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Short-term inflation projections model and its assessment in Latvia

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ABSTRACT

This paper builds a short-term inflation projections (STIP) model for Latvia. The model is designed to forecast highly disaggregated consumer prices using cointegrated ARDL approach of [Pesaran, M., & Shin, Y. (1998). An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis. *Econometric Society Monographs*, 31, 371–413.]. We assess the forecast accuracy of STIP model using out-of-sample forecast exercise and show that our model outperforms both aggregated and disaggregated AR (1) benchmarks. Across inflation components, the forecast accuracy gains are 20–30% forecasting 3 months ahead and 15–55% forecasting 12 months ahead.

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1. Introduction

Price stability is the ultimate goal of monetary policy in the euro area. Monetary policy decisions are based not only on the current level of inflation but also on the projected one. Therefore, short-term inflation projection is an important input in decision-making process. In the euro area, virtually each central bank develops short-term inflation projections for the respective country, which are then aggregated to euro area inflation projections, providing inputs to the ECB's monetary policy decisions.

Against this backdrop, we build a model, which projects inflation developments over a short-term horizon (12 months) in Latvia, and call it the STIP model. It plays an important role in assessing short-term inflation projections in the context of BMPEs/NIPEs, which are procedural frameworks of the Eurosystem/ECB macroeconomic projections.¹

The literature uses various econometric techniques to forecast inflation. Predominantly, authors exploit univariate and multivariate models, such as ARIMA (Huwiler & Kaufmann, 2013; Marcellino et al., 2006) vector autoregressions (Banbura et al., 2010; Giannone et al., 2014)) and dynamic factor models (Boivin & Ng, 2005; Stock & Watson, 1999, 2002). In this paper, we follow a growing amount of literature, which uses cointegration relationships in forecasting inflation (Antoniades et al., 2004; Aron & Muellbauer, 2012, 2013; Espasa & Albacete, 2007; Espasa et al., 2002; Senra et al., 2002; Stakenas, 2015). The literature finds out that isolating the equilibrating relationships contributes to greater

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accuracy of inflation forecasts relative to the benchmark models. The literature also traditionally uses standard cointegration tests of Engle and Granger (1987), Phillips and Ouliaris (1990) and Johansen (1995), which require variables to follow $I(1)$ process. This necessitates to run various unit root tests, as unit roots are known to suffer some power problems. In the paper, we use a cointegrated ARDL modelling approach introduced in Pesaran and Shin (1998) and Pesaran et al. (2001). Cointegrated ARDL model is robust to the misspecification of integration orders of variables and easy to implement.

Inflation can be significantly affected by various heterogeneous shocks. One may require to disaggregate headline inflation into components in order to better capture the impact of these shocks. There is a couple of merits of disaggregated approach. First, by disaggregating headline inflation, one can better capture dynamic properties using specific information for particular component and hence obtain more accurate forecasts. Second, forecast errors of individual components may partly cancel out leading to more accurate forecast of the aggregate (Hendry & Hubrich, 2011; Hubrich, 2005). On the contrary, misspecification of the dynamics of individual components may ruin forecast accuracy of the aggregate. Similarly, forecast errors might not cancel out if unexpected shock affects several components in the same direction. In empirical studies on consumer prices, there is an evidence that the disaggregated approach proved to be more accurate than the aggregated one, e.g. Duarte and Rua (2007), Moser et al. (2007), Reijer and Vlaar (2006), Bandt et al. (2007), Aron and Muellbauer (2012), and Marcellino et al. (2003).

The degree of disaggregation is usually somewhat ad hoc in the literature. As a rule of thumb, authors single out the most heterogeneous or volatile series, which apparently are driven by specific explanatory factors. The literature usually distinguish five consumer price aggregates: unprocessed food, processed food, energy, non-energy industrial goods and services. This approach is followed by Espasa et al. (2002), Fritzer et al. (2002), Reijer and Vlaar (2006), Duarte and Rua (2007), Bermingham and D'Agostino (2014) and Alvarez and Sánchez (2017). Several papers disaggregate the consumer price index even further, e.g. Aron and Muellbauer (2012) break down headline consumer prices in 10 components, Stakenas (2015) – in 21 components, Bermingham and D'Agostino (2014) – in 32 components, Duarte and Rua (2007) – in 59 components, Huwiler and Kaufmann (2013) – in 182 components. In this paper, we do not aim at studying the optimal degree of disaggregation but suggest our own level of disaggregation into 33 components which is largely based on expert judgement and remains fixed throughout the paper.

We find that the STIP model forecasts accurately inflation and its components over 12 months ahead. We assess the model's out-of-sample forecast accuracy and find that the STIP model statistically significantly outperforms an AR(1) benchmark in real time.

The structure of the paper is as follows. Section 2 describes the data and methods. Section 3 presents estimation results. Section 4 assesses the model's out-of-sample forecast performance, while Section 5 concludes.

2. Data and methods

2.1. Data

We use 95 individual HICP indices from Eurostat and the Central Statistical Bureau of Latvia (CSB) over the period from 2005 to 2018. The individual indices are aggregated

to obtain special aggregates (like unprocessed meat or non-energy industrial goods), which we use in modelling consumer prices according to ECOICOP5 classification.

We also use various data as determinants of consumer prices. To model car fuel prices, we use crude oil prices (Bloomberg, Brent mark, daily data), refined petrol and diesel prices (Bloomberg and Reuters respectively, daily data) and retail car fuel prices before and after taxes (the weekly Oil bulletin of the European Commission), as well as the EUR–USD exchange rate obtained from the ECB (Statistical Data Warehouse).

Global food commodity prices, which mainly affect consumer prices of food products, are represented by European farm-gate prices and other producer prices of cereals, dairy and meat and are published by the DG AGRI of the EC. For global prices of sugar and coffee, we employ international commodity prices (Bloomberg). We also use Nasdaq salmon spot prices as a proxy for international fish prices.

There are several domestic variables, which we use in modelling and forecasting consumer prices (all published by CSB) – the average wage rate as a measure of domestic labour costs, the hotel occupancy rate to control for demand pressures in accommodation services and the internet usage to explain communication prices.

Ultimately, explanatory variables should be attributed the future path over the forecast horizon in order to make inflation projections. Almost all foreign variables follow the assumptions provided by the ECB during official NIPE forecast rounds, i.e. crude oil prices, global food commodity prices and the exchange rate. Whereas the projections of labour costs, salmon prices, the hotel occupancy rate and internet usage are elaborated by Latvijas Banka internally. All consumer prices (except the administered prices and energy prices) are seasonally adjusted by X-12-ARIMA with default settings.

2.2. Modelling approach

We employ the ARDL modelling approach following Pesaran and Shin (1998) and Pesaran et al. (2001) to empirically assess long-run level relationships between consumer prices and their determinants. The ARDL approach enables us to test for a level relationship irrespective whether the regressors are of the order $I(0)$ or $I(1)$.

The general representation of ARDL is as follows:

$$y_t = a_0 + a_1 t + \sum_{i=1}^p \psi_i y_{t-i} + \sum_{j=1}^k \sum_{l_j=0}^{q_j} \beta_{j,l_j} x_{j,t-l_j} + \epsilon_t \quad (1)$$

where $\epsilon_t \sim i.i.d.N(0, \sigma^2)$, a_0 is a constant, t is a trend; a_1 , ψ_i , β_{j,l_j} are respectively the coefficients addressing the linear trend, lags of dependent variable y_t , and lags of independent variables $x_{j,t}$, for $j = 1, \dots, k$; and q_j is the number of lags for the independent variable j .

