THE PREDICTIVE CONTENT OF CO-MOVEMENT IN NON-ENERGY COMMODITY PRICE CHANGES

PILAR PONCELA
EVA SENRA
LYA PAOLA SIERRA

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De conformidad con la base quinta de la convocatoria del Programa de Estímulo a la Investigación, este trabajo ha sido sometido a evaluación externa anónima de especialistas cualificados a fin de contrastar su nivel técnico.

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Pilar Poncela[*]
Eva Senra[**]
Lya Paola Sierra[***]

ABSTRACT

The predictive content of the co-movement either of a large range of commodities, or the co-movement within a specific category of raw material prices is evaluated. This paper reports success in using small scale factor models in forecasting the nominal price of non-energy commodity changes on a monthly basis. Therefore, communalities of commodities in the same category, estimated by the Kalman filter, can be useful for forecasting purposes. Notably, category communalities in oils and protein meals, as well as metals seem to substantially improve the forecasting performance of the random walk model. In contrast, co-movement in extensive data of commodity prices, estimated through Principal Components, has poor predictive power over non-energy commodity prices, compared to the small-scale factors.

Key words: Commodity prices, co-movement, out-of-sample forecast performance.

JEL classification: E37, F00

Corresponding author: Lya Paola Sierra, Department of Economics, Pontificia Universidad Javeriana de Cali, Colombia. Calle 18 No. 118-250 Cali, Colombia (26239). Tel: 5723218200, Fax: 5725553587 E-mail: lyap@puj.edu.co.

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[*] Department of Economic Analysis: Quantitative Economics, Universidad Autónoma de Madrid, Spain. Tel: 34914975521, Fax: 34914974091, E-mail: pilar.poncela@uam.es
[**]Department of Economics, Universidad de Alcalá, Spain. Tel: 34918855232, Fax: 34918854201, E-mail: eva.senra@uah.es
[***] Department of Economics, Pontificia Universidad Javeriana de Cali, Colombia

1. Introduction

In a recent study Poncela, Senra and Sierra (2013) found that there has been an increase in co-movement in a large range of non-energy commodity prices since 2004, perhaps enhanced by the financialization in the commodity markets[1]. Thus, prices which should apparently not be correlated, increased their common evolution in time. According to this study, the variance of commodity prices explained by the common behavior of 44 non-energy commodity prices, jumped from 9% between February 1992 and November 2003, to 23% between December 2003 and December 2012. This means that after 2004 the common behavior of non-energy commodity prices accounts for a larger share of those fluctuations. It is therefore of interest to explore whether co-movement in prices of raw materials has some predictive power over each non energy commodity price.

To analyze the consequences of this stylized fact in forecasting, we compare several models against a baseline random walk alternative. We aim to explore the predictability of 44 non-fuel commodity spot prices measured on a monthly basis. For this purpose, we use a Dynamic Factor Model (DFM) to extract a latent factor that drives the co-movement on non-energy commodity prices. We evaluate two variants: a large-scale DFM that uses the whole commodity price data and estimate their co-movement through Principal Components and a small-scale DFM that takes into account the communalities into commodities of the same category and estimate factors by means of the Kalman filter. Our measure of forecasting performance is the out-of-sample root mean square error of prediction (RMSE) for one-step-ahead forecasts.

Although the literature on commodity price forecasts is extensive, it provides only scant empirical evidence of the role of co-movement in commodity prices as a possible source of predictability in non-energy spot prices. The recent literature has focused on evaluating whether macroeconomic and financial variables have some predictive power over commodity price spot indices, with mixed results. Chen, Rogoff and Rossi (2010) found that exchange rate fluctuations in a group of commodity-dependent countries have robust power in forecasting commodity price indices[2]. Groen and Pesenti (2011) used a large set of macroeconomic variables, apart from exchange rates, to evaluate

[1] Financialization in the commodity market is the name given to the substantial increase in commodity index fund investments starting in 2004. According to authors such as Büyüksahin and Robe (2012) and Henderson, Pearson and Wang (2012) financialization not only increases comovements among different types of commodities, but generates cross-market linkages, especially with the stock market. Other contributors to this literature include Tang and Xiong (2012) and Irwin, Sanders and Merrin (2009).

[2] Chen, Rogoff and Rossi (2010) examined how individual exchange rates of Australia, Canada, New Zealand, South Africa and Chile forecast the corresponding commodity price index for the country.

their predictive power over commodity indices. They did not find a robust validation of Chen et. al (2010)´s previous conclusions. Moreover, although the inclusion of multivariate macroeconomic variables improves the forecasts, it does not produce an overwhelming advantage of spot price predictability when compared with the random walk model. Gargano and Timmermann (2014) found that the predictability power of macroeconomic and financial variables depends on the state of the economy.

Another branch of the literature has focused on whether futures prices are good predictors of future spot prices. Chinn y Coibion (2013) evaluate the forecasts of a range of commodity prices finding that futures prices for precious and base metals display very limited predictive content for future price changes. In contrast, futures prices for energy and agricultural commodities do relatively better in terms of predicting subsequent price changes. In regard to oil prices, Alquist and Kilian (2010) use two models: one that considers the current level of futures prices as the predictor and the second which is based on the futures spread, to conclude that oil futures prices fail to improve on the accuracy of simple no-change forecasts[3].

Our paper considers the following research questions: First, does co-movement in non-energy commodity prices has predictive power over non-energy commodity prices? Second, has co-movement in commodity prices by category added power to the prediction in comparison with the large scale co-movement in commodity prices? Third, does the predictability of commodity prices vary across different types of categories, such as agricultural versus raw industrial commodities? We aim to answer these questions using dynamic factor models.

The paper is organized as follows. In section 2 we present the different models we estimate. In section 3 we describe the data and the methodological procedure we propose. In section 4 we report the estimation and forecasting results. Finally, in section 5 we conclude.

2. Model specifications

The first three models are limited to the information embedded in each commodity price time series itself: the first is a random walk model, used as benchmark, the second is a univariate autoregressive (AR) model over the first differences of log prices, and the

[3] Alquist and Kilian (2010) defined the oil futures spread as the percent deviation of the oil futures price from the spot price of oil.

third is a univariate ARMA model that takes into account the presence of possibly several types of outliers.

