mean	1.00	0.62	0.39	0.93	0.52	0.38
$\# < 1$	70	107	111	76	110	111
$\#p$-value< 0.1	25	85	87	35	70	42
$\#p$-value< 0.05	16	52	48	16	35	17
M_2: AR						
Median	0.97	0.66	0.47	0.92	0.50	0.41
Mean	0.99	0.65	0.49	0.91	0.54	0.46
$\# < 1$	70	106	108	79	107	110
$\#p$-value< 0.1	27	69	59	36	65	34
$\#p$-value< 0.05	18	45	35	16	25	18
M_3: TVP						
Median	1.00	0.76	0.70	0.97	0.65	0.61
Mean	1.03	0.78	0.70	0.98	0.65	0.63
$\# < 1$	60	102	102	74	107	105
$\#p$-value< 0.1	17	46	30	28	52	17
$\#p$-value< 0.05	9	28	9	13	18	4
M_4: KS						
Median	0.95	0.87	0.84	0.93	0.86	0.82
Mean	0.94	0.87	0.85	0.91	0.86	0.82
$\# < 1$	92	101	100	96	103	105
$\#p$-value< 0.1	44	41	17	44	44	34
$\#p$-value< 0.05	30	26	4	34	22	15
M_5: DMS						
Median	0.98	0.92	0.91	0.96	0.93	0.93
Mean	0.97	0.92	0.91	0.95	0.92	0.93
$\# < 1$	82	105	96	88	97	95
$\#p$-value< 0.1	34	44	16	44	45	13
$\#p$-value< 0.05	20	23	6	24	23	6

Notes: Rows for medians (means) report the median (mean) ratio of RMSPE from the DMA specification relative to that of the competing forecasting models calculated over all countries for the pre-COVID-19 period (2017.11-20.2) and the COVID-19 episode (2020.3-22.6). Values less than one imply that DMA has a lower RMSPE than does the competitive benchmark. The row $\# < 1$ reports the number of economies that show relative RMSPE lower than 1 for a particular forecast horizon (h) and model. The rows $\#p$-value< 0.1 and $\#p$-value< 0.05 report the number of economies that show a p-value lower than 0.1 and 0.05, respectively, for the null of equal predictive accuracy measured by the RMSPEs of the DMA and the alternative model. We use the Diebold-Mariano-West statistic modified by the Harvey et al (1997) adjustment for small samples. AR denotes the AR(1) model, RW is driftless the random walk model, TVP is the AR(6) model with time-varying parameters, KS denotes the "kitchen sink" approach with all the regressors and AR(6) component, DMS stands for dynamic model selection.

Once again, we usually obtain gains in forecasting DFPI with our null specification during this COVID-19 period. Regarding the median relative RMSPE, we can note that the values reported are below one and they are mostly lower during the COVID-19 period than in the prior period, which is a pattern also observed in the case of the GFC episode. The number of cases with p-values lower than 10% tend to be higher during the COVID-19 episode for the shortest forecast horizons ($h = 1, 6$). That is, although we have gains in predictive accuracy overall, such gains are statistically significant mainly in the (very) short term.

3.2.3. Can we forecast DFPI better during crisis periods?

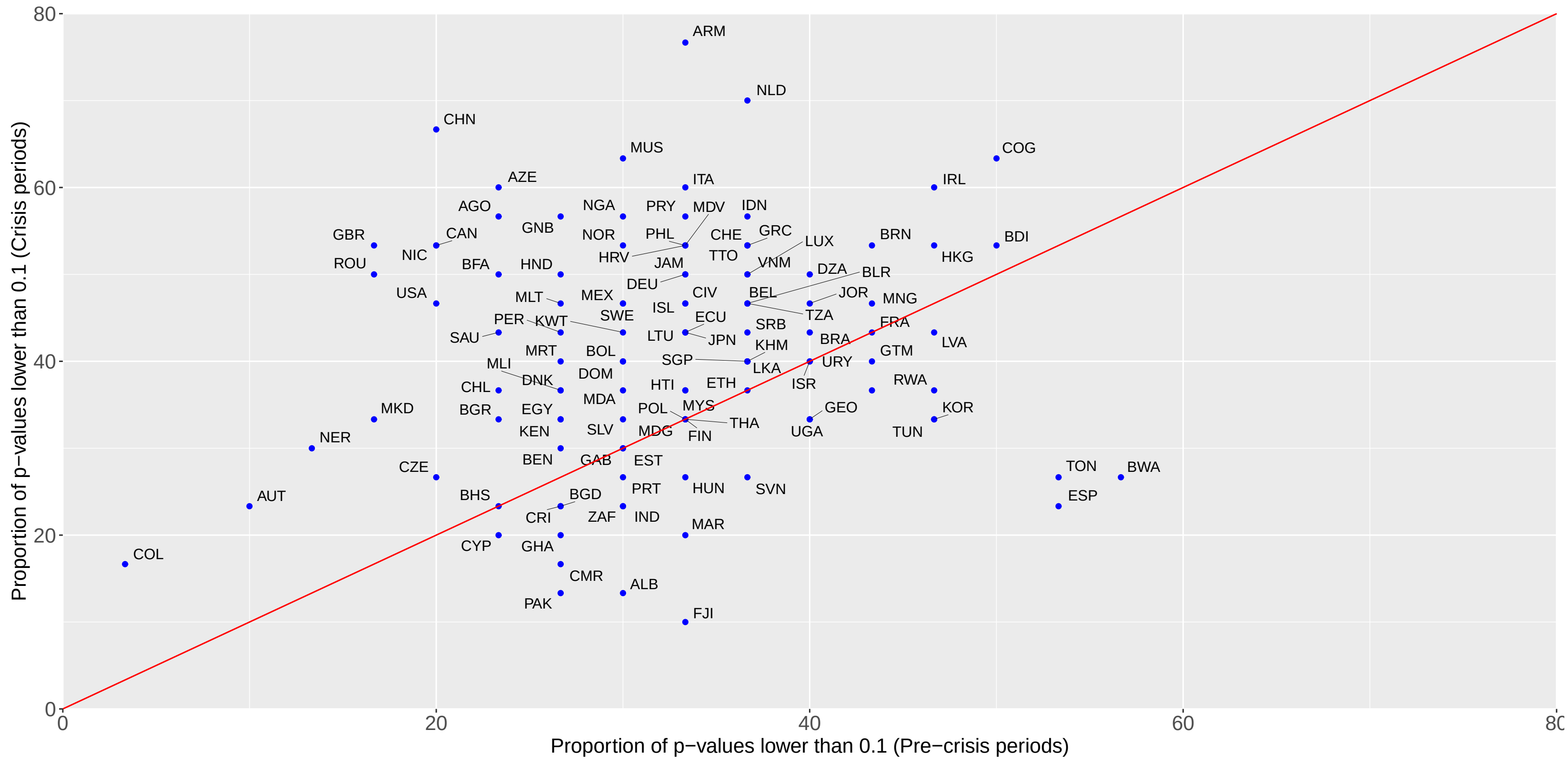
Figure 2 displays the proportion of p-values below 10% during the pre-crisis and crisis periods. Each proportion considers all the competing models and forecast horizons for both crises in each economy of our sample. Visually, the majority of the economies lie above the 45-degree line, indicating that the DMA method exhibits higher predictive accuracy than its competitors during the crisis periods compared with the pre-crisis periods.

Why might the DMA method be relatively more successful than the competing alternatives? Our preferred method offers several theoretical advantages. Firstly, the coefficients of the model predictors can change over time. This feature allows capturing structural breaks in the relations between predictors and the forecasted variable, which are often more prevalent during the crisis periods under examination. Previous research has confirmed the existence of structural shifts in (headline) inflation dynamics and its correlates since the Great Recession (Stock and Watson, 2010; Luengo-Prado et al., 2018) and the COVID-19 pandemic (Cavallo and Zavaleta, 2023). These studies include those addressing the so-called "missing disinflation puzzle" (Coibion and Gorodnichenko, 2015) and the "missing inflation puzzle" (Ciccarelli et al., 2017). The virtue of incorporating structural breaks allows the DMA specification to outperform fixed-parameter models like the RW and the autoregressive process in numerous cases.

Secondly, the DMA method has the capacity to incorporate many potential predictors while disregarding useless ones, thus effectively capturing various sources of shocks without introducing significant noise due to parameter estimation. As previously discussed in sub-section 3.1, we employ six lags of the dependent variable and twelve predictors. This extensive array of predictors translates into an even more substantial number of potential models, where models are defined as combinations of these predictors. We discuss the specific contribution of the main predictors in the next subsection. Moreover, the forecasting model might potentially change over time, allowing for automatic model updates during pre-crisis and crisis episodes. These features might be the reasons behind the relative success of the DMA specification, particularly when compared to the KS and DMS methods.

In summary, these attributes equip the DMA method with the capability to detect structural shifts in predictor-forecast variable relationships and consider potentially different models, which can be more effective during the turbulent times under study.

Figure 2: Proportion of P-values of the DMW Test Below 10%: Pre-Crisis and Crisis Periods



Note: The proportions are calculated for all the forecast horizons and competing models in each economy. The red diagonal represents the 45-degree line.

3.2.4. Which predictors are more useful to forecast DFPI during Global Crises?

In order to assess if certain predictors could perform better during an economic crisis, we calculate the probabilities of inclusion of each predictor for every country and period. The idea is to compare the predictor's contribution to forecast DFPI during both the pre-crisis and the crisis period.

