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The role of global relative price changes in international comovement of inflation

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Abstract

In this paper we investigate the impact of global relative price changes on domestic inflation. We use a dynamic hierarchical factor model (DHFM) to decompose consumer basket products' inflation in a panel of countries into (i) a global factor, common to all price series and all countries, (ii) a price change shock at product group level, (iii) a price change shock at product subgroup level, and (iv) an idiosyncratic component. Using monthly data for 29 economies from 2003 to 2018 we find that product inflation rates demonstrate different sensitivity to common price shocks. For energy, some food and manufactured goods, global relative price changes may account for up to 49% of inflation variation which is quite high for this frequency and level of disaggregation. Moreover, common factors from the DHFM have significant explanatory power for overall CPI and its aggregate components across different countries.

Keywords: Dynamic hierarchical factor model, global inflation, relative prices, Russia

JEL classification: C38, E31, F42

1 Introduction

Recent research has found a significant and growing role of global factors in explaining national inflation dynamics. Ciccarelli and Mojon [5] find that 70% of the variance of national inflation rates in 22 OECD countries can be explained by a common factor, the phenomenon they refer to as 'global inflation'. It means that for the analysis of national inflation dynamics it is important not to overestimate domestic determinants, but also to consider global factors. For instance, international comovement of inflation can be caused by global prices for commodities, a global business cycle, a high importance of the US dollar. Therefore, 'global inflation' is determined as a common factor from dynamics of domestic inflation process in different countries. At the same time, there is an evidence that the US domestic inflation dynamics could be explained by changes in sector relative prices as shown in Reis and Watson [18]. In this paper we try to identify those global relative price changes using international price data in order to better understand domestic inflation developments that is important for monetary policy in order to achieve price stability.

There are many approaches to define a global component of inflation due to various methodologies, different data and countries coverage, inflation measures, and level of disaggregation (see Ha et al. [10] for a summary of these studies). The main contribution of this paper is the estimation of global price component of international comovement of prices using a model that is well suited for the analysis of disaggregated data. That is, we try to provide additional insights for the question: 'to what extent global price changes at sectoral level affect domestic CPI?' We achieve this by using dynamic hierarchical factor model of Moench et al. [13] to estimate the relative price factors in inflation dynamics across 29 countries (mainly OECD) since the beginning of the 2000-s. The hierarchical structure of our model allows us to account for covariations that are not sufficiently pervasive to be treated as common factors, and, thus, separate effects of price changes at different sectoral levels. Moreover, we create a database for disaggregated consumer price data for Russia, the US, and Brazil and match it with harmonised index of consumer prices for OECD countries.

Our findings confirm previous results on the importance of global energy and food prices on short run dynamics of national inflation rates. We also find that global factors might be concentrated not only in energy and food markets. There is a large share of variance explained for manufactured goods by common factors. Moreover, we find a good interpretation for a global factor that traces euro area business cycle turning points and for a common factor from 'Energy' subblock that is very well aligned with oil prices.

In addition, we also analyse the role of the US dollar in a global inflation. We find a positive correlation between share of imports invoiced in the US dollar and share of overall CPI (excluding energy) variance explained by a global factor for a homogenous group of countries in the euro zone. This indirectly confirms the dominance of the US dollar in a global trade and inflation (Boz et al. [4], Egorov and Mukhin [7]).

In accordance with our calculations, domestic prices for some food and non-food products in Russia may be affected by global factors. However, their total share in overall CPI is not too high. Having said this, we also find out that global factors are of a little value for short-term Russia CPI forecasting. It may be caused by a faster pass of common price changes to local inflation.

1.1 Related literature

The paper of Cicarelli and Mojon [5] argued for a very large role for the global factor in determining domestic inflation rates. In their sample of annual CPI for 22 OECD countries a common factor accounted for nearly 70% of total variance. This impressive result stimulated discussion of the importance of 'global inflation' and its sources (e.g., Altansukh et al. [1], Auer et al. [2], Mumtaz and Surico [15], Neely and Rapach [16]). Monacelli and Sala [14] in their study of 948 CPI products' dynamics in the four largest OECD countries (United States, Germany, France, and United Kingdom) found that one common factor explains between 15% and 30% of the variance of consumer prices. Their results illustrate importance of data frequency and, particularly, aggregation for the final conclusions. The authors offer to view their estimates as a lower bound for the contribution of global factor to domestic inflation. These papers analyse data only for OECD countries. In our research we add some non-OECD countries to analysis and confirm the robustness of global inflation, as our global factors may explain up to 49% of inflation variation.

Several authors apply dynamic hierarchical factor model developed by Moench et al. [13] to study inflation across countries and regions. Forster and Tillmann [9] use quarterly data for 3 CPI baskets (energy, food, the remaining items) of 22 OECD countries and show that for the basket net of food and energy, the global and the basket-specific factor account for less than 20% of inflation variance. They show that common factor has a potential to explain only energy price inflation. Our results are in line with this paper and show a large share of variance explained by energy common factors (35%). A recent work of Parker [17] analyses a large data set covering CPI basket indices (the author also includes housing into analysis) for more than 200 countries. The analysis shows that common factors explain a large share of the variance in energy, but less so - for food, and almost none - for housing and other items. Using disaggregated price data for various product categories we define a share of explained variance for different goods more exactly. We also find that not only energy and food markets, but also some manufactured goods may depend on global inflation. At last, Deryugina et al. [6] apply transformed version of DHFM to investigate importance of regional and product factors in inflation series with around 40 product-level categories for 79 regions of Russia. They find the former to be almost insignificant, while the latter is shown to explain around 20% of total variance. In a hierarchical structure of our model we do not extract country-specific factor. We analyse only comovement of prices for different products across all countries in the sample.

Understanding international factors behind price changes may help to explain the behavior of macroeconomic parameters, such as inflation-output tradeoff. Boivin et al. [3] show that disaggregated prices seem to be less responsible to macroeconomic disturbances, than to sector-specific shocks. Mackowiak et al. [12] use factor analysis of disaggregated data to choose from several models of price setting. Finally, Reis and Watson [18] analyse disaggregated price data in the US to understand the importance of monetary and relative price shocks for inflation. With the use of a dynamic factor model, they separate product price inflation into three components: 'pure inflation', relative price and idiosyncratic components. They find that the latter accounts for roughly 70 percent of its variability, while the aggregate inflation variance is mostly driven by changes in sectoral relative price changes.

The remainder of this paper is organized as follows. Section 2 describes the data set. In Section 3, a hierarchical model is described and specified. In Section 4, this model is used to estimate factors behind inflation dynamics in 29 countries at disaggregated level. Section 5 concludes.

2 Data

We collected a cross section data set for monthly harmonised index of consumer prices (HICP) for 26 OECD countries from Federal Reserve Economic Database (FRED) for the period January, 2003 - June, 2018. We also added the national CPI for Russia, the US, and Brazil matched with the classification of individual consumption by purpose (COICOP). The data set lists 47 price series for product categories that correspond to 4-digit codes of COICOP. That is, a typical series in our data set is: COICOP 01.1.7 'Vegetables' for the UK, or COICOP 12.3.1 'Jewellery, clocks and watches' for Turkey.

