Cyclical fluctuations of global food prices: a predictive analysis

Błażej Mazur[1]

Abstract

Forecasting of fluctuations in worldwide food prices is of considerable practical importance – however, it is also difficult, especially for longer horizons. Standard econometric models often fail to take into account non-seasonal cyclicality present in some of the series under consideration. In particular in many cases the models either assume mean-reversion (so the forecast paths stabilize at some value) or a random-walk type behaviour (so the forecast paths are determined by the last observation available). In other words, it is not easy to obtain forecasts that reveal future turning points (so are capable of forecasting of out-of-sample deviations from mean).In order to deal with the issue we make use of Bayesian deterministic cycle models based on Flexible Fourier type representation in order to analyse dynamic behaviour of FAO food price indexes. We focus on prediction of individual year-on-year growth rates in horizons ranging from one to twenty four months ahead. As the purpose of the paper is to analyse performance of density forecasts, we investigate log-predictive score as well as continuous ranked probability score. We find a clear pattern of fluctuations in dairy prices and a bit less-evident cyclical-like fluctuations in meat prices, so the deterministic-cycle models are relevant for the series.

Keywords: *Bayesian inference, food prices, density prediction, periodicity*

JEL Classification:E37; E31; C53

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1 Introduction

The issue of food price forecasting is quite challenging.However, literature provides no clear conclusion indicating optimal techniques for probabilistic prediction of food prices in horizons of 1-2 years. The issue seems to be of considerable practical importance for a number of reasons – for example the recent increase in Polish inflation is to some extent due to transmission of high food prices (including the dairy products). Moreover, the development of some counter-cyclical policy is of vital importance for well-being and security of less-developed countries (see e.g. Myers, 2006; Kalkuhl et al., 2016). In the paper we tackle the related econometric issues asking whether the use of models that explicitly account for periodicity might improve the quality of density forecasts of food prices in longer horizons.

[1]Cracow University of Economics, Department of Econometrics and Operations Research, Rakowicka 27, 31-510 Kraków, Poland, e-mail: blazej.mazur@uek.krakow.pl.

2 The data: FAO food price indexes

The data considered here are obtained based on FAO price indexes (available at www.fao.org, as accessed on 07.06.2017). We make use of monthly deflated indexes (the total and five sub-indexes), converted into year-on-year growth rates, see Fig. 1. We analyse 317 monthly observations (1991 M1 – 2017 M5). In the paper we conduct a pseudo-real time analysis, hence we do not make an effort to control for data revisions – the recursive experiments are conducted using the same data vintage.

