The role of product specific component in global inflation*

Preliminary and incomplete results: do not quote

Aleksei Kiselev†

This version: September 28, 2018

Abstract

In this paper we investigate the degree of international comovement of inflation rates associated with inflation at the product level. We use a dynamic hierarchical factor model to decompose Consumer Price Index (CPI) inflation in a panel of countries into (i) a factor common to all inflation series and all countries, (ii) a factor specific to a given product group of the CPI, (iii) a factor specific to a given product subgroup (COICOP 4-digit), and (iv) an idiosyncratic component. The hierarchical structure of the model allows us to account for covariations that are not sufficiently pervasive to be treated as common factors, and, thus, separate effects at the product group and subgroup levels. Using monthly data for 26 OECD economies from 2000 to 2018 we find that subgroup inflation rates demonstrate different sensitivity to common factors. For energy and some foods, product specific factors on average account for 10-12% of inflation variation which is quite high for this frequency and level of disaggregation.

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 global factor, the phenomenon they refer to as 'global inflation'. Other authors questioned the strength of this link (e.g. Monacelli and Sala [11]), or relevance for non-OECD countries (Parker [14]). There is a going debate on origins of the global inflation (Altansukh et al. [1]), international comovement of inflation (Mumtaz and Surico [12], Neely and Rapach [13]), and to what extent globalization affects domestic inflation (Forbes [7]).

The main contribution of this paper is estimation of 'global micro' component of global inflation. That is, we try to provide an answer for the question: "to what extent sector specific, or product level, dynamics affect national inflation rates?" We achieve this by using dynamic hierarchical factor model of Moench, Ng, and Potter [10] to estimate the product specific factors in inflation dynamics across OECD countries since the beginning of the 2000-s. Usually, the literature on global inflation tends to be concentrated on quite a low level of disaggregation of CPI (product groups such as food, energy, and others), or on overall index (headline CPI). 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 at the product group and product category levels inside global inflation.

1.1 Related literature

There is a growing literature on the comovement of national inflation rates and, correspondingly, the role of global factors behind it. The seminal 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. Monacelli and Sala [11] in their study of 948 CPI products' dynamics in the four largest OECD

*I would like to thank seminar participants at the Central Bank of Russia for useful comments on the draft version of this paper.

†The Central Bank of Russia, 12 Neglinnaya St., Moscow, Russia. kiselevav01@cbr.ru

countries (United States, Germany, France, and United Kingdom) found that one common factor explains between 15% and 30% of the variance of consumer prices. Importantly, their results depend on the transformation applied to the data: unlike Cicarelli and Mojon [5], they used monthly, either seasonally adjusted month-over-month or year-over-year, changes. What is more, their results illustrate importance of data frequency and, particularly, aggregation for the final result. Thus, they offer to view their estimates as a lower bound for the contribution of global factor to domestic inflation.

There may be several factors behind the comovement in national inflation rates. The one extensively covered in the literature is that of globalization of inflation (Borio [4]) as a result of increased trade openness across the world. Proponents of this view, Auer and Borio [3] point at tightening link between global value chains and inflation sensitivity to global output gap. Monacelli and Sala [11] find that trade intensity increases significance of common factor in explaining inflation dynamics across product categories. Andrade and Zachariadis [2] point at the distinction between global macro (oil price or global liquidity shock) and global micro[1] (industry or product specific) factors, and show that there is different responsiveness of prices to these factors. Halka et al. [9] use the same disaggregation level, as we do, (up to 4 COICOP digits, see Section 2) in order to study importance of common drivers of inflation in CEE countries. Their estimates suggest that the overall contribution of sectoral factors is around 13%, on average, but differs drastically across sectors.

Several authors apply dynamic hierarchical factor model (hereafter DHFM) developed by Moench et al. [10] to study inflation across countries and regions. Forster and Tillmann [8] 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. A recent work of Parker [14] analyzes 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. 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.

The remainder of this paper is organized as follows. Section 2 describes the data set of national CPI inflation rates at the level of product categories. In Section 3, a four level hierarchical model is described and specified. In Section 4, this model is used to analyze factors behind common component of inflation dynamics in 26 OECD countries. We find that comovement at the subblock-level tends to be more important than comovement at the block level, at least for some product categories. What is also important, prior hierarchy helps us better explain sources of global component of inflation. Section 5 concludes.