We apply several data filtering and transformation techniques. We exclude countries with population less than 1 million people: our model (see next section) does not have any kind of weighting scheme for country-product price series, so we try to avoid possible statistical anomalies associated with small economies statistics. Next, we exclude some of the several countries' product categories for which data were not available over the time interval from January, 2003 to June, 2018. Therefore, inside each block and subblock there could be data for slightly different set of countries. We transform data into month-over-month growth rates and standardize it to have mean zero and standard deviation of unity for each series. All time series are seasonally adjusted with X-13 ARIMA-SEATS procedure.

As our model requires stationarity of time series, we test the presence of a unit root using Augmented Dickey-Fuller (hereafter ADF) test with several specifications. According to the obtained results (Table 6 of the Appendix), most of time series are stationary for product categories across countries at 5% or 1% significance level. There are only few series showing persistent dynamics across countries.

The complete data set includes 1194 series spanning from January, 2003 to June, 2018. The final list of countries that we used in our analysis is presented in the Table 4 of the Appendix.

Further in our analysis, we use aggregated data for components of CPI from the Eurostat. It is overall CPI, food CPI, energy CPI, non-energy industrial goods CPI and core CPI for all countries in the sample and for the euro area as a whole.

3 Model

3.1 Dynamic Hierarchical Factor Model

In order to find out what the contribution of relative price factor to national product price movements is, we have estimated a dynamic hierarchical factor model (hereafter DHFM). A detailed description of the DHFM can be found in the original work of Moench et al. [13]. Our description also closely follows their original text, using the same notations.

We assume that the dynamics of the data Z_{bsit} (particularly, CPI time series i of $s-th$ subblock of $b-th$ block at the time t) is influenced by 4 different components:

1. F_t, which denotes the set of global, common to all blocks factors,
2. G_{bt}, which denotes the set of block-level factors, common to all subblocks in that block,
3. H_{bst}, which denotes the set of subblock-level factors, common to all series in any subblock,
4. e_{Zbsit}, which denotes the idiosyncratic price component for each series.

The so called 4-level 'pyramidal' DHFM structure can be represented in the following way:

$$Z_{bsit} = \Lambda_{H.bsi}(L)H_{bst} + e_{Zbsit} \quad \Psi_{Z.bsi}(L)e_{Zbsit} = \epsilon_{Zbsit}$$

$$H_{bst} = \Lambda_{G.bs}(L)G_{bt} + e_{Hbst} \quad \Psi_{H.bs}(L)e_{Hbst} = \epsilon_{Hbst}$$

$$G_{bt} = \Lambda_{F.b}(L)F_t + e_{Gbt} \quad \Psi_{G.b}(L)e_{Gbt} = \epsilon_{Gbt}$$

$$\Psi_{F.k}(L)F_{kt} = \epsilon_{Fkt}$$

where, $b = [1, ..., N_b]$ - the number of blocks, $s = [1, ..., N_s]$ - the (possibly different) number of subblocks in each block, $i = [1, ..., N_i]$ - the number of individual time series, $t = [1, ..., T]$ - the time index, $\Lambda_{H.bsi}$, $\Lambda_{G.bs}$, $\Lambda_{F.b}$ are the corresponding set of constant factor loadings, $k = [1, ..., K_F]$ - the number of common factors.

The model allows compact representation of the data. Particularly, any $i-th$ series in the $b-th$ block and $s-th$ subblock can be decomposed into idiosyncratic shock (e_{Zbsit}) plus common component, influencing all series in that subblock ($\Lambda_{H.bsi}(L)H_{bst}$). In its turn, every subblock-level factor H_{bst} can be decomposed into subblock-specific shock (e_{Hbst}), and the common component ($\Lambda_{G.bs}(L)G_{bt}$). Every block-specific factor can be decomposed into block-specific shock (e_{Gbt}) and common factor ($\Lambda_{F.b}(L)F_t$). Finally, global factor F_t is assumed to follow a simple AR(1) process and defines the dynamic essence of the model.

We stress that e_{Gbt} and e_{Hbst} represent relative price shocks common to the block and subblock levels, respectively. In order to match persistence assumptions, the equations for the AR models innovation terms are set as:

$$\epsilon_{Zbsit} \sim \mathcal{N}(0, \sigma^2_{Zbsi})$$
$$\epsilon_{Hbst} \sim \mathcal{N}(0, \sigma^2_{Hbs})$$
$$\epsilon_{Gbt} \sim \mathcal{N}(0, \sigma^2_{Gb})$$
$$\epsilon_{Ft} \sim \mathcal{N}(0, \sigma^2_{F})$$

In order to estimate the posterior distribution of the parameters of interest we apply Markov Chain Monte Carlo (MCMC) iterative techniques together with the Kalman Filter. The estimating procedure in details has been described in Moench et al. [13], and we replicate it with minor changes[1].

[1]The estimation of the model here is made with the help of the MATLAB code available on Serena Ng's website.

3.2 Specification

Here we provide a detailed structure of the estimated model. We divide all the data into 2 blocks that we call 'product groups', which are intended to represent the first level classification of consumption. We further subdivide blocks into 4 subblocks each, which we call 'product categories', represented in the Table 1.

Table 1: Block and subblock structure of the data

Block	**Subblock**	**# of series**
Food	Meat and fish	2
	Bread, milk, oils	3
	Vegetables and fruit	2
	Others	4
Manufactured goods	Durables	10
	Semi- and non-durables	16
	Alcohol and tobacco	4
	Energy	6

Note: Inside each subblock, there are COICOP 4-digit product category series that were available for all 29 countries listed in Table 4 of the Appendix.

The core idea is that we try to exploit differences in price determination for these product categories by using prior information about the structure of the data. This helps us to separate effect of a global relative price change, not only at the product group, but also at the product category level. Moench et al. [13] note that '...if the [subblock] and [block] variations are not properly modeled, they would either appear as weak common factors, or as idiosyncratic errors that would be cross-correlated amongst series in the same [block]' (p. 1). Thus, modelling these block and subblock variations may allow us to better understand common shocks in price dynamics by separating them from global and idiosyncratic shocks.

4 Results

In this section we provide two versions of the DHFM model: with blocks only (3 level - Model B) and with blocks and subblocks (4 level - Model BS). Comparing the results from them would allow us to evaluate the importance of using hierarchical representation of CPI data. Block share of variation explained by the Model B represents the importance of developments in relative prices at product group level. In Model BS, block *and* subblock share of variation explained by the model represent the sectoral relative price components of price dynamics.

Further, we do several robustness checks by using different composition of the countries included in the sample. This allows us to control for possible currency effects on the factors' estimates.

4.1 Variance decomposition

Estimation of Model B[2] illustrates importance of relative price component at product group level for food and manufactured goods (Table 2). We find that there is no considerable difference between these blocks regarding common relative price factor. Moreover, idiosyncratic component tends to dominate in both cases. At the same time, food products show stronger comovement to global price movements rather than manufactured products.