Let $P_{i,t}$ be the spot price of the *i-th* commodity at time t, *i*=1,…n and $t = 1, \ldots\ldots, T$. Then $y_{i,t}$= ln($P_{i,t}$)-ln($P_{i,t-1}$) denotes its related non-energy commodity price inflation. Then, the unconditional mean benchmark model is:

$$y_{i,t} = \alpha_i + \epsilon_{i,t}, \qquad (1)$$

which implies that the best forecast of the spot price of commodities is simply the current spot price plus the drift α_i if it were different from zero.

The AR(p_i) model for the *i-th* commodity, *i=1,….,n* follows the specification:

$$y_{i,t} = \alpha_i + \beta_{i,1} y_{i,t-1} + \cdots + \beta_{i,p_i} y_{i,t-p_i} + \epsilon_{i,t}, \quad t = 1, \ldots, T. \qquad (2)$$

Additionally, we include a univariate ARMA model which takes into account outliers estimated automatically, using Gómez and Maravall (1996)´s TRAMO program (Time series Regression with ARIMA noise, Missing values and Outliers), which follows the specification: $y_{i,t} = \frac{\theta_i(B)}{\phi_i(B)} \varepsilon_{it} + outliers$, where $\phi_i(B)$ and $\theta_i(B)$ are Autoregresive and Moving Average polynomials of order p_i and q_i respectively on the backshift operator B [4].

The subsequent models include a latent variable, or factor, that represents the common pattern of commodity prices. The general DFM specification assumes that the *i-th* commodity price inflation, labelled as y_{it}, is driven by a latent component, f_t,which is common to all series plus an idiosyncratic component, $\varepsilon_{i,t}$[5]. For instance, specifically for each i we obtain:

$$y_{it} = \lambda_i f_t + \varepsilon_{i,t}, \qquad \forall i \qquad i = 1, \ldots, N \qquad (3)$$

where λ_i is the loading of the common factor into the i-*th* commodity. The first DFM specification is a large-scale factor model that accounts for the common variability of all available non-energy commodity prices. We estimate the common factor by Principal Components as the large number of commodities used to evaluate the factor in the

[4] TRAMO is available at the Bank of Spain webpage: http://www.bde.es/bde/es/secciones/servicios/Profesionales/Programas_estadi/Programas_estad_d9fa7f3710fd821.html

[5] Although the DFM may have multiple factors, we have identified the factor structure using the information criteria proposed by Bai and Ng (2002), which confirm that there is one factor in the commodity price data.

large-scale DFM, allows us to assume consistency of this estimator[6]. To forecast price inflation at *t+1* with information until time *t*, we use factor based regressions of the form:

$$y_{i,t+1} = \beta_i f_t + u_{i,t+1.} \quad (4)$$

We also evaluate whether the inclusion of the forecast of the idiosyncratic component of the DFM, $\varepsilon_{i,t}$, improves the forecasting performance, or it is only the forecast of the common part what is valuable for forecasting[7]. Then, the factor based regression related to the large-scale DFM that takes into account the idiosyncratic component follows the specification:

$$y_{i,t+1} = \beta_{1i} f_t + \beta_{2i}\varepsilon_{i,t} + u_{i,t+1.} \quad (5)$$

Besides estimating a large-scale DFM, which takes into account a single common factor to all the commodity price series (equations 4-5), in this paper we also estimate a set of small-scale DFM models by introducing dynamic factors which are common only to the series within each set. More precisely, let us consider L commodity categories, and for each category (category *l=1,2,…,L*) k_l commodity price series. Then, the baseline model for each commodity price in the l^{th}category can be decomposed into the following components:$\forall l$

$$y_{i,t} = a_i^l c_{l,t} + \varepsilon_{i,t,}^l \qquad l = 1, \dots k_l, \qquad \forall i \qquad (6)$$

where within each category *l*, $c_{l,t}$ is the factor or co-movement variable common to all series in the category, a_i^l represents the factor loading, and $\varepsilon_{i,}^l$ named idiosyncratic component, collects the dynamics specific to each commodity price inflation. Both the common factor and the idiosyncratic component may follow AR processes of order q_i and p_i, respectively.

$$c_{l,t} = \vartheta_{0,1}^l c_{l,t-1} + \cdots + \vartheta_{0,q}^l c_{l,t-q} + \eta_{0,t}^l \qquad (7)$$

$$\varepsilon_{i,t}^l = \phi_{i,1}^l \varepsilon_{i,t-1}^l + \cdots + \phi_{i,p_i}^l \varepsilon_{i,t-p_i}^l + \sigma_i^l \eta_{i,t}^l, \qquad (8)$$

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[6] For a discussion of dynamic factor models and its estimation methods see, for instance, Stock and Watson (2011).

[7] Currently, small-scale factor models also include the forecasting of the idiosyncratic component (see, for instance, Camacho and Perez-Quiros, 2010) while forecasting through large-scale factor models only uses the common factors embedded in a forecasting equation with lags of the target variable to reproduce specific dynamics (see, for instance, Stock and Watson, 2011). The advantage of including the forecast of the idiosyncratic component instead of the target variable lags could be that the idiosyncratic component is uncorrelated with the common factors. We aim to check the usefulness of the idiosyncratic component in factor forecasting.

where σ_i is the standard deviation of the idiosyncratic component, and $\eta_{i,t} \sim N(0,1)$ $i = l, \dots k_l, l = 1, \dots, L,$ are the innovations to the law motions for equations (7) and (3.8), respectively. We also evaluate whether the inclusion of the forecast of the idiosyncratic component of the DFM improves the forecasting performance in the small-scale DFMs.

We estimate the small-scale DFMs in the state-space using the Kalman filter. The smaller number of variables involved in the factor models by category impedes us from using the estimator of principal components in this latter case. The Kalman filter also produces filtered inferences of the common factor that can be used in the prediction equation (9 and 10) to compute OLS forecasts of the variable $y^l_{i,t+1}$.