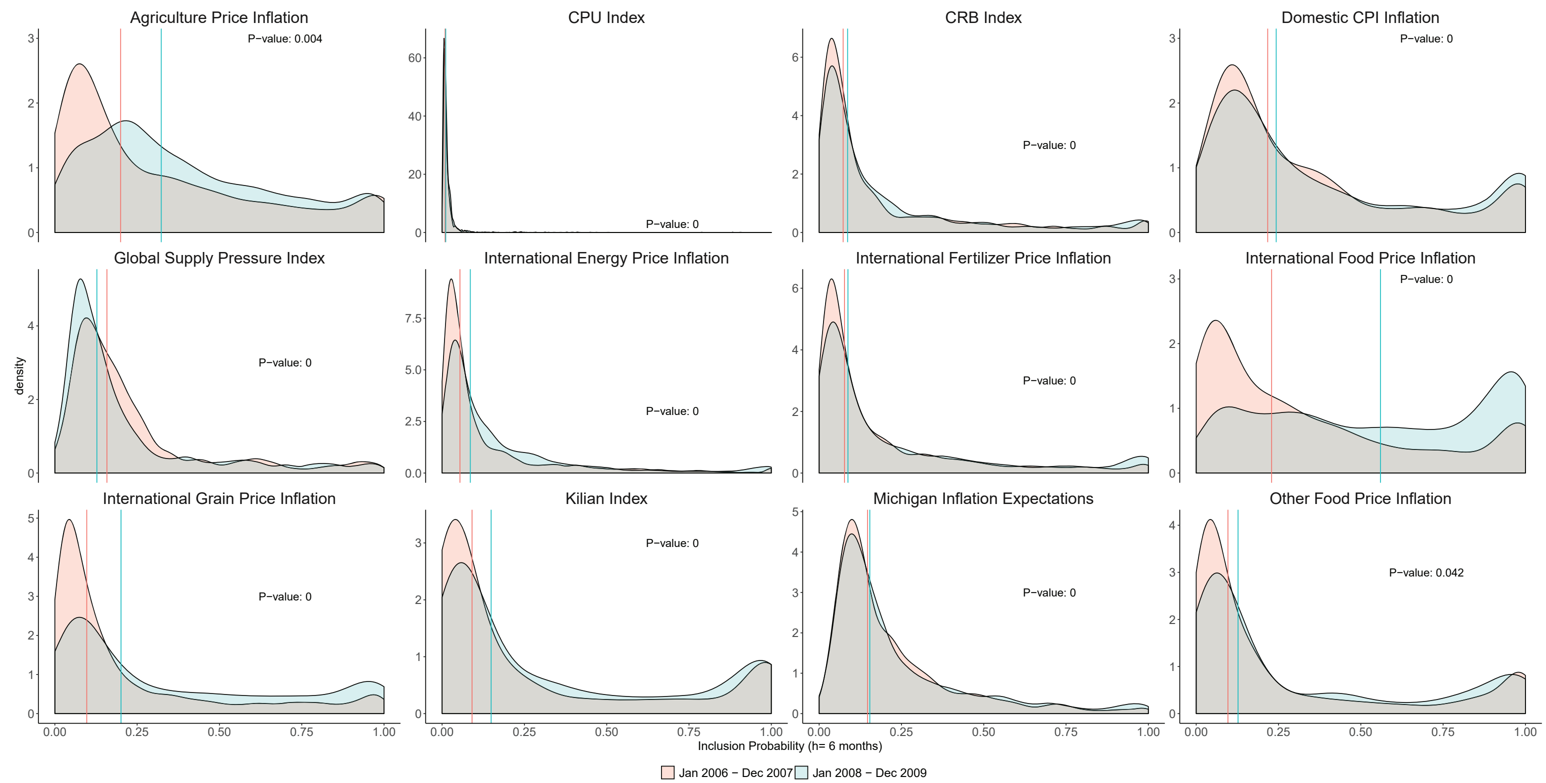
The DMA method allows the calculation of such probabilities using the posterior distribution of each estimated model. For a given value of the forgetting factor δ, the DMA method updates the (posterior) probability of each model at each period t. For a given model, its posterior probability at t depends on the predictive likelihood of that model to predict DFPI at t. These model probabilities are used to calculate a weighted average of the forecasts of all the estimated models at each period. Since a high predictive likelihood indicates that the predictors used in that model are relevant for forecasting DFPI, the model probabilities are also used to calculate a probability of inclusion for each predictor. Thus, even though the inclusion of predictors in a model is pre-determined by all the possible combinations of them, this posterior probability of inclusion can be calculated as the sum of all these model probabilities in which the predictor was included. Then, a predictor with a probability of inclusion equal to zero means that the predictor was included in models that have a zero posterior predictive probability. That is, it was included in models that were not used in the calculation of the forecast.

Figures 3 and 4 show kernel density estimates of the probabilities of inclusion during the pre-GFC and the GFC periods for 6- and 12-month ahead forecasts, respectively. We use the Gaussian kernel function and the Silverman's bandwidth estimator adjusted by 0.8. To simplify the exposition, we disregard the case when $h = 1$ because the DMA's gains in predictive accuracy tend to be more substantial when there is more uncertainty; that is at $h = 6$ and $h = 12$. The median of each density is displayed with a vertical line (the median for the pre-crisis period is represented in pastel pink, while that for the crisis period is shown in pastel blue). We also report the p-value associated with the Kruskal and Wallis (1952) test to compare the distribution of probabilities are before and during the GFC.[17]

The figures mostly show right-skewed distributions for both forecast horizons. During the GFC, most of the densities and their corresponding medians shift to the right. The most significant shifts are observed for certain predictors such as the international food price inflation (at $h = 6, 12$) as well as the domestic CPI inflation and the Kilian index (at $h = 12$). In most of these cases, the median probability of inclusion of the predictors increases above 0.25.

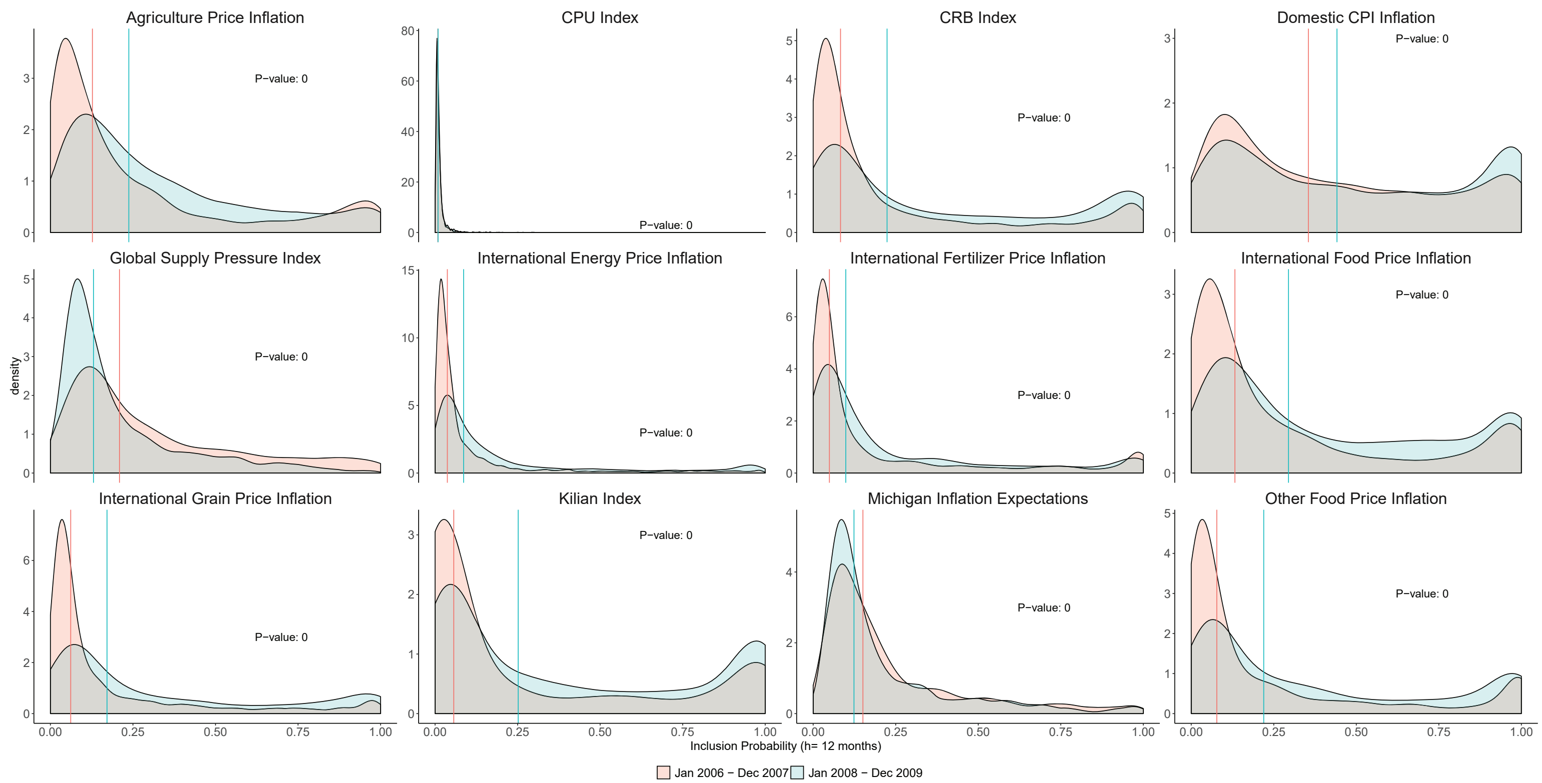
[17] P-values close to zero suggest evidence that distribution of the probabilities of inclusion differs between crisis and pre-crisis periods. We interpret the results of the Kruskal-Wallis test with caution because it is assumed that the observations within and between groups are independent.

Figure 3: Kernel Densities of the Posterior Probabilities of Inclusion—Pre-GFC and GFC Periods ($h = 6$)



Note: The median probability for the pre-GFC period is represented in pastel pink, while that for the GFC period is shown in pastel blue, both marked with a vertical line.

Figure 4: Kernel Densities of the Posterior Probabilities of Inclusion—Pre-GFC and GFC Periods ($h = 12$)



Note: The median probability for the pre-GFC period is represented in pastel pink, while that for the GFC period is shown in pastel blue, both marked with a vertical line.