Somewhat 'low' share of the variation explained at the block level should not confuse reader. In the original paper on DHFM, Moench et al. [13] illustrate their model with a factor analysis of real economic activity in the US. They use data with *monthly* frequency, as we do. The authors get a common factor that closely tracks the US business cycle chronology of NBER (p. 9), yet it explains from 1 (!) to 16% of variation of the original series, with median closer to 3% (p. 14). The same is true for block and subblock shocks, as the average share of idiosyncratic variance is around 65-90%. This result holds for the data that are a priori closely interconnected (different sectors of

[2]Each model uses only one common factor at each global and block stages.

Table 2: Variance decomposition of DHF Model with Blocks, median share of explained variance (in percents)

Block	**Global**	**Product group**	**Idiosyncratic**
Food	15.8	15.6	68.6
	[14.7,17.0]	[14.5,16.7]	[66.3,70.6]
Manufactured goods	0.1	15.3	84.6
	[0.0,0.3]	[14.2,16.7]	[83.3,85.6]

Note: Inside each block, there are COICOP 4-digit product category series that were available for up to 29 countries listed in Table 4 of the Appendix (depending on data availability). Figures in squared brackets represent 10% and 90% percentile points of distribution of a share explained by a factor inside a given block across different product category for different countries.

one country economy), so it is questionable whether one could get high share of explained variance at this level of disaggregation as we have.

Estimation of the model *with* subblock hierarchy, Model BS, allows us to further analyse drivers behind product price dynamics. First, now we can separate block and subblock factors, which have different strength depending on the product category (Table 3). Energy subblock variance decomposition share (35%) confirms the importance of global component in determining local energy products price dynamics. Food product categories demonstrate different sensitivity to common relative price shocks (see Table 3, rows 1-4). Interestingly, our model shows that several subblocks demonstrate large share of variance connected to global component: in 'Bread, milk, oils' (36%) and 'Vegetables and fruit' (22%). The former subblock median share of explained variance is comparable to that of energy products, but is estimated less precisely.

Paradoxically, durable and other manufactured goods (see Table 3, rows 5-6) have a large share of variance explained by common factors. They are not estimated as tightly as other factors (numbers in square brackets), but their magnitude proves that there is strong connection between price dynamics in many goods across countries, not only in commodities such as food and petroleum. In addition, alcohol and tobacco have a low share of variance connected to global component due to country-specific taxation and pricing policies.

Table 3: Variance decomposition of DHF Model with Blocks and Subblocks, median share of explained variance (in percents)

Block	**Subblock**	**Global**	**Product group**	**Product category**	**Idiosyncratic**
Food	Meat and fish	7.4	1.9	1.7	89.0
		[6.1,8.8]	[1.6,2.2]	[1.5,2.0]	[87.6,90.4]
	Bread, milk, oils	0.8	0.2	**35.5**	63.4
		[0.1,2.0]	[0.0,0.5]	[30.3,41.0]	[58.7,67.9]
	Vegetables and fruit	0.4	0.1	**21.8**	77.8
		[0.0,0.8]	[0.0,0.2]	[20.2,23.3]	[76.2,79.3]
	Others	0.7	0.2	8.7	90.4
		[0.1,1.5]	[0.0,0.4]	[7.0,10.7]	[88.9,91.8]
Manufactured goods	Durables	0.3	6.2	**25.8**	67.8
		[0.0,0.7]	[4.7,7.8]	[21.8,30.2]	[63.5,71.6]
	Semi- and non-durables	0.0	0.1	**49.1**	50.8
		[0.0,0.0]	[0.0,0.3]	[42.1,57.4]	[42.6,57.7]
	Alcohol and tobacco	0.0	0.2	6.5	93.3
		[0.0,0.0]	[0.0,0.6]	[5.5,7.4]	[92.4,94.2]
	Energy	0.0	0.8	**34.5**	64.7
		[0.0,0.1]	[0.1,2.0]	[32.9,35.9]	[63.6,65.9]

Note: Inside each subblock, there are COICOP 4-digit product category series that were available for up to 29 countries listed in Table 4 of the Appendix (depending on data availability). Figures in squared brackets represent 10% and 90% percentile points of distribution of a share explained by a factor inside a given subblock across different product category for different countries. Notable changes compared to Table 2 are in bold.

Secondly, introduction of additional level of hierarchy allows us to estimate common factors more precisely. Idiosyncratic component at the level of subgroups (last column in Table 3) is reduced substantially for some product categories compared to the corresponding share in the Model B (last column in Table 2). That is, explicitly modelling subblock variation presumably helps us not to confound shocks at this level with block level or idiosyncratic shocks.

Overall, these results suggest that product inflation dynamics and, hence, general inflation across countries may be driven by relative price shocks at sectoral level. We find that the explanatory power of DHFM factors is comparable to corresponding values for real economic activity indicators (see above). There is still large share of idiosyncratic variance in product price dynamics, but it may be well explained by intraregional variation in economic conditions, sales and promotions, or measurement errors.

This decomposition of price dynamics may be important for explaining and forecasting domestic inflation. COICOP 01 product group 'Food and non-alcoholic beverages' comprise a significant share of consumer basket. Even for middle income group countries, such as Russia, Spain, and Turkey, food share in total CPI fluctuates around 20-30%, while energy adds another 10% (Eurostat). Explaining product-specific variance for such a large share of consumer basket may help policy-makers make more timely and accurate decisions. In the presence of near-zero inflation, this possibility seems to be even more attractive.

4.2 Interpretation of factors

In this subsection we show that some dynamic factors have nice interpretation. In order to show this, we compare their dynamics with those of different market prices, such as the Food and Agriculture Organization (FAO) Food Price Indices and oil prices (Brent and Urals).

First, our findings illustrate that some of the dynamic factors from the DHF Model (with subblocks) are closely related to oil prices, while other factors are harder to interpret. FAO Food Price Index and its components (cereals, meat, dairy, oils and sugar) show quite low degree of comovement with factors from corresponding subblocks ($R^2 < 0.2$). At the same time, oil prices are very well aligned with factors from 'Energy' subblock with R^2 slightly greater than 0.6 (Figure 1).

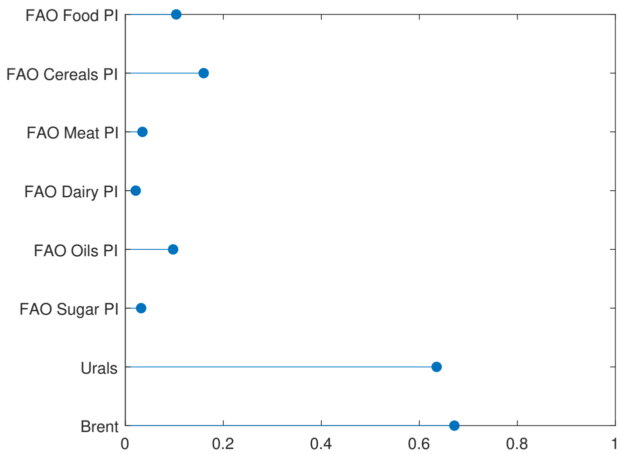

Figure 1: R^2 for the regressions with market prices as an explained variable and subblock-level factors H as regressors

We also observe comparable results in a comovement between these factors and other commodity price data from the International Monetary Fund (IMF) (Figure 7 of the Appendix). In addition, we plot 12-month moving average for estimated food and energy factors against the market price indices from the IMF (Figure 2, and Figure 3). Our global energy and food factors track international prices very well with a time lag.