To sum up, the different models, and its variations, that we estimate and compare in terms of forecasting with the baseline random walk in this study can be summarized as:

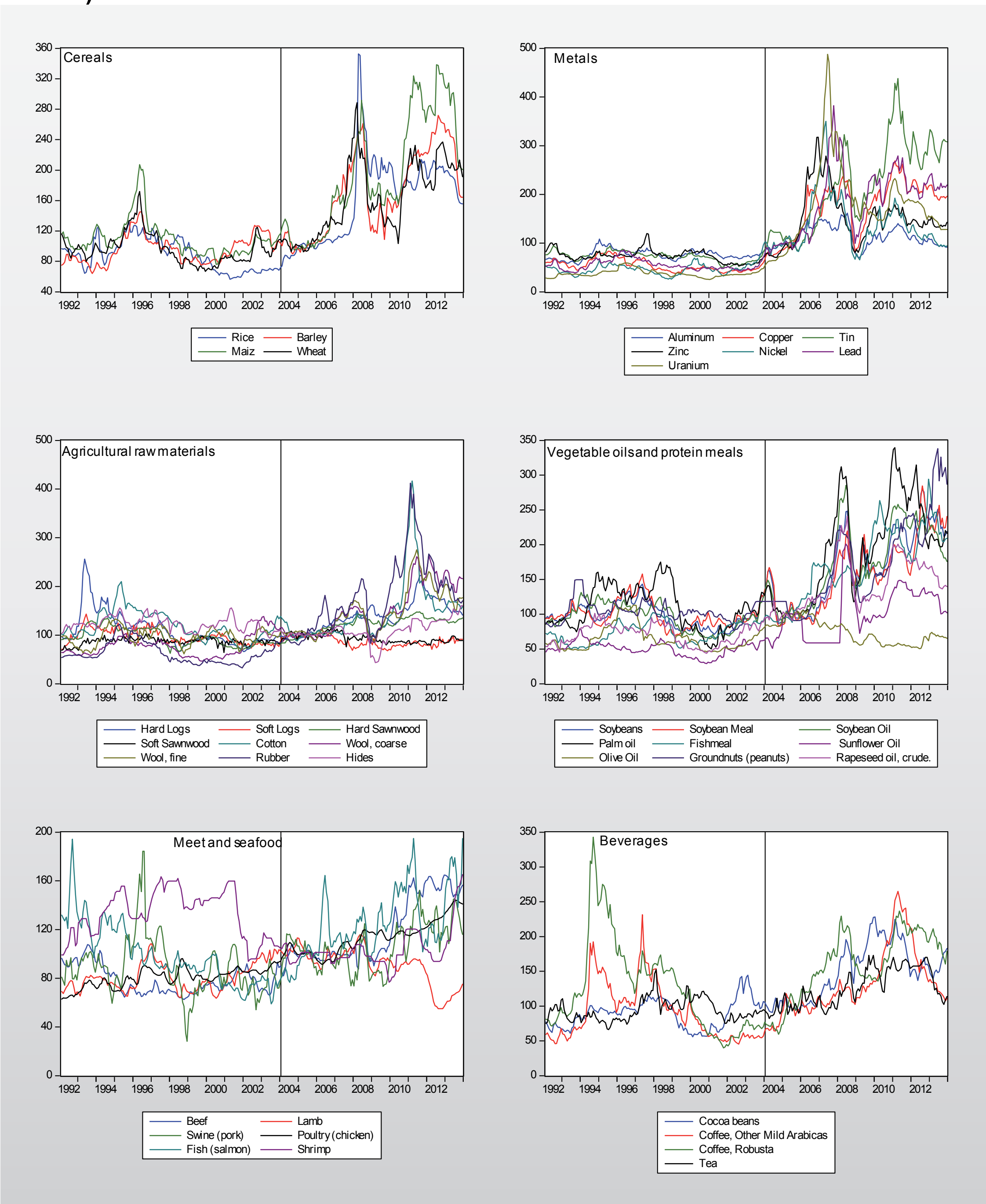
1. Autoregressive (AR) model.
2. Univariate ARMA model with outliers.
3. Large-scale DFM
   - 3.1. Large-scale DFM with idiosyncratic component.
   - 3.2. Large-scale DFM without idiosyncratic component.
4. Small-Scale DFM
   - 4.1. Small-Scale DFM with idiosyncratic component.
   - 4.2. Small-Scale DFM without idiosyncratic component.

3. Data description and empirical strategy.

We use 44 monthly non-fuel commodity price series from the International Monetary Fund database (IMF IFS). In accordance with the increase in the co-movement in non-energy commodity prices found in Poncela, et al. (2013), we began our sample in January 2004 and finished in December 2013. We include in our study the raw materials available in the following categories: cereals, meat and seafood, beverages, vegetable oil and protein meals, agricultural raw materials and metals. A summary of the commodities and their categories is shown in appendix 1.

Figure 1 presents the non-energy commodity prices per category from January 1980 to December 2013. The starting date of our sample, January 2004, is marked with a vertical line in all plots. Our sample is characterized by a great upsurge in several of the non-energy commodity prices until mid-2008, and a drastic decline during the global financial crisis. After mid-2009, prices began to recover the upswing in several of the categories, being remarkable: agricultural raw material, cereals and metals. Notably, if we compare both the pre-2004 and post-2004 samples, there is an increase in the scale of the boom and bust cycles for industrial inputs such as agricultural raw material and metals, and edibles such as cereals, vegetable oils and protein meals.

Figure 1: Non-energy commodity prices per category (2005=100, in terms of U.S. dollars).



Source: International Monetary Fund, IMF

Table 1 shows the descriptive statistics of the non-energy commodity price inflation for the period 2004:1-2013:12. Average inflation of non-energy commodities over the considered period are mostly positive, only three commodities have negative nominal average inflation (nickel, olive oil and lamb). The largest mean inflation correspond to metals such as copper and tin, with 0.99% and 1.10% per month, respectively. The biggest values of volatility also coincide with the metal category: nickel, copper and lead reports the greatest volatilities. Other commodities that exhibit large volatilities are: rubber, sunflower oil and swine (pork). Finally, as it can be seen in bottom of table 1, the serial correlation term suggests first order autocorrelation is present in most of commodity prices, which justifies a first lagged term in equation (2).

Table 1: Summary statistics for non-energy commodity price inflation

Agricultural raw materials	Hard Logs	Soft Logs	Hard Sawnwood	Soft Sawnwood	Cotton	Wool, coarse	Wool, fine	Rubber	Hides
Mean (%)	0,317	0,146	0,421	0,065	0,144	0,556	0,495	0,588	0,325
Std. Dev. (%)	3,370	6,352	2,247	5,823	6,898	6,002	5,954	8,970	7,498
Skewness	0,032	0,304	-0,404	0,364	-0,623	-0,168	0,244	-1,061	-2,689
Kurtosis	3,927	3,803	4,781	5,936	6,606	5,817	4,397	6,159	27,844
AR(1)	0,332	0,362	0,133	0,330	0,401	0,345	0,333	0,267	0,199

