FORECASTING LITHUANIAN INFLATION

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Abstract

The paper presents a short-term Lithuanian inflation forecasting model for predicting monthly inflation of 5 main HICP subgroups. We model inflation employing a set of univariate equations, which are mainly based on firms’ mark-up pricing. We make use of disaggregate HICP data, consisting of 92 price series, which naturally evokes discussion of potential pros and cons of forecasting disaggregate series vs. forecasting an aggregate. Besides exploring potential gains of using disaggregate data, we are also interested in the international commodity prices transmission mechanism, which we implement employing a distributed lag model. To examine the performance of model’s forecasts, we employ a recursive pseudo real-time out-of–sample forecasting exercise, generating inflation forecasts up to 15 months ahead. We find that our suggested set of univariate equations produce more accurate forecasts than the competing factor model, VARX model and various benchmark models for all 5 HICP subgroups.

Keywords: inflation, forecast aggregation, forecast cross-validation
JEL classification: C52, C53, E37

Santrauka


Raktiniai žodžiai: inflacija, prognozių agregavimas, prognozių kryžminė patikra
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Introduction

In the presence of widespread long-term nominal commitments, it becomes vital to understand the phenomenon of inflation and to be able to forecast the level of future prices. The need for inflation forecasting is shared by both, regulatory institutions and private economic agents. Households use inflation forecasts/perception to predict their future purchasing power which in turn leads to decisions regarding their present and future saving, consumption and investment. As for regulatory institution such as central bank, price stability being one of its main objectives, inflation forecasts play an essential role in monetary policy planning process. Sound monetary policy, based on credible inflation forecasts, should help to keep inflation around its desirable target level, thus avoiding unnecessary distortions in economic decision making, which could possibly hurt long-run economic growth.

The main purpose of this paper is to present Lithuanian inflation forecasting model suitable to forecast main HICP subcomponents and evaluate its prediction accuracy. Forecasts of separate HICP components at the Bank of Lithuania are primarily needed for internal purposes – inflation monitoring and analysis of its sources. As a result of the forthcoming euro adoption, HICP component forecasts would be also required by the ECB, to conduct the euro area narrow inflation projection exercise (NIPE). To make this study comparable with the HICP component forecasting models developed in other European countries (e.g. Reijer and Vlaar (2006), Célérer (2009)), the composition, used for HICP component aggregation, is the same as in the NIPE. To put it more specifically, the model, presented in the paper, is intended to be used for forecasting monthly price changes up to the horizon of 15 months of five HICP components: processed food, unprocessed food, industrial goods excluding energy, services, and energy.

Apart from the pure accuracy of our model forecasts, we are also interested in the transmission mechanism of raw material price changes in the EU/world market to Lithuanian consumer prices. In the context of globalization, when prices in different countries are becoming more and more interconnected, changes in raw material prices play an important role in consumer price formation. The effect in consumer prices, however, is usually observed with a certain lag, which makes raw commodity prices a useful source of information for inflation forecasting. To measure the price transmission, we resorted to a distributed lag model, possibly coupling it with a cointegrating relation.

Another important issue addressed in this paper is the question of aggregation/disaggregation. As the forecasts of the HICP components (services, goods and etc.) are often (but not necessarily) obtained using bottom-up approach (i.e. aggregating forecasts of the subcomponents), choosing appropriate level of disaggregation, in our view, may be just as important as specifying the equations themselves. Therefore, in this study we also focus on finding optimal level of disaggregation, treating it as a part of model specification process.

The paper proceeds as follows: we start with a somewhat general/theoretical approach introducing the set of methods used in our forecasting model in Section 1 and
discussing potential gains and losses of combining disaggregate forecasts vs. forecasting the aggregate in Section 2. In the empirical part of the paper, we discuss the data-related issues in Section 3, present estimates of the model in Section 4, and examine the accuracy of model’s forecasts employing the out-of-sample forecasting exercise in Section 5. Lastly, the conclusions are laid out in Section 6.

1. Inflation forecasting model

The model, presented in this paper, consists of a set of separate univariate equations, related only through common assumptions of exogenous variables. The use of univariate equations, in our opinion, can be justified by the rather short (up to 15 months) forecasting horizon. For longer forecasting horizons, VAR or other type models, incorporating spillovers between components, would be more appropriate. On the other hand, usage of univariate equations not only reduces the number of estimated parameters, but also makes modelling procedure very flexible: the equations can be of different type, some HICP prices can be excluded from the more aggregated component and modelled separately (which is frequently applied). Such flexibility and easy to use/alter implementation was also a big factor, motivating the modelling choice.