Pesaran et al. (2001) show that the vector autoregression framework could be reduced to the conditional error correction (CEC) form under certain assumptions. Moreover, they show that there is a one-to-one correspondence between the CEC model and the ARDL model presented in Equation (1). Hence, the ARDL model representation could be

transformed to the following CEC form:

$$\begin{aligned} \Delta y_t = & a_0 + a_1 t + b_0 y_{t-1} + \sum_{j=1}^k b_j x_{j,t-1} + \sum_{i=1}^{p-1} c_{0,i} \Delta y_{t-i} + \sum_{j=1}^k \sum_{l_j=1}^{q_j-1} c_{j,l_j} \Delta x_{j,t-l_j} \\ & + \sum_{j=1}^k d_j \Delta x_{j,t} + \epsilon_t \end{aligned} \quad (2)$$

where the third and fourth terms of Equation (2), i.e. the lagged terms of dependent variable y_{t-1} and regressors $x_{j,t-1}$ represent a cointegration relationship. Pesaran et al. (2001) propose a bounds test for cointegration as a test on the significance of parameters in the cointegration relationship. In fact, the null hypothesis tests whether coefficients $b_0 = b_j = 0$, for all j , mean that there is no long-run relationship between y_t and x_t .

Alternatively, if the coefficients are not zeros, we reject the null and conclude that there is a cointegration relationship. The proposed test is a standard F -test, but since asymptotic distributions of this statistic are non-standard under the null, Pesaran et al. (2001) provide critical values. Pesaran et al. (2001) also distinguish five different specifications of the CEC model depending on whether the constant and trend integrate (mutually or separately) into the error correction term. In our equation specifications we additionally report whether the trend or constant is included into the cointegration relationship.

The methodology mainly requires that the order of integration of the variables is not greater than $I(1)$, which is indeed true for most economic variables, and ARDL equations should not exhibit serial correlation to ensure cointegration among the variables. We test for the integration order of variables using ADF test statistics, and all of them are not greater than $I(1)$, meaning that variables are first difference stationary (see Table A1). The cointegration results between consumer prices and their determinants are tested using the Pesaran–Shin–Smith bounds test and reported in Table A2. The null hypothesis of no serial correlation is tested using the Breusch–Godfrey LM test and is not rejected in all equations (see Table A3). Heteroskedasticity is tested using the Breusch–Pagan–Godfrey test. The null hypothesis is not rejected in a large number of equations, meaning that the errors are homoskedastic. But in cases where heteroskedasticity is present, we use Newey–West adjusted standard errors. Other statistics of the estimated equations are reported in Table A4.

3. Model overview

We pursue a disaggregated approach setting up the STIP model. We break down headline consumer price index into 33 components: 5 components of unprocessed food prices, 12 components of processed food prices, 5 components of energy prices, 3 components of non-energy industrial goods (NEIG) prices and 8 components of services prices (the total sum of the consumer price weights of all 33 components is equal to 100%). The reason for such a detailed disaggregation is that different driving forces affect various components of consumer prices. Even within broad price aggregates, such as food or services prices, determinants may significantly differ. For instance, some service prices may respond to energy and food price developments. Consequently, if disaggregation of services prices is not sufficient, it may fail to identify linkages to global energy and food prices and is

likely to produce biased forecasts. Second, a pass-through of costs to consumer prices differ in terms of speed and magnitude among consumption products. Hence, detailed disaggregation allows us to estimate more accurately the speed and magnitude of the pass-through to HICP components.

There is no any methodology or statistical tests which allows to determine an optimal number of components to forecast inflation. This is a pure empirical question. We do not aim at studying the optimal level of disaggregation, nonetheless we suggest our own level of disaggregation as stated before. As a rule of thumb, we single out the most heterogeneous and volatile components (e.g. travel-related components), and the components, which have sensible explanatory variables available in public domain (e.g. domestic meat prices are followed by developments in the global meat prices).

As an overview, consumer prices are affected by the four main factors in our model. Crude oil prices are the main factor directly driving consumer prices of energy and indirectly, through car fuel prices, affect consumer prices of food and some services. Global food commodity prices exert a pressure mainly on consumer prices of unprocessed and processed food, which indirectly affect also consumer prices of catering services. The impact of nominal effective exchange rate (NEER) is mainly found in consumer prices of non-energy industrial goods (NEIG). Finally, domestic labour costs -- directly and indirectly -- affect almost all components of consumer prices. All the components of consumer prices and its determinants are described in the next sections.

3.1. Unprocessed food prices

We model consumer prices of unprocessed food, disaggregating them into five components. They are mainly driven by global food commodity prices and domestic labour costs (Table 1).

Error correction seems to be particularly fast for unprocessed vegetables and unprocessed fruits, with 26–30% of the adjustment towards fundamental price level taking place within 1 month. Such a fast price adjustment might reflect the fact that the respective consumer prices are highly volatile and depend on (rapidly changing) weather conditions.

Consumer prices of several unprocessed food items are closely linked to the global food commodity prices. The long-run elasticity of unprocessed meat consumer prices to the EU producer prices of meat is about 0.5. Elasticity of unprocessed fish consumer prices to international salmon price index is of similar magnitude. We do not find any statistically significant relationship between consumer prices of unprocessed fruits and the respective DG AGRI indices, which could reflect the fact that for many fruits DG AGRI prices are missing at least for some periods of time. Thus we linked consumer prices of unprocessed fruits to the total DG AGRI food price index. Furthermore, we linked consumer prices of eggs to DG AGRI prices of cereals, since cereals are used as a feed for chickens and thus account for some part of egg production costs.

The long-run elasticity of unprocessed food consumer prices to domestic labour costs is about 0.47–0.56, except for unprocessed fish which recorded somewhat lower elasticity at 0.33. Note that unprocessed fish prices are the only unprocessed food item showing a robust association with car fuel prices.

Table 1. Modelling unprocessed food prices: error correction and long-run coefficients.

	Error correction	Long-run coefficients				Constant
		Labour costs	Car fuel	Global food	Trend	
Unprocessed meat	−0.13*** (0.02)	0.50*** (0.06)		0.53*** (DG AGRI meat) (0.11)	−0.002*** (0.00)	
Unprocessed fish	−0.12*** (0.02)	0.33*** (0.09)	0.36*** (0.11)	0.50*** (Nasdaq salmon) (0.09)		
Eggs	−0.11*** (0.02)	0.47*** (0.07)		0.23** (DG AGRI cereals) (0.10)		
Unprocessed fruits	−0.26*** (0.04)	0.56*** (0.07)		0.37*** (DG AGRI food) (0.09)	−0.002*** (0.00)	
Unprocessed vegetables	−0.30*** (0.06)	0.47*** (0.06)				1.50*** (0.41)

Notes: * ** and *** define statistical significance level at 10%, 5% and 1% respectively. Standard errors are in parentheses. Models are estimated using monthly data from January 2005 to December 2018. All variables are seasonally adjusted and expressed in logs. The lag order is selected by minimizing the Schwarz criterion. Time dummies are included in the estimation of unprocessed meat (2008m06, 2015m06), unprocessed fish (2007m02, 2010m03, 2013m08, 2018m06, 2018m12), eggs (2012m04, 2017m11, 2017m12), unprocessed fruits (2005m07, 2009m08, 2013m09, 2018m08), unprocessed vegetables (2005m02, 2018m09).

We also identify a negative trend in consumer prices of unprocessed meat and unprocessed fruits, controlling for price determinants. This negative trend might reflect a growing competition among retailers or a greater availability of cheaper imports.