Veg. Oil and Prot. Meal	Soybeans	Soybean Meal	Soybean Oil	Palm oil	Fishmeal	Sunflower Oil	Olive Oil	Ground-nuts	Rapeseed oil
Mean (%)	0,455	0,551	0,286	0,423	0,702	0,414	-0,166	0,739	0,377
Std. Dev. (%)	6,982	7,725	6,235	7,699	5,181	10,398	4,251	5,307	6,047
Skewness	-0,710	-0,663	-0,561	-0,788	1,297	2,384	1,175	0,050	-0,265
Kurtosis	5,135	5,030	4,615	5,810	8,056	21,403	6,786	6,061	4,743
AR(1)	0,334	0,316	0,361	0,433	0,297	0,417	0,261	0,288	0,235

Metals	Aluminum	Copper	Tin	Zinc	Nickel	Lead	Uranium
Mean (%)	0,061	0,989	1,103	0,587	-0,016	0,942	0,821
Std. Dev. (%)	5,823	8,112	7,508	7,847	9,864	9,204	7,233
Skewness	-0,608	-0,892	-0,317	-0,483	-0,340	-0,762	-0,430
Kurtosis	4,222	6,941	3,185	4,096	3,968	4,048	5,732
AR(1)	0,308	0,441	0,279	0,327	0,299	0,251	0,454

Beverages	Cocoa beans	Coffee, Arabicas	Coffee, Robusta	Tea
Mean (%)	0,450	0,558	0,777	0,150
Std. Dev. (%)	5,784	6,143	5,817	7,641
Skewness	-0,153	0,315	-0,051	0,071
Kurtosis	3,328	2,971	3,216	3,593
AR(1)	0,204	0,113	0,217	0,123

Cereals	Rice	Barley	Maiz	Wheat
Mean (%)	0,684	0,366	0,473	0,472
Std. Dev. (%)	6,899	7,165	7,086	7,268
Skewness	2,470	-0,364	-0,210	0,476
Kurtosis	16,131	5,316	4,559	5,027

AR(1)	0,521	0,295	0,226	0,225		
Meat seafood	Beef	Lamb	Swine (pork)	Poultry (chicken)	Fish (salmon)	Shrimp
Mean (%)	0,473	-0,268	0,399	0,344	0,775	0,371
Std. Dev. (%)	4,137	3,292	8,309	1,370	7,492	3,651
Skewness	-0,113	-0,285	0,036	-0,040	-0,241	0,707
Kurtosis	8,249	4,009	3,223	2,978	3,477	9,059
AR(1)	0,176	0,473	0,069	0,749	0,252	0,373

Once the different factor model alternatives have been exposed in the previous section, our procedure in analyzing the data is as follows:

1. Following Stock and Watson (2011), we transform the data to achieve stationarity. In particular, we log differentiated and standardized commodity price data, prior to the factor extraction either by Principal Components or Kalman filter.
2. We determine the number of factors of the large-scale DFM using information criteria proposed by Bai and Ng (2002). For small factor models we analyze the eigenstructure of their variance-covariance matrix to determine the number of factors.
3. We estimate the DFM through both principal components and the Kalman filter.
4. We generate one-step-ahead forecasts. We start our out-of-sample forecasts in 2010:12, re-estimate the models adding one data point at the time. In other words, we use an expanding window. The evaluation period is 2010:01–2013:12.
5. We compute the RMSE for each model to assess its forecasting performance.
6. We compare the RMSE of every model with that of the random walk.

Regarding univariate models, we choose the AR(p) model by means of adjustment criteria, and for the ARMA model with outliers we use the TRAMO program and run it in an automatic mode. Subsequently, we continue with steps 4 to 6 mentioned above.

7. Empirical results

In this section we evaluate the co-movement content for predicting inflation of non-energy commodities. In particular, we examine whether joint movements of commodity prices can be used as predictors of the inflation of each non-energy commodity.

Estimation results for univariate AR models show that an AR(1) is suitable for most commodities inflation. Automatic modelling shows mostly the same specification, except for a small number of series where it appears to be a minor stationary seasonality . As regards the factor models, we confirm the presence of only one factor, which we call co-movement, in both large-scale DFM and small-scale DFMs .

Forecasting results for the univariate models as well as the DFMs are presented in table 2. The table compares the forecasting results in terms of the ratio of the RMSE of every model over the RMSE of the random walk forecast. Hence, a ratio less than one means that the model improves the benchmark forecast, while values above one suggest the opposite. We evaluate the statistical significance of the out-of-sample predictability results using the test statistics proposed by Diebold and Mariano (1995).

The first and second columns of table 2 show the RMSE ratios of the univariate models: univariate with outliers and AR model, while the third and fourth columns show the RMSE ratios of the large-scale factor model without and with idiosyncratic components, respectively. The results indicate that both univariate models usually outperform the random walk model in predicting non-energy commodity price inflation. In particular, for the AR model we found that 24 of these improvements were significant at the 10 percent level according to the test of Diebold and Mariano (1995), while the random walk model was found significantly better than AR only once. Since the ARMA model with outliers does not seem to outperform the AR model, for further analysis we will only consider the AR model as the univariate alternative (besides the random walk). In addition, for 38 commodities the large-scale DFM beats the random walk forecasts, although for only 16 of these the differences between both models are significant. We did not find any differences, in terms of number of commodities that outperform the random walk predictions, between large-scale factor model forecasts that take into account the idiosyncratic component of the factor analysis, and models that do not.

With regard to the small-scale factor models the results are more encouraging. Columns 5 and 6 in table 2 report forecasting performance of these models relative to the naïve random walk model. First and foremost, the small-scale factor models provide better predictions than the large-scale DFM approach and univariate models in most of the commodities within the categories beverages, vegetable oils and protein meals, as well as agricultural raw materials and metals, which means that co-movements by commodity category added power to predictions. Predictability results of the small-scale factor models for cereals and meat and seafood are mixed. In order to better visualize which of the models has the best result in terms of predictability for each commodity, we mark in bold type in table 2 the lower RMSE ratio for every non-energy commodity price inflation.

Table 2: Ratios of the RMSE of the univariate models and DFMs over the RMSE of the random walk model for the period of analysis 2004:1-2013:12.