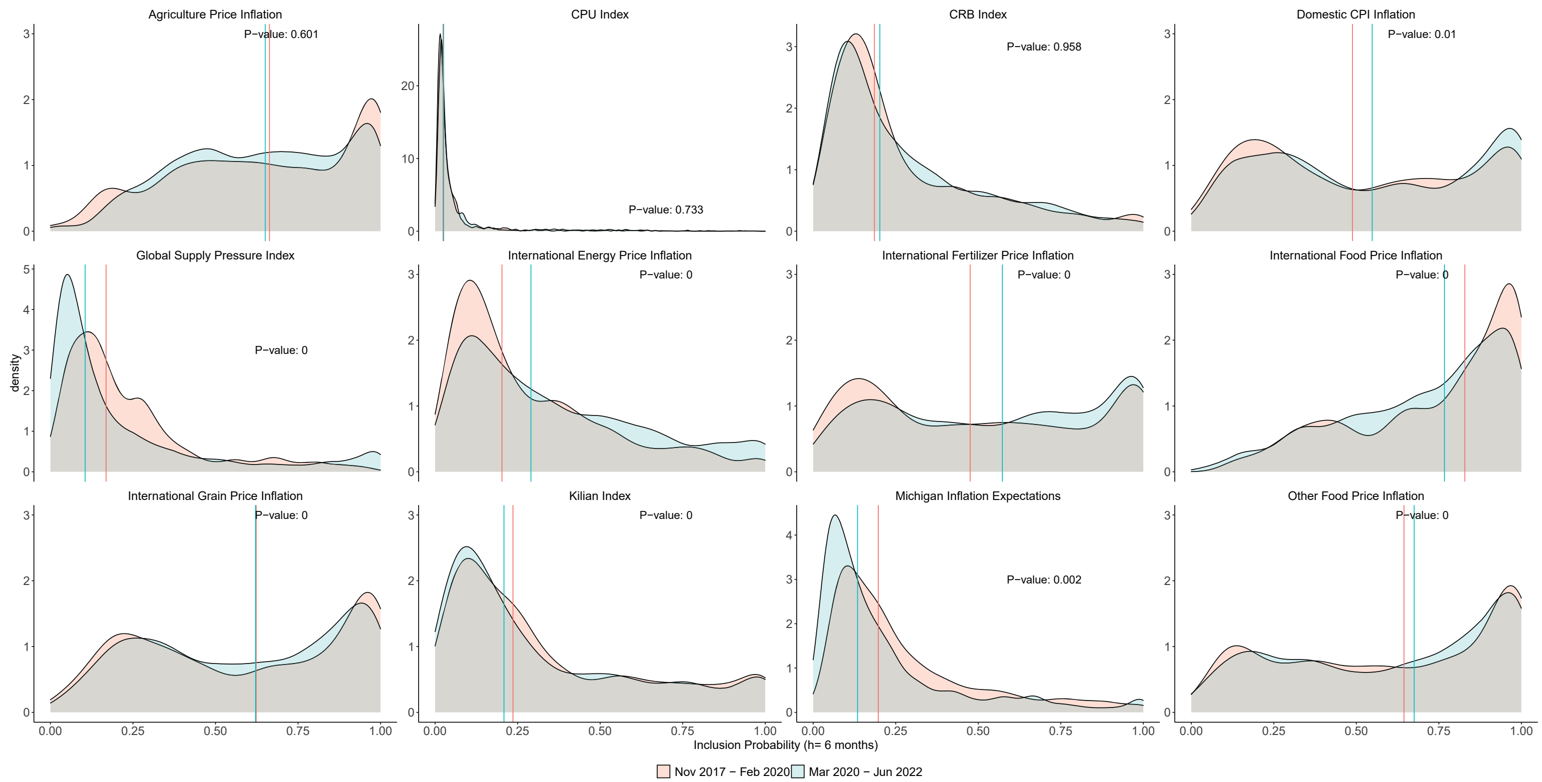
The previous estimates are also calculated to compare the most recent economic crisis, driven by the COVID-19 pandemic period, and its corresponding pre-crisis period (see Figures 5 and 6).

These figures show now a mix of right-skewed and left-skewed distributions. In the latter group, we have those of the domestic CPI inflation and the inflation of international prices of agriculture commodities, food and other food items, and fertilizers. In terms of the median probability of inclusion, the international food price inflation is a predictor with a very high forecasting ability during the COVID-19 pandemic with a median probability of inclusion around 0.75.

Aside from the indicators mentioned above, relevant predictors of DFPI with medians above the 0.25 threshold are the international price inflation of fertilizers and grains. Except for the CPU index, other indicators such as the international price inflation of energy, expected inflation, and the Kilian index among others, could be important to predict food inflation for some countries, but their inclusion probabilities are generally concentrated at low values. In other words, we cannot disregard the contribution of such predictors to DFPI forecasting in certain economies, especially for the largest forecast horizon ($h = 12$).

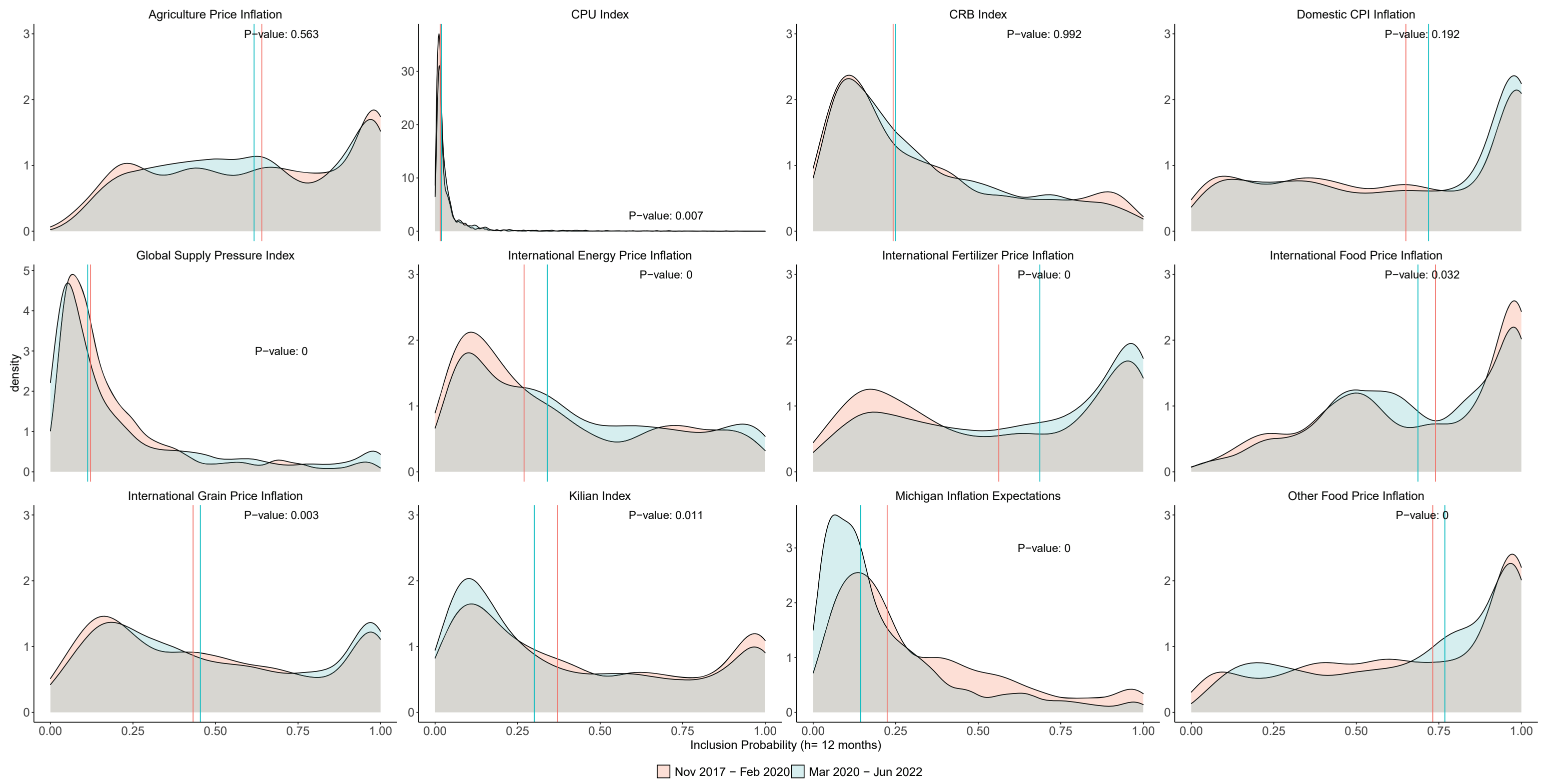
Overall, the distributions of the probabilities of inclusion suggest that after the GFC, domestic food price inflation can be better forecasted using domestic CPI inflation as well as the international price inflation of food, other food items, fertilizers, grains, and agricultural commodities. In particular, these variables improve their forecasting ability for many countries during the COVID-19 pandemic and its aftermath.

Figure 5: Kernel Densities of the Posterior Probabilities of Inclusion—Pre-COVID-19 and COVID-19 Periods ($h = 6$)



Note: The median probability for the pre-COVID-19 period is represented in pastel pink, while that for the COVID-19 pandemic and its aftermath is shown in pastel blue, both marked with a vertical line.

Figure 6: Kernel Densities of the Posterior Probabilities of Inclusion—Pre-COVID-19 and COVID-19 Periods ($h = 12$)



Note: The median probability for the pre-COVID-19 period is represented in pastel pink, while that for the COVID-19 pandemic and its aftermath is shown in pastel blue, both marked with a vertical line.

Regarding the lags of DFPI used as predictors, the probabilities of inclusion predominantly cluster around values below 0.20, with medians rarely exceeding 0.15. The exception is the first lag, where the median probability of inclusion nears 0.9 for the GFC period. This observation could suggest that after the GFC, more distant history of the DFPI itself ceases to provide relevant information for accurate forecasting. For the sake of simplicity, we opt to report the graphs of these distribution in the Appendix Figures A1-A4.