3.2. Processed food prices

We model consumer prices of processed food, disaggregating them into 12 components. The monthly speed of adjustment towards the equilibrium price level is somewhat slower than in the case of unprocessed food (often below 10%), with a notable exception of processed meat prices (18%). In all cases, however, error correction coefficients remain highly statistically significant (Table 2).

The highest long-run elasticity of consumer prices to global food commodity prices is evident for the consumer prices of dairy products (as well as oils and fats) to the EU producer prices of dairy products at about 0.6–0.7. A high elasticity might reflect the fact that dairy is the only DG AGRI index, which partly consists of processed products ready for the final consumption (such as cheese).

Elasticity of non-alcoholic beverages consumer prices to global coffee prices is 0.42. The magnitude of elasticity is plausible, considering that share of coffee in non-alcoholic beverage consumption is about 45%. In turn, consumer prices of sugar and chocolate, and other miscellaneous food react to international sugar prices with elasticity close to 0.3. Consumer prices of bread and cereals tend to react to DG AGRI cereals price index; a moderate elasticity points to the fact that the price of grain reflects a minor part of bread production costs.

Several HICP components of processed food depend on the prices of the respective unprocessed food. This link is particularly obvious for the prices of processed meat, fish and vegetables. Several prices of processed food are affected also by retail prices of car fuel (with long-run elasticity of about 0.2–0.3). Furthermore, all consumer prices of processed food directly or indirectly are affected by domestic labour costs. The magnitude of elasticities broadly reflects the share of labour costs and transportation costs in the respective industry. For instance, in the case of dairy products (as well as of sugar and

Table 2. Modelling processed food prices: error correction and long-run coefficients.

	Error correction	Long-run coefficients					
		Labour costs	Unprocessed HICP	Car fuel	Global food	NEER	Constant
Processed meat	−0.18*** (0.02)		0.85*** (meat) (0.02)			0.21*** (0.07)	0.71*** (0.07)
Processed fish	−0.07*** (0.01)	0.21*** (0.07)	0.18** (fish) (0.07)	0.20*** (0.06)			1.43*** (0.30)
Processed fruits	−0.09*** (0.02)	0.65*** (0.05)		0.31*** (0.09)			
Processed vegetables	−0.08*** (0.02)		0.81*** (vegetables) (0.08)				0.99*** (0.34)
Dairy products	−0.11*** (0.01)	0.41*** (0.03)		0.20*** (0.07)	0.57*** (dairy) (0.11)		−1.67*** (0.30)
Bread and cereals	−0.09*** (0.01)	0.74*** (0.07)			0.26*** (cereals) (0.03)	−0.002*** (0.0004)	
Oils and fats	−0.05*** (0.01)	0.45*** (0.10)			0.72*** (dairy) (0.23)		
Sugar and chocolate	−0.06*** (0.01)	0.38*** (0.05)		0.18*** (0.08)	0.27*** (sugar) (0.06)		
Other food	−0.07*** (0.01)	0.33*** (0.05)			0.31*** (food) (0.06)		
					0.22*** (sugar) (0.03)		
Non-alcoholic beverages	−0.11*** (0.01)	0.16*** (0.04)		0.27*** (0.06)	0.42*** (coffee) (0.04)		
Alcoholic beverages	−0.08*** (0.01)	0.24*** (0.05)			0.10*** (cereals) (0.04)		2.56*** (0.25)
Tobacco	−0.004*** (0.0008)	0.79*** (0.08)					

Notes: *, ** and *** define statistical significance level at 10%, 5% and 1% respectively. Standard errors are in parentheses. Models are estimated using monthly data from January 2005 to December 2018. All variables are seasonally adjusted and expressed in logs. The lag order was selected by minimizing the Schwarz criterion. Time dummies are included in the estimation of processed meat (2011m09, 2012m12), processed fish (2008m11, 2009m01, 2014m04), processed fruits (2008m03, 2014m10, 2015m03, 2015m08), processed vegetables (2011m07, 2006m07, 2009m07, 2009m08, 2010m06, 2010m07, 2013m06, 2013m08, 2015m06), dairy products (2009m01, 2009m02, 2011m01, 2007m10, 2007m11, 2014m09), bread and cereals (2006m11, 2007m11, 2010m10, 2013m05), oils and fats (2007m10, 2008m01, 2017m01, 2017m08, 2018m05, 2018m07), other food (2005m07, 2008m04, 2009m01, 2009m12, 2011m04), non-alcoholic beverages (2009m02, 2012m01, 2012m09, 2014m05, 2018m02, 2018m11), alcoholic beverages (2009m02, 2009m07, 2018m03). NEER stands for nominal effective exchange rate.

chocolate), the elasticity of consumer prices to labour costs is at least twice higher than to car fuel. On the contrary, consumer prices of non-alcoholic beverages tend to react to car fuel prices more than to domestic labour costs. We also find a positive relation between consumer prices of processed meat and the nominal effective exchange rate (NEER). It might reflect large meat imports from Poland – a country whose currency showed large exchange rate fluctuations vis-à-vis the euro during the past 15 years.² Moreover, controlling for respective price determinants, we add a negative trend into the respective long-run equation of bread and cereals, which apparently reflects the growing competition in the industry.³

3.3. Energy prices

We distinguish five components of HICP energy prices: car fuel, natural gas, heat energy, electricity and solid fuel.

Developments in consumer car fuel prices strongly reflect movements in crude oil prices in global markets. We model these relationships in the spirit of Meyler (2009) – from upstream to downstream prices – accounting for refining, distribution, retailing margins and indirect taxes. Since margins and excise tax rates differ for major car fuel types, thus diesel and petrol prices are modelled separately and then aggregated to consumer car fuel price. The equations in Table 3 depict elasticities of refined petrol and diesel prices to crude oil prices.⁴ Elasticities are close to one in both cases, meaning that an oil price increase by 1 euro cent per litre translates into the price increase of refined petrol and refined diesel by about 1 euro cent. At the next stage, refined oil prices feed into retail consumer prices without taxes (both in euro per litre). Again, elasticities are close to one for retail prices of both petrol and diesel. Finally, we add excise and VAT taxes, which account for a large share in consumer car fuel prices.

There is also a strong long-term link between crude oil prices and the consumer prices of natural gas and heat energy (Table 4). In Latvia the prices of natural gas are entirely dependent on prices of crude oil, even though there is no direct link between them in a sense of production costs. Given the fact that in Latvia almost all gas supply is imported from Russia, determination of ‘fair’ price of natural gas is based on the principle of price of energy source. Hence the price of natural gas is naturally linked to the price of crude oil.

Table 3. Modelling car fuel prices: error correction and long-run coefficients.

	Error correction	Long-run coefficients			
		Oil (euro)	Refined prices	Labour costs	Trend
Refined petrol	–0.09*** (0.01)	0.95*** (0.04)			0.00006*** (0.00)
Refined diesel	–0.06*** (0.01)	1.12*** (0.04)			
Retail petrol	–0.10*** (0.02)		0.99*** (0.03)	0.00006*** (0.00)	
Retail diesel	–0.17*** (0.02)		1.04*** (0.02)	0.00008*** (0.00)	
					Constant
					0.08*** (0.02)
					0.07*** (0.01)

Notes: *, ** and *** define statistical significance level at 10%, 5% and 1% respectively. Standard errors are in parentheses. Models are estimated using weekly data from January 2005 to December 2018. All variables are expressed in euro per litre. The lag order is selected by minimizing the Schwarz criterion. Time dummies are included in the estimation of refined petrol (29/08/2005), retail petrol (05/09/2005, 12/09/2005, 02/02/2009, 02/03/2009), retail diesel (09/03/2015).