RMSPE Model/RMSPE random walk.	Univariate + outliers	(AR) model	Large-Scale DFM (1)	Large-Scale DFM (2)	Small-Scale DFM (1)	Small-Scale DFM (2)
Beverages						
Cocoa beans	0.790	0.825	0.856	0.858	**0.673***	0.674*
Coffee, Other Mild Arabicas,	0.695	0.820***	0.832**	0.835**	**0.630***	0.631*
Coffee, Robusta	0.929	0.788**	0.787**	0.792**	**0.746***	0.749*
Tea	1.166**	**0.891***	0.927	0.928	0.928	0.926
Vegetable oils and protein meals						
Soybeans	0.890	0.810	0.846	0.849	**0.561****	0.562**
Soybean Meal	0.807	0.808	0.837	0.838	**0.437*****	0.440***
Soybean Oil	0.838	0.800*	0.833**	0.843**	**0.723***	0.724*
Palm oil	0.840***	0.807**	0.814*	0.820*	0.465***	**0.463*****
Fishmeal	0.974*	0.842**	0.899	0.899	0.520**	**0.517****
Sunflower Oil	0.992	0.806**	0.812	0.818	0.609*	**0.606***
Olive Oil	0.760	0.797	0.796	0.797	**0.480****	0.482**
Groundnuts (peanuts)	0.738	0.782	0.680**	0.680**	**0.338*****	0.341***
Rapeseed oil, crude.	0.877***	**0.762***	0.787*	0.795*	0.792*	0.791*
Metals						
Aluminum	0.798*	0.761***	0.736**	0.740**	**0.640**	0.641**
Copper	0.827	0.820*	0.856	0.865	**0.749**	0.750*
Tin	0.827***	0.787	0.795	0.800	**0.456**	0.457***
Zinc	0.894*	0.752***	0.697***	0.699***	**0.527**	0.531***
Nickel	0.778***	0.789	0.805*	0.818	0.514	**0.513*****
Lead	0.789***	0.749***	0.732**	0.737**	**0.509**	0.513***
Uranium	1.165	**0.899**	1.081	1.086	1.083	1.067
Agricultural raw materials						
Hard Logs	1.065	**0.932**	1.046	1.046	1.470	1.470
Soft Logs	0.530***	0.515***	0.578***	0.578***	**0.431*****	0.432***
Hard Sawnwood	0.842***	**0.779***	0.788*	0.789*	2.207	2.207
Soft Sawnwood	0.721***	0.711**	**0.681****	0.680**	0.928	0.925
Cotton	0.903**	0.833	0.854	0.857	0.550**	**0.549****
Wool, coarse	0.880***	0.813	0.843	0.845	**0.696***	0.697*
Wool, fine	0.826	0.840	0.902	0.906	**0.784**	0.785
Rubber	0.779**	0.788	0.795	0.803	**0.521*****	0.522***
Hides	0.666*	0.710	0.667	0.667	**0.665**	0.669
Cereals						

Rice	1.032**	**0.872***	1.002	1.004	1.634*	1.641*
Barley	1.188**	**0.956**	1.094	1.103	1.565	1.565
Maiz	0.799**	0.785*	0.799	0.802	0.724*	**0.723***
Wheat	0.774***	0.756*	0.755*	0.756*	0.755*	**0.754***
Meet and seafood						
Beef	**0.754****	0.785	0.819	0.819	1.020	1.025
Lamb	1.089*	1.042**	1.356**	1.357*	1.410*	1.406*
Swine (pork)	0.700	0.716*	0.708*	0.708*	**0.298***	0.301*
Poultry (chicken)	1.152**	**0.934**	1.266*	1.266*	6.666*	6.669*
Fish (salmon)	0.748**	0.800*	0.804	0.805	0.303***	**0.302*****
Shrimp	1.012	**0.971**	1.155	1.155	1.154	1.147
Sugar, bananas and orange						
Sugar, European import Price	0.723***	0.761*	**0.722****	0.724**	5.770***	5.771***
Sugar, Free Market	0.839**	**0.812****	0.841	0.841	1.488	1.488
Sugar, U.S. import price	0.879	**0.873**	0.966	0.966	2.601**	2.601**
Bananas	0.891	0.795**	**0.784**	0.788	2.526**	2.526**
Oranges	0.840***	0.807**	0.814*	0.820*	**0.731**	0.732

Notes: This table reports the ratio of the root mean square error of prediction of the models, to the root mean square error of prediction of the random walk model, $RMSPE_{Model}/RMSPE_{random\ walk}$. Values smaller than one indicate that the model perform better than the random walk. We compute the Diebold-Mariano (1995) test statistic for the null hypothesis that the corresponding MSE differential is zero.
*** Indicates statistical significance at the 1% level.
** Indicates statistical significance at the 5% level.
* Indicates statistical significance at the 10% level.
(1) Means the DFM without idiosyncratic component
(2) Means the DFM with idiosyncratic component

8. Robustness checks

As a robustness check we estimate all models for a prior period (1992:2-2003:12) and compare their forecasting performance, in terms of RMSE ratios, with the second period in order to assess whether commodity prices were more or less predictable in different subsamples. Results for the AR model, large-scale factor models as well as the small-scale models for the first period are presented in appendix 2.

The methodology for estimating each model is the same as described in previous sections. Regarding the first period, we begin the out-of-sample forecasts in 2000:12, therefore, the evaluation period is 2001:1-2003:12. We follow the same procedure explained in section 3.3, and use an expanding window with a size of 36 months. We compare the predictive content for every model *i* in both of the periods (pre-2004 and post -2004) by means of the following difference:

$$\left(\frac{RMSE_{model_i}}{RMSE_{RW}}\right)_{pre-2004} - \left(\frac{RMSE_{model_i}}{RMSE_{RW}}\right)_{post-2004} \qquad (3.9)$$

When there is a value over zero in the above difference, the predictive content of the model is enhanced in the second period, given that the RMSE against the random walk model is lower in the post-2004 period compared with the pre-2004 period. Results are shown in appendix 3.

In general, small-scale models both with and without idiosyncratic component, performed better in the second period. In the post-2004 period, compared to pre-2004, the small-scale models with and without specific component improved their prediction versus random walk in 27 commodities. Importantly, the ratio between the RMSE of the small-scale DFM to the RMSE of the random walk reduced more for commodities in the categories of vegetables and protein meal, agricultural raw materials, and metals. These results suggest that the increase in the overall movement of non-energy commodity prices since 2004 has caused the small-scale dynamic factor models to improve their predictive content, in particularly in the categories above mentioned.

Regarding the AR model, as well, as the large-scale DFM we found inconclusive results since approximately half of commodities´ prediction improved with these models and half worsened for the second period.