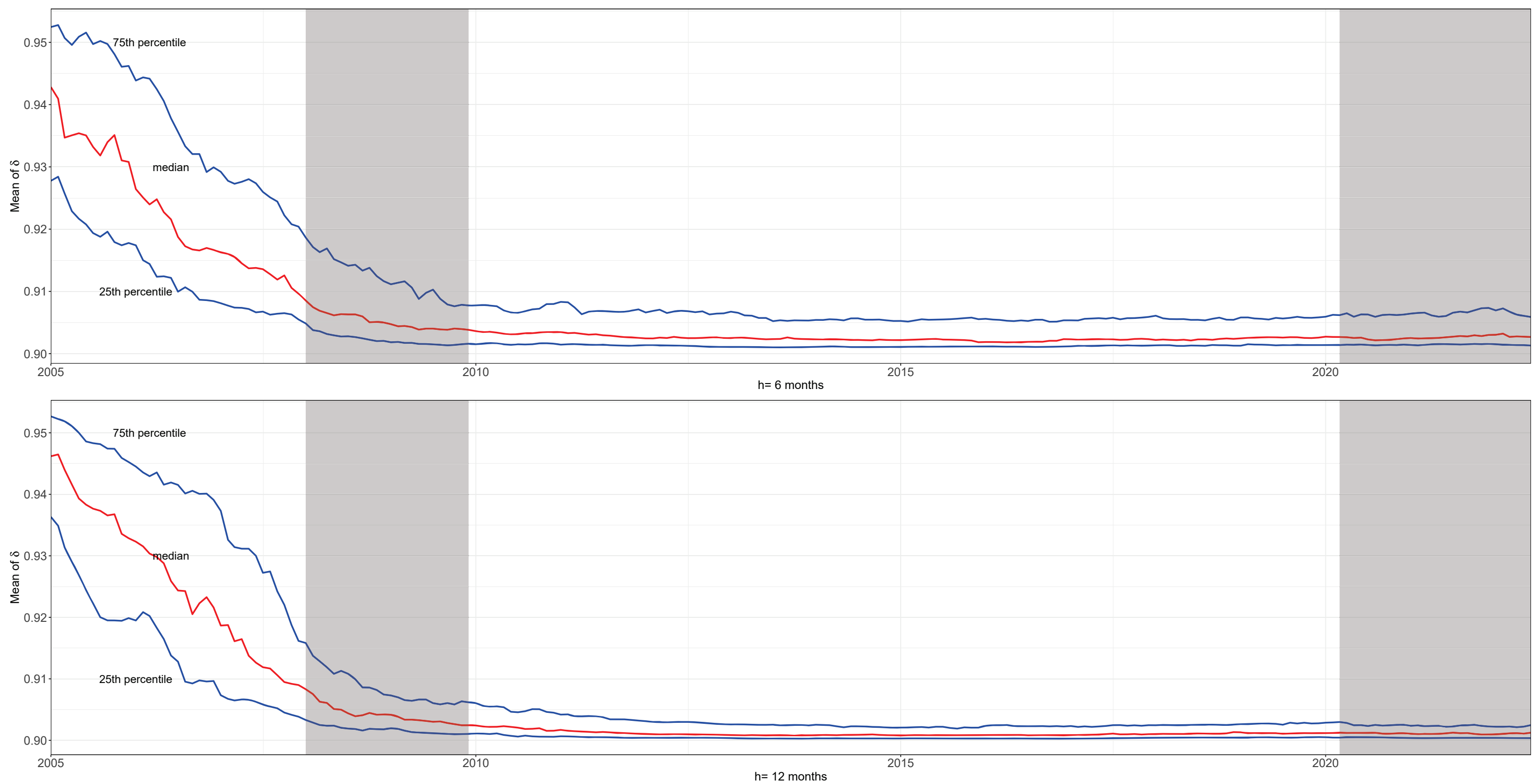
Further evidence that supports this argument is provided by the evolution of the forgetting factor δ. Recall that the predictive likelihood of a model depends on this parameter. We use a grid of 11 values of δ (from 0.9 to 1) and their corresponding probabilities are updated at each period.[18] Figure 7 displays the percentiles 25, 50, and 75 associated with the distribution of the weighted δ at each period starting in January 2005. For a given country and forecast horizon, we use the updated probability for each δ to calculate the country's weighted average of δ. Percentiles are calculated at each period using these cross-country samples of the weighted average estimates of δ.

The figure allows two interesting insights. First, it is apparent that all the percentiles of this distribution decline during the GFC compared with its pre-crisis period. This observation aligns with Catania and Nonejad (2018), who argue that a lower δ is expected during recessions or periods of market turmoil, when there is increased time variability in the model's slope parameters. Let us recall that smaller values of δ indicate more instability on the predictors' parameters. Following Catania and Nonejad (2018), a value of δ equal to 0.91 imply that observations from 12 (24) months ago receive approximately 32% (10%) as much weight as the last period's observation. This result is also consistent with the need to use more predictors to forecast DFPI with more precision after the GFC (more on this below).

Second, the downward trend of all the percentiles in Figure 7 appears to stabilize at lower values, converging towards 0.9, extending from the post-GFC period through to the end of the sample, including the COVID-19 crisis period. This fact seems to suggest that since the GFC, the global economy has entered a regime of persistently high instability in terms of the parameters of the DFPI's predictors.

[18] The initial prior for each of these probabilities is 0.091. Thus, for a given model, its posterior probability is weighted using the updated probability for each of the δ values.

Figure 7: Percentiles of the Posterior Weighted Average Estimate of δ $(h = 6, 12)$

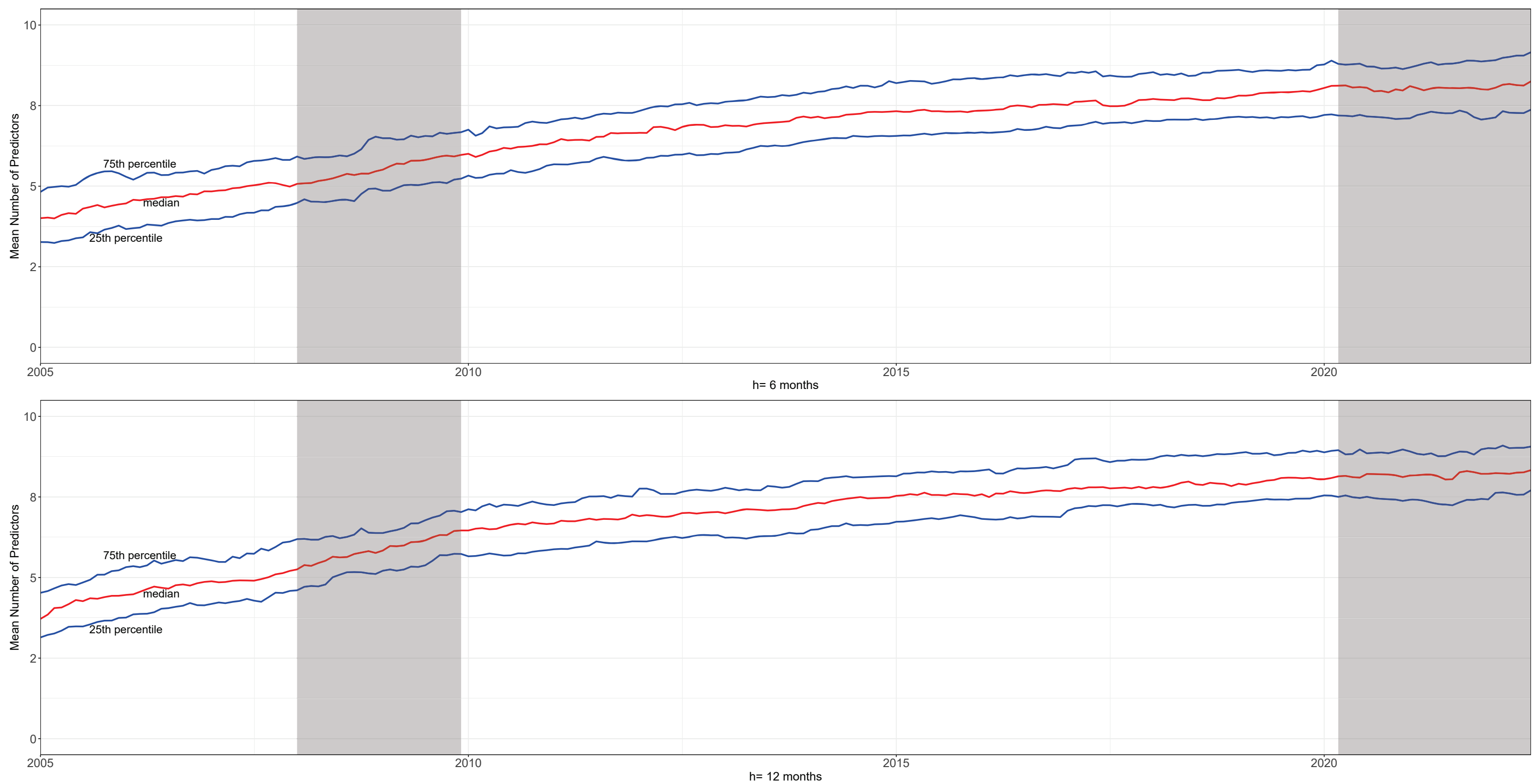


Note: The graph plots the percentiles of the distribution of the posterior weighted average estimate of the forgetting factor δ across economies for every period.

Finally, Figure 8 provides percentiles for the mean number of predictors. This metric is computed using the updated model probabilities as weights, resulting in a weighted average number of predictors for each country and forecast horizon. Percentiles are calculated at each period using these cross-country samples of averages. On average, there is an increase in the required number of predictors to forecast DFPI accurately, especially when looking 12 months ahead.

In summary, the dynamics of these measures (i.e., inclusion probabilities, weighted average estimates of δ, and the mean number of predictors) indicate that predicting DFPI using its own historical data becomes more challenging after the GFC. Given the time variability in model parameters, the use of the most recent lags of DFPI coupled with the international price inflation of food, other food categories, fertilizers, grains, and agricultural commodities can be more useful to predict DFPI more accurately.

Figure 8: Mean Number of Predictors $(h = 6, 12)$



Note: The graph plots the percentiles of the distribution of the mean number of predictors across economies for every period.

3.3. Robustness checks

3.3.1. Additional models

We also run the forecasting horserace using the following variants of the random walk and the autoregressive process:

- M_6: Atkeson and Ohanian (2001) random walk (AO-RW). In this case, $\pi_{t+h} = \frac{1}{6}\sum_{i=1}^{6}\pi_{t-i+1}$, for any forecast horizon $h > 0$.
- M_7: Autoregressive model (AR(p)) with fixed parameters and $p = 6$ lags.
- M_8: Autoregressive model (AR(p)-BIC) with fixed parameters and p chosen using the Bayesian Information Criterion (BIC).

While the RW-AO model may seem like a trivial approach (just a simple average of the most recent values of the DFPI rates), it has found its place as a benchmark model in the forecasting toolkit for headline inflation (see, e.g., Faust and Wright, 2013; Duncan and Martínez-García, 2019). This unit-root process has proved to be useful especially as a benchmark for CPI inflation forecasting among emerging market economies. The reason is that the RW-AO model provides a straightforward method to downweight later data, which is a useful strategy when there are unknown structural breaks and model misspecification (Duncan and Martínez-García, 2019). Based on the median relative RMSPEs, the results are somewhat similar to those of the standard driftless RW with a positive but slight difference in favor of the latter (see Appendix Tables A2-A4).

Furthermore, we investigate the performance of two autoregressive models, namely the AR(6) and the AR(p)-BIC process (M_7 and M_8), where the optimal lag (p) is determined using the BIC statistic for each period, economy, and forecast horizon. The maximum number of possible lags assumed is 12. Appendix Tables A2-A4 present the outcomes of this analysis. The AR(6) exhibits slightly higher median relative RMSPE ratio compared with its AR(1) counterpart in the full sample for all the forecast horizons (see Tables 5 and A2). In contrast, the AR(p)-BIC tends to outperform the AR(1) model particularly at longer horizons ($h = 6, 12$). This finding would indicate that the key to enhanced forecasting may not solely lie in the number of lags present within the autoregressive component of the models used in this study.