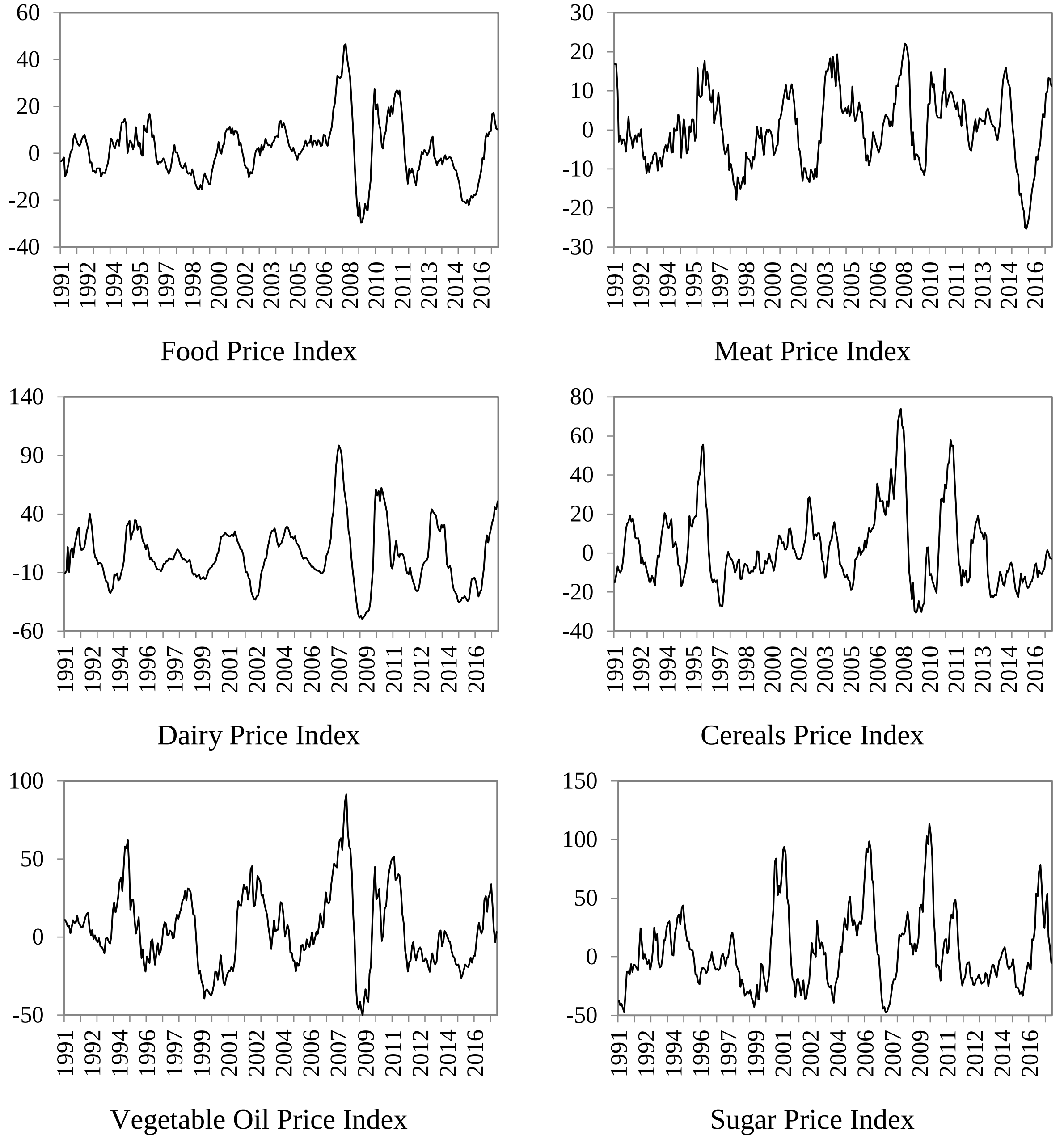


Fig. 1. The data: year-on-year growth rates of deflated FAO price indexes (as of 07.06.2017).

The series clearly display some sort of mean-reversion (which might take a regular, perhaps periodic pattern). There is also evident co-dependence (for example a noticeable influence of the global financial crisis) – however, in the paper we focus on univariate methods. Certain advanced problems of co-dependence between food prices and other prices are considered by e.g. Śmiech et al. (2017).

3 Models and methods for density predictions of series displaying periodicity

One of concepts used in order to avoid potential inadequacy of stationary time-series models without the need for accepting certain disadvantages of $I(1)$ nonstationarity is that of cyclostationarity. One of modelling approaches motivated by the idea is that of deterministic cycle models. Although the assumptions underlying the models used in the paper seem to be somewhat restrictive (as the pattern of cyclical fluctuations is assumed to be regular), the models easily allow for considering more than just one frequency of fluctuations.

Lenart et al. (2016) use Bayesian inference methods for in-sample analysis conducted with a time-series model defined as Gaussian AR(p) deviations from a periodic (hence time-varying) unconditional mean μ_t defined as follows:

$$\mu_t = \delta + \sum_{f=1}^{F} \alpha_f \sin(\varphi_f t) + \beta_f \cos(\varphi_f t), \tag{1}$$

where F controls number of frequencies (or order of the Flexible Fourier approximation), α's and β's control phase shifts and amplitudes while φ's control frequency (and hence period length) of individual Fourier components. Inference on φ's and in particular obtaining density forecasts that account for estimation uncertainty is non-trivial and justifies the use of the Bayesian approach (details are given by Lenart and Mazur, 2017 and references cited therein). Crucially, one has to set F: $F = 0$ implies time-invariant mean in (1) and hence the model becomes a stationary AR(p) process with iid Gaussian errors. Large values of F result in a risk of overfitting (and might lead to very complicated posteriors). Here we consider models with $F = 0,1,2,3,4$ and $p = 12$ and a model with $F = 0$ and $p = 24$, which gives a total of 6 models (two being stationary Gaussian autoregressive processes, see Table 1).