1.1. Mark-up model

The underpinning for the main forecasting equations in our model is the so-called mark-up model. We assume, that in monopolistic competition environment, firms are maximizing their profit, setting marginal revenue equal to marginal cost, and thus resulting in setting the price of their product as a mark-up over marginal cost \( \text{price} = (1+\text{mark-up}) \times \text{marginal cost} \). Mark-up model’s suitability for inflation forecasting in Lithuania has some empirical evidence stated in Virbickas (2010). In the aforementioned paper, Virbickas analyses results of the survey on Lithuanian firms’ price and wage setting behaviour during the year 2007. The study reveals, that in the presence of an increase in the cost of an intermediate input or increase in wages, fraction of firms responding with a change of prices of their own product (possibly in combination with other measures), is 74% and 69% respectively. Hence, we can infer that firms in Lithuania actively adjust their prices to the changes of production costs, and costs changes may as well be one of the main factors of inflation. On the other hand, the same study reveals that 52% of firms changed their prices due to slowdown in demand. While in this case the percentage of firms changing their prices is lower, opposite sign of the shock makes two cases less comparable. Therefore, we should not dismiss the possibility that the mark-up model may not always be well suited for inflation forecasting, as changes in demand may be just as important inflation factor as changes in costs.

The core of our model consists of a set of univariate equations, which have a general form of single-equation conditional error correction model (ECM):
\[ \Delta p_t = \alpha_0 + \sum_{i=1}^{n_1}(\alpha_i \Delta p_{t-i}) + \sum_{j=1}^{n_2} \sum_{k=1}^{n_3}(\beta_{j,k} \Delta x_{j,t-k}) + \sum_{l=1}^{n_2}(\theta_l x_{l,t-1}) + \gamma p_{t-1} + \varepsilon_t, \tag{1} \]

where: \( \Delta p_t = \log(P_t) - \log(P_{t-1}) \), \( P_t \) – monthly price index of a HICP subcomponent, \( x_{i,t} \) – log of an exogenous variable\(^1\) (of monthly frequency), \( i = 1 \ldots n_2 \), \( \varepsilon_t \sim (0, \sigma^2) \), \( E(\varepsilon_t, \varepsilon_j) = 0, t, j = 1 \ldots T, j \neq t \).

The three terms included into equation (1) (autoregressive, distributed lag and cointegration relation) help to catch specific aspects of inflation behaviour and deserve some commentary on their respective roles and motivation.

HICP level in equation (1) is linked to linear combination of levels of production costs (\( \sum_{l=1}^{n_2}(\theta_l x_{l,t-1}) \)) through cointegrating relation. Such specification does not enter all equations in the model as it is susceptible to shifts in HICP level due to changes in value added taxes, excise duties or other unaccounted reasons. One way to overcome this weakness is to use cointegration between annual inflation rates – according to Reijer and Vlaar (2006), “it appears that the economic rationale for a long-run relationship among price levels is less obvious than among inflation rates”. Regardless of such criticism, specification with cointegration between levels was chosen, as not cutting the memory of cointegration relation at the limit of one year has its own advantages.

The main channel, through which production costs in equation (1) are transmitted to consumer prices, is the monthly changes in production costs (\( \sum_{j=1}^{n_2} \sum_{k=1}^{n_3}(\beta_{j,k} \Delta x_{j,t-k}) \)). Using lags of monthly production costs changes, a rather diverse and realistic consumer price reaction to production costs shock can be achieved. Contrary to the behaviour which would be implicated, if cointegration relation would be the only cost transmission mechanism used, in equation (1) HICP is not restricted to react to costs’ changes already the following month and the response does not necessarily has to be largest in magnitude one month after the shock and diminishing afterwards. Of course, the problem of reliable coefficient estimates and selection of maximum lag number still remains an issue in this setting.