Comparing crisis and pre-crisis periods, once again, we find that the relative RMSPE ratios are mostly below one and they are usually lower during the GFC and the COVID-19 pandemic than their corresponding pre-crisis episodes. However, the statistical significance varies depending on the model, horizon, and crisis period under consideration. More precisely, the gains in predictive accuracy are primarily more significant during the GFC times.

3.3.2. Alternative definition of the GFC

In this subsection, we analyze the sensitivity of our results to an alternative definition of the GFC period. It can be argued that this global crisis started in December 2007 and ended in June 2009 as in the US economy (see the Business Cycle Dating at the National Bureau of Economic Research's website).

Table A5 confirms that the relative RMSPEs from the redefined GFC period are mostly below one and often smaller than those from the pre-crisis period. A comparable tendency favoring the null model is observed regarding the number of cases with p-values below 10%. Additionally, we confirm that the DMS (M_5) specification remains as the DMA's closest competitor among the alternative models.

4. Concluding Remarks

This paper focuses on forecasting domestic food price inflation (DFPI), a notably volatile component of headline inflation, with a particular emphasis on periods of macroeconomic turbulence, including the Global Financial Crisis (GFC) and the COVID-19 pandemic and its subsequent repercussions. Our study considers a diverse array of economies, spanning from high-income to low-income economies. We systematically evaluate different specifications and methods, as well as the effectiveness of various predictors during each crisis.

We find that the dynamic model averaging (DMA) method, combined with a set of global commodity price indices, mostly outperforms conventional time-series models commonly employed in the forecasting literature. We identify the international food price inflation as the most influential indicator to forecast DFPI during crises in numerous economies. Other relevant predictors, especially during the COVID-19 episode, are domestic headline inflation, and the international inflation of agricultural commodities, fertilizers, and other food categories.

Our results also reveal that after the GFC, the global economy has entered a regime with greater instability in the parameters of predictors. This suggests that given the current context, distant historical data might not sufficiently provide the necessary information for predicting the DFPI. Methods such as DMA, which accounts for model and parameter uncertainty, are better suited for forecasting DFPI.

References

Arndt, C., Hussain, M.A., Salvucci, V. and Østerdal, L.P. 2016. Effects of food price shocks on child malnutrition: The Mozambican experience 2008/2009. Economics & Human Biology, 22, 1-13.

Attanasio, O., Di Maro, V., Lechene, V. and Phillips, D. 2013. Welfare consequences of food prices increases: Evidence from rural Mexico. Journal of Development Economics, 104, 136-151.

Atkeson, A. and L. E. Ohanian. 2001. Are Phillips Curves Useful for Forecasting Inflation? Federal Reserve Bank of Minneapolis Quarterly Review, 25 1, 211. Winter.

Baek, Jungho and Won W, Koo. 2010. Analyzing Factors Affecting U.S. Food Price Inflation, Canadian Journal of Agricultural Economics 58, 303–320.

Baines, Joseph. 2014. Food Price Inflation as Redistribution: Towards a New Analysis of Corporate Power in the World Food System, New Political Economy, 19:1, 79-112.

Barkan, O., Benchimol, J., Caspi, I., Cohen, E., Hammer, A. and Koenigstein, N., 2023. Forecasting CPI inflation components with hierarchical recurrent neural networks. International Journal of Forecasting, 39(3), 1145-1162.

Bellemare, M.F., 2015. Rising food prices, food price volatility, and social unrest. American Journal of Agricultural Economics, 97(1), 1-21.

Benigno, G., di Giovanni, J., Groen, J.J. and Noble, A.I. 2022. The GSCPI: A New Barometer of Global Supply Chain Pressures. FRB of New York Staff Report, 1017.

Binder, C. and Kamdar, R., 2022. Expected and realized inflation in historical perspective. Journal of Economic Perspectives, 36(3), 131-155.

Capehart, T. and Richardson, J., 2008. Food price inflation: Causes and impacts.

Castelnuovo, E., 2019. Domestic and global uncertainty: A survey and some new results.

Catania, L. and N. Nonejad. 2018. Dynamic Model Averaging for Practitioners in Economics and Finance: The eDMA Package. Journal of Statistical Software 84 11, 1-39.

Cavallo, A. and Zavaleta, G.G., 2023. Detecting Structural Breaks in Inflation Trends: A High-Frequency Approach.

Ciccarelli, M., Osbat, C., Bobeica, E., Jardet, C., Jarocinski, M., Mendicino, C., Notarpietro, A., Santoro, S. and Stevens, A., 2017. Low inflation in the euro area: Causes and consequences. ECB occasional paper, (181).

Coibion, O. and Gorodnichenko, Y., 2015. Is the Phillips curve alive and well after all? Inflation expectations and the missing disinflation. American Economic Journal: Macroeconomics, 7(1), 197-232.

Cornelsen, L., Green, R., Turner, R., Dangour, A.D., Shankar, B., Mazzocchi, M. and Smith, R.D., 2015. What happens to patterns of food consumption when food prices change? Evidence from a systematic review and meta-analysis of food price elasticities globally. Health Economics, 24(12), 1548-1559.

Diebold FX, Mariano RS. 1995. Comparing predictive accuracy. Journal of Business and Economic Statistics 133: 253–263.

Di Filippo, G., 2015. Dynamic model averaging and CPI inflation forecasts: A comparison between the Euro area and the United States. Journal of Forecasting, 34(8), 619-648.

Di Giovanni, J., Kalemli-Özcan, S., Silva, A. and Yildirim, M.A., 2022. Global supply chain pressures, international trade, and inflation (No. w30240). National Bureau of Economic Research.

Dufour, J.M., 1984. Unbiasedness of predictions from estimated autoregressions when the true order is unknown. Econometrica: Journal of the Econometric Society, 209-215.

Duncan, R. and E. Martínez-García. 2019. New Perspectives on Forecasting Inflation in Emerging Market Economies: An Empirical Assessment. International Journal of Forecasting 35 3, 1008-1031.

Duncan, R. and Martínez-García, E., 2023. Forecasting inflation in open economies: What can a NOEM model do? Journal of Forecasting, 42(3), 481-513.

Faust, J. and J. H. Wright. 2013. Forecasting Inflation, Volume 2A of Handbook of Economic Forecasting, Chapter 1, 2-56. Elsevier.

Fujii, T. 2013. Impact of food inflation on poverty in the Philippines. Food Policy, 39, 13-27.

Gavriilidis, K., 2021. Measuring climate policy uncertainty. Available at SSRN 3847388.

Ginn, W. and Pourroy, M. 2020. Should a central bank react to food inflation? Evidence from an estimated model for Chile. Economic Modelling, 90, 221-234.

Gómez, M.I., González, E.R. and Melo, L.F. 2012. Forecasting food inflation in developing countries with inflation targeting regimes. American Journal of Agricultural Economics, 941, 153-173.

Ha, J., Kose, M.A. and Ohnsorge, F. eds. 2019. Inflation in emerging and developing economies: Evolution, drivers, and policies. World Bank Publications.

Harvey, D., S. Leybourne, and P. Newbold. 1997. Testing the Equality of Prediction Mean Squared Errors. International Journal of Forecasting 13 2, 281–291.

Hubrich, K. and Skudelny, F., 2017. Forecast combination for euro area inflation: a cure in times of crisis?. Journal of Forecasting, 36(5), 515-540.

Ing, C.-K. 2003. Multistep Prediction in Autoregressive Processes. Econometric Theory 19 2, 254–279.

Irz, X., Niemi, J. and Liu, X., 2013. Determinants of food price inflation in Finland—The role of energy. Energy Policy, 63, 656-663.

Joutz, F.L., 1997. Forecasting CPI food prices: an assessment. American journal of agricultural economics, 79(5), 1681-1685.

Kidane, D. and Woldemichael, A. 2020. Does inflation kill? Exposure to food inflation and child mortality. Food Policy, 92, p.101838.

Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. American Economic Review, 99(3), 1053-1069.

Koop, G. and D. Korobilis. 2012. Forecasting Inflation Using Dynamic Model Averaging. International Economic Review 53 3, 867-886.

Kruskal, W.H. and Wallis, W.A., 1952. Use of ranks in one-criterion variance analysis. Journal of the American Statistical Association, 47(260), 583-621.

Kuhns, A., Leibtag, E., Volpe, R. and Roeger, E., 2015. How USDA Forecasts Retail Food Price Inflation.

Luengo-Prado, M.J., Rao, N. and Sheremirov, V., 2018. Sectoral inflation and the Phillips curve: What has changed since the Great Recession?. Economics Letters, 172, 63-68.

Macias, P., Stelmasiak, D. and Szafranek, K. 2022. Nowcasting food inflation with a massive amount of online prices. International Journal of Forecasting.

Mandalinci, Z. 2017. Forecasting Inflation in Emerging Markets: An Evaluation of Alternative Models. International Journal of Forecasting 33, 1082–1104.

Marcellino, M., J. H. Stock, and M. W. Watson. 2006. A Comparison of Direct and Iterated Multistep AR Methods for Forecasting Macroeconomic Time Series. Journal of Econometrics 135 1-2, 499–526.

Moser, G., Rumler, F. and Scharler, J., 2007. Forecasting austrian inflation. Economic Modelling, 24(3), pp.470-480.

Nonejad, N. 2021. An Overview of Dynamic Model Averaging Techniques in Time-Series Econometrics. Journal of Economic Surveys 35(2), 566-614.

Peersman, G., 2022. International food commodity prices and missing (dis) inflation in the euro area. Review of Economics and Statistics, 104(1), 85-100.

Raftery, A. E., M. Kárný, and P. Ettler 2010. Online Prediction Under Model Uncertainty via Dynamic Model Averaging: Application to a Cold Rolling Mill. Technometrics 52 1, 52–66.

Stock, J.H. and Watson, M.W., 2010. Modeling inflation after the crisis (No. w16488). National Bureau of Economic Research.

West KD. 1996. Asymptotic inference about predictive ability. Econometrica 64: 1067–1084.

Woldemichael, A., Kidane, D. and Shimeles, A. 2022. Food Inflation and Child Health. The World Bank Economic Review.