Table 4. Modelling other energy prices: error correction and long-run coefficients.

	Error correction	Long-run coefficients		
		Oil (euro)	Timber	Labour costs
Natural Gas	−0.019*** (0.005)	1.04*** (0.19)		
Heat Energy	−0.017*** (0.004)	0.79*** (0.10)		
Solid fuel	−0.07*** (0.01)		0.50*** (0.15)	0.41*** (0.08)

Notes: *, ** and *** define statistical significance level at 10%, 5% and 1% respectively. Standard errors are in parentheses. Models are estimated using monthly data from January 2005 to December 2018. All variables are seasonally adjusted and expressed in logs. The lag order is selected by minimizing the Schwarz criterion. Time dummies are included in the estimation of natural gas (2004m12, 2005m10, 2008m10, 2009m07, 2010m07), heat energy (2007m10, 2008m02, 2008m10, 2009m05, 2010m04, 2012m01), solid fuel (2006m09, 2007m02, 2013m10, 2018m01, 2018m10).

Heat energy prices are also linked to crude oil prices. This reflects the fact that most of the heat energy in Latvia is produced using natural gas, which again ultimately links heat energy prices to crude oil prices. Consumer solid fuel prices in Latvia mainly represent the price of firewood. Thus we link solid fuel prices to Latvian timber prices and domestic labour costs.

We do not model electricity prices and there is a couple reasons. First, electricity market in Latvia was fully regulated before 2015 and it prevents us to use econometric techniques. Second, despite the fact that since 2015 electricity wholesale prices strongly correlate with the respective prices in Estonia, Lithuania and the Scandinavian countries due to the connection to the Nord Pool electricity market, retail electricity consumer prices resemble behaviour of administered prices. The majority of households have fixed-price contracts with the main electricity supplier, thereby consumer price of electricity changes infrequently. Hence, during forecast exercises we set electricity prices unchanged (flat).

3.4. Non-energy industrial goods prices

Developments in prices of individual NEIG items exhibited opposite patterns over the last 15 years. The prices of durable goods were broadly stable up to 2008 and then significantly and monotonically decreased over the last 10 years. The major share of these goods is imported, and their prices might reflect hardly measurable factors, such as global technical progress or integration of low-wage countries into global value chains. Consumer prices of semi-durable goods (mainly clothes and footwear) show considerable seasonality, but over the years the price level remained almost unchanged. In turn, consumer prices of non-durable industrial goods were steady rising over time. Such a variation in trends and volatilities of NEIG prices precludes us to model NEIG prices as a single aggregate. Instead, we divide NEIG items in three parts – (i) NEIG prices, which to a large extent are driven by domestic activity, (ii) other NEIG prices, (iii) administered prices (i.e. water supply). In order to understand which NEIG prices are driven by domestic economic activity and correlate with domestic labour costs, we regress each NEIG item on labour costs separately. Those NEIG items, which statistically significantly correlate with labour costs, we aggregate them and classify as non-energy industrial goods with domestic value added.⁵ The rest of NEIG prices are aggregated and classified as ‘other goods’ (Table A5). The former is modelled using ARDL, but the latter follows AR model with

Table 5. Modelling NEIG prices: error correction and long-run coefficients.

	Error correction	Long-run coefficients		
		Labour costs	NEER	Trend
NEIG with domestic value added	−0.11*** (0.01)	0.30*** (0.02)	0.26* (0.14)	−0.001*** (0.00)

Notes: *, ** and *** define statistical significance level at 10%, 5% and 1% respectively. Standard errors are in parentheses. Models are estimated using monthly data from January 2005 to December 2018. All variables are seasonally adjusted and expressed in logs. The NEER is defined as an increase means depreciation. The lag order is selected by minimizing the Schwarz criterion. Time dummies are included in the estimation of NEIG (2009m01, 2010m12, 2011m08, 2013m04).

optimal number of lags. Water supply is administered price and changes infrequently. Therefore we do not model it and during forecast exercises we set price of water supply unchanged (flat).

NEIG with domestic value added account for more than a half in consumer spending on non-energy industrial goods. Its long-run elasticity to domestic labour costs is about 0.30 (Table 5). As some of these goods are imported, we find a positive correlation of consumer prices with the NEER. We also include a negative trend in equation for NEIG with domestic value added, which are likely to reflect the increasing competition or greater availability of cheap imports.⁶

3.5. Services prices

Services prices, akin to NEIG, also reflect many various behaviour patterns and trends. Therefore, we divide all services prices in eight components: prices of catering, communication, accommodation, air transport, package holidays, education, administered prices and other market services prices (hereinafter, labour-intensive services prices).

Labour-intensive services are the largest group of services (see Table A6; more than 40% of consumer spending on services), which shares a common price dynamics and exhibits a very high long-run price elasticity to labour costs (0.77; Table 6). Likewise, a high elasticity to labour costs is also observed in catering services.

Accommodation prices are affected not only by labour costs but also by interaction of demand and supply, reflected by the hotel room occupancy rate. In turn, package holiday prices are affected both by labour costs and prices of air transport, since package holidays are defined as holidays whose costs of travel and accommodation are bundled and sold in one transaction. We link the prices of communication services to labour costs and internet usage, while consumer prices of air transport to the costs of fuel. Administered services prices ultimately represent labour costs. Education services in Latvia are mostly publicly financed and price changes occur infrequently and largely in conjunction with a start of academic year. This regularity precludes to use econometric techniques. We single out education services prices out of services prices and set them flat during forecast exercises.

4. Forecast evaluation

This section takes a formal forecast evaluation exercise. We assess forecast accuracy in terms of RMSFEs and compare the results of STIP model with a benchmark AR(1) model.

Table 6. Modelling services prices: error correction and long-run coefficients.

	Error correction	Long-run coefficients			
		Labour costs	HICP item	Other variables	Trend Constant
Labour-intensive services	−0.14*** (0.02)	0.77*** (0.03)			−0.001*** (0.00)
Catering	−0.11*** (0.02)	0.75*** (0.05)	0.12** (food) (0.05)		−0.001*** (0.00)
Administered Services	−0.05*** (0.005)	0.99*** (0.22)			−0.002*** (0.001)
Communication	−0.02*** (0.003)	0.89*** (0.31)		−0.96*** (0.33) (internet usage; %)	2.80** (1.41)
Accommodation	−0.28*** (0.04)	0.10** (0.05)		0.38*** (0.04) (hotel occupancy; %)	−0.002*** (0.00)
Air transport	−0.06*** (0.01)		0.76*** (fuel) (0.25)		−0.005*** (0.00)
Package holidays	−0.19*** (0.04)	0.50*** (0.07)	0.32** (0.13) (air transport)		−0.001** (0.00)

Notes: *, ** and *** define statistical significance level at 10%, 5% and 1% respectively. Standard errors are in parentheses. Models are estimated using monthly data from January 2005 to December 2018. All variables are seasonally adjusted and expressed in logs. The lag order is selected by minimizing the Schwarz criterion. HICP for food means HICP for food prices, excluding alcohol and tobacco. Time dummies are included in the estimation of labour-intensive services (2007m05, 2008m02, 2009m01, 2009m09, 2014m01, 2016m07, 2018m01), catering (2005m09, 2009m01, 2009m09, 2013m01, 2013m10, 2014m01), administered services (2007m02), communication (2005m11, 2006m06, 2008m01, 2008m02, 2009m01, 2012m10, 2016m12, 2015m06, 2015m07, 2016m05, 2016m07), accommodation (2006m05, 2006m06, 2007m04, 2008m11, 2013m07, 2013m08, 2013m09, 2014m07, 2014m08, 2015m07, 2016m10, 2017m06, 2018m09).