The use of lagged inflation is quite common in inflation modelling literature: in Phillips curve type models, past inflation was used to represent adaptively formed expectations or so-called “built-in” inflation (see e.g. Gordon (1982)), whereas in hybrid new Keynesian Phillips curve models lagged inflation has also found its place, representing “rule-of-thumb” price setters (Galí and Gertler (1999)), or indexation (Christiano et al. (2005)). In the case of mark-up model, use of inflation lags is more difficult to justify as we are not explicitly modelling inflationary expectations – firms are only reacting to changing production costs. Nevertheless, the role of lagged inflation can be warranted not only by better empirical fit, but also by presence of price rigidities and competition. We expect that due to stiff competition, firms might be reluctant to be the first to act in case of rising production costs. Therefore, in the environment where prices possess some kind of nominal rigidities, inflation lags should help to describe such situation when consumer price reaction to changes in production costs varies from a typical behaviour. Autoregressive terms should also help to model the effect of change in marginal costs omitted from the model, when inflation exhibits persistence due to e.g. existence of contracts.

\(^1\) The complete list of exogenous variables, used in the study, is presented in Appendix’s A Table 11.
The model in equation (1) is formulated in monthly changes, which is convenient, as HICP forecasts can be renewed every month, once the new data is published. However, this advantage also comes with a necessity to estimate large number of parameters of often highly correlated regressors. High correlation among regressors may produce parameter estimates which are statistically insignificant, possessing economically incorrect sign, or at least unsmooth (e.g. fluctuating estimates for neighbouring lags of a variable). To cope with this problem, some parameters were restricted to lie on a polynomial of a small degree, i.e. Almon lag model was used (see Almon (1965)).

1.2. Supplementary methods

The mark-up model was not the best modelling choice for certain Lithuanian HICP components, because these prices were poorly correlated with the general economic environment and were often determined by trends in global markets (e.g. technological progress causing quality adjustments), or such unpredictable factors as weather conditions (relevant for the prices of agricultural products). In these cases we chose to use models of less theoretical relevance, the suite of which we call “supplementary methods”.

Atkeson and Ohanian (2001) introduced a very simple benchmark method, while testing the accuracy of some standard specification Phillips curve model forecasts. Their forecast of an annual inflation was simply inflation over the previous year: \[ E_t \left( \frac{P_{t+12}}{P_t} \right) = \frac{P_t}{P_{t-12}}. \] Surprisingly, in their study such forecasts outperformed Phillips curve models’ forecasts. In our case, as one of the models used to forecast prices possessing slowly changing trend, we employ a moving average over the last 12 months, which in nature is analogous to the method used by Atkeson and Ohanian. We forecast future logarithmic returns to be equal to the average of logarithmic returns over the previous 12 months:

\[
\ln\left( \frac{P_{t+k}}{P_{t+k-1}} \right) = \frac{1}{12} \sum_{i=0}^{11} \ln\left( \frac{P_{t-l}}{P_{t-l-1}} \right) = \frac{1}{12} \ln\left( \frac{P_t}{P_{t-12}} \right),
\]

or:

\[
\frac{P_{t+k}}{P_t} = \left( \frac{P_t}{P_{t-12}} \right)^{\frac{k}{12}} = \frac{1}{12}, k = 1, 2, \ldots,
\]

which is identical to Atkeson and Ohanian random walk model when \( k = 12 \).

Other supplementary forecasting methods used in our model include single exponential smoothing and autoregressive-moving average (ARMA) models, which are a frequent choice for short-term forecasting.
2. Combining forecasts of disaggregates vs. forecasting the aggregate

Having chosen the mark-up model as our preferred inflation modelling tool, the purpose of this section is to lay down arguments which would help to select “optimal” disaggregation level of the model. The reasoning presented in this section motivates the choice of forecasting model specification in Section 4.

In this section we will follow the forecast error decomposition framework presented in Hendry and Hubrich (2010). Firstly, we will make an assumption regarding data generating process (DGP) (which in our case is the mark-up model), and then we will compare sources of possible forecasting errors using disaggregated and aggregated approach. Lastly, we will consider the impact of weight changes to the forecasting accuracy of the two methods.