A. Appendix

A.1. Sample

Group of high-income economies (43): Austria, Bahamas, Belgium, Brunei Darussalam, Canada, Chile, China, Hong Kong SAR, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Kuwait, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Norway, Poland, Portugal, Republic of Korea, Romania, Saudi Arabia, Singapore, Slovenia, Spain, Sweden, Switzerland, Trinidad and Tobago, United Kingdom of Great Britain and Northern Ireland, United States of America, and Uruguay.

Group of middle- and low-income economies (68): Albania, Algeria, Angola, Armenia, Azerbaijan, Bangladesh, Belarus, Benin, Bolivia (Plurinational State of), Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, China, mainland, Colombia, Congo, Costa Rica, Cote d'Ivoire, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Fiji, Gabon, Georgia, Ghana, Guatemala, Guinea-Bissau, Haiti, Honduras, India, Indonesia, Jamaica, Jordan, Kenya, Madagascar, Malaysia, Maldives, Mali, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Nicaragua, Niger, Nigeria, North Macedonia, Pakistan, Paraguay, Peru, Philippines, Republic of Moldova, Rwanda, Serbia, South Africa, Sri Lanka, Thailand, Tonga, Tunisia, Turkiye, Uganda, United Republic of Tanzania, and Vietnam.

A.2. Data sources

- The DFPI series is sourced from the Food and Agriculture Organization (FAO) database. Accessed on 12.15.2022. The DFPI rate is the year-over-year change in the logged DFPI series.

- Headline CPI inflation is obtained from the International Financial Statistics (IFS) database of the International Monetary Fund. It is defined as the year-over-year percent change in the CPI series. Accessed on 12.23.2022.

- International price indices (agriculture, food, other food, energy, grains, fertilizers) are from the World Bank database. Roughly, the agriculture index includes beverages, food, and raw materials. The basket of the food subindex contains oils and meals, grains, and other food. The latter contains bananas, beef, chicken, oranges, and sugar. Energy includes coal, crude oil, and natural gas. Grains consider barley, maize, rice, and wheat. Fertilizers contain natural phosphate rock, diammonium phosphate, potassium, and urea. Accessed on 12.02.2022.

- The Global Supply Chain Pressure Index (GSCPI) is proposed by Benigno et al. (2022). The index is standardized such that positive (negative) values represent how many standard deviations the index is above (below) its historical average value reflecting higher (lower) supply chain pressures (Benigno et al., 2022). Accessed on 12.15.2022.

- The Kilian (2009) index measures global real economic activity in industrial commodity markets. As other business-cycle indicators, this is expressed in percent deviations from trend. Accessed on 3.15.2023.

- The Climate Policy Uncertainty index is developed by Gavriilidis (2021). We use it to approximate aggregate uncertainty about climate change and related policies in the US. This indicator calculates the number of relevant articles published in eight leading US newspapers every month. The average of the rescaled series is normalized to have a mean value of 100 (or 4.61 in logarithmic scale). Accessed on 3.15.2023.

- The expected inflation rate (the median expected price change next 12 months) is sourced from the Surveys of Consumers, University of Michigan, University of Michigan: Consumer Sentiment © [MICH], retrieved from FRED, Federal Reserve Bank of St. Louis. Accessed on 3.16.2023.

- The Commodity Research Bureau (CRB) index is a commodity futures price index that comprises 19 commodities. The source is stooq.com. We use the close value of the index. The agriculture commodities are cocoa, coffee, corn, cotton, Lean Hogs, live cattle, orange juice, soybeans, sugar, and wheat). The non-agriculture commodities are aluminum, copper, crude oil, gold, heating oil, natural gas, nickel, silver, and unleaded gas. Accessed on 10.02.2023.

A.3. Average Forecast Error of the Competing Models

Table A1: Average Forecast Error of the Competing Models

	$h = 1$	$h = 6$	$h = 12$
M_1 : RW			
Median	0.03	0.14	0.14
Mean	0.04	0.14	0.14
#p-value> 0.05	111	111	111
#p-value> 0.1	111	111	111
M_2 : AR			
Median	-0.01	0.00	0.27
Mean	-0.08	0.16	0.59
#p-value> 0.05	97	87	63
#p-value> 0.1	92	83	56
M_3 : TVP			
Median	0.00	0.02	0.06
Mean	-0.03	0.02	0.19
#p-value> 0.05	106	105	104
#p-value> 0.1	102	101	101
M_4 : KS			
Median	0.03	-0.02	-0.01
Mean	0.01	-0.09	-0.01
#p-value> 0.05	107	107	104
#p-value> 0.1	96	98	96
M_5 : DMS			
Median	0.01	0.04	-0.01
Mean	-0.01	0.06	0.04
#p-value> 0.05	109	107	108
#p-value> 0.1	107	102	105

Notes: Rows for medians (means) report the median (mean) of the average forecast error from the competing specifications calculated over all countries. The rows #p-value> 0.05 and #p-value> 0.1 report the number of economies with a p-value greater than 0.05 and 0.1, respectively, for the null hypothesis of an average forecast error is equal to zero using Newey-West HAC standard errors. AR denotes the AR(1) model, RW is driftless the random walk model, TVP is the AR(6) model with time-varying parameters, KS denotes the "kitchen sink" approach with all the regressors and AR(6) component, DMS stands for dynamic model selection.

A.4. Robustness checks

Table A2: RMSPE of the DMA Specification Relative to Additional Competing Models—Full Sample

	Full Sample			
	$h=1$	$h=6$	$h=12$	Mean
M_6 : RWAO				
Median	0.51	0.48	0.38	0.46
Mean	0.54	0.85	0.54	0.64
$\# < 1$	109	108	106	108
$\#p$-value< 0.1	106	105	103	105
$\#p$-value< 0.05	105	104	103	104
M_7 : AR(6)				
Median	0.97	0.60	0.46	0.68
Mean	0.98	1.00	0.62	0.87
$\# < 1$	80	106	106	97
$\#p$-value< 0.1	39	105	104	83
$\#p$-value< 0.05	28	102	102	77
M_8 : AR(p)-BIC				
Median	0.99	0.57	0.39	0.65
Mean	1.06	0.98	0.55	0.86
$\# < 1$	66	107	105	93
$\#p$-value< 0.1	30	103	103	79
$\#p$-value< 0.05	14	103	103	73

Notes: Rows for medians (means) report the median (mean) ratio of RMSPE from the DMA specification relative to that of the competing forecasting models calculated over all countries for the full sample. Values less than one imply that DMA has a lower RMSPE than does the competitive benchmark. The row $\# < 1$ reports the number of economies that show relative RMSPE lower than 1 for a particular forecast horizon (h) and model. The rows $\#p$-value< 0.1 and $\#p$-value< 0.05 report the number of economies that show a p-value lower than 0.1 and 0.05, respectively, for the null of equal predictive accuracy measured by the RMSPEs of the DMA and the alternative model. We use the Diebold-Mariano-West statistic modified by the Harvey et al (1997) adjustment for small samples. RWAO (M_6) denotes the random walk model proposed by Atkeson and Ohanian (2001). The AR(p)-BIC model (M_8) is estimated using an optimal lag chosen by the Bayesian information criterion for each period, economy, and forecast horizon.

Table A3: RMSPE of the DMA Specification Relative to Additional Competing Models—GFC Period

	Pre-GFC period			GFC period		
	$h = 1$	$h = 6$	$h = 12$	$h = 1$	$h = 6$	$h = 12$
M_6 : RWAO						
Median	0.62	0.64	0.52	0.41	0.38	0.33
Mean	0.63	0.68	0.56	0.47	0.68	0.39
$\# < 1$	107	101	104	108	108	109
$\#p$-value< 0.1	89	73	47	104	96	83
$\#p$-value< 0.05	67	34	20	96	86	42
M_7 : AR(6)						
Median	0.98	0.68	0.52	0.95	0.53	0.40
Mean	0.98	0.69	0.57	0.99	0.86	0.44
$\# < 1$	73	101	104	75	106	108
$\#p$-value< 0.1	27	56	45	30	81	70
$\#p$-value< 0.05	15	34	25	23	57	33
M_8 : AR(p)-BIC						
Median	1.00	0.67	0.52	0.98	0.49	0.34
Mean	1.02	0.74	0.54	0.99	0.78	0.37
$\# < 1$	57	105	107	66	108	110
$\#p$-value< 0.1	13	57	42	30	88	85
$\#p$-value< 0.05	5	30	15	19	72	43

Notes: Rows for medians (means) report the median (mean) ratio of RMSPE from the DMA specification relative to that of the competing forecasting models calculated over all countries for the pre-GFC period (2006.1-2007.12) and the GFC episode (2008.1-2009.12). Values less than one imply that DMA has a lower RMSPE than does the competitive benchmark. The row $\# < 1$ reports the number of economies that show relative RMSPE lower than 1 for a particular forecast horizon (h) and model. The rows $\#p$-value< 0.1 and $\#p$-value< 0.05 report the number of economies that show a p-value lower than 0.1 and 0.05, respectively, for the null of equal predictive accuracy measured by the RMSPEs of the DMA and the alternative model. We use the Diebold-Mariano-West statistic modified by the Harvey et al (1997) adjustment for small samples. RWAO (M_6) denotes the random walk model proposed by Atkeson and Ohanian (2001). The AR(p)-BIC model (M_8) is estimated using an optimal lag chosen by the Bayesian information criterion for each period, economy, and forecast horizon.

Table A4: RMSPE of the DMA Specification Relative to Additional Competing Models—COVID-19 Period

	Pre-COVID-19 period			COVID-19 period		
	$h = 1$	$h = 6$	$h = 12$	$h = 1$	$h = 6$	$h = 12$
M_6 : RWAO						
Median	0.60	0.57	0.40	0.49	0.47	0.38
Mean	0.63	0.59	0.44	0.52	0.48	0.40
$\# < 1$	108	106	111	108	111	111
$\#p$-value< 0.1	94	80	70	93	70	38
$\#p$-value< 0.05	79	59	34	72	38	15
M_7 : AR(6)						
Median	0.98	0.61	0.41	0.95	0.52	0.40
Mean	0.98	0.62	0.44	0.93	0.55	0.44
$\# < 1$	73	105	110	80	110	109
$\#p$-value< 0.1	29	76	70	33	64	44
$\#p$-value< 0.05	18	59	45	18	36	24
M_8 : AR(p)-BIC						
Median	0.98	0.63	0.39	0.96	0.51	0.37
Mean	1.03	0.66	0.41	0.99	0.57	0.40
$\# < 1$	67	107	109	75	110	110
$\#p$-value< 0.1	26	75	85	34	73	40
$\#p$-value< 0.05	20	53	48	14	29	17

Notes: Rows for medians (means) report the median (mean) ratio of RMSPE from the DMA specification relative to that of the competing forecasting models calculated over all countries for the pre-COVID-19 period (2017.11-2020.2) and the COVID-19 episode (2020.3-2022.6). Values less than one imply that DMA has a lower RMSPE than does the competitive benchmark. The row $\# < 1$ reports the number of economies that show relative RMSPE lower than 1 for a particular forecast horizon (h) and model. The rows $\#p$-value< 0.1 and $\#p$-value< 0.05 report the number of economies that show a p-value lower than 0.1 and 0.05, respectively, for the null of equal predictive accuracy measured by the RMSPEs of the DMA and the alternative model. We use the Diebold-Mariano-West statistic modified by the Harvey et al (1997) adjustment for small samples. RWAO (M_6) denotes the random walk model proposed by Atkeson and Ohanian (2001). The AR(p)-BIC model (M_8) is estimated using an optimal lag chosen by the Bayesian information criterion for each period, economy, and forecast horizon.