We conduct an out-of-sample forecast evaluation exercise in order to simulate forecast errors as if they were generated in real time. Initially two-thirds of the sample (2005–2013) is used for the in-sample estimation, while one-third (2014–2018) is used for the out-of-sample forecast evaluation.

Latvia joined the euro area in January 2014, and since then Latvijas Banka regularly contributes inflation projections to the Eurosystem's Broad Macroeconomic Projection Exercise. In line with the Eurosystem's forecasting framework, euro area central banks develop their inflation projections based on a set of common assumptions (e.g. crude oil prices, DG AGRI prices and the exchange rate). As a result, we compile a database of each assumption at every time vintage used in the production of STIP forecasts to mimic forecast rounds in real time.

We closely follow Giannone et al. (2014) notation in setting up an evaluation exercise. First, let us define p_t as the natural logarithm of the consumer price index under consideration. Then the target variable is h -period ahead the change in prices as follows:

$$\pi_{t+h} = p_{t+h} - p_t \quad (3)$$

Each month we make projections 12 months ahead (horizon h) using the STIP model and store forecasts. Further, we compare forecasts with outturns and obtain the RMSFE as follows:

$$RMSFE_h = \sqrt{\frac{1}{K_h} \sum_{v=Jan2014}^{Dec2018-h} (\pi_{v,v+h} + \pi_{v+h})^2} \quad (4)$$

K_h is the number of forecast vintages between January 2014 and December 2018 for horizon h ; $\pi_{v,v+h}$ is the change in prices for the date $v+h$ using vintage data v , and π_{v+h} is the observed change in prices h periods ahead.

We select AR(1) model as a benchmark model, which is frequently used in the literature:

$$\Delta y_t = a_0 + c_0 \Delta y_{t-1} + \epsilon_t \quad (5)$$

We produce three sets of forecasts: AR(1) aggregated approach, AR(1) disaggregated approach and STIP, where the first two used as benchmarks. We summarize the results of the forecast evaluation exercise in Table 7, where the ratio of forecast errors less than 1 indicates an improvement of STIP forecasts over disaggregated AR(1) model.

We find that the forecast errors of the STIP model are more accurate compared to both aggregated and disaggregated AR(1) benchmarks. Across broad components, the forecast accuracy gains are 20–30% forecasting 3 months ahead and 15–55% forecasting 12 months ahead. Note that the forecast errors are increasing along the forecast horizon, which is a standard result. It should be noted also that the highest forecast errors are observed in the food and energy components. The consumer prices of these components depend on the developments of global prices, which are highly volatile. In turn, the lowest forecast errors are in NEIG and services – these consumer prices, to a large extent, are determined by domestic economic activity.

We check whether forecast accuracy is statistically different between the STIP and disaggregated AR(1) model using Diebold–Mariano (DM) test and find statistically significant

Table 7. Forecast errors for the STIP and AR(1) models.

	HICP	Unprocessed food	Processed food	Energy	NEIG	Services
STIP:						
3M	0.47	2.16	0.69	2.19	0.39	0.56
6M	0.69	2.66	1.18	3.16	0.46	0.79
12M	1.09	2.92	2.02	5.24	0.60	1.05
AR(1) aggregated:						
3M	0.66	–	–	–	–	–
6M	1.23	–	–	–	–	–
12M	2.39	–	–	–	–	–
AR(1) disaggregated:						
3M	0.69	2.57	0.96	2.62	0.39	0.54
6M	1.26	2.99	1.82	4.26	0.46	0.86
12M	2.41	4.37	3.47	6.98	0.69	1.58
Ratio (STIP / AR(1) disaggregated):						
3M	0.69	0.84	0.72	0.83	1.00	1.04
6M	0.55	0.89	0.65	0.74	1.01	0.93
12M	0.45	0.67	0.58	0.75	0.86	0.67
Modified DM test (t-statistics):						
3M	2.35***	3.05***	1.84**	1.70*	-0.02	0.17
6M	2.07**	1.60	1.70*	1.90*	-0.12	1.01
12M	1.55	2.67**	1.55	1.04	1.00	1.63*

Notes: The table reports forecast errors in terms of the RMSFE. The out-of-sample forecasting exercise is run from January 2014 to December 2018, while models are estimated from January 2005 through December 2013. We employ the DM test with a Harvey et al. (1997) correction (i.e. taking into account that forecast errors can be correlated among forecast horizons). *, ** and *** define statistical significance level at 10%, 5% and 1% respectively. We also cross-checked the statistical significance of difference in forecast accuracy using the Clark and West (2007) test and found that the results overall do not change the conclusion.

forecast accuracy improvements both for the headline inflation and several components (see Table 7 bottom panel). In the short horizon (3 months), the test indicates that the forecast errors of the STIP model are statistically significantly different from those of disaggregated AR(1) for unprocessed food, processed food and energy. In the longer horizon (12 months), the forecast errors of services and unprocessed food prices are statistically different from AR(1). In turn, the forecast errors of NEIG are not statistically significantly different from AR(1) model at any horizon. Note, however, that the level of the NEIG forecast errors is already quite low in the benchmark AR(1) model compared to other HICP components.

Forecast errors of all 33 HICP components are shown in Table 8. The results show that the forecast accuracy is greater for most components using STIP model compared to disaggregated AR(1) model. The forecast accuracy gains vary from 30% forecasting 3 months ahead to 60% forecasting 12 months ahead.

Table 8. Forecast errors of the HICP components.

	STIP			AR(1)			Ratio (STIP/AR(1))		
	M3	M6	M12	M3	M6	M12	M3	M6	M12
Headline HICP	0.47	0.69	1.09	0.69	1.26	2.41	0.69	0.55	0.45
Unprocessed meat	1.70	2.12	3.03	1.99	2.77	4.14	0.85	0.77	0.73
Unprocessed fish	3.85	4.24	5.50	4.62	6.08	9.02	0.83	0.70	0.61
Unprocessed eggs	3.88	4.78	6.95	3.96	4.76	6.98	0.98	1.00	1.00
Unprocessed fruits	3.78	4.24	4.69	4.37	4.58	6.38	0.87	0.93	0.74
Unprocessed vegetables	7.91	7.94	7.96	9.36	9.62	12.12	0.85	0.83	0.66
Processed meat	1.13	1.69	2.66	1.22	1.90	3.29	0.93	0.89	0.81
Processed fish	1.16	1.96	2.96	1.08	1.83	3.33	1.07	1.07	0.89
Processed fruits	2.27	2.90	3.49	2.53	3.26	4.36	0.90	0.89	0.80
Processed vegetables	4.17	6.01	8.14	4.64	6.42	8.54	0.90	0.94	0.95
Dairy	2.75	4.33	6.80	3.02	4.90	8.58	0.91	0.88	0.79
Cereals	1.01	1.44	1.94	1.22	2.16	3.78	0.83	0.67	0.51
Oils	2.93	4.72	7.98	3.10	5.04	8.31	0.95	0.94	0.96
Sugar	1.88	2.75	4.71	1.94	3.01	5.08	0.97	0.91	0.93
Other food	1.09	1.65	2.23	0.98	1.49	2.27	1.11	1.11	0.98
Drink	1.76	2.23	3.87	2.06	2.74	3.95	0.86	0.81	0.98
Alcohol	1.55	1.96	2.33	1.72	2.35	3.22	0.90	0.83	0.72
Tobacco	1.34	1.98	2.38	1.64	3.00	5.87	0.81	0.66	0.40
NEIG with domestic value added	0.44	0.58	0.75	0.63	1.07	1.85	0.70	0.55	0.40
Other NEIG	0.81	0.94	1.29	0.82	0.96	1.62	0.99	0.99	0.80
Administered NEIG	3.25	4.70	6.41	3.25	4.70	6.41	1.00	1.00	1.00
Market services	0.80	1.15	1.83	0.91	1.30	2.11	0.88	0.88	0.87
Catering services	0.81	1.20	1.39	0.57	1.02	2.07	1.43	1.18	0.67
Administered services	1.39	2.01	3.19	1.62	2.59	4.59	0.86	0.77	0.69
Communications	0.99	1.54	2.59	1.49	2.74	5.32	0.67	0.56	0.49
Accommodation	2.69	2.87	3.26	2.88	3.11	4.36	0.93	0.92	0.75
Education	1.05	1.41	1.67	1.05	1.41	1.67	1.00	1.00	1.00
Air transport	5.86	7.71	11.10	6.09	8.13	12.34	0.96	0.95	0.90
Package holidays	3.41	4.72	6.27	4.01	5.85	9.13	0.85	0.81	0.69
Car fuel	5.75	8.08	11.07	6.28	9.33	13.35	0.92	0.87	0.83
Natural gas	4.15	5.35	9.67	4.65	7.22	13.05	0.89	0.74	0.74
Electricity	5.78	8.26	11.56	5.78	8.26	11.56	1.00	1.00	1.00
Heating energy	2.59	4.51	8.98	3.19	5.95	11.19	0.81	0.76	0.80
Solid fuel	2.32	3.00	4.23	2.60	4.36	7.20	0.89	0.69	0.59