Next, we find that global and block-level factors (apart from 'Food' block) do not have such interpretation. In fact, it is subblock-level factors H that are correlated either with market prices or aggregate components of CPI. Statistically, inclusion of global F or block-level G factors does not improve the results significantly, and hence are difficult to interpret in terms of observable economic variables.

An important exception is that global factor traces euro area business cycle turning points of the 2000-s (Figure 4). Global factors, estimated from month-over-month price dynamics, reaches

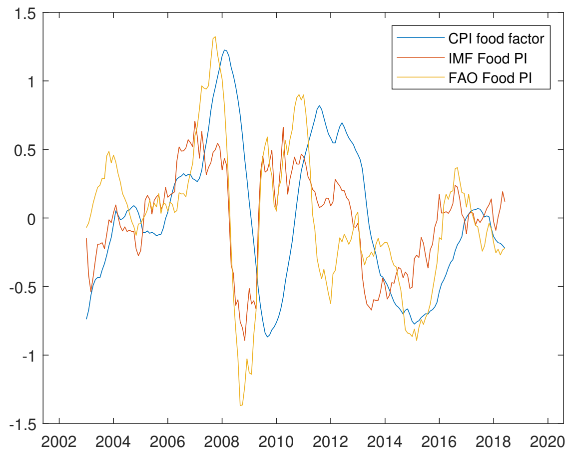

Figure 2: 12-month moving average for the posterior mean of CPI food factor G from the Model BS and food price indices

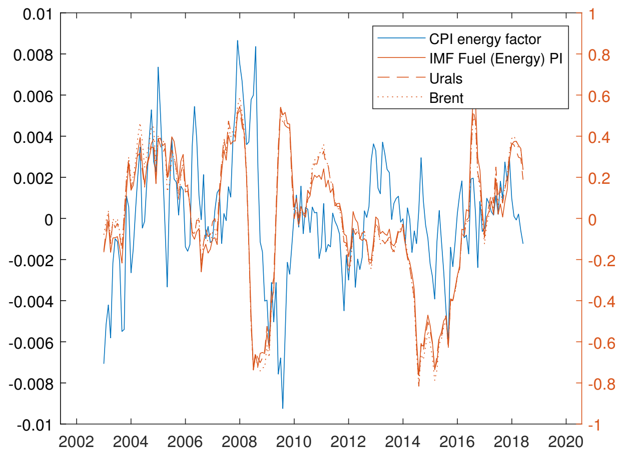

Figure 3: 12-month moving average for the posterior mean of CPI energy factor H from the Model BS, oil prices and energy price index

its local peaks in October, 2007, and April, 2011, which roughly corresponds to euro area economy peaks (CEPR methodology[3]). Local minima are October, 2009, and June, 2015, - thus, only the former coincides with cycle's estimated through. So, there is some evidence that global factor may be interpreted as a measure of global inflation pressure for the countries included in the sample and, thus, is interesting on its own.

4.3 Using factors to explain and predict country inflation dynamics

In order to understand whether common factors' dynamics could be useful for explaining country level CPI, we look at the correlation between dynamic factors estimates from the 4-level model and aggregate CPI components. Namely, we use overall CPI, food CPI, energy CPI, and non-food CPI excluding energy as LHS variables in the regression on dynamic factors. We also compare results from this analysis to the regressions with commodities' market prices as explanatory variables.

Our results suggest that common factors are important drivers of local inflation. First, overall CPI dynamics is in part explained by several factors, including global factor F, 2 block-level factors G (1 for each block) and 2 subblock-level factors H which correspond to common factors in energy-related goods, such as petroleum. Moreover, the addition of other subblock-level factors H for food and manufactured goods further rises explanatory power of these factors. On average, all global factors explain around 42% of CPI variance at monthly frequency (Figure 5, top left).

Secondly, further decomposition of CPI shows us that this result is mostly driven by comovement in energy and food prices. The former category is correlated with common factors H with an

[3]The chronology of euro area business cycles is available on the CEPR's website, https://cepr.org/content/euro-area-business-cycle-dating-committee.

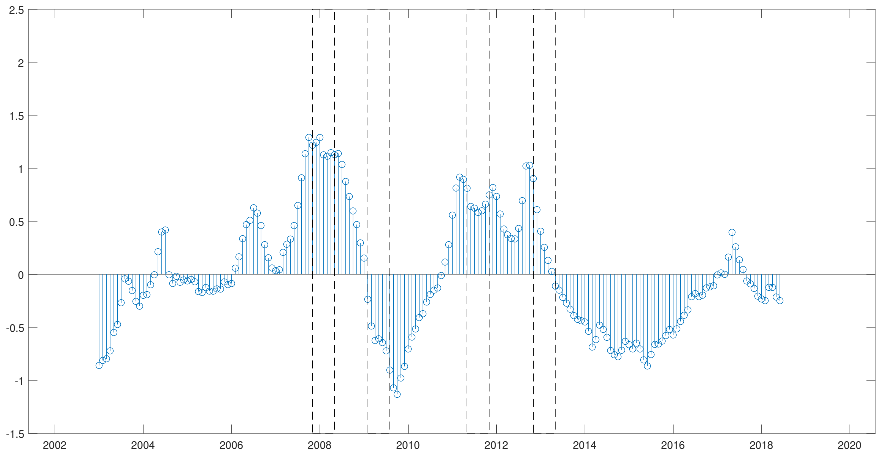

Figure 4: The posterior mean of dynamic global factor F from the Model BS. Dashed lines correspond to peaks (1 and 3 from the left) and troughs (2 and 4) of the euro area business cycles

average R^2 of 0.6 across euro area countries and 0.4 - in the rest of the sample (Figure 5, bottom right). The latter demonstrates lower degree of comovement, yet R^2 of 0.3 is still a non-negligible result (Figure 5, top right). We also analyse how factors explain core inflation. There are no significant improvements in terms of R^2 for euro area countries and others in general. However, the result for Russia becomes better, when we regress modified core inflation indicator excluding the most volatile components (instead of Rosstat's core inflation) on DHFM factors.

Lastly, there is only marginal effect of common factor movements on the dynamics of other manufactured goods price index (Figure 5, bottom left), despite high explained share of variance at 4-digit COICOP level. For example, this may happen partly due to some noise in data for Romania that has an anomalous peak in R^2 for this aggregated product level.