2.1. Data generating process

Let \( p_t = (p_{1,t}, p_{2,t}, ..., p_{N,t})' \) denote vector of \( N \) disaggregate log price series \( p_{i,t} = \log(p_{i,t}) \), where \( p_{i,t} \) is HICP price subindex. The DGP of \( \Delta p_t = (p_{1,t} - p_{1,t-1}, p_{2,t} - p_{2,t-1}, ..., p_{N,t} - p_{N,t-1})' \) is assumed to be stationary and to have the following form:

\[
\Delta p_t = M + A \Delta p_{t-1} + B \Delta x_{t-1} + \Theta x_{t-1} + \Gamma p_{t-1} + \varepsilon_t, \tag{3}
\]

where \( M \) is a \( (N \times 1) \) vector of constants, \( A \) is \( (N \times N) \) matrix of autoregressive coefficients, \( B \) and \( \Theta \) are \( (N \times N_{\text{exog}}) \) coefficient matrices, \( \Gamma \) is a \( (N \times N) \) dimensional matrix with error correction coefficients on the diagonal, \( x_{t-1} = (x_{1,t-1}, ..., x_{N_{\text{exog},t-1}})' \) – vector of exogenous variables, \( \varepsilon_t \) are identically distributed random vectors with mean \( \mu_{\varepsilon} \) and covariance matrix \( \Sigma_{\varepsilon} \) and \( t = 1 \ldots (T + 1) \).

Our assumed DGP in (3) represents a simplified version of a multivariate case of the mark-up model (1). The maximum lag number in (3) was reduced to 1 for readability reasons (additional lags would affect the forecasting error the same way as the included one).

DGP in (3) is formulated for log differences to match the formulation in equation (1). However, price aggregation using linear transformation cannot be performed for logarithmic differences, therefore, we rewrite DGP in (3) to obtain \( y_t \) on the left-hand side instead of \( \Delta p_t \) (with \( y_t \) defined as a vector of price indices’ ratios: \( y_t = (y_{1,t}, y_{2,t}, ..., y_{N,t})' \), \( y_{i,t} = \frac{p_{i,t}}{p_{i,t-1}} \)):

\[
y_t = M^* + A y_{t-1} + B \Delta x_{t-1} + \Theta x_{t-1} + \Gamma p_{t-1} + \tilde{E}_t + \varepsilon_t, \tag{4}
\]

where \( M^* = M + (I_N - A)1_{N \times 1} \), \( 1_{N \times 1} \) – a \( N \times 1 \) vector of ones, \( \tilde{E}_t = AE_{t-1} - E_t \), and \( E_t \) is a vector of approximation errors with its elements defined as \( E_{i,t} = \Delta p_{i,t} - y_{i,t} + 1 = \log((y_{i,t} - 1) + 1) - (y_{i,t} - 1) \) (errors are expected to be small, as \( \log(1 + x) \approx x \) for “small” \( x \)).
Of course, the approximating error term $E_t$ could be eliminated, if the initial DGP formulation in (3) was for price ratios $y_t$, however, our intention was to link DGP to the forecasting model (1) and models are typically stated in log differences.

2.2. Aggregation of HICP components

We now turn our attention to the aggregation of HICP components. Price indices $P_{t,t}$ are aggregated to chain-linked $HICP_t$ employing the following formula:

$$HICP_t = \sum_{i=1}^{N} \left( w_{i,t} \frac{P_{i,t}}{P_{i,t,base}} \right) HICP_{base} = \sum_{i=1}^{N} \left( w_{i,t} y_{i,t} y_{i,t-1} \ldots y_{i,t,base+1} \right) HICP_{base},$$

where $w_{i,t}$ are weights of disaggregate components ($\sum_{i=1}^{N} w_{i,t} = 1$) and $t_{base}$ is a base period, used for chain-linking (for monthly data we use previous December as a base period).

Similarly, as in the case of disaggregated data, we consider formula for HICP level ratio to its previous value:

$$y_t^a = \frac{HICP_t}{HICP_{t-1}} = \frac{\sum_{i=1}^{N} \left( w_{i,t} y_{i,t} y_{i,t-1} \ldots y_{i,t,base+1} \right) HICP_{base}}{\sum_{j=1}^{N} \left( w_{j,t-1} y_{j,t-1} \ldots y_{j,t,base+1} \right) HICP_{base}}$$