2 Data

We collected a cross section of monthly price indexes for 26 OECD countries from Federal Reserve Economic Database (FRED). The data set lists 39 price series for product categories that correspond to 4-digit codes of the classification of individual consumption by purpose (hereafter COICOP). That is, a typical series in our data set are: 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. First, we exclude countries with population less than 1 million people: as our sample includes countries of different size, and our procedure does not have any kind of weighting scheme, we try to avoid possible statistical anomalies by excluding outliers at this stage. Secondly, we exclude the countries which data were not available over the time interval from December, 2000 to July, 2018. The data for Switzerland and Croatia were not available before the December, 2004, and, therefore, we have decided to exclude them. Next, we transform all our time series into year-over-year growth rates, as it is the measure monetary policy typically focuses on ([8], p.7). Finally, we standardize all series to have mean zero and standard deviation of 1 for each country - product category.

[1]The notation that was coined by Andrade et al. [2]

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. These are: with no constant and trend, with 1 and 2 lags, respectively. According to the obtained results for both specifications, presented in the Table 6 of the Appendix, time series are mostly stationary for product categories across countries at 5% significance level, and somewhat less - at 1% level. There are only few series showing persistent dynamics across countries.

There are at least two things we need to take into account while interpreting those results: a) unit root tests, made in this work, do not take into account possible structural breaks in the series, and hence, their power may be low in some cases; b) ADF test is not universal technique and could not provide us with accurate and final conclusion about unit root existence and often struggles to reject the null in 'near-unity' cases. Given the low power of the ADF tests, and results from the previous work on inflation dynamics cited above, it is reasonable to assume that the inflation rates in our data set are stationary and that the DHFM is appropriate.

The complete data set includes 1014 series spanning from December, 2001 to July, 2018. The main summary statistics of product categories are given in Table 1. The final list of countries that we used in our analysis is presented in the Table 5 of the Appendix.

Table 1: Mean and standard deviation by product group

COICOP classification	**Mean (%, y-o-y)**	**SD (p.p.)**
01.1.1 - Bread and cereals	3.0	4.5
01.1.2 - Meat	2.0	3.8
01.1.3 - Fish and seafood	3.3	3.9
01.1.4 - Milk, cheese and eggs	2.8	5.2
01.1.5 - Oils and fats	3.8	7.6
01.1.6 - Fruit	3.1	7.2
01.1.7 - Vegetables	2.9	9.2
01.1.8 - Sugar, jam, honey, chocolate and confectionery	2.5	4.2
01.1.9 - Food products n.e.c.	2.3	2.9
01.2.1 - Coffee, tea and cocoa	2.4	5.3
01.2.2 - Mineral waters, soft drinks, fruit and vegetable juices	2.1	3.3
02.1.1 - Spirits	2.7	4.4
02.1.2 - Wine	2.4	3.1
02.1.3 - Beer	2.8	3.9
02.2.0 - Tobacco	6.7	6.0
03.1.2 - Garments	0.0	2.9
03.1.3 - Other articles of clothing and clothing accessories	1.3	3.2
04.3.1 - Materials for the maintenance and repair of the dwelling	2.3	2.5
04.5.1 - Electricity	4.1	7.2
05.1.1 - Furniture and furnishings	1.1	2.3
05.1.2 - Carpets and other floor coverings	0.9	2.8
05.2.0 - Household textiles	0.9	2.7
05.3.1 - Major household appliances whether electric or not	-0.5	2.2
05.4.0 - Glassware, tableware and household utensils	1.6	2.4
05.6.1 - Non-durable household goods	1.0	3.0
06.1.1 - Pharmaceutical products	1.7	4.5
06.1.2 - Other medical products	1.7	2.8
07.1.1 - Motor cars	-0.2	3.2
07.1.2 - Motor cycles	0.9	2.8
07.2.1 - Spare parts and accessories for personal transport equipment	1.7	2.6
07.2.2 - Fuels and lubricants for personal transport equipment	3.2	10.2
09.1.1 - Equipment for recording and reproduction of sound&picture	-7.1	4.8
09.1.2 - Photographic and cinematographic equipment	-8.0	7.1
09.3.1 - Games, toys and hobbies	-0.3	2.9
09.3.2 - Equipment for sport, camping and open-air recreation	-0.1	3.2
09.5.3 - Miscellaneous printed matter	2.3	2.2
12.1.2 - Electric appliances for personal care	1.1	2.4
12.3.1 - Jewellery, clocks and watches	4.8	5.2
12.3.2 - Other personal effects	1.0	2.5

Note: For every product group mean and standard deviation were calculated from y-o-y 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.