Notes: The table reports forecast errors of the STIP model and AR(1) model in terms of the RMSFE. Headline HICP of AR(1) relates to disaggregated approach. Consumer prices of water supply, education and electricity are largely administered and change infrequently, therefore STIP and AR(1) model projections are set unchanged (flat) over horizon. The out-of-sample forecasting exercise is run from January 2014 to December 2018. *, ** and *** define statistical significance level at 10%, 5% and 1% respectively. M3, M6 and M12 are projections 3, 6 and 12 months ahead respectively.

5. Conclusion

We build a short-term inflation projections (STIP) model for Latvia, currently used by the Bank of Latvia for ECB macroeconomic projection rounds. The model is based on ARDL framework, introducing long run relationships between consumer prices and their determinants, and a correction towards equilibrium. It employs disaggregated forecasting approach, dividing HICP into 33 components and making projections for each of them. In our model, consumer prices are affected by the four main factors. Crude oil prices are the main factor directly driving consumer prices of energy; and indirectly, through car fuel prices, affect consumer prices of food and some services. Global food commodity prices exert a pressure mainly on consumer prices of unprocessed and processed foods, which indirectly affect also consumer prices of catering services. The impact of nominal effective exchange rate (NEER) is mainly found in consumer prices of non-energy industrial goods (NEIG). Finally, domestic labour costs -- directly and indirectly -- affect almost all components of consumer prices.

We assess the forecast accuracy of the STIP model by running the real-time out-of-sample forecast exercise. For this purpose, we compile a database of each assumption at every time vintage used in the production of STIP forecasts to mimic forecast rounds in real time (over 2014–2018), while two-thirds of the sample (2005–2013) are used for the in-sample estimation. We find that consumer price forecasts of the STIP model are significantly more accurate compared to both aggregated and disaggregated AR(1) benchmarks. Across inflation components, the forecast accuracy gains are 20–30% forecasting 3 months ahead and 15–55% forecasting 12 months ahead.

Notes

1. The BMPE is a broad macroeconomic projection exercise conducted by the Eurosystem twice per year, while the NIPE is a narrow inflation projection exercise concomitant to the BMPE, but conducted four times per year over a shorter forecast horizon to monitor inflation developments. For details, see ECB, 2016.
2. Poland is a main exporter of meat products to Latvia accounting for more than a quarter of total meat imports over 2005–2018.
3. There is an anecdotal evidence that the bread baking industry in Latvia faces an ever-increasing competition from many small producers entering the market and from some supermarkets building their own bread baking facilities.
4. Note that petrol and diesel prices are the only HICP items whose prices are modelled in euro per litre rather than in logs. See Meyler (2009) on the merits of levels versus logs in the forecasting of car fuel prices.
5. This definition does not necessarily mean that these products are made in Latvia. The definition rather reflects the correlation with domestic labour costs, which might represent domestic value added of the good.
6. There is an anecdotal evidence that the number of large department stores and supermarkets increased markedly in Latvia during the last 15 years. Also, imports from China increased almost five times between 2005 and 2018.

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No potential conflict of interest was reported by the authors.

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Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

- Alvarez, L. J., & Sánchez, I. (2017). A suite of inflation forecasting models. *Occasional papers number 1703*. Banco de España; Occasional Papers Homepage. <https://ideas.repec.org/p/bde/opaper/1703.html>.
- Antoniades, A., Peach, R., & Rich, R. W. (2004). The historical and recent behavior of goods and services inflation. *Economic Policy Review*, 10(3), 19–31. <https://ideas.repec.org/a/fip/fednep/y2004idecp19-31nv.10no.3.html>
- Aron, J., & Muellbauer, J. (2012). Improving forecasting in an emerging economy, South Africa: Changing trends, long run restrictions and disaggregation. *International Journal of Forecasting*, 28(2), 456–476. <https://doi.org/10.1016/j.ijforecast.2011.05.004>
- Aron, J., & Muellbauer, J. (2013). New methods for forecasting inflation, applied to the US. *Oxford Bulletin of Economics and Statistics*, 75(5), 637–661. <https://doi.org/10.1111/obes.2013.75.issue-5>
- Banbura, M., Giannone, D., & Reichlin, L. (2010). Large Bayesian vector auto regressions. *Journal of Applied Econometrics*, 25(1), 71–92. <https://doi.org/10.1002/jae.1137>
- Bandt, O. D., Michaux, E., Bruneau, C., & Flageollet, A. (2007). Forecasting inflation using economic indicators: the case of France. *Journal of Forecasting*, 26(1), 1–22. <https://doi.org/10.1002/for.1001>
- Birmingham, C., & D'Agostino, A. (2014). Understanding and forecasting aggregate and disaggregate price dynamics. *Empirical Economics*, 46(2), 765–788. <https://doi.org/10.1007/s00181-013-0685-6>