Market prices, mentioned above, perform worse as regressors: their dynamics explain only a little share of variance in aggregate CPI components.

There is a number of possible reasons of the different explanatory power of global factors for local CPIs. First, we confirm the results from previous studies that countries with common exchange rate and monetary policy (the euro area) tend to have a higher share of variance explained compared to other OECD countries with lower income. Secondly, Figure 5 (bottom right) illustrates different comovement between energy inflation rates and global energy factors. It is reasonable to expect the strong relationship for energy prices with global inflation in oil exporting countries with liberalized retail fuel market as, for instance, in the US. In contrast, the government regulation of energy prices in Russia and Brazil is stronger, therefore they are less reliant on global oil prices. Paradoxically, Norway has a low degree of comovement with energy factors, though, the retail price of gasoline is highly correlated with world oil prices. A marginal role of global inflation for Norway also were identified in Kearns [11].

We also look at the correlation between factors estimates from the 4-level model and disaggregated CPI components for Russia (Figure 8 of the Appendix). We find a low dependence of domestic food prices in Russia on global food factors except for such products as 'Milk, cheese and eggs', and 'Oils and fats' (R^2 is around $0.5 - 0.6$, total weight in the consumer basket - 6%). Some categories from non-food products such as 'Garments', 'Household utensils', and 'Other personal effects' demonstrate slightly weaker degree of comovement with R^2 of 0.4 (total weight in the consumer basket - 7%). However, our dynamic factors do not predict much for disaggregate level of inflation in Russia and do not perform well when it comes to forecasting. Our calculations show that there is only slight and insignificant improvement when compared to simple AR models.

Finally, we analyse the role of the US dollar in a global inflation. The US dollar is a dominant currency for global trade, and most international prices are sticky in US dollars (see, e.g., Egorov and Mukhin [7]). The stronger US dollar raises prices of imported goods in local currency. It may increase inflation directly or through cost spike of all firms that use imported goods in their production. Therefore, the US dollar exchange rate should trace global prices very well.

In order to confirm this statement we use the share of overall CPI (excluding energy) variance explained by a global factor F for majority of countries in the sample, and the share of imports

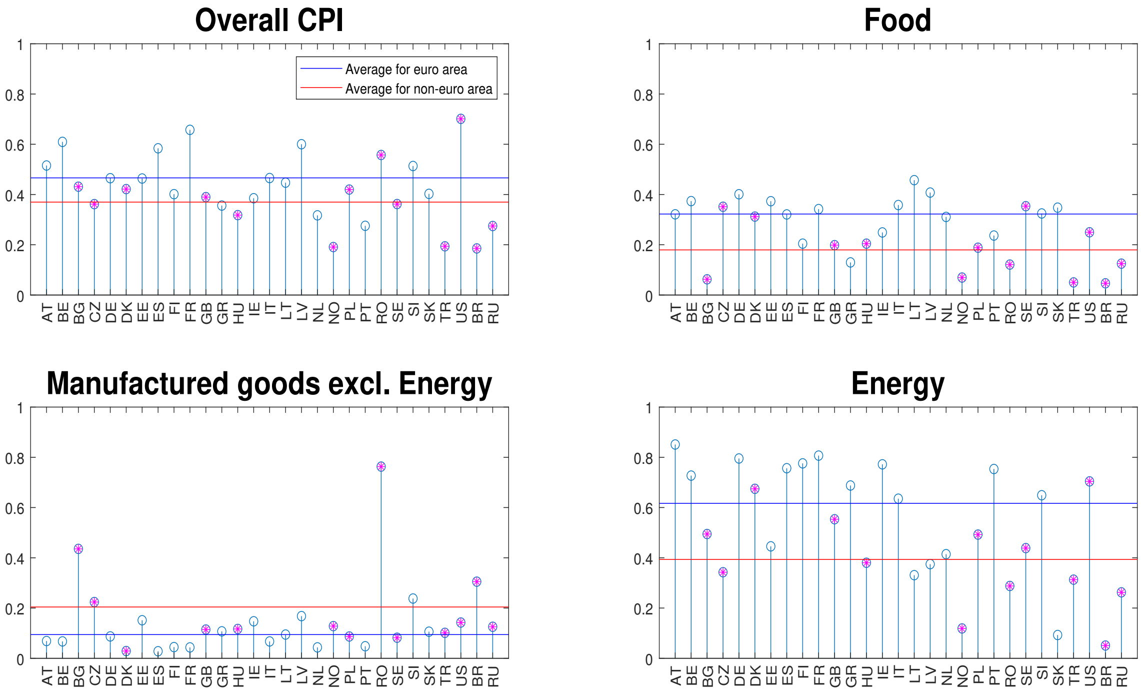

Figure 5: R^2 for the regressions with aggregate CPI component as an explained variable and corresponding factors as regressors

invoiced in the US dollar. A source for the latter data is Boz et al. [4][4].

We find a positive correlation between the values of indicators for a homogenous group of countries in the euro zone: R^2 is equal to 0.6 (Figure 6). This indirectly confirms the dominance of the US dollar in a global trade and inflation. However, the connection for non-euro area countries is weaker. This might indicate that the large dependence of imports on the US dollar does not influence a strong dependence of inflation. This may be attributed to the relative importance of a domestic market compared to imports in these countries.

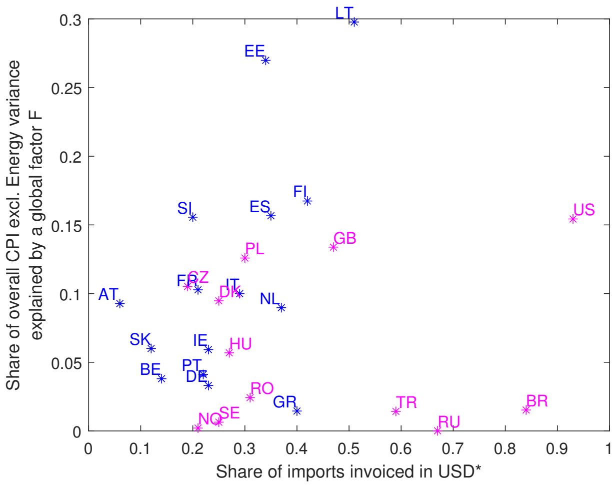

Figure 6: Indirect dominant currency pricing test. Euro area countries are highlighted in blue, others - in magenta. *Sources: Boz et al. [4], the Bank of Russia.

[4]The data for Russia are from the Bank of Russia web site, http://www.cbr.ru/eng/statistics/macro$_{i}tm/svs/$. It is important to take into account that the data for Russia include not only imported goods, but also services, that inflates the estimate.

4.4 Robustness checks

There are circumstances under which our model could be misspecified. First, an issue that arises when using international price data is exchange rate fluctuations and its pass-through into domestic prices. From the DHFM perspective, price changes associated with a country's exchange rate movements are not related to any of the factors inside the block structure and, thus, should be identified as idiosyncratic component. However, such changes may result in worse model fit. Secondly, sample composition itself could lead to different factors' estimates. In our case, it is non-EU market countries, such as Russia, which may in fact have separate unobservable factor dynamics not associated with common developments in the EU.