3 Model

3.1 Dynamic Hierarchical Factor Model

In order to find out what the contribution of global micro factor to national inflation 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. [10]. Our description also closely follows their original text, using the same notations.

We assume that the dynamics of the data Z_{sbit} (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 set of global, or all economies-wide factors, common to all blocks,
2. G_{bt}, which denotes the set of block-level, or product group specific, factors, common to all subblocks in that block,
3. H_{bst}, which denotes the set of subblock-level, or product category specific, factors, common to all subblocks in any block,
4. e_{Zbsit}, which denotes the idiosyncratic component for each series.

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

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

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

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

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

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.

The model allows neat representation of the data that we collected. Particularly, any $i-th$ series in the $b-th$ block and $s-th$ subblock can be decomposed into idiosyncratic component (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 block-specific part (e_{Hbst}), and the common component ($\Lambda_{G.bs}(L)G_{bt}$), which is shared with all the rest blocks. Every block-specific factor can be decomposed into block-specific factor (e_{Gbt}) and common factor $\Lambda_{F.b} * F_t$, which has an influence on all blocks in the model. Finally, global factor F_t is assumed to follow a simple AR(1) process - this mostly defines the dynamic essence of the model.

Following Moench et al. [10], we assume F_t, ϵ_{Xbit}, ϵ_{Gbjt} to follow the AR-processes. Also note that we consider only one global factor F_t, hence ρ_F is a scalar. In order to match persistence assumptions, the equations for the AR models innovation terms are set as:

$$\epsilon_{Zbsi} \sim \mathcal{N}(0, \sigma^2_{Zbsi})$$
$$\epsilon_{Hbs} \sim \mathcal{N}(0, \sigma^2_{Hbs})$$
$$\epsilon_{Gb} \sim \mathcal{N}(0, \sigma^2_{Gb})$$
$$\epsilon_F \sim \mathcal{N}(0, \sigma^2_F)$$

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. [10], and we replicated it with minor changes[2].

[2]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 4 blocks, that we call 'product groups;, that are intended to represent the first level classification of consumption. These blocks are: 'Food', 'Alcohol and tobacco', 'Other manufactured goods', and 'Energy'. We further subdivide blocks into several subblocks, that we call 'product categories', represented in the Table 2.

Table 2: Block and subblock structure of the data

Block	**Subblock**	**Number of COICOP 4-digit categories**
Food	Meat and fish	2
	Bread, milk, oils	3
	Vegetables and fruit	2
	Others	4
Alcohol and tobacco	Alcohol	3
	Tobacco	1
Other manufactured goods	Durables	8
	Semi-durables	9
	Non-durables	5
Energy	-	2

Note: Inside each subblock, there are COICOP 4-digit product category series that were available for all 26 OECD countries listed in Table 5 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 price change, not only at the product group, but also at the product category level. To put it formally, Moench et al. [10] 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 factor in product category dynamics.

Additionally, disaggregation helps us to abstract composition bias associated with changes in composition of overall CPI. This might be important for countries that experienced significant transformation of consumption during last 18 years: particularly, in the share of foods in consumption basket.

4 Results

In this section we provide two versions of the DHFM model: with blocks only (Model B) and with blocks and subblocks (Model BS). Comparing the results from them would allow us to evaluate the importance of using hierarchical representation of CPI data. Note that both versions of the model are built in the way that allows us to estimate product specific, or *global micro*, component of the global inflation. That is, block share of variation explained by the Model B represents the importance of developments at product group level for national CPI dynamics. That is the level that authors that used DHFM to model product and country-specific factors worked with. Here, we try to take full advantage of hierarchical structure of CPI data and work at the product category level by employing Model BS. In this model, block *and* subblock share of variation explained by the model represent the product specific, or global micro, component for national CPI dynamics.