We consider prediction horizons from $h = 1$ to $h = 24$ months ahead and analyse a sequence of 120 expanding subsamples (with sample size increasing from 317-120 to 317-1). Each model is re-estimated with each subsample, and a predictive distribution over the next 24 months is obtained using these estimates. Such an exercise, with six series considered here, represents quite a considerable numerical burden. The models are estimated using

MCMC techniques (with M-H steps within a Gibbs sampler), priors for φ's and the autoregressive parameters are uniform (with $0 < \phi_L < \varphi < \phi_U < \pi$).

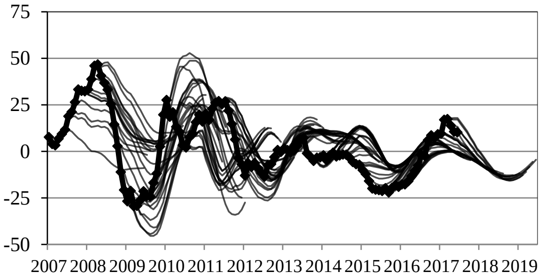
Table 1. Ex-post predictive accuracy of density forecasts: LPS and CRPS scores.

	M1	**M2**	**M3**	**M4**	**M5**	**M6**	**M1**	**M2**	**M3**	**M4**	**M5**	**M6**
F	0	0	1	2	3	4	0	0	1	2	3	4
p	12	24	12	12	12	12	12	24	12	12	12	12
H	**LPS**						**CRPS**					
Food Price Index												
24	-155.8	-165.5	-155.8	*-154.3*	-155.3	-156.8	7.4	9.0	7.2	*7.1*	7.3	7.8
20	-168.1	-176.4	*-166.4*	*-166.4*	-167.0	-169.5	8.3	10.3	*8.1*	*8.1*	*8.1*	8.7
16	-180.9	-186.3	*-180.7*	-182.3	-184.2	-187.1	9.5	10.6	*9.4*	9.7	9.9	10.2
12	*-196.7*	-200.5	-202.1	-204.4	-208.6	-211.7	*10.6*	11.4	11.3	11.6	12.0	12.2
8	-209.4	*-208.5*	-211.4	-218.3	-218.8	-227.2	10.6	*10.5*	11.0	11.2	11.6	12.2
4	-199.3	*-195.0*	-197.4	-199.4	-201.8	-206.7	7.2	*6.9*	7.0	7.1	7.3	7.7
1	-163.6	*-144.2*	-146.7	-146.9	-146.7	-147.3	2.5	*2.4*	*2.4*	*2.4*	*2.4*	2.5
Dairy Price Index												
24	-187.1	-186.2	-180.1	-180.2	*-179.7*	-181.4	16.9	16.3	14.1	14.0	14.0	*13.9*
20	-196.6	-193.6	-191.7	*-191.4*	-192.2	-192.4	16.7	16.1	14.7	*14.5*	14.6	*14.5*
16	-202.1	-199.5	-199.2	*-198.9*	-199.2	-199.2	15.3	15.4	13.9	13.8	13.8	*13.7*
12	-207.9	-208.8	-204.2	-204.0	*-203.9*	-204.3	14.6	16.0	13.0	12.9	*12.8*	*12.8*
8	-217.6	-218.8	*-211.0*	-212.8	-212.7	-211.0	14.0	15.0	12.6	12.5	*12.4*	12.5
4	-218.3	-218.7	-211.3	-210.5	*-210.4*	-210.5	10.7	10.6	10.1	*10.0*	*10.0*	*10.0*
1	-164.5	-164.9	-188.7	*-164.1*	-164.4	-164.4	4.0	*3.9*	4.0	4.0	4.0	4.0
Meat Price Index												
24	-150.5	-149.0	*-144.3*	-145.2	-146.4	-148.2	5.8	5.8	*5.3*	5.5	5.7	5.9
20	-154.2	-155.2	*-150.9*	-151.6	-153.3	-154.2	5.6	5.8	*5.4*	5.5	5.7	5.8
16	-159.7	-161.6	*-157.3*	-158.4	-159.4	-159.7	5.5	5.9	*5.4*	5.6	5.7	5.7
12	-171.1	-169.7	*-167.7*	-169.1	-170.2	-170.6	5.9	6.1	*5.7*	5.9	5.9	6.0
8	-182.8	*-176.6*	-180.9	-184.5	-184.7	-185.0	6.1	6.1	*6.0*	6.2	6.2	6.2
4	-177.2	*-169.8*	-176.7	-179.8	-179.7	-179.6	4.7	*4.5*	4.7	4.8	4.7	4.7
1	-131.4	*-128.1*	-131.0	-131.5	-131.7	-131.8	1.9	*1.8*	1.9	1.9	2.0	2.0