Table A5: RMSPE of the DMA Specification Relative to Competing Models—Alternative Definition of the GFC Period

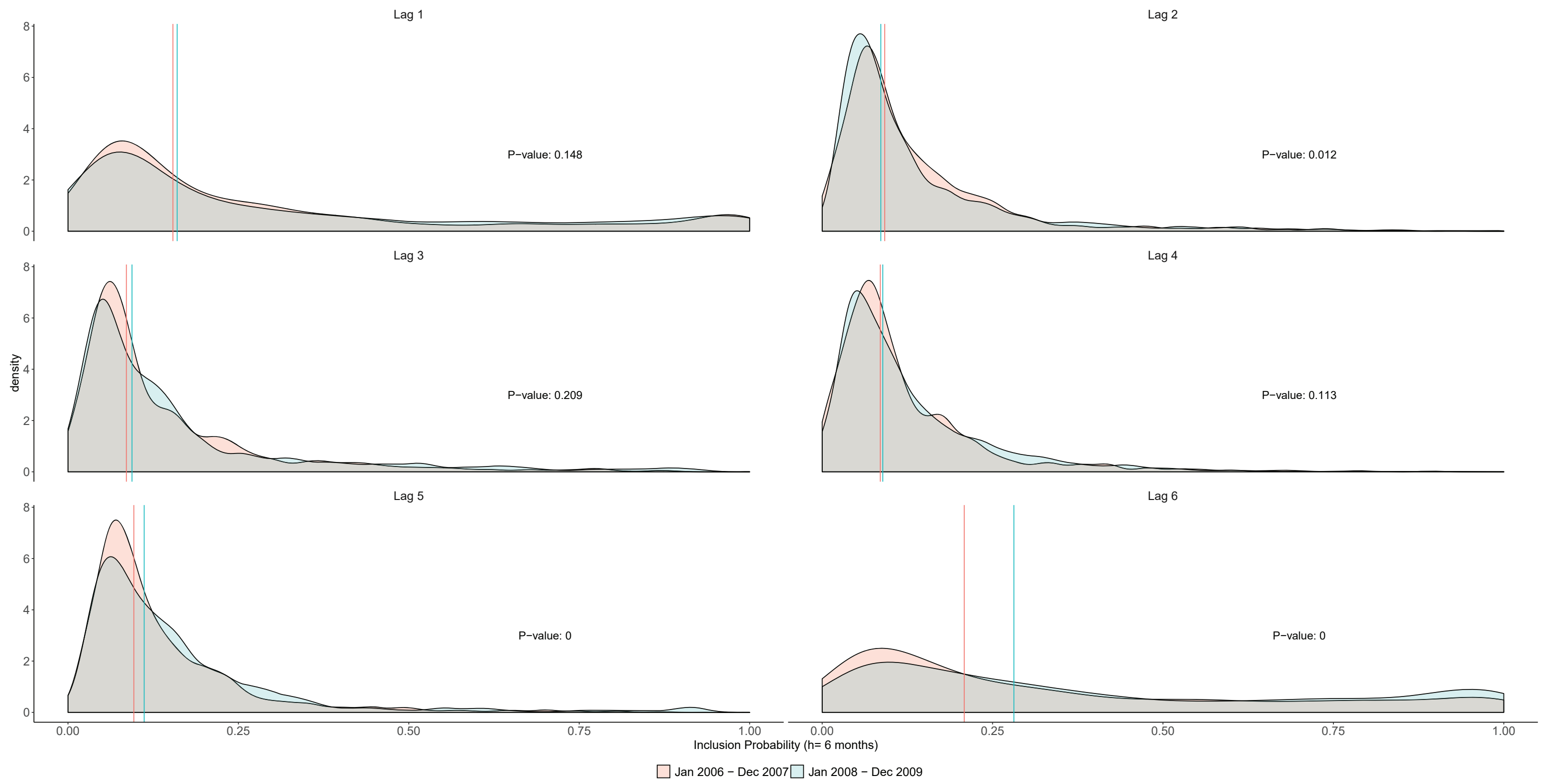
	Pre-GFC period			GFC period		
	$h = 1$	$h = 6$	$h = 12$	$h = 1$	$h = 6$	$h = 12$
$M1$ (RW)						
Median	1.01	0.70	0.52	0.95	0.50	0.38
Mean	1.01	0.75	0.56	0.98	0.82	0.42
$\# < 1$	47	105	104	75	109	109
$\#p$-value< 0.1	13	39	9	29	77	25
$\#p$-value< 0.05	5	18	3	14	53	2
$M2$ (AR)						
Median	0.99	0.76	0.64	0.90	0.50	0.39
Mean	0.99	0.78	0.67	0.94	0.82	0.45
$\# < 1$	59	96	100	88	108	109
$\#p$-value< 0.1	14	38	22	41	78	27
$\#p$-value< 0.05	7	15	11	27	48	15
$M3$ (TVP)						
Median	0.98	0.82	0.73	0.96	0.62	0.56
Mean	0.99	0.83	0.76	1.02	1.00	0.62
$\# < 1$	70	94	97	75	108	107
$\#p$-value< 0.1	18	25	7	22	56	17
$\#p$-value< 0.05	10	9	3	15	25	3
$M4$ (KS)						
Median	0.86	0.89	0.88	0.84	0.85	0.85
Mean	0.85	0.88	0.88	0.87	0.86	0.87
$\# < 1$	97	85	88	95	93	83
$\#p$-value< 0.1	55	14	3	56	32	2
$\#p$-value< 0.05	37	7	1	39	15	0
$M5$ (DMS)						
Median	0.97	0.95	0.95	0.91	0.91	0.95
Mean	0.95	0.94	0.93	0.92	0.91	0.94
$\# < 1$	80	85	86	92	95	86
$\#p$-value< 0.1	27	14	0	57	26	0
$\#p$-value< 0.05	17	7	0	36	12	0

Notes: Rows for medians and means report the median/mean ratio of RMSPE from the DMA specification relative to that of the competing forecasting models calculated over all countries for the pre-GFC period (2006.5-2007.11) and the GFC episode (2007.12-2009.6). Values less than one imply that DMA has a lower RMSPE than does the competitive benchmark. The row $\# < 1$ reports the number of economies that show relative RMSPE lower than 1 for a particular forecast horizon (h) and model. The rows $\#p - value < 0.1$ and $\#p - value < 0.1$ report the number of economies that show a p-value lower than 0.1 and 0.05, respectively, for the null of equal predictive accuracy measured by the RMSPEs of the DMA and the alternative model. We use the Diebold-Mariano-West statistic modified by the Harvey et al. (1997) adjustment for small samples. AR denotes the AR(1) model, RW is driftless the random walk model, TVP is the AR(6) model with time-varying parameters, KS denotes the "kitchen sink" approach with all the regressors and AR(6) component, DMS stands for dynamic model selection.

A.5. Kernel Densities of the Posterior Probabilities of Inclusion—Lags of DFPI

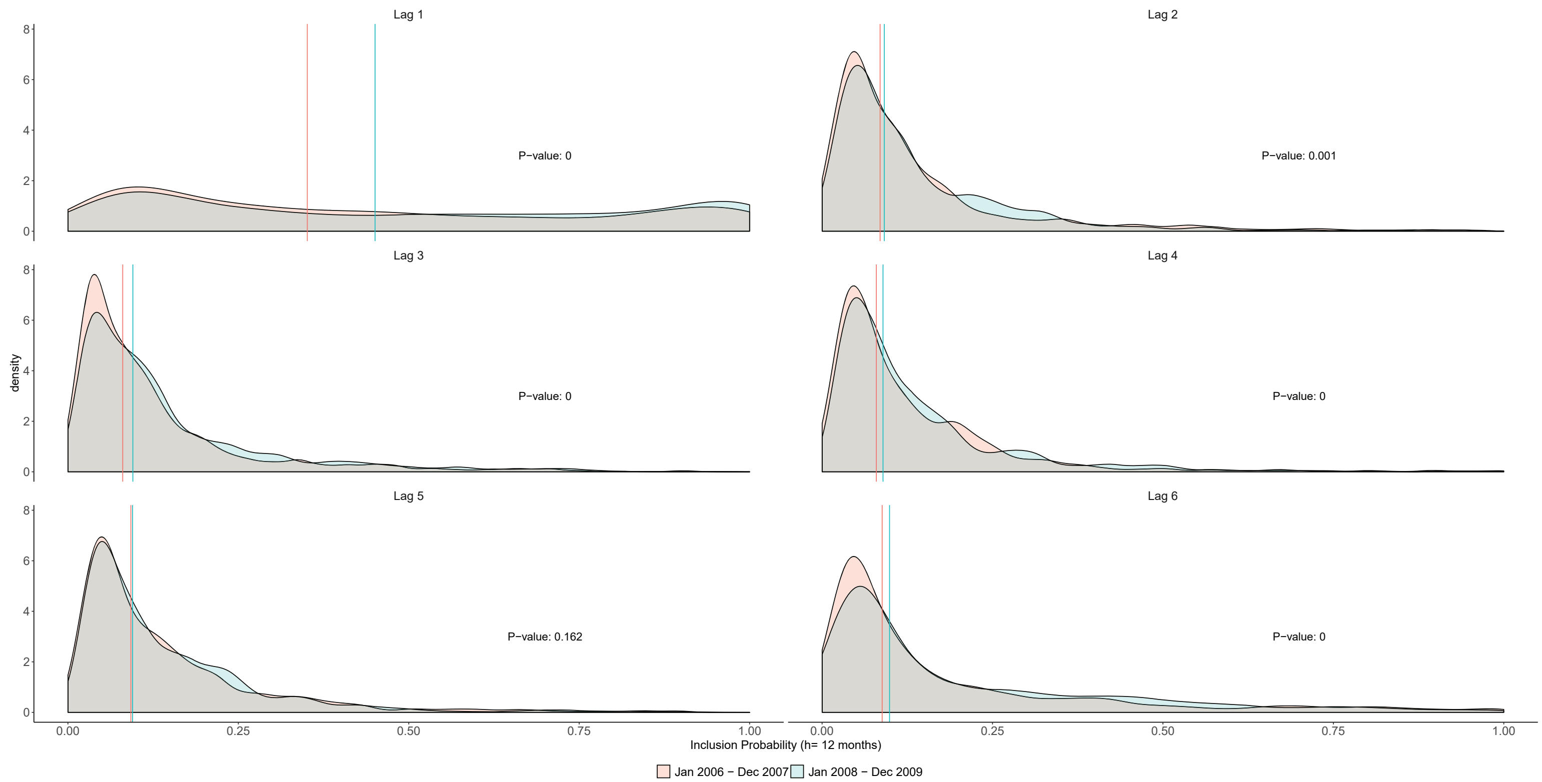
The Figures A1-A4 below report the kernel density estimates of the probabilities of inclusion associated with the six lags of the dependent variable (DFPI) during the pre-GFC, the GFC, the pre-COVID-19, and COVID-19 periods for 6- and 12-month ahead forecasts, respectively.