In addition to the comparison between periods of each model, we perform an analysis of the different models in each period. That is, we compare the forecasting performance among models, in terms of their RMSE ratios, in order to assess which model has the best behavior in each period. Specifically, we compare the predictive capability between models i and j for each period by means of the following ratio:

$$\left(\frac{RMSE_{model_i}}{RMSE_{model_j}}\right)_{pre-2004},$$

$$\left(\frac{RMSE_{model_i}}{RMSE_{model_j}}\right)_{post-2004} \qquad (3.10)$$

Values above one mean that the model j outperforms the model prediction of i, since j has a RMSE lower than RMSE of the model i, and vice versa. The results can be summarized as:

a. In both the first and the second periods, the AR model outperforms the large scale factor models in its ability to predict changes in the prices of non-energy commodities. The ratios of the RMSE of the large scale models to the RMSE of the AR model are lower than one in approximately 33 to 37 commodities. Ratios of RMSE of models to AR models are shown in appendix 4.
b. Results show that the large-scale DFM model without idiosyncratic component performs better, in terms of predictability, than the large-scale DFM with idiosyncratic component for both periods. For the first period, for 32 commodities, the large-scale DFM without idiosyncratic component beats the model with this element, while for the second period, it does so for 38 commodities[8].
c. Regarding the small-scale models, in both periods the model without idiosyncratic component reports lower ratios to the small-scale DFM with idiosyncratic component. For the first period, for 31 commodities, the small-scale DFM without idiosyncratic component outperforms, in terms of forecasting performance, the small-scale DFM with idiosyncratic component. For the second period, it does so for 25 commodities.
d. While comparing the AR model with the small-scale DFM, we found interesting results. For the first period, say pre-2004, the ratios of the RMSE of the small-scale models over the RMSE of the AR model forecast were lower than one for 18 commodities (for both models with and without idiosyncratic component). In contrast, for the second period, say post-2004, the small-scale models increased their predictive content to overcome the AR model in 26 commodities for both models with and without idiosyncratic component, see appendix 4.
e. As in the previous point, we found an increase in the predictability of small-scale DFM in the second period in comparison to the large-scale DFM. That is, pre-2004, the large-scale model beats the small-scale DFMs in 24 commodities. In contrast, for the post-2004 period, the small-scale DFM outperform the large-scale DFM in 27 to 29 commodities. Therefore it is only the common part what is informative for forecasting commodity returns.

These results reaffirm the increase in the predictive content of the small-scale factor models compared with both the autoregressive model and the large-scale DFM for the second period. In addition, the results in both forecasting samples highlight that for DFM, the inclusion of the idiosyncratic component does not improve the forecasting

[8] Estimation results for the rest of the points are available upon request.

performance of these models in relation to the naïve random walk model. Therefore, it is only the common part what is informative for forecasting commodity returns.

9. Conclusions

To understand and predict changes in commodity prices it is important not only for commodity dependent countries, due to the fact that commodity price swings directly affect their term of trade and cycle, but also for commodity importing countries, because commodity prices impact inflation and may interfere with monetary policy goals.

We examine the predictability of non-energy commodity price changes when we take into account the co-movement of either a large range of commodities, or the co-movement within a specific category of raw material prices. We use a dynamic factor model approach and estimate the communalities of non-energy commodity price inflation either by Principal Components, for the case of large-scale factor, or Kalman Filter, in the case of the small-scale (category) factor.

We found that co-movement in extensive data of commodity prices has poorer predictive power over non-energy commodity prices since 2004 when comparing to the small-scale factor models and univariate AR model. Conversely, communalities into categories such as oils and protein meals, as well as metals seem to substantially improve the forecasting performance of the random walk model. For these categories we found reductions in the RMSE up to 50%. In the robustness checks, we found that small-scale DFM has gained predictive power since 2004. In fact, in the previous period, say 1992:2-2003:12, the predictability of small and large-scale factor models were similar. Finally, adding the forecast of the idiosyncratic component did not improve the results and, therefore, it is only the common part what is valuable for forecasting.

Before 2004 non-energy commodity prices were quite stable, especially for industrial inputs such as agricultural raw material and metals, and edibles such as cereals, vegetables oils and protein meals. On the contrary, after 2004, assets allocated to commodity indices increased, leading to the so-called financialization in the commodity markets. This new feature generates not only greater synchronization among commodities (co-movement), but also introduces higher levels of uncertainty to the market. In this paper we have studied the predictive power of co-movement in non-energy commodity prices, further work should include the recent role of uncertainty in commodity markets as a possible source of predictability.

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11. Appendix

Appendix 1. Non-energy commodity prices

IMF Category		Commodity	
Edibles	**Cereals**	Rice	Maiz
		Barley	Wheat
	Meet and seafood	Beef	Poultry (chicken)
		Lamb	Fish (salmon)
		Swine (pork)	Shrimp
	Beverages	Cocoa beans	Coffee, Robusta
		Coffee, Other Mild Arabicas,	Tea
	Vegetable oils and protein meals	Soybeans	Sunflower Oil
		Soybean Meal	Olive Oil
		Soybean Oil	Groundnuts (peanuts)
		Palm oil	Rapeseed oil, crude.
		Fishmeal	
	Other Edibles	Sugar EU.	Oranges
		Sugar US.	
		Bananas	
Industrial Inputs	**Agricultural raw materials**	Hard Logs	
		Soft Logs	Wool, fine
		Hard Sawnwood	Rubber
		Soft Sawnwood	Hides
		Cotton	Wool, coarse
	Metals	Aluminum	Zinc
		Tin	Nickel
		Uranium	Lead
		Tin	

Appendix 2. Ratios of the RMSE of the univariate autoregressive (AR) model, large-scale and small-scale factor models over the RMSE of the random walk model for the first period of analysis (1992:2-2013:12).

