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FORECASTING THE INDEX OF COMMODITIES PRICES USING VARIOUS BAYESIAN MODELS

Abstract:

Bayesian dynamic mixture models offer a flexible framework for capturing evolving relationships between dependent and independent variables over time. They address both structural and variable uncertainty, incorporating real-time market information through dynamic updating. Unlike static approaches, they allow the underlying process to change, which is particularly relevant for the fluctuating nature of commodity markets. In scenarios with a large number of possible predictors, various regression models can be employed, each yielding its own probability distribution for the coefficients. Forecasts are then constructed by combining these distributions using time-varying weights. This paper utilizes Bayesian dynamic mixture models to allow both the regression parameters and their associated weights to change over time. Computational efficiency is maintained by preserving distributional forms and limiting numerical approximations to statistics distributions. The study uses monthly Global Price Index of All Commodities from the International Monetary Fund, spanning the period 2003–2024. Key explanatory variables include interest rates, exchange rates, and stock market indices. The forecasting performance of the proposed models is compared to other techniques such as Dynamic Model Averaging, LASSO, ridge regression, and ARIMA, etc. Evaluation is conducted using the Diebold-Mariano test, Giacomini-Rossi test, Model Confidence Set procedure, and Clark-West test. (This research was funded in whole by National Science Centre, Poland, grant number 2022/45/B/HS4/00510.)

Keywords:

Bayesian dynamic mixture models; Commodities prices; Mixture models; Model averaging; Time-series forecasting; Variable uncertainty

JEL Classification: C32, C53, Q02

1 Introduction

This study presents an analysis of different forecasting models applied to economic and financial time series, with a particular focus on Bayesian dynamic mixture models. The research incorporates methodologies established in the literature proposed by Nagy and Suzdaleva (2013) and Nagy et al. (2011), along with traditional forecasting techniques explored by Diebold and Mariano (1995), Giacomini and Rossi (2010), and others (Clark and West, 2007). The study applies them to selected macroeconomic indicators, the objective is to assess the predictive performance of these models and compare them with conventional forecasting approaches.

Forecasting accuracy is assessed by comparing various configurations of Bayesian Dynamic Mixture Models with several benchmark methodologies, including Dynamic Model Averaging, Bayesian Model Averaging, LASSO and ridge regressions, ARIMA, and the no-change method. In order to evaluate forecasting accuracy, out-of-sample forecasting performance was evaluated through the application of standard metrics, including Root Mean Squared Error (RMSE), Normalized Root Mean Squared Error (N-RMSE), Mean Absolute Error (MAE), and Mean Absolute Scaled Error (MASE), in conjunction with the Diebold-Mariano test for predictive accuracy (Diebold and Mariano, 1995). Further robustness was achieved by employing the Giacomini-Rossi fluctuation test (Giacomini and Rossi, 2010) and the Model Confidence Set test (Hansen et al., 2011). To provide a comprehensive assessment, encompassing evaluations were conducted using the Clark-West test (Clark and West, 2007) and related methodologies.

2 Literature Review

Accurate commodity price forecasting informs strategic decision-making, optimizes resource allocation, enhances risk management, and supports financial planning. It is vital for operational efficiency, sustainability, and innovation across sectors such as supply chain, energy, agriculture, and manufacturing, while also enabling resilience against economic shocks and global market volatility (Vassolo et al., 2024; Gaudenzi et al., 2020; Buhl et al., 2011).

Commodity price fluctuations significantly impact economic growth, inflation management, and financial stability (Staritz, 2012). Due to the complexity inherent in commodity markets, forecasting approaches must continually adapt to shifting economic conditions and structural changes. Standard econometric methods often face difficulties in accurately capturing nonlinear behaviours and sudden structural shifts (Stock and Watson, 1996). Advances in Bayesian approaches, specifically Bayesian dynamic mixture models (BDMMs), offer enhanced flexibility by accounting for evolving relationships among explanatory variables and target prices (Nagy and Suzdaleva, 2013; Nagy et al., 2011; Primiceri, 2005).