In order to check robustness of our results to these possible problems, we re-estimated the model using a sample which included only 14 EU members[5], 3 of which used local currency and others - euro as a national currency at least from January, 2003 (our sample start date). The results we get suggest that the key common factors are robustly estimated: single global factor, one product group factor and factors corresponding to 'Meat and fish', 'Bread, milk, oils', 'Others' and 'Energy' subblocks show very high correlation (~ 0.9) with factors estimated from the full sample. These factors demonstrate the highest explanatory power for overall CPI and its aggregated components. At the same time, other common factors (mainly, for manufactured goods apart from energy) showed very different dynamics and low correlation with the full sample estimates. This suggests that it could be indeed better not to include some countries as this would make the sample heterogeneous.

We also re-estimated the model adding in a sample the data for China starting from January, 2005. The addition of a new country did not change strongly results of the estimation because of equal weights for each country in the sample [6]. Nonetheless, we get almost the same results in a median share of explained variance for all product subblocks apart from 'Bread, milk, oils': the share increased from 36% to 49% (Table 7 of the Appendix). In addition, our estimates demonstrates a weak comovement of a local inflation in China with global factors (Figure 9 of the Appendix). This may be caused by relatively closed China's economy. The case of China deserves a separate research. For instance, Eickmeier and Kühnlenz[8] study the significance of China in global inflation dynamics analysing their contribution and the transmission mechanism into world price dynamics.

5 Conclusions

This paper uses the data set of consumer prices at the level of 4-digit COICOP classification for 29 countries for the period 2003–2018 to examine the importance of sectoral price shocks in international comovement of prices. Application of dynamic hierarchical factor model of Moench et al. [13] allows us to separate effects at sectoral level and examine importance of these price changes for domestic inflation dynamics.

We confirm previous findings on the importance of global energy and food price dynamics. Factors at the corresponding subblock levels are correlated both with aggregate measures of energy and food prices and with individual price series at monthly frequency. On average, 5 common factors explain around 40% of overall CPI variance for all countries in the sample and 30% for Russia.

We also find that for manufactured goods common price shocks drive large share of their variance. That could have meant that channels through which 'global inflation' operates might be concentrated not only in energy and food markets. There is a strong common tendency for prices to change simultaneously across different countries, therefore, creating short-term comovement of inflation rates. However, this relation does not hold for aggregate CPI components (products excluding food and energy) and we explain this by instability of the estimates for these factors.

In addition, despite the fact that global factor is weakly correlated with CPI it traces euro area business cycle turning points, and may be interpreted as a measure of global inflation pressure for the countries under consideration.

[5] We consider Belgium, France, Germany, Italy, Netherlands, Denmark, Ireland, United Kingdom, Greece, Portugal, Spain, Austria, Finland, Sweden.

[6] We do not include China in our initial analysis due to lack of data: short sample size, and small number of consumer product price series. Moreover, the National Bureau of Statistics in China does not reveal the weights for categories in the CPI basket.

We find that domestic prices for some food and non-food products in Russia might depend on global inflation. However, their total share in overall CPI is not too high. Having said this, we do not find evidence that common factor dynamics help predict CPI dynamics in Russia.

We indirectly confirm that the US dollar drives a global component of inflation due to a dominant currency pricing. This holds for a homogenous group of countries in the euro zone. For other group of countries the connection is weaker. This may be attributed to the importance of a domestic market rather than imports.

This paper would be extended in several directions. Firstly, our further research could be concentrated on testing predictive ability of common price factors for forecasting domestic inflation in Russia using more complicated models. Secondly, future research could aim to analyse the transmission mechanism of global inflation into domestic inflation in Russia.

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6 Appendix

Table 4: Final list of countries included in the analysis (with population more than 1 million people)

Country	**Abbreviation**
Austria	AT
Belgium	BE
Bulgaria	BG
Brazil	BR
Czech	CZ
Germany	DE
Denmark	DK
Estonia	EE
Spain	ES
Finland	FI
France	FR
Great Britain	GB
Greece	GR
Hungary	HU
Ireland	IE
Italy	IT
Lithuania	LT
Latvia	LV
Netherlands	NL
Norway	NO
Poland	PL
Portugal	PT
Romania	RO
Russia	RU
Sweden	SE
Slovenia	SI
Slovakia	SK
Turkey	TR
The US	US

Table 5: Mean and standard deviation by product group

COICOP classification	**Mean (%, m-o-m)**	**SD (p.p.)**
01.1.1 - Bread and cereals	0.27	0.75
01.1.2 - Meat	0.21	0.71
01.1.3 - Fish and seafood	0.28	0.96
01.1.4 - Milk, cheese and eggs	0.26	0.95
01.1.5 - Oils and fats	0.31	1.43
01.1.6 - Fruit	0.26	2.34
01.1.7 - Vegetables	0.27	3.06
01.1.8 - Sugar, jam, honey, chocolate and confectionery	0.21	0.91
01.1.9 - Food products n.e.c.	0.19	0.56
01.2.1 - Coffee, tea and cocoa	0.25	1.17
01.2.2 - Mineral waters, soft drinks, fruit and vegetable juices	0.19	0.73
02.1.1 - Spirits	0.21	0.89
02.1.2 - Wine	0.20	0.66
02.1.3 - Beer	0.25	0.96
02.2.0 - Tobacco	0.63	1.19
03.1.1 - Clothing materials	0.17	1.06
03.1.2 - Garments	0.02	0.58
03.1.3 - Other articles of clothing and clothing accessories	0.08	0.86
04.3.1 - Materials for the maintenance and repair of the dwelling	0.20	0.51
04.5.1 - Electricity	0.38	2.16
04.5.2 - Gas	0.34	2.27
04.5.3 - Liquid fuels	0.40	4.09
04.5.4 - Solid fuels	0.39	1.15
04.5.5 - Heat energy	0.33	2.10
05.1.1 - Furniture and furnishings	0.10	0.51
05.1.2 - Carpets and other floor coverings	0.08	0.93
05.2.0 - Household textiles	0.06	0.67
05.3.1 - Major household appliances whether electric or not	-0.03	0.51
05.4.0 - Glassware, tableware and household utensils	0.12	0.60
05.6.1 - Non-durable household goods	0.10	0.54
06.1.1 - Pharmaceutical products	0.15	1.05
06.1.2 - Other medical products	0.15	0.68
07.1.1 - Motor cars	-0.01	0.58
07.1.2 - Motor cycles	0.09	0.70
07.2.1 - Spare parts and accessories for personal transport equipment	0.13	0.47
07.2.2 - Fuels and lubricants for personal transport equipment	0.34	2.85
08.2.0 - Telephone and telefax equipment	-0.84	3.28
09.1.1 - Equipment for recording and reproduction of sound&picture	-0.59	0.90
09.1.2 - Photographic and cinematographic equipment	-0.63	1.18
09.2.1 - Major durables for outdoor recreation	0.11	0.59
09.3.1 - Games, toys and hobbies	-0.02	0.79
09.3.2 - Equipment for sport, camping and open-air recreation	0.00	0.80
09.3.3 - Gardens, plants and flowers	0.14	1.01
09.5.3 - Miscellaneous printed matter	0.17	0.51
12.1.2 - Electric appliances for personal care	0.07	0.42
12.3.1 - Jewellery, clocks and watches	0.41	0.95
12.3.2 - Other personal effects	0.09	0.51

Note: For every product group mean and standard deviation were calculated from m-o-m change series. The mean values were computed as a mean across all countries and all time periods. The standard deviation values were computed as a mean of standard deviations for each country.