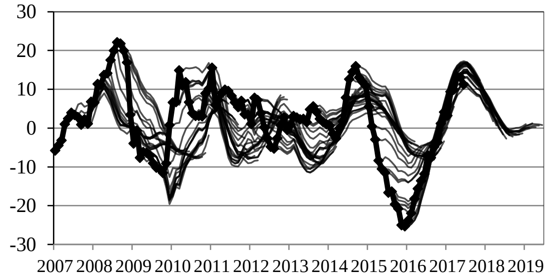
In order to evaluate the resulting density forecasts we make use of scoring rules: log-predictive score and continuous ranked probability score (see Gneiting and Raftery, 2007). In order to gain some insights into differences across models we informally examine sequences of point forecasts (predictive expectations). We also consider a future tendency index (FTI) discussed by Mazur (2017a, pp. 443) that provides information as to prevailing trends in the forecast period (taking into account the cross-horizon stochastic dependence).

4 Discussion of the empirical results

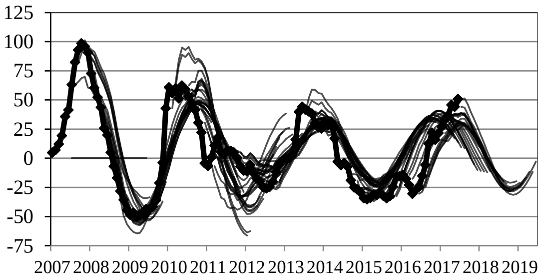
Despite the fact that the point of interest here is that of density prediction, we begin with analysis of paths of point forecasts. This is because such analysis sheds some light at differences across models in terms of out-of-sample behaviour.



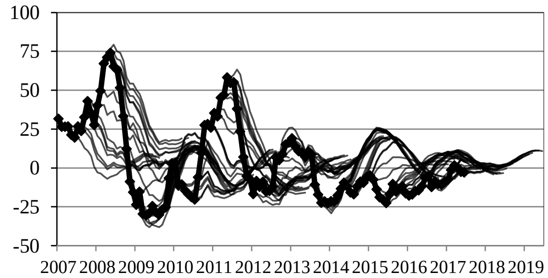
Food Price Index, M5



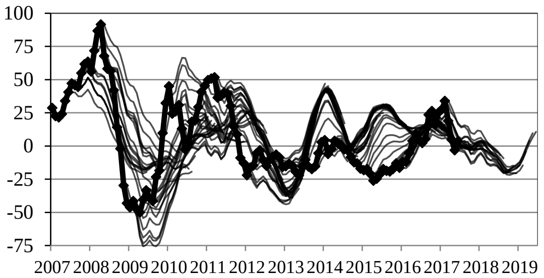
Meat Price Index, M5



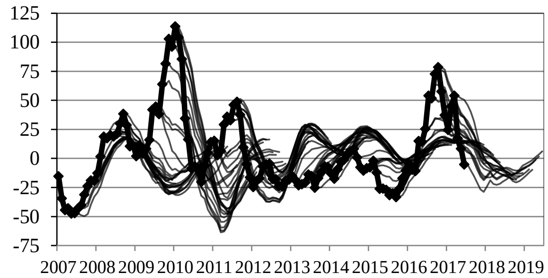
Dairy Price Index, M5



Cereals Price Index, M5



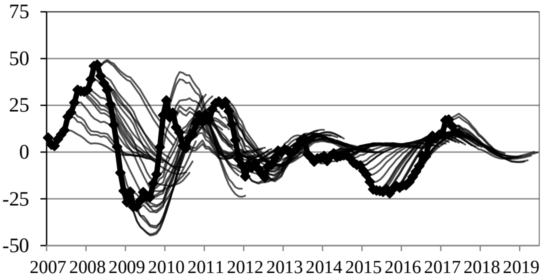
Vegetable Oil Price Index, M5



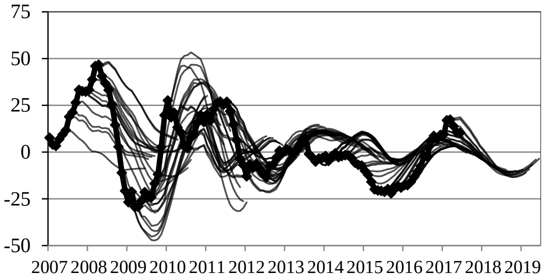
Sugar Price Index, M5

Fig. 2. Recursive sequences of point forecasts from a model with $F = 3$.