- Boivin, J., & Ng, S. (2005). Understanding and comparing factor-based forecasts. *International Journal of Central Banking*, 1(3), 117–151. <https://ideas.repec.org/a/ijc/ijcjou/y2005q4a4.html>
- Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138(1), 291–311. <https://doi.org/10.1016/j.jeconom.2006.05.023>
- Duarte, C., & Rua, A. (2007). Forecasting inflation through a bottom-up approach: How bottom is bottom?. *Economic Modelling*, 24(6), 941–953. <https://doi.org/10.1016/j.econmod.2007.03.004>
- ECB (2016). A guide to the Eurosystem/ECB staff macroeconomic projection exercises. *Working Paper Series number 2378*. European Central Bank. <https://www.ecb.europa.eu/pub/pdf/other/staffprojectionsguide201607.en.pdf>.
- Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, 55(2), 251–276. <https://doi.org/10.2307/1913236>
- Espasa, A., & Albacete, R. (2007). Econometric modelling for short-term inflation forecasting in the euro area. *Journal of Forecasting*, 26(5), 303–316. [https://doi.org/10.1002/\(ISSN\)1099-131X](https://doi.org/10.1002/(ISSN)1099-131X)
- Espasa, A., Senra, E., & Albacete, R. (2002). Forecasting inflation in the European monetary union: A disaggregated approach by countries and by sectors. *The European Journal of Finance*, 8(4), 402–421. <https://doi.org/10.1080/13518470210167284>
- Fritzer, F., Moser, G., & Scharler, J. (2002). Forecasting austrian HICP and its components using VAR and ARIMA models. *Working Papers number 73*. Oesterreichische Nationalbank (Austrian Central Bank). <https://ideas.repec.org/p/onb/oenbwp/73.html>.
- Giannone, D., Lenza, M., Momferatou, D., & Onorante, L. (2014). Short-term inflation projections: A bayesian vector autoregressive approach. *International Journal of Forecasting*, 30(3), 635–644. <https://doi.org/10.1016/j.ijforecast.2013.01.012>
- Harvey, D., Leybourne, S., & Newbold, P. (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting*, 13(2), 281–291. [https://doi.org/10.1016/S0169-2070\(96\)00719-4](https://doi.org/10.1016/S0169-2070(96)00719-4)
- Hendry, D. F., & Hubrich, K. (2011). Combining disaggregate forecasts or combining disaggregate information to forecast an aggregate. *Journal of Business & Economic Statistics*, 29(2), 216–227. <https://doi.org/10.1198/jbes.2009.07112>
- Hubrich, K. (2005). Forecasting euro area inflation: Does aggregating forecasts by HICP component improve forecast accuracy?. *International Journal of Forecasting*, 21(1), 119–136. <https://doi.org/10.1016/j.ijforecast.2004.04.005>
- Huwiler, M., & Kaufmann, D. (2013). Combining disaggregate forecasts for inflation: The SNB's ARIMA model. *Economic studies number 2013-07*. Swiss National Bank. <https://ideas.repec.org/p/snb/snbecs/2013-07.html>.
- Johansen, S. (1995). Likelihood-based inference in cointegrated vector autoregressive models. *Number 9780198774501 in OUP Catalogue*, Oxford University Press. <https://ideas.repec.org/b/oxp/obooks/9780198774501.html>.
- Marcellino, M., Stock, J. H., & Watson, M. W. (2003). Macroeconomic forecasting in the Euro area: Country specific versus area-wide information. *European Economic Review*, 47(1), 1–18. [https://doi.org/10.1016/S0014-2921\(02\)00206-4](https://doi.org/10.1016/S0014-2921(02)00206-4)
- Marcellino, M., Stock, J. H., & Watson, M. W. (2006). A comparison of direct and iterated multistep AR methods for forecasting macroeconomic time series. *Journal of Econometrics*, 135(1–2), 499–526. <https://doi.org/10.1016/j.jeconom.2005.07.020>
- Meyler, A. (2009). The pass through of oil prices into euro area consumer liquid fuel prices in an environment of high and volatile oil prices. *Energy Economics*, 31(6), 867–881. <https://doi.org/10.1016/j.eneco.2009.07.002>
- Moser, G., Rumler, F., & Scharler, J. (2007). Forecasting Austrian inflation. *Economic Modelling*, 24(3), 470–480. <https://doi.org/10.1016/j.econmod.2006.10.003>
- Pesaran M. H., & Shin, Y. 1998. An autoregressive distributed lag modelling approach to cointegration analysis. In: S. Strom (Ed.), *Econometrics and Economic Theory: The Ragnar Frish Centennial Symposium*. Econometric Society Monographs (pp. 371–413). Cambridge University Press. <https://doi.org/10.1017/CCOL521633230>
- Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289–326. [https://doi.org/10.1002/\(ISSN\)1099-1255](https://doi.org/10.1002/(ISSN)1099-1255)

- Phillips, P. C. B., & Ouliaris, S. (1990). Asymptotic properties of residual based tests for cointegration. *Econometrica*, 58(1), 165–193. <https://doi.org/10.2307/2938339>
- Reijer, A., & Vlaar, P. (2006). Forecasting inflation: An art as well as a science!. *De Economist*, 154(1), 19–40. <https://doi.org/10.1007/s10645-006-0002-2>
- Senra, E., Poncela, P., & Espasa, A. (2002). Forecasting monthly us consumer price indexes through a disaggregated I(2) analysis. *DES -- Working Papers*. Statistics and Econometrics. WS ws020301. Universidad Carlos III de Madrid. Departamento de Estadística. <https://ideas.repec.org/p/cte/wsrepe/ws020301.html>.
- Stakenas, J. (2015). Forecasting lithuanian inflation. *Bank of Lithuania working paper series 17*. Bank of Lithuania. <https://ideas.repec.org/p/lie/wpaper/17.html>.
- Stock, J. H., & Watson, M. W. (1999). Forecasting inflation. *Journal of Monetary Economics*, 44(2), 293–335. [https://doi.org/10.1016/S0304-3932\(99\)00027-6](https://doi.org/10.1016/S0304-3932(99)00027-6)
- Stock, J. H., & Watson, M. W. (2002). Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association*, 97(460), 1167–1179. <https://doi.org/10.1198/016214502388618960>

Appendix

Table A1. ADF unit root test results for the first differences.

HICP components	<i>p</i> -value	Lag length	Observations
Unprocessed meat	0.000	0	168
Unprocessed fish	0.000	6	168
Eggs	0.000	0	168
Unprocessed fruits	0.000	0	168
Unprocessed vegetables	0.000	0	168
Processed meat	0.001	3	168
Processed fish	0.000	1	168
Processed fruits	0.000	0	168
Processed vegetables	0.000	0	168
Dairy products	0.000	0	168
Bread and cereals	0.000	1	168
Oils and fats	0.000	2	168
Sugar and chocolate	0.000	2	168
Other food	0.000	0	168
Non-alcoholic beverages	0.000	0	168
Alcoholic beverages	0.000	0	168
Tobacco	0.000	0	168
Car fuel	0.000	0	168
Natural gas	0.000	0	168
Heat energy	0.000	0	168
Solid fuels	0.000	0	168
NEIG with domestic value added	0.001	3	168
Labour-intensive services ^a	0.000	1	168
Catering services ^a	0.000	0	168
Administered services	0.000	1	168
Communication services	0.000	0	168
Accommodation services	0.000	1	168
Air transport	0.000	0	168
Package holidays	0.000	0	168
Other variables			
DG AGRI cereals	0.000	2	168
DG AGRI dairy	0.000	1	168
DG AGRI total food	0.000	2	168
DG AGRI meat	0.000	0	168
Global sugar	0.000	1	168
Global coffee	0.000	0	168
Nasdaq salmon	0.000	0	166
NEER	0.004	9	168
Wage	0.009	3	163
Hotel occupancy rate	0.000	0	168
Internet usage	0.009	3	168
Timber	0.004	1	147
Oil, euro	0.000	0	732
Refined diesel	0.000	0	732
Refined petrol	0.000	0	732
Retail diesel	0.000	1	728
Retail petrol	0.000	1	728

Notes: Series are tested over the period 2005–2018. *P*-values below 0.05 indicate that the respective time series do not have a unit root in the first differences at 5% significance level. The lag length is selected based on the Schwarz information criterion. ^aLabour-intensive and catering services prices are tested using ADF test with breaking points in trend and intercept.

Table A2. Pesaran–Shin–Smith cointegration test results.