$$= \sum_{i=1}^{N} \left[ \frac{w_{i,t} y_{i,t-1} \ldots y_{i,t,base+1}}{\sum_{j=1}^{N} \left( w_{j,t-1} y_{j,t-1} \ldots y_{j,t,base+1} \right)} \right] y_{i,t} = \sum_{i=1}^{N} \left( \tilde{w}_{i,t} y_{i,t} \right) = \tilde{w}_t' y_t,$$

where weight vector $\tilde{w}_t = (\tilde{w}_{1,t}, \ldots, \tilde{w}_{N,t})'$ and $\tilde{w}_{i,t} = \frac{w_{i,t} y_{i,t-1} \ldots y_{i,t,base+1}}{\sum_{j=1}^{N} \left( w_{j,t-1} y_{j,t-1} \ldots y_{j,t,base+1} \right)}$.

It follows from the equation (6), that ratios of disaggregate prices may be aggregated to ratios of HICP using linear transformation with redefined weights. One interesting feature of the derived formula, is that recent relatively higher increase (relatively to other disaggregate prices) in the price of a disaggregate $i$ increases the importance/weight of the latest change of $y_{i,t}$ in the computation of aggregated HICP change. Such behaviour can be explained by the assumption of consumers’ inelastic demand during the course of the year (implemented through fixed consumer basket weights): change in the price of a commodity does not change its consumed quantity, however, it may change the share of consumer’s expenditure on that commodity.

In the next subsection we will assume, that weights $\tilde{w}_t$ are fixed over time, and thus $\tilde{w}_t = \tilde{w}$. The impact changing weights have to the forecasting error will be discussed in the subsection 2.5.
2.3. Forecast error decomposition

Although forecast error decomposition does not give any clear answer regarding which of the two methods is better suited for HICP forecasting, we find it to be a useful framework for model comparison purposes. Decomposing forecast error should help to identify potential sources of errors in aggregated and disaggregated inflation models and hence, to develop better performing forecasting model. Error decomposition is done following the study of Hendry and Hubrich (2010), however, we will restrict our attention only to misspecification and estimation errors, omitting possible cases of forecast origin mismeasurement and structural breaks in the parameter values (in the aforementioned study these cases are found to have no influence for the relative forecasting accuracy).

We will compare HICP forecasts obtained employing two methods: aggregation of components’ forecasts and direct HICP forecasting.

One step ahead forecast of vector \( y_{T+1} \) is computed as:

\[
\hat{y}_{T+1|T} = \hat{M}^* + \hat{A} y_T + \hat{B} \Delta x_T + \hat{\Theta} x_T + \hat{\Gamma} p_T + \hat{\varepsilon}_{T+1},
\]

where \( \hat{M}^*, \hat{A}, \hat{B}, \hat{\Theta}, \hat{\Gamma} \) are estimated parameter values of (4), obtained using the sample 1 ... \( T \). We also assume that \( E(\hat{M}^*) = M_e^* \), \( E(\hat{A}) = A_e \), \( E(\hat{B}) = B_e \), \( E(\hat{\Theta}) = \Theta_e \), \( E(\hat{\Gamma}) = \Gamma_e \).

For convenience reasons, we focus on decomposing forecasting error of HICP ratios (instead of decomposing forecasting error of HICP level). When the true DGP process of the disaggregate data is defined by equation (4), one step ahead forecasting error of \( y_{T+1}^a \) is obtained as:

\[
y_{T+1}^a - \hat{y}_{T+1|T}^a = \tilde{w}'(y_{T+1} - \hat{y}_{T+1|T})
\]

\[
= \tilde{w}' \left[ (M^* + Ay_T + B \Delta x_T + \Theta x_T + \Gamma p_T + \varepsilon_{T+1}) - (\hat{M}^* + \hat{A} y_T + \hat{B} \Delta x_T + \hat{\Theta} x_T + \hat{\Gamma} p_T + \hat{\varepsilon}_{T+1}) \right].
\]

Adding and subtracting proper terms, forecasting error in (8) may be decomposed into specification error, measurement error, approximation error and innovation error:

- **specification error** \( \tilde{w}'(M^* - M_e^*) + \tilde{w}'(A - A_e)y_T + \tilde{w}'(B - B_e)\Delta x_T + \tilde{w}'(\Theta - \Theta_e)x_T + \tilde{w}'(\Gamma - \Gamma_e)p_T, \)

- **measurement error** \( \tilde{w}'(M_e^* - \hat{M}^*) + \tilde{w}'(A_e - \hat{A})y_T + \tilde{w}'(B_e - \hat{B})\Delta x_T + \tilde{w}'(\Theta_e - \hat{\Theta})x_T + \tilde{w}'(\Gamma_e - \hat{\Gamma})p_T, \)

- **approximation error** \( \tilde{w}'(\hat{\varepsilon}_{T+1} - \hat{\varepsilon}_{T+1}), \)

- **innovation error** \( \tilde{w}'(\varepsilon_{T+1} - \hat{\varepsilon}_{T+1}), \)


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innovation error = \tilde{\omega}' \varepsilon_{T+1}.