RMSPE Model/RMSPE random walk.	(AR) model	Large-Scale DFM (1)	Large-Scale DFM (2)	Small-Scale DFM (1)	Small-Scale DFM (2)
Beverages					
Cocoa beans	0.804	0.818	0.818	0.537**	0.537**
Coffee, Other Mild Arabicas,	0.749***	0.750**	0.750**	0.662**	0.665**
Coffee, Robusta	0.766**	0.769**	0.769**	0.565***	0.564***
Tea	0.750*	0.749*	0.749*	0.750*	0.749*
Vegetable oils and protein meals					
Soybeans	0.854	0.898	0.900	0.984	0.985
Soybean Meal	0.864	0.904	0.905	0.974	0.977
Soybean Oil	0.801*	0.820	0.821	0.784	0.784
Palm oil	0.790**	0.800*	0.802*	0.493***	0.490***
Fishmeal	0.810*	0.839	0.839	1.789**	1.791**
Sunflower Oil	0.798**	0.822*	0.823*	0.610**	0.608**
Olive Oil	0.875	0.930	0.931	1.920***	1.918***
Groundnuts (peanuts)	0.915	1.049	1.049	1.773**	1.772**
Rapeseed oil, crude.	0.790*	0.782*	0.785*	0.770*	0.769*
Metals					
Aluminum	0.741***	0.745**	0.745**	0.821	0.821
Copper	0.837*	0.890	0.891	0.887	0.887
Tin	0.865	0.894	0.894	0.629*	0.629*
Zinc	0.742***	0.732***	0.733***	0.704**	0.704**
Nickel	0.853	0.918	0.919	0.458***	0.459***
Lead	0.752***	0.743**	0.744**	0.539***	0.536***
Uranium	0.878	0.928	0.928	0.936	0.930
Agricultural raw materials					
Hard Logs	0.914	1.090	1.090	1.906	1.909
Soft Logs	0.476***	0.567***	0.566***	0.590	0.586
Hard Sawnwood	0.783*	0.802	0.802	2.157	2.159
Soft Sawnwood	0.494**	0.572**	0.572**	0.378	0.379
Cotton	0.893	1.072	1.074	1.026	1.030
Wool, coarse	0.887	0.929	0.929	0.868	0.868
Wool, fine	0.831	0.858	0.859	0.664	0.665
Rubber	0.811	0.833	0.833	0.720	0.720
Hides	0.925	1.038	1.038	1.039	1.032
Cereals					
Rice	0.787*	0.806	0.806	1.515*	1.518*
Barley	0.884	1.029	1.032	1.252	1.253
Maiz	0.808*	0.838	0.842	1.226	1.227

Wheat	0.818	0.844	0.845	0.839	0.838
Meet and seafood					
Beef	0.851	0.900	0.900	0.823	0.825
Lamb	0.744***	0.703**	0.703**	0.763	0.764
Swine (pork)	0.752*	0.756	0.756	0.356***	0.357***
Poultry (chicken)	0.903	1.123	1.124	4.347***	4.350***
Fish (salmon)	0.826*	0.870	0.870	0.647	0.650
Shrimp	0.830	0.861	0.862	0.863	0.863
Sugar, bananas and orange					
Sugar, European import price	0.788*	0.810	0.810	1.380***	1.382***
Sugar, Free Market	0.730**	0.695**	0.695**	1.370*	1.373*
Sugar, U.S. import price	0.875	0.956	0.956	1.894***	1.895***
Bananas	0.699**	0.694**	0.695**	0.613**	0.619**
Oranges	0.790**	0.800*	0.802*	0.835	0.825

Notes: This table reports the ratio of the root mean square error of prediction of the models, to the root mean square error of prediction of the random walk model, $RMSPE_{Model}/RMSPE_{random\ walk}$. Values smaller than one indicate that the model perform better than the random walk. We compute the Diebold-Mariano (1995) test statistic for the null hypothesis that the corresponding MSE differential is zero.
*** Indicates statistical significance at the 1% level.
** Indicates statistical significance at the 5% level.
* Indicates statistical significance at the 10% level.
(1) Means the DFM without idiosyncratic component
(2) Means the DFM with idiosyncratic component

Appendix 3. Differences of the RMSPE between both periods (pre-2004 and post-2004)

(RMSPE *i*/RMSPE rw)*pre-2004* - (RMSPE i/RMSPE rw)*post-2004*	(AR) model	Large-Scale DFM (1)	Large-Scale DFM (2)	Small-Scale DFM (1)	Small-Scale DFM (2)
Cereals					
Rice	-0.085	-0.197	-0.199	-0.118	-0.123
Barley	-0.072	-0.065	-0.071	-0.312	-0.311
Maiz	**0.023**	**0.039**	**0.040**	**0.503**	**0.503**
Wheat	**0.064**	**0.089**	**0.089**	**0.083**	**0.083**
Meet and seafood					
Beef	**0.066**	**0.081**	**0.081**	-0.197	-0.200
Lamb	-0.298	-0.653	-0.654	-0.648	-0.642
Swine (pork)	**0.036**	**0.048**	**0.048**	**0.058**	**0.056**
Poultry (chicken)	-0.031	-0.143	-0.143	-2.319	-2.318
Fish (salmon)	**0.026**	**0.067**	**0.065**	**0.343**	**0.348**
Shrimp	-0.141	-0.294	-0.294	-0.292	-0.285
Beverages					
Cocoa beans	-0.021	-0.038	-0.040	-0.136	-0.136
Coffee, Other Mild Arabicas,	-0.071	-0.082	-0.085	**0.031**	**0.034**
Coffee, Robusta	-0.022	-0.018	-0.023	-0.181	-0.184
Tea	-0.141	-0.178	-0.179	-0.178	-0.177
Vegetable oils and protein meals					
Soybeans	**0.043**	**0.052**	**0.050**	**0.423**	**0.422**
Soybean Meal	**0.055**	**0.067**	**0.067**	**0.537**	**0.537**
Soybean Oil	**0.001**	-0.013	-0.022	**0.060**	**0.059**
Palm oil	-0.017	-0.014	-0.018	**0.028**	**0.027**
Fishmeal	-0.032	-0.060	-0.060	**1.270**	**1.274**
Sunflower Oil	-0.008	**0.010**	**0.005**	**0.000**	**0.001**
Olive Oil	**0.078**	**0.135**	**0.134**	**1.440**	**1.436**
Groundnuts (peanuts)	**0.133**	**0.369**	**0.369**	**1.435**	**1.431**
Rapeseed oil, crude.	**0.028**	-0.005	-0.010	-0.022	-0.022
Sugar, bananas and orange					
Sugar, European import price	**0.027**	**0.087**	**0.086**	**1.610**	**1.611**
Sugar, Free Market	-0.082	-0.146	-0.146	-0.117	-0.115
Sugar, U.S. import price	**0.002**	-0.010	-0.011	**8.292**	**8.294**
Bananas	-0.096	-0.090	-0.093	-1.913	-1.906
Oranges	-0.017	-0.014	-0.018	**0.102**	**0.093**
Agricultural raw materials					
Hard Logs	-0.018	**0.044**	**0.044**	**0.436**	**0.439**
Soft Logs	-0.039	-0.011	-0.012	**0.159**	**0.154**
Hard Sawnwood	**0.004**	**0.014**	**0.013**	-0.050	-0.047
Soft Sawnwood	-0.217	-0.108	-0.108	-0.550	-0.546
Cotton	**0.060**	0.218	**0.217**	**0.475**	**0.481**