The literature increasingly emphasizes the effectiveness of advanced statistical and machine learning methods in commodity forecasting. For instance, Kriechbaumer et al. (2014) utilized a wavelet-ARIMA approach to predict metal price dynamics, effectively modelling cyclical patterns. Other studies highlight macroeconomic influences, like Mo et al. (2018), who analysed how commodity price volatility relates to economic activity, exchange rates, and interest rates. Furthermore, recent deep learning methods show promising results in modelling complex nonlinear predictor interactions (Zhang et al., 2024).

3 Methodology and Data

The primary response variable in the study is the monthly Global Price Index of All Commodities, obtained from the International Monetary Fund (IMF, 2025). The dataset consists of the monthly observations from the period from 2003 to 2024. Explanatory variables include: U.S. 3-month treasury bill: secondary market rate, U.S. 10-year government bond yields, U.S industrial production index, Kilian's index of global economic activity, term spread (i.e., U.S. 10-year treasury constant maturity minus U.S. 2-year treasury constant maturity), St. Louis Fed Financial Stress Index, VIX index of implied volatility, Geopolitical risk (GPR) index, S&P 500 index, Dow Jones Industrial - U.S. index, Shanghai Composite Index, MSCI EM (emerging markets) index, gold price (London Bullion Market Association), WTI oil price, exchange rates to U.S. dollar for Australia, New Zealand, Canada, Chile and South Africa (Chicago Board Options Exchange, 2025; FRED, 2025; MSCI, 2025; OECD, 2025; Shanghai Futures Exchange, 2025; Stooq, 2025; World Bank, 2025; Caldara and Iacoviello, 2022; Iacoviello, 2025; Kilian, 2009).

A structured methodology was employed to ensure a robust comparison between forecasting techniques. The dataset was prepared by selecting key economic indicators from publicly available sources. The variables were transformed appropriately to ensure stationarity where necessary.

Application of the methods developed by Nagy and Suzdaleva (2013) and Nagy et al. (2011) extends traditional mixture estimation by incorporating state-space components and a Markov model of switching. Unlike static models, these approaches enable both regression coefficients and mixture weights to evolve dynamically over time. By preserving the functional forms of probability density functions and limiting numerical approximations to their statistics, these methods efficiently address computational challenges while capturing time-varying relationships in economic data.

Roughly speaking, for Bayesian dynamic mixture models (Nagy and Suzdaleva, 2013; Nagy et al., 2011), given a large number of potential explanatory variables, several candidate linear regression models can be constructed. Each of these models is represented by a probability density function (pdf) of the regression coefficients given the data. A mixture of the pdfs of these candidate models gives rise to a mixture distribution through a weighted average, from which regression coefficients can be extracted for the final forecast.

Table 1 presents the list of all models considered in this research. Their detailed descriptions can be available, for example, in Drachal and Jędrzejewska (2025a; 2025b), Drachal and Pawłowski (2024) and Drachal (2023). Because too large number of individual models can be constructed from so many explanatory variables, they were grouped into: interest rates, economic activity indicators, market stress indicators, stock prices indices, other commodities prices, and exchange rates. Then, two types of grouping can be done. Either, an in an individual component model all variables from a given group are always taken together; or only a given group is considered, but all possible of combinations of variable selection amongst this group (Drachal and Jędrzejewska, 2025a; 2025b).

Table 1 List of the estimated models

BDMM-SS	Bayesian dynamic mixture model with state-space components
BDMM-SS-A	Bayesian dynamic mixture model with state-space components and averaging