Let us now consider the case of direct HICP forecasting. The true value of $y_{t+1}^a$ is obtained the same way as in the case of indirect forecasting (i.e. aggregating approximation errors should be negligible, we will concentrate only on potential As the innovation errors in direct and indirect forecasting cases are equal, and restrictive treatment on autoregressive and error correction coefficients. These restrictions imply that in the aggregate model, reaction to past inflation, as well as rate

2.4. Comparison of forecasting errors

As the innovation errors in direct and indirect forecasting cases are equal, and approximation errors should be negligible, we will concentrate only on potential differences in specification and measurement errors of the two methods.

Comparing the decompositions of forecasting error for aggregate and disaggregate approaches, we expect aggregate model to possess larger specification error due to its restrictive treatment on autoregressive and error correction coefficients. These restrictions imply that in the aggregate model, reaction to past inflation, as well as rate
of return from deviation from the long-run path, is equal across all subcomponents. On the other hand, if the number of disaggregate components $N$ is large (which is exactly our case), avoiding large measurement errors we will have to restrict matrix $A$ in the disaggregate model as well. Common restriction for matrix $A$ (which we also use in specifications in Section 4), is to set the off-diagonal elements equal to zero. As it is pointed out by Sbrana and Silvestrini (2009), in such case, when we treat our DGP as given (and thus measurement errors can be neglected), unless all components are independent, disaggregate model does not necessary produce smaller forecasting errors – results will depend on the actual DGP in (4). Thus, we infer that the restricted disaggregate forecasting approach is preferred in case of independent (or poorly dependent) HICP components.

We expect smaller specification error caused by differences in exogenous variable coefficients to be the main area, where disaggregate inflation forecasting model can improve forecasts of the aggregate model. Although forecast error decomposition in equation (14) does not show aggregate model to be restrictive on exogenous variable coefficients, some restrictions will most likely be made (variables omitted), to keep measurement error low and to avoid statistically insignificant coefficients. Emphasizing this point - it may be only natural to include world market prices of wheat to forecast the price of bread, however, it will probably be excluded from the specification of an aggregate model resulting in larger specification error.

Sometimes we may find it too costly to study and evaluate an actual production costs’ indicator which would be responsible for changes in disaggregate price. One of the typical examples would be falling prices of computers – we know that computers are getting cheaper due to technological progress, however, it might be too costly to model such detailed level of production costs. As a solution in disaggregate model, we assume that we cannot identify production costs (though we know they exist) and simply rewrite equation (3) as a model with (perhaps slowly) changing intercept: $\Delta p_t = \tilde{M}_t + \epsilon_t$. The intercept $\tilde{M}_t$ is then estimated either using 12 month moving average as in (2), or with single exponential smoothing. We expect such ad hoc approach to be another area, where disaggregate model could improve forecasts over aggregate model.

2.5. Forecasting in the presence of time-varying weights

So far we have assumed that aggregation weights are constant over time: $\tilde{w}_t = \tilde{w}$. However, this simplification may not always be plausible. In this subsection we will assume, that weights are changing over time, though, they are known at the time of forecasting.