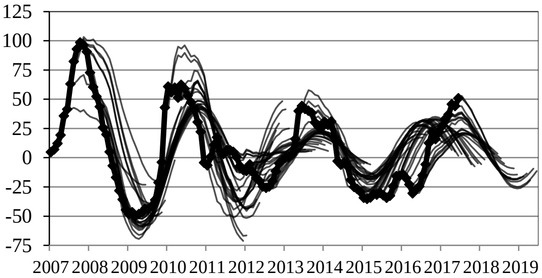
Fig. 2 presents recursively obtained sequences of forecast paths using a model with $p = 12$ and $F = 3$, hence allowing for quite a complicated pattern of quasi-periodic fluctuations. One might note that the pattern seems particularly adequate for the Dairy Price Index. However, for the remaining series the evidence is rather mixed: the forecasts display out-of-sample fluctuations even at longer horizons, but the fluctuations are not necessarily adequate.



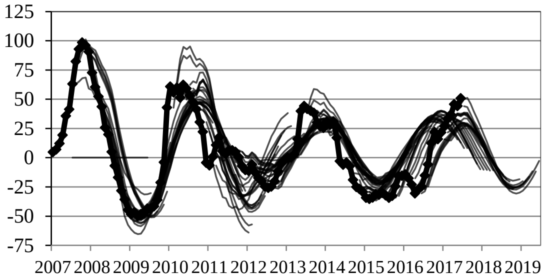
Food Price Index, M1 (F = 0)



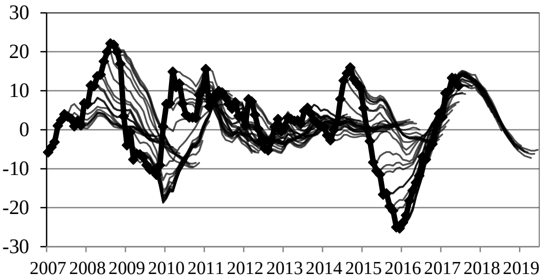
Food Price Index, M4 (F = 2)



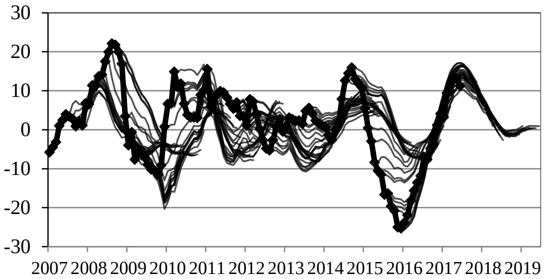
Dairy Price Index, M1 (F = 0)



Dairy Price Index, M4 (F = 2)



Meat Price Index, M1 (F = 0)



Meat Price Index, M4 (F = 2)

Fig. 3. Recursive sequences of point forecasts from models with F = 2 and F = 0.

The informal analysis is consistent with information conveyed by formal criteria: Table 1 contains ex-post characteristics of predictive accuracy for three selected series: the overall index as well as Dairy and Meat sub-indices. We report LPS and CRPS scores across models and selected horizons (please note that for each horizon we use the last 121-h realized values, ending with 2017 M5). The LPS values (the higher the better) are cumulated across realizations (computed with natural logs) hence differences between the scores for h = 1 can be interpreted in terms of predictive BayesFactors. The CRPS scores are averaged across realizations and the orientation is chosen to mimic that of mean absolute error: the smaller the better. For longer horizons both criteria tend to indicate models with F> 0, although the effect is most evident for the Dairy series; for short horizons (Food, Meat), the AR(24) seems to be the most successful one. The differences between models are not large. This is probably due to two reasons. Firstly, for variables other than Dairy the periodic pattern is not that regular.

Secondly, the lag length p = 12 (or 24) is considerable and hence the AR(p) models are capable of delivering a periodic-like behaviour out-of-sample (formally being stationary).