Each model uses only one common factor at each stage (global, block, and subblock). Here, we intentionally try to make model as simple as possible in order to articulate differences between two specifications connected only to the degree of disaggregation.

Estimation of Model B illustrates importance of product group factor for CPI dynamics (Table 3). Although idiosyncratic component tends to dominate, there is a considerable difference between blocks regarding product group factor. As in previous literature (Forster and Tillmann [8], Parker [14]), 'Energy' products (such as fuels for personal transport equipment) show the largest dependence on sector-specific factor. 'Food' is the second group of products which components have some common, product specific dynamics. And we see virtually no significant common factor in two other product groups. Here we should stress that the authors that worked with quarterly frequency ([8],[14]) estimated higher share of common factors due to lower variance of original data set. This point has been already emphasized by Monacelli and Sala [11], but we reiterate it in order to clarify seemingly different results.

Table 3: Variance decomposition of DHF Model B, median share of explained variance (in percents)

Block	**Global factor**	**Product group factor**	**Idiosyncratic**
Food	0.0	3.6	96.3
	[0.0,0.2]	[0.4,19.6]	[80.1,99.6]
Alcohol and tobacco	0.0	0.7	99.3
	[0.0,0.0]	[0.2,3.1]	[96.8,99.8]
Other manufactured goods	0.1	0.1	99.8
	[0.0,0.4]	[0.0,0.4]	[99.2,100.0]
Energy	0.0	10.4	89.5
	[0.0,0.3]	[0.1,72.0]	[27.7,99.9]

Note: Figures in squared brackets represent 20% and 80% percentile points of distribution of a share explained by a factor inside given block across different product category for different countries.

Somewhat 'low' share of the variation explained at the block (and subblock, as we are going to see below) level should not confuse reader. In their original paper on DHFM, Moench et al. [10] illustrate their model with a factor analysis of real economic activity in the US. Importantly, they use data with *monthly* frequency, as we do. The authors get a common factor that closely tracks 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 common factors: the average share of unexplained variance at a subblock level is around 65-90%. This result holds for the data that are a priori closely interconnected (different sectors of one country economy), so it is questionable whether one could get high share of explained variance at this level of disaggregation as we have[3].

Estimation of the model with subblock hierarchy, Model BS, allows us to further analyze drivers behind 'global inflation' component in national inflation rates. First, now we can separate block and subblock factors, which have different strength depending on the product category (Table 4). Energy group variance decomposition, that has no subblocks, remained almost the same as in the Model B. 'Food' product categories demonstrate different sensitivity to common factors: 'Bread,

[3] A good analogy could be that of explaining each single observation dynamics with their average.

milk, oils' and 'Others' (see Table 1) are driven by common, product category, factor; 'Meat and fish' has a significant global component, but almost no product (neither group, nor category) factor. In other blocks the difference is not very large, but, still, we can see varying degree of global inflation component in different categories.

Table 4: Variance decomposition of DHF Model BS, median share of explained variance (in percents)

Block	Subblock	Global	Product group	Product category	Idiosyncratic
Food	Meat and fish	**3.1** [0.3,6.5]	1.0 [0.1,2.1]	0.3 [0.0,0.6]	95.7 [90.8,99.6]
	Bread, milk, oils	0.5 [0.1,0.9]	0.2 [0.0,0.3]	**12.2** [3.0,24.3]	87.2 [74.4,96.8]
	Vegetables and fruit	0.1 [0.0,0.8]	0.0 [0.0,0.2]	2.8 [0.8,26.9]	97.1 [72.1,99.2]
	Others	0.4 [0.1,0.7]	0.1 [0.0,0.2]	**11.8** [2.3,21.3]	87.7 [77.7,97.6]
Alcohol and tobacco	Alcohol	0.0 [0.0,0.0]	**2.0** [0.2, 7.0]	0.1 [0.0,0.4]	97.9 [92.6,99.8]
	Tobacco	0.0 [0.0,0.0]	0.1 [0.0,0.2]	0.6 [0.1,1.6]	99.4 [98.2,99.9]
Other manufactured goods	Durables	0.1 [0.0,0.4]	0.5 [0.1,2.5]	0.1 [0.0,0.4]	99.3 [96.7,99.9]
	Semi-durables	0.0 [0.0,0.0]	0.0 [0.0,0.0]	**2.2** [0.2,13.3]	97.8 [86.7,99.8]
	Non-durables	0.0 [0.0,0.0]	0.0 [0.0,0.0]	0.3 [0.0,1.9]	99.7 [98.1,100.0]
Energy	-	0.4 [0.0,2.9]	**9.5** [0.1,70.2]	- -	90.1 [26.8,99.9]