Table 6: Results for unit root testing for different product categories across all countries, numbers correspond to the number of countries that passed the corresponding test

COICOP 4-digit classification	Number of countries	$ADF_{5\%,1lag}$	$ADF_{5\%,2lag}$	$ADF_{1\%,1lag}$	$ADF_{1\%,2lag}$
01.1.1 - Bread and cereals	29	29	29	29	29
01.1.2 - Meat	29	29	29	28	28
01.1.3 - Fish and seafood	29	29	28	27	27
01.1.4 - Milk, cheese and eggs	29	29	29	29	29
01.1.5 - Oils and fats	29	29	29	29	29
01.1.6 - Fruit	29	29	29	29	29
01.1.7 - Vegetables	29	29	29	29	29
01.1.8 - Sugar, jam, honey, chocolate	29	29	29	28	28
01.1.9 - Food products n.e.c.	28	28	28	27	26
01.2.1 - Coffee, tea and cocoa	29	29	29	28	28
01.2.2 - Mineral waters, soft drinks, juices	29	29	28	28	27
02.1.1 - Spirits	24	24	24	24	24
02.1.2 - Wine	27	27	27	26	25
02.1.3 - Beer	29	28	28	28	28
02.2.0 - Tobacco	15	14	14	14	14
03.1.1 - Clothing materials	16	16	16	16	15
03.1.2 - Garments	27	26	25	26	24
03.1.3 - Other articles of clothing	24	24	24	23	23
04.3.1 - Materials for the maintenance dwelling	27	27	27	27	24
04.5.1 - Electricity	8	8	8	8	8
04.5.2 - Gas	19	19	19	19	19
04.5.3 - Liquid fuels	18	18	18	18	18
04.5.4 - Solid fuels	23	23	23	23	22
04.5.5 - Heat energy	10	9	9	9	8
05.1.1 - Furniture and furnishings	29	29	29	29	28
05.1.2 - Carpets and other floor coverings	29	29	29	29	29
05.2.0 - Household textiles	27	26	26	26	25
05.3.1 - Major household appliances	29	27	28	27	26
05.4.0 - Glassware, tableware and household utensils	27	25	25	24	23
05.6.1 - Non-durable household goods	29	28	27	26	24
06.1.1 - Pharmaceutical products	24	24	24	24	24
06.1.2 - Other medical products	27	27	27	27	27
07.1.1 - Motor cars	28	28	28	28	28
07.1.2 - Motor cycles	26	26	26	26	26
07.2.1 - Spare parts for personal transport equipment	26	26	26	25	25
07.2.2 - Fuels and lubricants for personal transport equipment	29	29	29	29	29
08.2.0 - Telephone and telefax equipment	19	19	19	19	16
09.1.1 - Equipment for reproduction of sound and picture	28	25	24	24	20
09.1.2 - Photographic and cinematographic equipment	29	29	28	28	25
09.2.1 - Major durables for outdoor recreation	17	17	17	17	17
09.3.1 - Games, toys and hobbies	29	29	29	28	28
09.3.2 - Equipment for sport, camping and open-air recreation	27	27	27	27	27
09.3.3 - Gardens, plants and flowers	26	26	26	26	26
09.5.3 - Miscellaneous printed matter	26	26	26	26	25
12.1.2 - Electric appliances for personal care	26	26	25	25	24
12.3.1 - Jewellery, clocks and watches	26	26	26	26	24
12.3.2 - Other personal effects	26	24	23	23	22

Note: we used two ADF test specifications, both with no intercept and trend applied to month-over-month changes variables. The column $ADF_{5\%,1lag}$, for example, represents the number of countries for which the null hypothesis rejects at 5% significance levels in 1lag test specification for each product group. The null hypothesis for ADF test is that there is a unit root in the series.

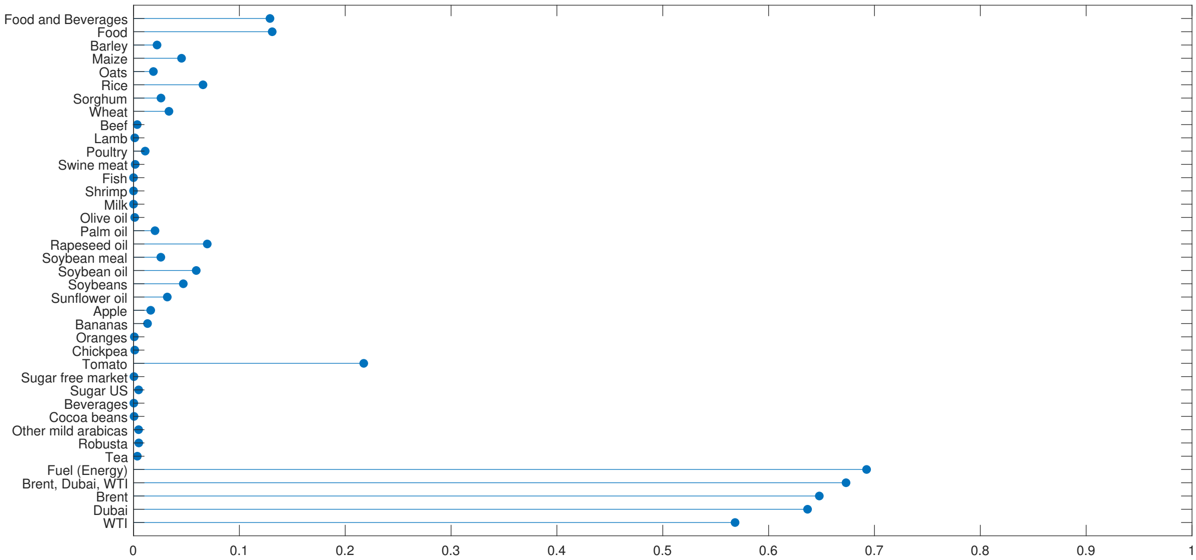

Figure 7: R^2 for the regressions with market prices from the IMF as an explained variable and subblock-level factors H as regressors