Fig. 3 presents a comparison of forecast paths of models with periodicity (F> 0) and a pure autoregressive processes (F = 0). The results seem to reinforce the above conclusion – even for the dairy series the model with F = 0 is capable of generating periodic-like forecast paths (however, the periodic effectsare somewhat more evident with F> 0).

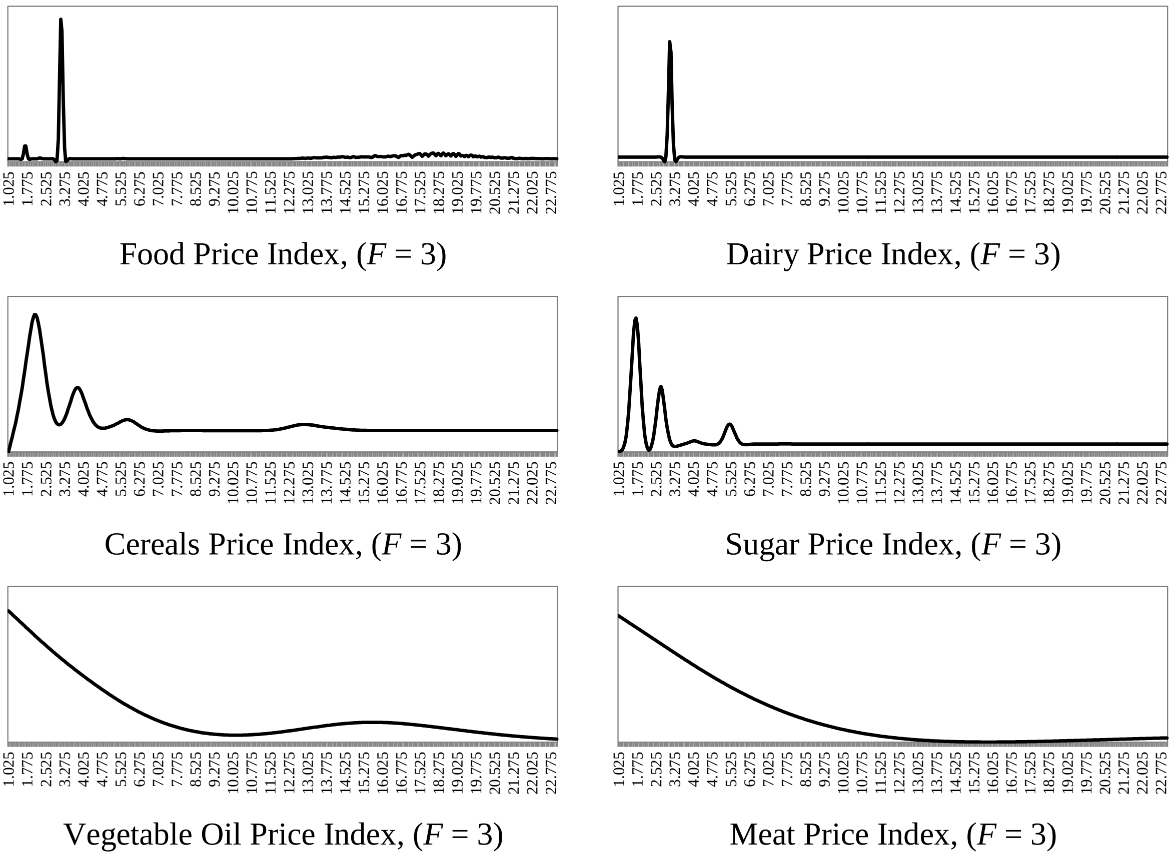
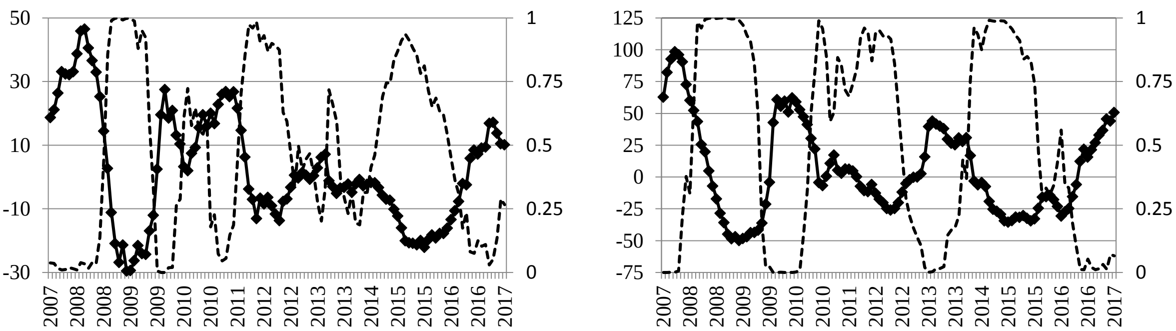


Fig. 4. Inference on period length (in years) based on posterior for φ_f from M5, full sample.