Equation	<i>F</i> -statistics	<i>I</i> (0) threshold	<i>I</i> (1) threshold
Unprocessed meat	11.53	3.88	4.61
Unprocessed fish	9.81	2.45	3.63
Eggs	12.01	3.79	4.85
Unprocessed fruits	9.47	3.88	4.61
Unprocessed vegetables	9.60	3.62	4.16
Processed meat	22.80	3.10	3.87
Processed fish	12.90	2.79	3.67
Processed fruits	9.74	3.79	4.85
Processed vegetables	7.44	3.62	4.16
Dairy products	12.83	2.79	3.67
Bread and cereals	22.64	3.88	4.61
Oils and fats	6.54	3.79	4.85
Sugar and chocolate	4.67	2.45	3.63
Other food	13.95	2.45	3.63
Non-alcoholic beverages	23.78	3.23	4.35
Alcoholic beverages	6.76	3.10	3.87
Tobacco	15.29	3.15	4.11
Refined diesel	9.58	3.62	4.16
Refined petrol	14.80	4.68	5.15
Retail diesel	16.91	3.10	3.87
Retail petrol	9.51	3.10	3.87
Natural gas	5.90	3.62	4.16
Heat energy	6.29	3.62	4.16
Solid fuels	10.37	2.72	3.83
NEIG with domestic value added	18.13	3.88	4.61
Labour-intensive services	20.91	4.68	5.15
Catering services	9.61	3.88	4.61
Administered services	28.06	4.68	5.15
Communication services	12.04	3.10	3.87
Accommodation services	14.31	3.88	4.61
Air transport	5.27	4.68	5.15
Package holidays	5.92	3.88	4.61

Notes: *F*-statistics greater than the *I*(1) threshold indicates that the variables in the particular equation are cointegrated.

Table A3. Results of serial correlation and heteroskedasticity tests.

Equation	Serial correlation test		Heteroskedasticity test	
	<i>F</i> -statistics	<i>p</i> -value	<i>F</i> -statistics	<i>p</i> -value
Unprocessed meat	1.50	0.23	0.90	0.50
Unprocessed fish	2.31	0.10	1.57	0.11
Eggs	1.42	0.24	3.34	0.00
Unprocessed fruits	0.06	0.94	0.79	0.64
Unprocessed vegetables	1.12	0.33	1.29	0.28
Processed meat	1.23	0.29	2.01	0.06
Processed fish	0.77	0.46	0.85	0.57
Processed fruits	1.21	0.30	1.07	0.39
Processed vegetables	3.68	0.03	1.16	0.31
Dairy products	1.89	0.15	0.36	0.97
Bread and cereals	0.36	0.70	2.72	0.00
Oils and fats	2.24	0.11	1.50	0.13
Sugar and chocolate	0.42	0.66	1.82	0.09
Other food	0.45	0.64	0.62	0.81
Non-alcoholic beverages	0.13	0.88	1.54	0.10
Alcoholic beverages	1.65	0.20	1.45	0.15
Tobacco	1.52	0.22	1.76	0.07
Refined diesel	0.21	0.81	18.85	0.00

(Continued)

Table A3. Continued.

	Serial correlation test		Heteroskedasticity test	
Refined petrol	0.53	0.59	1.80	0.07
Retail diesel	1.64	0.19	1.68	0.07
Retail petrol	0.13	0.87	1.78	0.04
Natural gas	0.16	0.85	0.11	1.00
Heat energy	1.89	0.15	1.10	0.36
Solid fuels	0.79	0.46	1.10	0.37
NEIG with domestic value added	0.78	0.46	1.04	0.41
Labour-intensive services	0.94	0.39	1.14	0.33
Catering services	0.78	0.46	3.66	0.00
Administered services	0.87	0.42	7.38	0.00
Communication services	0.31	0.74	0.98	0.48
Accommodation services	1.87	0.16	0.81	0.72
Air transport	0.44	0.65	4.48	0.00
Package holidays	0.48	0.62	3.72	0.00

Notes: We use the Breusch–Godfrey serial correlation LM test where the null hypothesis states that there is no serial correlation; in the Breusch–Pagan–Godfrey test used for heteroskedasticity, null states homoskedasticity.

Table A4. Models' in-sample explanatory power.

Equation	R^2 in levels	R^2 in differences	Observations
Unprocessed meat	0.9945	0.3376	168
Unprocessed fish	0.9912	0.4211	167
Eggs	0.9895	0.5596	168
Unprocessed fruits	0.9706	0.4846	168
Unprocessed vegetables	0.8253	0.2685	168
Processed meat	0.9965	0.3779	168
Processed fish	0.9988	0.5200	168
Processed fruits	0.9968	0.4321	168
Processed vegetables	0.9542	0.6692	168
Dairy products	0.9980	0.6723	168
Bread and cereals	0.9990	0.7243	167
Oils and fats	0.9974	0.5135	168
Sugar and chocolate	0.9959	0.1650	168
Other food	0.9987	0.4813	167
Non-alcoholic beverages	0.9977	0.5472	167
Alcoholic beverages	0.9956	0.5611	165
Tobacco	0.9997	0.9227	168
Natural gas	0.9979	0.6706	228
Heat energy	0.9989	0.6909	228
Solid fuels	0.9949	0.5844	150
NEIG with domestic value added	0.9983	0.6997	165
Labour-intensive services	0.9997	0.7981	165
Catering services	0.9996	0.8050	163
Communication services	0.9985	0.8127	166
Administered services	0.9990	0.5076	165
Accommodation services	0.9581	0.8576	168
Air transport	0.9326	0.1213	168
Package holidays	0.9574	0.1577	168
Refined diesel	0.9974	0.8132	732
Refined petrol	0.9908	0.5877	732
Retail diesel	0.9948	0.4520	728
Retail petrol	0.9934	0.5477	729

Notes: Refined (retail) diesel and petrol are weekly data, other variables are monthly data.

Table A5. Individual NEIG items, which are included in the aggregate 'goods with domestic value added' and other goods.

Goods with domestic value added:
Books
Spare parts and accessories for personal transport equipment
Other personal effects
Glassware and tableware and household utensils
Household textiles
Tools and equipment for house and garden
Newspapers and periodicals
Materials for the maintenance and repair of the dwelling
Other medical products, therapeutic appliances and equipment
Gardens, plants and flowers
Products for pets
Non-durable household goods
Electrical appliances for personal care, other appliances articles and products for personal care
Miscellaneous printed matter, stationery and drawing materials
Pharmaceutical products
Furniture and furnishings
Jewellery, clocks and watches
Carpets and other floor coverings
Other goods:
Motor cars
Motorcycles and bicycles
Information processing equipment
Telephone and telefax equipment
Photographic and cinematographic equipment and optical instruments
Recording media
Games, toys and hobbies
Equipment for sport, camping and open-air recreation
Garments
Clothing materials
Shoes and other footwear
Other articles of clothing and clothing accessories
Major household appliances whether electric or not and small electric household appliances
Equipment for the reception recording and reproduction of sound and picture

Table A6. Individual services items, which are included in the aggregate 'labour-intensive services'.

Labour-intensive services:
Actual rentals for housing
Services for the maintenance and repair of the dwelling
Other services relating to the dwelling n.e.c.
Repair of household appliances
Domestic services and household services
Insurance connected with the dwelling
Medical and paramedical services
Dental services
Financial services n.e.c.
Other services n.e.c.
Cleaning, repair and hire of clothing
Repair and hire of footwear
Repair of audio-visual photographic and information processing equipment
Veterinary and other services for pets
Recreational and sporting services
Cultural services
Hairdressing salons and personal grooming establishments
Maintenance and repair of personal transport equipment
Other services in respect of personal transport equipment
Passenger transport by sea and inland waterway
Insurance connected with transport