Note: Figures in squared brackets represent 20% and 80% percentile points of distribution of a share explained by a factor inside given subblock across different product category for different countries. Notable changes compared to Table 3 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 4) is reduced substantially compared to the corresponding share in the Model B. That is, explicitly modelling subblock variation presumably helps us not to confound shocks at this level with block level or idiosyncratic shocks.

Our results also demonstrate high level of heterogeneity between countries. Numbers in square brackets in Table 3 and 4 show 20% and 80% percentile points of distribution of shares explained by a factor inside given subblock across countries: those numbers vary greatly for some product groups and categories. For example, 'Energy' products' variance in some countries is driven mostly by product specific factor, while for 50% of series in 'Bread, milk, oils' this share is larger than 12%, for 20% - larger than 25%, which is quite significant for monthly frequency data (see discussion above).

This decomposition of global inflation component 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%. 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.

5 Conclusions

This paper uses a data set of consumer prices at the level of 4-digit COICOP classification for 26 OECD countries for the period 2000–2018 to test the importance of product specific factors in national inflation rate dynamics. Application of dynamic hierarchical factor model of Moench et al. [10] allows us to separate effects at product group and product category levels in the right way and examine importance of product level inflation.

We confirm previous findings on the importance of global component in energy and food price dynamics. At the same time we show that global inflation may be driven by global micro, or product specific, component that has varying impact on different subblocks, particularly in foods. This means that channels through which global inflation operates might be concentrated primarily in energy and some food markets. This, in turn, may have important consequences for monetary policy actions.

Using this data set we extend the literature on the role of global inflation factors in national inflation rates to a deeper product disaggregation level. We also confirm the findings of Monacelli and Sala [11] and Parker [14] that global factors can explain some variance of advanced economies' inflation, but this result relies heavily on the frequency and the degree of data disaggregation in product space.

This paper would be extended in several directions. Our further research is concentrated on widening and deepening of the data set, particularly, including emerging economies data. Next, we aim at testing predictive ability of product category common factors, and the degree of dependence of idiosyncratic component to country specific factors, such as monetary and fiscal policy stance and degree of openness to trade.

References

[1] G. Altansukh, R. Becker, G. Bratsiotis, and D. R. Osborn. What is the globalisation of inflation? *Journal of Economic Dynamics and Control*, 74:1–27, Jan. 2017.

[2] P. Andrade and M. Zachariadis. Global versus local shocks in micro price dynamics. *Journal of International Economics*, 98:78–92, Jan. 2016.

[3] R. Auer, C. E. Borio, and A. J. Filardo. The globalisation of inflation: the growing importance of global value chains. *CEPR Discussion Paper No. DP11905*, 2017.

[4] C. Borio and A. Filardo. Globalisation and inflation: New cross-country evidence on the global determinants of domestic inflation. *BIS Working Paper No. 227*, 2007.

[5] M. Ciccarelli and B. Mojon. Global Inflation. *The Review of Economics and Statistics*, 92(3):524–535, May 2010.

[6] E. Deryugina, N. Karlova, A. Ponomarenko, and A. Tsvetkova. The role of regional and sectoral factors in Russian inflation developments. *Economic Change and Restructuring*, pages 1–22, July 2018.

[7] K. J. Forbes. Has Globalization Changed the Inflation Process? *Paper prepared for the 17th BIS Annual Research Conference*, 2018.