The equation (6) suggests that weights $\tilde{w}_t$ change due to two reasons: varying consumer prices during the calendar year (effect expected to be small) and change in consumer basket weights. The change in consumer basket weights in Lithuania was, actually, quite substantial during the period analysed: in 1996 expenditure on food products constituted 50% of total expenditure, whereas in 2013 the number dropped to 23%. This variation in weights leads to another source of forecasting error, unaccounted previously.
Variation of aggregation weights in our framework does not have any impact on disaggregated model forecasts, however, it does deteriorate forecasts of the aggregated model. To demonstrate this, we write out the true aggregated model, aggregated from DGP in equation (4) using the weights $\tilde{\omega}_t'$:

$$y_t^a = \tilde{\omega}_t'y_t = \tilde{\omega}_t'(M^* + Ay_{t-1} + B\Delta x_{t-1} + \Theta x_{t-1} + \Gamma p_{t-1} + \tilde{E}_t + \epsilon_t)$$

$$= M^*_t + \tilde{\omega}_t^A y_{t-1} + B_t \Delta x_{t-1} + \Theta_t x_{t-1} + \tilde{\omega}_t^B p_{t-1} + \tilde{\omega}_t^\epsilon_t \Delta E_t + \tilde{\omega}_t^\epsilon_t \epsilon_t,$$

where $M^*_t = \tilde{\omega}_t'M^*, B_t = \tilde{\omega}_t'B, \Theta_t = \tilde{\omega}_t'\Theta$.

Equation (16) indicates that intercept and parameters of exogenous variables are changing over time in the actual aggregated DGP. Comparison of equations (16) and (11) reveals that this variation is an additional source of specification error for the aggregated model, the magnitude of which will depend on variation in $\tilde{\omega}_t$.

A simple, yet effective way to reduce specification error, induced by variation of weights in the aggregate model, is to keep consumer basket weights constant over time, e.g. we may pick the latest observed expenditure weights and use them for aggregation in all periods. The use of latest observed weights is justified by our primary interest to apply the model for future HICP forecasting, which dictates that we should use the weights which closest resemble spending structure of future HICP. In the context of out-of-sample forecasting exercise implemented in Section 5, this imply that we are interested in studying the behaviour of model specifications, which best explain inflation with current/ future (and not past) consumer spending structure.

We should also recognise that treating NIPE aggregates as given, their forecasts have a potential advantage over disaggregate case as we do not need to worry about the forecasting error induced by changing future aggregation weights. Whether this advantage actually outweighs the arguments presented by (16) is an entirely empirical question.

3. The data

In this section we briefly describe the data, its origin, performed transformations, and properties relevant for the modelling process. The most important information on variables used is summarized in the Appendix’s Table 11.

The raw HICP data, used in the study, consists of 92 series of monthly disaggregate prices and corresponding consumer basket weights, spanning the period of 1996 m1 – 2013 m9. Due to the reasons stated in subsection 2.5., in our analysis, weights of the expenditure structure were kept fixed over time, equalling them to the weights observed in the year 2013. All subsequent aggregations into broader components were performed using the aforementioned fixed weights and aggregation formula defined in equation (5).
The exogenous variables, used in the study, can be broadly summarized into 2 main groups: Lithuanian macroeconomic variables (import deflator, variables describing labour costs) and international commodity prices (used for commodity price transmission). Due to common agricultural policy and geographical proximity, our preference was to use EU food commodity prices (published by the European Commission), however, in some cases, world food prices (published by the Food and Agriculture Organization of the United Nations) were chosen instead, as they produced better results. We believe in these few cases world prices were more helpful due to the better correspondence to Lithuanian food products’ consumption pattern. It should be also noted, that although foreign exchange rates are not seen entering the equations of the model directly, they are widely used to convert currency of commodity prices to the national currency litas.

Our analysis also required few variable transformations. Some exogenous variables, normally observed in quarterly frequency, were converted to monthly frequency – conversion was performed applying cubic splines. We chose spline method mainly due to its simple and convenient implementation, although in other studies different temporal disaggregation methods can also be found (e.g. “quadratic match average” method in Célérier (2009), Lisman/ Sandee procedure in Reijer and Vlaar (2006)). Besides temporal disaggregation, some variables were also seasonally adjusted (implemented using x-12-arima procedure) and logarithmic transformation was applied for all exogenous variables.

The stationarity of the data was tested using the augmented Dickey-Fuller test (Dickey, Fuller (1979)) – the corresponding p-values for the test statistics can be found in the Table 12 of the Appendix A. The unit root tests show, that all variables, except for “wages”, are I(1) with a significance level $\alpha = 0.05$. As the p-value for “wages” test statistic is, actually, very close to 0.05, we find it appropriate to treat all variables as I(1), and to use equations of type (1) for our model.