BDMM-SS-H	Bayesian dynamic mixture model with state-space components and highest posterior probability selection
BDMM-NR	Bayesian dynamic mixture model with normal regression components
BDMM-NR-H	Bayesian dynamic mixture model with normal regression components and highest posterior probability selection
DMA	Dynamic Model Averaging
DMS	Dynamic Model Selection
DMP	Dynamic Model Selection with median probability
DMA-1VAR	DMA over only one-variable models
DMS-1VAR	DMS over only one-variable models
BMA	Bayesian Model Averaging
BMS	Bayesian Model Selection
BMP	Bayesian Model Selection with median probability
BMA-1VAR	BMA over only one-variable models
BMS-1VAR	BMS over only one-variable models
LASSO	LASSO regression
RIDGE	RIDGE regression
EL-NET	Elastic Net regression
B-LASSO	Bayesian LASSO
B-RIDGE	Bayesian RIDGE
LARS	Least-Angle Regression
TVP	Time-Varying Parameters regression
TVP-FOR	Time-Varying Parameters regression with forgetting
ARIMA	Auto ARIMA
NAIVE	No-change
HA	Historical averages (expanding window)
HA-ROLL	Historical averages (rolling window)

Source Own estimation and Drachal and Pawłowski (2024)

4 Results and Discussion

The results indicate that Bayesian dynamic mixture models consistently improve forecasting accuracy by allowing for time-varying model weights. The BDMM-NR and BDMM-NR-H models demonstrated superior performance, particularly the BDMM-NR-H model, which showed the most accurate forecasts across all four metrics. Statistical significance of these results was further validated through the Diebold-Mariano, Giacomini-Rossi, and Clark-West tests, reinforcing the accuracy of the models.

Table 2 reports forecast accuracy measures (with first 100 observations taken as in-sample). They are ordered according to MASE, and only models more accurate than the NAÏVE method are reported.

Table 2 Forecast accuracy measures

First grouping					Second grouping				
	RMSE	N-RMSE	MAE	MASE		RMSE	N-RMSE	MAE	MASE
RIDGE	6.6601	0.0456	4.4695	0.9449	**BDMM-NR-H**	6.2028	0.0425	4.3005	0.9092
LARS	6.6559	0.0456	4.5091	0.9533	**BDMM-NR**	6.4041	0.0438	4.4647	0.9439
BDMM-NR-H	6.3499	0.0435	4.5130	0.9541	**BDMM-SS-A-K**	6.6714	0.0457	4.4692	0.9448
EL-NET	6.7190	0.0460	4.5188	0.9553	**RIDGE**	6.6601	0.0456	4.4695	0.9449
TVP-K	6.8334	0.0468	4.5312	0.9579	**LARS**	6.6559	0.0456	4.5091	0.9533
B-RIDGE	6.6636	0.0456	4.5424	0.9603	**EL-NET**	6.719	0.0460	4.5188	0.9553
B-LASSO	6.6284	0.0454	4.5519	0.9623	**TVP-K**	6.8334	0.0468	4.5312	0.9579
BDMM-NR-1MOD	6.8339	0.0468	4.5743	0.9670	**B-RIDGE**	6.6636	0.0456	4.5424	0.9603
BDMM-NR	6.6008	0.0452	4.5862	0.9696	**B-LASSO**	6.6284	0.0454	4.5519	0.9623
BDMM-SS-A-K	6.6471	0.0455	4.5881	0.9700	**BDMM-NR-1MOD**	6.8339	0.0468	4.5743	0.9670
LASSO	6.7566	0.0462	4.6036	0.9732	**LASSO**	6.7566	0.0462	4.6036	0.9732
BMS-1VAR	6.6938	0.0458	4.6385	0.9806	**BMS-1VAR**	6.6938	0.0458	4.6385	0.9806
BMA-1VAR	6.6938	0.0458	4.6385	0.9806	**BMA-1VAR**	6.6938	0.0458	4.6385	0.9806
DMA-1VAR	6.7489	0.0462	4.666	0.9864	**DMA-1VAR**	6.7489	0.0462	4.666	0.9864
DMS-1VAR	6.7365	0.0461	4.6707	0.9874	**DMS-1VAR**	6.7365	0.0461	4.6707	0.9874
BMA-1VAR-K	6.7012	0.0459	4.6732	0.9880	**BMA-1VAR-K**	6.7012	0.0459	4.6732	0.9880
BMS-1VAR-K	6.7012	0.0459	4.6733	0.9880	**BMS-1VAR-K**	6.7012	0.0459	4.6733	0.9880
DMA-1VAR-K	6.7393	0.0461	4.6912	0.9918	**BDMM-SS-H-K**	6.8559	0.0469	4.6903	0.9916
DMS-1VAR-K	6.7391	0.0461	4.694	0.9923	**DMA-1VAR-K**	6.7393	0.0461	4.6912	0.9918