[8] M. Förster and P. Tillmann. Reconsidering the International Comovement of Inflation. *Open Economies Review*, 25(5):841–863, Nov. 2014.

[9] A. Halka and G. Szafrański. What common factors are driving inflation in CEE countries? *National Bank of Poland Working Paper No. 225*, 2015.

[10] E. Moench, S. Ng, and S. Potter. Dynamic Hierarchical Factor Models. *The Review of Economics and Statistics*, 95(5):1811–1817, Apr. 2013.

[11] T. Monacelli and L. Sala. The international dimension of inflation: evidence from disaggregated consumer price data. *Journal of Money, Credit and Banking*, 41:101–120, 2009.

[12] H. Mumtaz and P. Surico. Evolving international inflation dynamics: world and country-specific factors. *Journal of the European Economic Association*, 10(4):716–734, 2012.

[13] C. J. Neely and D. E. Rapach. International comovements in inflation rates and country characteristics. *Journal of International Money and Finance*, 30(7):1471–1490, 2011.

[14] M. Parker. How global is "global inflation"? *Journal of Macroeconomics*, 58:174–197, Sept. 2018.

6 Appendix

Table 5: Final list of OECD countries included in the analysis (with population more than 1 million people).

Country	**Abbreviation**
Austria	AT
Belgium	BE
Bulgaria	BG
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
Sweden	SE
Slovenia	SI
Slovakia	SK
Turkey	TR

Table 6: Results for unit root testing for different product categories across 26 OECD countries, numbers correspond to the number of countries that passed the corresponding test.

COICOP 4-digit classification	$ADF_{5\%,1lag}$	$ADF_{5\%,2lag}$	$ADF_{1\%,1lag}$	$ADF_{1\%,2lag}$
01.1.1 - Bread and cereals	13	21	6	7
01.1.2 - Meat	24	21	11	11
01.1.3 - Fish and seafood	22	19	12	10
01.1.4 - Milk, cheese and eggs	23	25	10	17
01.1.5 - Oils and fats	20	25	9	19
01.1.6 - Fruit	26	26	26	26
01.1.7 - Vegetables	26	26	26	26
01.1.8 - Sugar, jam, honey, chocolate	19	22	7	7
01.1.9 - Food products n.e.c.	14	14	6	6
01.2.1 - Coffee, tea and cocoa	19	26	7	9
01.2.2 - Mineral waters, soft drinks, juices	15	16	6	6
02.1.1 - Spirits	20	20	11	11
02.1.2 - Wine	16	15	4	5
02.1.3 - Beer	19	16	10	8
02.2.0 - Tobacco	14	12	5	3
03.1.2 - Garments	21	21	17	16
03.1.3 - Other articles of clothing	24	25	19	17
04.3.1 - Materials for the maintenance dwelling	12	11	6	5
04.5.1 - Electricity	23	23	11	14
05.1.1 - Furniture and furnishings	12	16	8	4
05.1.2 - Carpets and other floor coverings	24	24	18	16
05.2.0 - Household textiles	22	20	15	12
05.3.1 - Major household appliances	14	13	6	6
05.4.0 - Glassware, tableware and household utensils	17	16	9	8
05.6.1 - Non-durable household goods	18	18	7	6
06.1.1 - Pharmaceutical products	22	23	17	17
06.1.2 - Other medical products	18	18	16	14
07.1.1 - Motor cars	13	15	8	10
07.1.2 - Motor cycles	22	19	15	14
07.2.1 - Spare parts for personal transport equipment	13	16	6	5
07.2.2 - Fuels and lubricants for personal transport equipment	26	26	25	25
09.1.1 - Equipment for reproduction of sound and picture	3	3	2	2
09.1.2 - Photographic and cinematographic equipment	4	3	2	2
09.3.1 - Games, toys and hobbies	20	19	13	13
09.3.2 - Equipment for sport, camping and open-air recreation	23	23	15	14
09.5.3 - Miscellaneous printed matter	16	14	10	10
12.1.2 - Electric appliances for personal care	18	17	9	6
12.3.1 - Jewellery, clocks and watches	5	5	1	1
12.3.2 - Other personal effects	20	19	16	13

Note: we used two ADF test specifications, both with no intercept and trend applied to year-over-year 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.