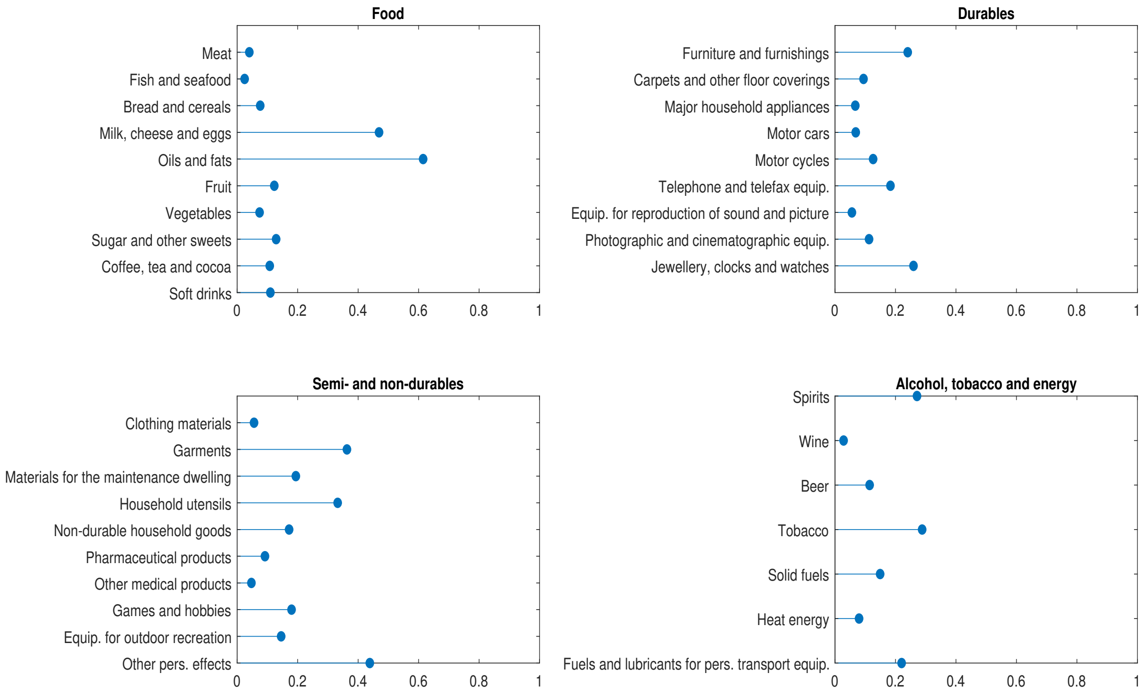

Figure 8: R^2 for the regressions with disaggregate CPI component as an explained variable and corresponding factors as regressors for Russia

Table 7: Variance decomposition of DHF Model with Blocks and Subblocks, median share of explained variance (in percents)

Block	Subblock	Global	Product group	Product category	Idiosyncratic
Food	Meat and fish	8.4	2.0	1.8	87.8
		[6.7,10.2]	[1.7,2.4]	[1.6,2.1]	[86.0,89.5]
	Bread, milk, oils	0.8	0.2	**48.9**	50.1
		[0.0,2.2]	[0.0,0.5]	[41.2,56.5]	[43.3,56.6]
	Vegetables and fruit	0.4	0.1	21.8	77.7
		[0.1,1.0]	[0.0,0.3]	[20.2,23.4]	[76.0,79.3]
	Others	1.0	0.2	10.4	88.4
		[0.2,2.1]	[0.0,0.5]	[8.0,12.9]	[86.5,90.1]
Manufactured goods	Durables	0.5	9.3	29.4	60.9
		[0.0,1.2]	[7.5,11.1]	[22.4,37.2]	[54.2,66.9]
	Semi- and non-durables	0.0	0.2	46.1	53.6
		[0.0,0.0]	[0.0,0.5]	[39.4,54.3]	[45.6,60.2]
	Alcohol and tobacco	0.0	0.2	6.3	93.5
		[0.0,0.0]	[0.0,0.6]	[5.4,7.3]	[92.4,94.5]
	Energy	0.1	1.0	34.4	64.6
		[0.0,0.1]	[0.1,2.4]	[32.7,36.0]	[63.4,65.7]

Note: Inside each subblock, there are COICOP 4-digit product category series that were available for up to 29 countries listed in Table 4 of the Appendix with the addition of China since January, 2005. Figures in squared brackets represent 10% and 90% percentile points of distribution of a share explained by a factor inside a given subblock across different product category for different countries. Notable changes compared to Table 3 are in bold.

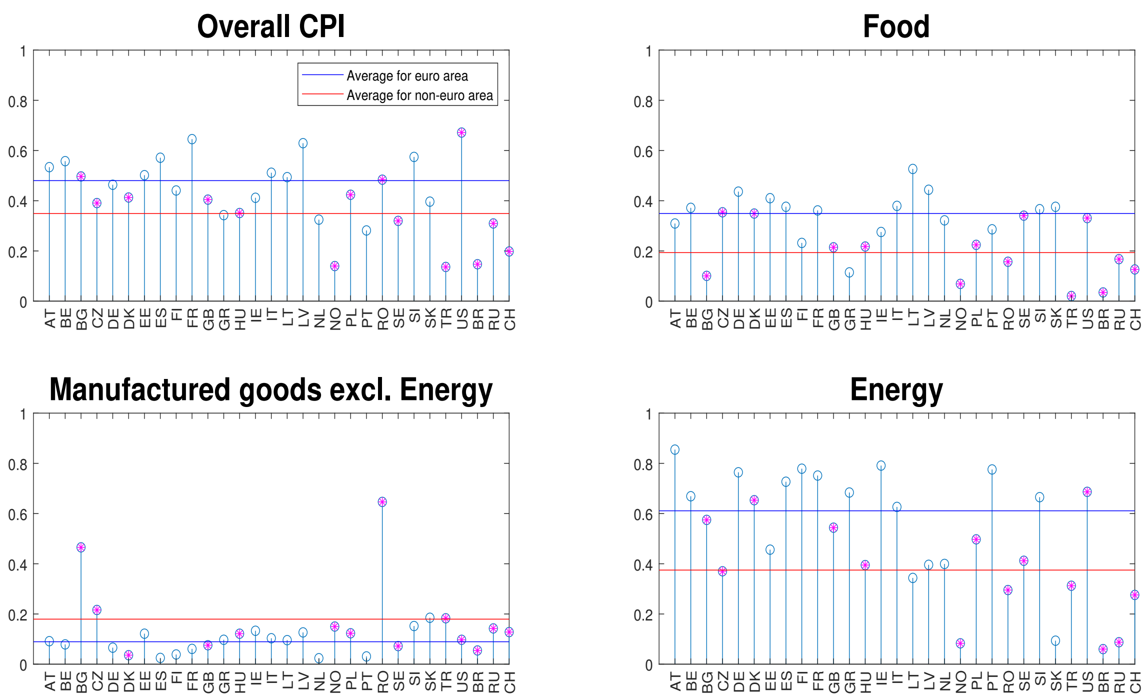

Figure 9: R^2 for the regressions with aggregate CPI component as an explained variable and corresponding factors as regressors with the addition of China since January, 2005