BMA	6.7412	0.0461	4.7008	0.9938	**DMS-1VAR-K**	6.7391	0.0461	4.694	0.9923
ARIMA	6.9154	0.0473	4.7055	0.9948	**ARIMA**	6.9154	0.0473	4.7055	0.9948
BMA-K	6.7490	0.0462	4.7177	0.9974	**DMA-K**	6.8724	0.0470	4.7285	0.9997
NAIVE	6.8818	0.0471	4.7302	1	**NAIVE**	6.8818	0.0471	4.7302	1

Source Own estimation

Table 3 presents the outcomes from the Diebold-Mariano test with the alternative hypothesis formulated as the forecast from the competing method is less accurate than those from the BDMM-NR-H model. This particular model was chosen, because according to the second version of grouping explanatory variables it generated most accurate forecasts; and for the first version it was the third most accurate method, still the most accurate amongst BDMM type of models. Outcomes from tests for the models with first version of grouping explanatory variables are reported (and the squared errors loss function); but the outcomes for the second version of grouping are similar.

Table 3 The outcomes from the Diebold-Mariano test

	statistics	**p-value**		**statistics**	**p-value**
BDMM-SS	1.9091	0.0290	**DMS-1VAR-K**	1.7230	0.0434
BDMM-SS-A	1.4065	0.0807	**BMA-K**	1.8003	0.0368
BDMM-SS-H	1.8563	0.0326	**BMS-K**	1.8103	0.0361
BDMM-SS-K	2.4406	0.0079	**BMA-1VAR-K**	1.6251	0.0530
BDMM-SS-A-K	1.5188	0.0654	**BMS-1VAR-K**	1.6251	0.0530
BDMM-SS-H-K	1.5576	0.0606	**LASSO**	1.6338	0.0521
BDMM-NR	1.2614	0.1045	**RIDGE**	1.3582	0.0882
BDMM-NR-1MOD	1.6737	0.0481	**EL-NET**	1.4996	0.0678
DMA	2.0141	0.0228	**B-LASSO**	1.3753	0.0855
DMS	2.1555	0.0163	**B-RIDGE**	1.4403	0.0759
DMA-1VAR	1.8573	0.0325	**LARS**	1.3358	0.0917
DMS-1VAR	1.8117	0.0359	**TVP**	3.7535	0.0001
BMA	1.8860	0.0306	**TVP-FOR**	3.1018	0.0011
BMS	1.8852	0.0306	**TVP-K**	1.6588	0.0496
BMA-1VAR	1.7190	0.0438	**TVP-FOR-K**	1.9755	0.0250
BMS-1VAR	1.7188	0.0438	**ARIMA**	1.3236	0.0938
DMA-K	1.8613	0.0323	**NAIVE**	2.3702	0.0095
DMS-K	2.4187	0.0083	**HA**	8.8213	0.0000
DMA-1VAR-K	1.7330	0.0425	**HA-ROLL**	9.5108	0.0000

Source Own estimation

Table 4 presents the outcomes from the Diebold-Mariano test with the alternative hypothesis formulated as the forecast from the both methods have different accuracies. For the given model its version with the first and the second grouping of explanatory variables is compared. Both squared errors loss function (SE) and absolute scaled error loss function (ASE) were used.