Fig. 4 contains (un-normalized) full-sample based posteriors for period length induced from marginal posteriors for φ_f parameters (the period length in months is given by $2\pi/\varphi_f$). The values of prior hyperparameters ϕ_L and ϕ_U are chosen to exclude cycles shorter than one year and longer than 24 years. One might note a single spike corresponding to approx. 3 years for the Dairy series. It is also visible in Food series, though there is one additional peak indicating shorter cycles and some probability mass distributed along values corresponding to cycles of 15-20 yrs. Please note that for Cereals and Sugar series the spikes are much less concentrated (leaving more estimation uncertainty) and the dominant period is shorter; there are two more evident modes and some less-elevated local maxima. However, for Meat and

Oils series, the results are quite different – as no distinct spikes are visible, the results might suggest rather different pattern of dynamics (presumably a more stochastic one).

We also consider a probabilistic index of future tendencies (FTI_M), as described in Mazur (2017a, p. 443).It goes beyond horizon-specific marginal density forecasts, making use of the joint predictive distribution (over all the horizons) instead.Each value of the FTI_{12} index in Fig. 5 represents the probability that (based on information up to agiven time T) the predicted quantity averaged over the second half of the prediction period(here: $12<h<24$) would be higher than the average over the first half of the prediction period ($0<h<13$), hence the index is supposed to lead actual changes of trends by about a year or so.



Food Price Index, M4 (F = 2) Dairy Price Index, M5 (F = 3)

Fig. 5. Realized data (solid line) vs. values of predictive tendency index FTI_{12}(dotted).

For the dairy series (with more evident periodicity) the index takes more extreme values. The index is close to zero in 2013 (just as the dairy prices seem to hit an upper turning point). Moreover, it gets close to one in 2014 and 2015, with increasing prices in 2016 and 2017. Interestingly, the index again hits the minimum level at the sample end, indicating that the upturn in dairy prices would revert in late 2017 or 2018. For the food prices the index hits the maximum just before a turning point in price dynamics in 2015. The values closer to the sample end indicate that it would be more likely to observe decreasing tendency in food prices.

Conclusions

We discuss practical importance of Bayesian deterministic-cycle models with many frequencies. In-sample applications have been considered by e.g. Lenartet al. (2016) or Mazur (2016). In this paper we focus on assessment of the predictive adequacy, with emphasis on density forecasting performance. The issue has certain empirical relevance as the models display interesting out-of-sample properties, since the forecast paths differ from those of random-walk type models as well as from stationary ones.

In particular we examine density forecasts of y-on-y growth rates of deflated FAO food price indexes within a recursive expanding-window experiment. We find quite a considerable heterogeneity across the series under consideration. For the Dairy data there is evidence that deterministic cycle models have superior forecast accuracy. However, the periodic signal in the series is quite strong and might be captured to some extent by other models as well. The effect seems to carry over to the aggregate index to some extent. On the other hand, Meat prices and Vegetable Oil Prices either display strong time-inhomogeneity or the dynamic pattern is much more stochastic – hence, the deterministic cycle models seem to be of no use here. For the Cereals and Sugar series the evidence is mixed (as it is for the aggregate index) - there seems to be some periodicity, but it is weaker (compared to that of the Dairy series).

Therefore one might conclude that for the purpose of modelling of all the indexes one should consider a more heterogeneous model classes. Possibly stochastic cycle models or models with time-varying periodic behaviour could be adequate for the Cereals and Sugar series, while a fully stochastic models should be used for Meat and Vegetable Oils series. Moreover, it would be very interesting to see whether the aggregate index could be more accurately predicted based on heterogeneous disaggregate forecasts of the five sub-indexes. A similar case (where the aggregate forecast benefits from accounting for heterogeneity of the sub-aggregates) is discussed by Mazur (2017b) for Polish macroeconomic data at quarterly frequency.

Acknowledgements

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