Wool, coarse	**0.074**	**0.086**	**0.084**	**0.171**	**0.171**
Wool, fine	-0.008	-0.044	-0.047	-0.120	-0.120
Rubber	**0.024**	**0.038**	**0.030**	**0.198**	**0.197**
Hides	**0.215**	**0.373**	**0.371**	**0.373**	**0.364**
Metals					
Aluminum	-0.020	**0.009**	**0.005**	**0.180**	**0.180**
Copper	**0.017**	**0.035**	**0.026**	**0.138**	**0.136**
Tin	**0.078**	**0.099**	**0.094**	**0.172**	**0.172**
Zinc	-0.010	**0.035**	**0.034**	**0.177**	**0.174**
Nickel	**0.064**	**0.113**	**0.101**	-0.055	-0.054
Lead	**0.003**	**0.011**	**0.007**	**0.030**	**0.023**
Uranium	-0.021	-0.153	-0.158	-0.146	-0.137

Notes: This table reports the difference of the RMSPE of the models to the RMSPE of the random walk model for the first period (pre-2004), minus the RMSPE ratio for the second period (post-2004). Values over zero, mark in bold in table, indicate that the predictive content of the model is enhance in the second period.

(1) Means the DFM without idiosyncratic component

(2) Means the DFM with idiosyncratic component

Appendix 4. Ratios of the RMSE of the large-scale and small-scale factor models over the RMSE of the AR model.

RMSPE Model/RMSPE AR.	Large-Scale DFM (1)		Large-Scale DFM (2)		Small-Scale DFM (1)		Small-Scale DFM (2)	
	pre-2004	post-2004	pre-2004	post-2004	pre-2004	post-2004	pre-2004	post-2004
Cereals								
Rice	1.023	1.149	1.152	1.024	1.929	1.874	1.932	1.882
Barley	1.164	1.144	1.154	1.168	1.457	1.637	1.458	1.637
Maiz	1.036	1.017	1.021	1.041	1.507	0.921	1.508	0.921
Wheat	1.032	1.001	1.002	1.033	1.034	1.001	1.034	1.000
Meet and seafood								
Beef	1.058	1.044	1.044	1.058	1.064	1.300	1.068	1.306
Lamb	0.946	1.301	1.302	0.945	1.032	1.353	1.034	1.350
Swine (pork)	1.004	0.990	0.990	1.004	0.454	0.417	0.455	0.421
Poultry (chicken)	1.244	1.357	1.357	1.245	4.908	7.140	4.912	7.143
Fish (salmon)	1.053	1.004	1.006	1.053	0.804	0.379	0.807	0.378
Shrimp	1.038	1.190	1.190	1.038	1.040	1.189	1.040	1.181
Beverages								
Cocoa beans	1.018	1.039	1.040	1.018	0.673	0.818	0.673	0.818
Coffee, Other Mild Arabicas,	1.002	1.015	1.019	1.002	0.886	0.769	0.891	0.770
Coffee, Robusta	1.004	0.999	1.006	1.003	0.745	0.947	0.743	0.950
Tea	0.999	1.041	1.042	0.999	1.002	1.041	1.001	1.039
Vegetable oils and protein meals								
Soybeans	1.052	1.044	1.049	1.054	1.152	0.693	1.154	0.695
Soybean Meal	1.046	1.035	1.037	1.048	1.162	0.541	1.166	0.545
Soybean Oil	1.023	1.041	1.053	1.025	0.986	0.905	0.985	0.905
Palm oil	1.013	1.009	1.016	1.016	0.622	0.577	0.619	0.575
Fishmeal	1.035	1.067	1.067	1.036	1.975	0.617	1.977	0.614
Sunflower Oil	1.031	1.007	1.015	1.032	0.756	0.756	0.753	0.753
Olive Oil	1.063	0.999	1.000	1.064	2.175	0.603	2.173	0.606
Groundnuts (peanuts)	1.147	0.870	0.870	1.147	1.922	0.433	1.920	0.436
Rapeseed oil, crude.	0.989	1.033	1.043	0.994	0.971	1.040	0.970	1.038
Sugar, bananas and orange								
Sugar, European import price	1.026	0.950	0.951	1.027	9.065	7.577	9.067	7.578
Sugar, Free Market	0.952	1.036	1.035	0.952	1.850	1.830	1.854	1.831
Sugar, U.S. import price	1.092	1.106	1.107	1.092	11.981	2.980	11.983	2.980
Bananas	0.992	0.986	0.991	0.994	0.903	3.176	0.913	3.175
Oranges	1.013	1.009	1.016	1.016	1.653	2.218	1.634	2.218
Agricultural raw materials								
Hard Logs	1.192	1.122	1.122	1.192	2.046	1.578	2.049	1.578
Soft Logs	1.192	1.124	1.123	1.191	1.210	0.838	1.201	0.839
Hard Sawnwood	1.023	1.011	1.013	1.023	2.740	2.830	2.743	2.829
Soft Sawnwood	1.157	0.956	0.956	1.157	0.702	1.304	0.703	1.299
Cotton	1.201	1.025	1.029	1.202	1.209	0.661	1.215	0.659

Wool, coarse	1.046	1.037	1.039	1.046	0.939	0.857	0.939	0.858
Wool, fine	1.032	1.074	1.079	1.033	0.793	0.934	0.795	0.935
Rubber	1.027	1.009	1.020	1.027	0.886	0.662	0.886	0.664
Hides	1.123	0.938	0.940	1.123	1.121	0.938	1.114	0.942
Metals								
Aluminum	1.006	0.968	0.973	1.006	1.099	0.841	1.099	0.842
Copper	1.064	1.043	1.055	1.065	0.992	0.913	0.993	0.915
Tin	1.034	1.010	1.017	1.034	0.764	0.581	0.764	0.581
Zinc	0.987	0.927	0.930	0.988	0.958	0.701	0.958	0.706
Nickel	1.077	1.022	1.037	1.078	0.544	0.651	0.545	0.651
Lead	0.988	0.977	0.984	0.989	0.719	0.679	0.715	0.686
Uranium	1.057	1.203	1.208	1.057	1.080	1.205	1.073	1.187

Notes: This table reports the ratio of the root mean square error of prediction of the models, to the root mean square error of prediction of the AR model, $RMSPE_{Model}/RMSPE_{rAR}$. Values smaller than one indicate that the model perform better than the AR.
(1) Means the DFM without idiosyncratic component
(2) Means the DFM with idiosyncratic component