Table 4 The outcomes from the Diebold-Mariano test (first grouping vs. second grouping)

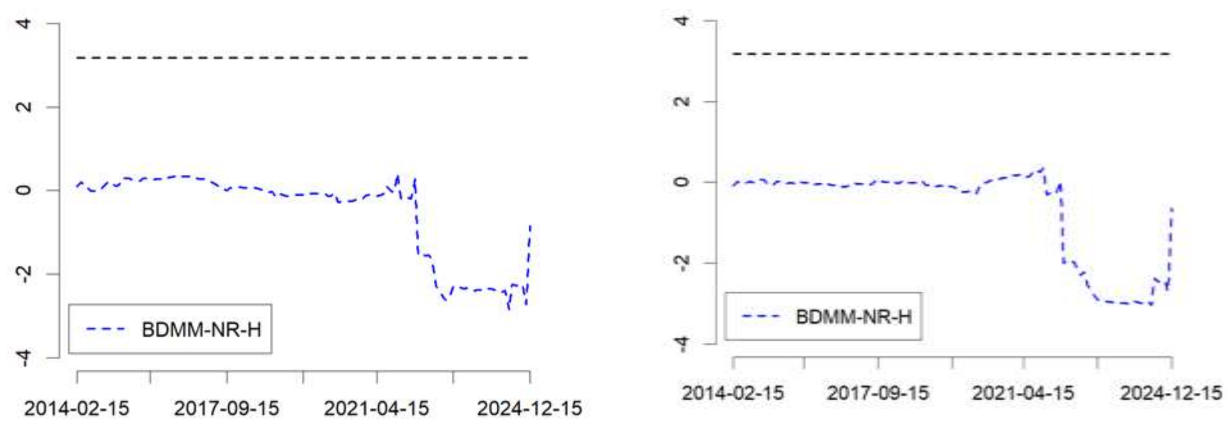
	SE statistic	SE p-value	ASE statistic	ASE p-value
BDMM-SS	4.3610	0.0000	5.1479	0.0000
BDMM-SS-A	-0.8071	0.4208	-0.8303	0.4076
BDMM-SS-H	0.2040	0.8386	1.1496	0.2520
BDMM-SS-K	5.5105	0.0000	7.9238	0.0000
BDMM-SS-A-K	-0.1668	0.8678	0.9970	0.3203
BDMM-SS-H-K	0.4783	0.6331	0.9914	0.3230
BDMM-NR	2.3373	0.0207	1.5352	0.1267
BDMM-NR-H	0.6289	0.5303	1.4889	0.1385
DMA	-0.8332	0.4060	-0.5719	0.5682
DMS	-1.1630	0.2465	-0.8082	0.4202
BMA	-1.4203	0.1575	-1.9279	0.0556
BMS	-1.1588	0.2482	-0.5561	0.5789
DMA-K	-0.4716	0.6378	0.1834	0.8547
DMS-K	-1.2832	0.2013	-1.6331	0.1044
BMA-K	-1.0577	0.2918	-1.5418	0.1251
BMS-K	-0.7541	0.4519	-1.3891	0.1667

Source Own estimation

Figure 1 presents the outcomes from the Giacomini-Rossi fluctuation test over approx. 3 year window period. Assuming 5% significance level, the null hypothesis that BDMM-NR-H forecasting performance is the same as that of the ARIMA method cannot be rejected (in favor of the alternative hypothesis that the BDMM-NR-H model performs worse than the ARIMA).

In case of the Model Confidence Set test BDMM-SS-K, TVP-FOR, HA and HA-ROLL methods were eliminated (for both versions of explanatory variables grouping).

Figure 1 Giacomini-Rossi fluctuation test (first grouping on the left; second – on the right)



Source Own estimation

Table 5 reports the outcomes from the Clark-West (CW), the West (W), the Fair-Shiller (FS), the Harvey-Leybourne-Newbold (HLN) and the Mizon-Richard (MR) encompassing tests (Cook, 2014). 5% significance level is assumed, and the second version of explanatory variables grouping. For CW test the alternative hypothesis is that the larger model is encompassing the null model. For W test the null hypothesis is that the larger model is encompassing the null model. FS and MR tests are procedures based on some steps, so it is indicated if the larger models is encompassing the null model according to the selected procedure. HLN test can be based on the analysis of significance of regression coefficients (reg) or the Spearman correlation (cor). In both versions the null hypothesis is that the larger model is encompassing the null model.