Figure A1: Kernel Densities of the Posterior Probabilities of Inclusion—Lags of DFPI, Pre-GFC and GFC Periods ($h = 6$)



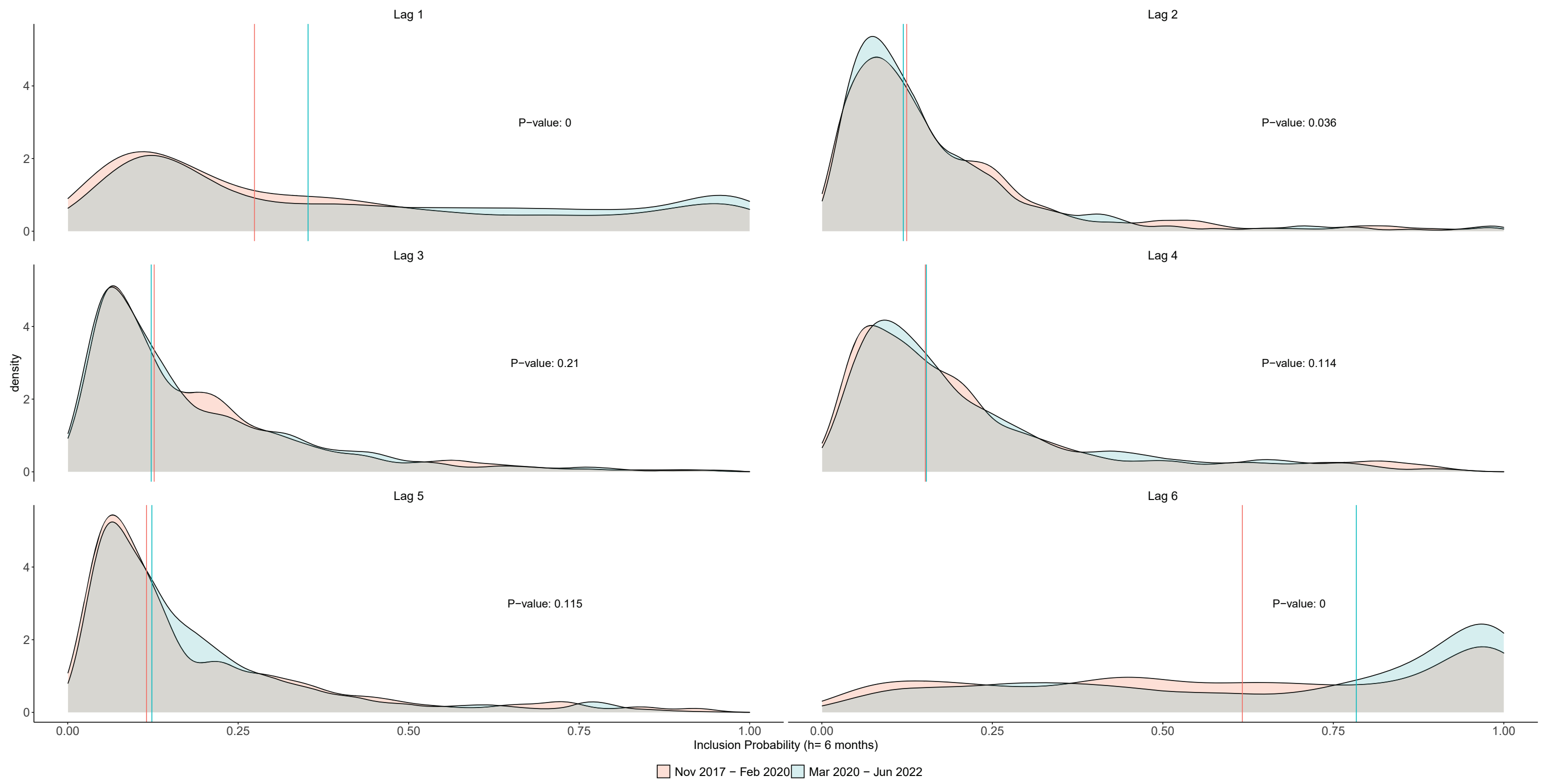
Note: The median probability for the pre-GFC period is represented in pastel pink, while that for the GFC period is shown in pastel blue, both marked with a vertical line.

Figure A2: Kernel Densities of the Posterior Probabilities of Inclusion—Lags of DFPI, Pre-GFC and GFC Periods ($h = 12$)



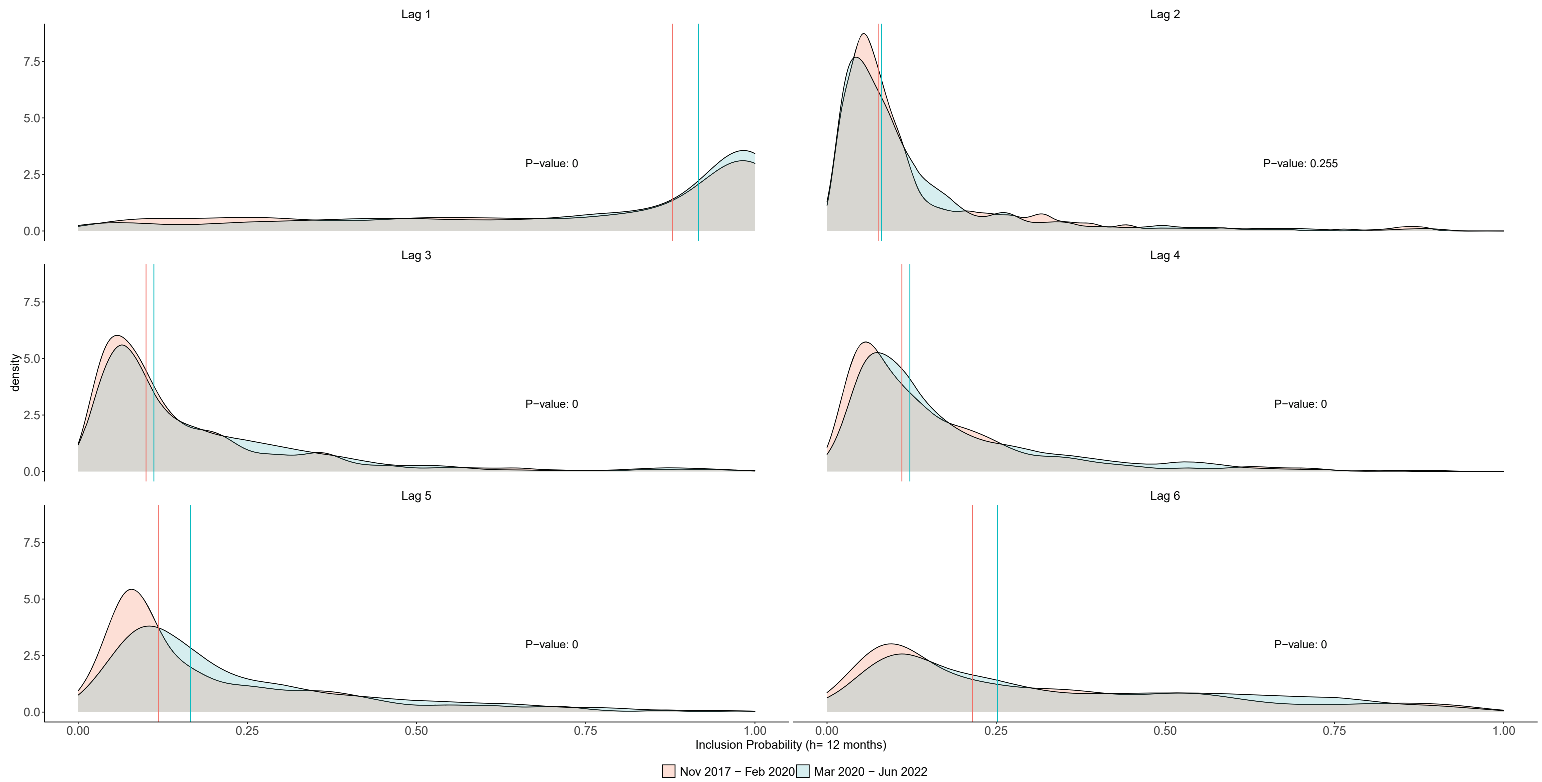
Note: The median probability for the pre-GFC period is represented in pastel pink, while that for the GFC period is shown in pastel blue, both marked with a vertical line.

Figure A3: Kernel Densities of the Posterior Probabilities of Inclusion—Lags of DFPI, Pre-COVID-19 and COVID-19 Periods ($h = 6$)



Note: The median probability for the pre-COVID-19 period is represented in pastel pink, while that for the COVID-19 period is shown in pastel blue, both marked with a vertical line.

Figure A4: Kernel Densities of the Posterior Probabilities of Inclusion—Lags of DFPI, Pre-COVID-19 and COVID-19 Periods ($h = 12$)



Note: The median probability for the pre-COVID-19 period is represented in pastel pink, while that for the COVID-19 period is shown in pastel blue, both marked with a vertical line.