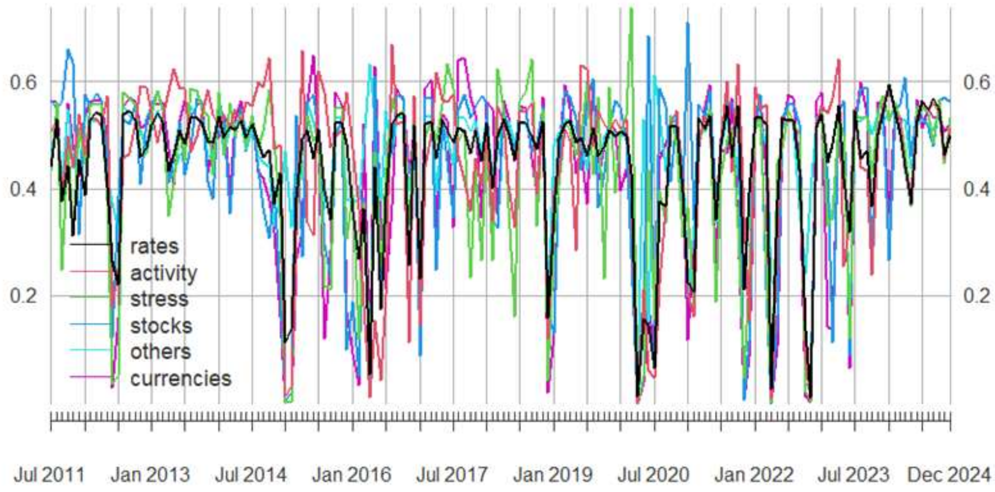
Table 5 The outcomes from the encompassing tests

larger	null	CW p-value	W p-value	FS outcome	HLN reg p-value	HLN cor p-value	MR outcome
BDMM-SS	TVP	0.0249	0.0000		0.0000	0.0000	
BDMM-SS-A	TVP	0.0020	0.0000		0.0000	0.0041	
BDMM-SS-H	TVP	0.0004	0.0001	yes	0.0136	0.0395	
BDMM-SS-K	TVP-K	0.8577	0.0000		0.0000	0.0000	
BDMM-SS-A-K	TVP-K	0.0154	0.0137	yes	0.9887	0.2007	
BDMM-SS-H-K	TVP-K	0.0540	0.0003		0.0059	0.0000	
BDMM-NR	BDMM-NR-1MOD	0.0021	0.0668	yes	0.4376	0.0014	
BDMM-NR-H	BDMM-NR-1MOD	0.0017	0.1038	yes	0.2741	0.0025	yes
DMA	TVP-FOR	0.0000	0.0390	yes	0.3145	0.7407	yes
DMS	TVP-FOR	0.0000	0.0137		0.0750	0.3603	yes
BMA	TVP	0.0000	0.1077	yes	0.1996	0.3764	yes
BMS	TVP	0.0000	0.1078	yes	0.1994	0.3708	yes
DMA-K	TVP-FOR-K	0.0014	0.0341	yes	0.4018	0.0432	
DMS-K	TVP-FOR-K	0.0051	0.0013		0.0105	0.0003	yes
BMA-K	TVP-K	0.0110	0.0054		0.0229	0.0007	yes
BMS-K	TVP-K	0.0134	0.0036		0.0132	0.0003	yes

Source Own estimation

Figure 2 presents relative variable importances for the BDMM-NR-H model based on the second version of explanatory variables grouping. Relative variable importance is the sum of weights of exactly those component models which contain a given explanatory variable.

Figure 2 Relative variable importances



Source Own estimation

5 Conclusions

This study discusses application of various forecasting models to economic and financial time series, with a focus on Bayesian Dynamic Mixture Models. A comprehensive set of macroeconomic indicators was applied, and models were evaluated using out-of-sample forecasting methods, mimicking real-time conditions. By leveraging the dynamic adjustment of model weights and incorporating state-space components, the models outperformed benchmark models across multiple evaluation metrics and statistical tests. The findings suggest that allowing for time-varying model weights significantly enhances forecasting accuracy, especially in capturing the complex and evolving nature of economic data. These results contribute to the growing body of literature supporting the use of dynamic Bayesian techniques in economic forecasting, offering a robust approach to handling model uncertainty and improving predictive performance.

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