The information on excise and value added tax changes may be regarded as another source of data, employed in the modelling process. In the forecasting literature, the effect of tax changes is usually modelled by dummy variables, however, due to extensive use of autoregressive lags, we took a slightly “unusual” way to estimate them. Our objective is to use dummy variables to estimate the effects of tax changes, and at the same time to prevent model’s autoregressive components from predicting similar behaviour in the future. It follows, that to achieve such goal, forecasts should be obtained, and autoregressive coefficients should be estimated on data, “cleaned” from administrative decisions. To estimate the effect of tax changes we use the following process: firstly we define our initial assessment of dummy variables (e.g. all inflation during specific months is due to tax changes), then we “clean” our data from these regulatory changes and estimate the model. The next step is to revise our initial estimate of the dummy variables, so that model’s residuals during the months, when dummy variables are used, would be zero. Such iterative procedure of obtaining dummy variables’ estimates and estimating model’s coefficients is repeated until convergence is achieved. One of the method’s shortcomings (besides cumbersome implementation) is the overstated degrees of freedom in the OLS estimation (overstated by the number of
dummy variables used), which, however, should have only minimal effect on the estimates.

4. Estimates of the model

This section is devoted to presenting the estimates of the actual equations, used for Lithuanian HICP forecasting. Following the framework of NIPE, the results are grouped into 5 main categories: unprocessed food (UF), processed food (PF), non-energy industrial goods (NEIG), services (SERV) and energy. Before starting with the presentation of the estimates, let us clarify few details on the estimation and specification process.

The estimation was carried out using ordinary least squares method, with p-values for error correction coefficients (these p-values are as well used to test cointegration) obtained following the paper of Ericsson and MacKinnon (2002) (the program ecmtest.xls (version 1.0) generating p-values is provided by the authors of the aforementioned paper).

Our main focus during the specification of the model was to obtain a model, providing as accurate forecasts as possible, and yet another desired property of the model was to keep it acceptable from the economic standpoint (acceptable in a sense, that it possesses coefficients of interpretable signs and magnitude, and does not have any omitted major factors). As the good results of the out-of-sample forecasting exercise was the main criterion to pick particular model specification, we believe, keeping it economically acceptable safeguards it somewhat from “adjusting model to the data”. The statistical significance of the estimated coefficients was a desirable outcome, however, some insignificant coefficients were included into specifications as well, mainly in times when they helped to improve the forecasts and they were economically interpretable.

The specification of a polynomial distributed lag models involved firstly specifying maximum lag length of a variable, and then picking a degree of polynomial used to approximate the parameters. The maximum lag length was determined testing various cases of unconstrained distributed lag regressions as well as using economic intuition. The process of choosing a degree of polynomial, used for parameter approximation, usually started estimating a model employing a third degree polynomial (we believe a third degree polynomial can generate sufficiently diverse shapes to approximate lagged variable influence and greater degree polynomials are not required). The degree of polynomial was subsequently reduced in case of insignificant parameters, continuing the process until a satisfactory model was obtained, or until all coefficients became significant.

In the estimated equations we denote “\(pd_{i}(\Delta x_{t-1}, q, n)\)” an \(i\)-th regressor \((i = 1 \ldots q + 1)\) of polynomial distributed lag function, which approximates regression coefficients of \(\Delta x_{t-1}, \Delta x_{t-2}, \ldots, \Delta x_{t-1-n}\) with a \(q\)-th degree polynomial. The regressors are defined as follows:
\[ pdl_t(\Delta x_{t-1}, q, n)_t = \sum_{j=0}^{n}(j^{i-1}\Delta x_{t-1-j}). \] \hspace{1cm} (17)

The estimated equations are presented using the “\(pdl_t(\Delta x_{t-1}, q, n)\)” regressors only to demonstrate the statistical significance of their coefficients, and thus to motivate use of a specific degree polynomial. The actual (and more intuitive) coefficients, used for exogenous variable lags can be further derived using the estimated “\(pdl_t(\Delta x_{t-1}, q, n)\)” coefficient values (some graphs of the derived coefficients are presented in the Appendix B).

The presence of residual autocorrelation and heteroscedasticity is tested using Breusch-Godfrey and Breusch-Pagan tests respectively (in case of ARMA model, Li-McLeod test is applied instead of Breusch-Godfrey test). In case of the residual heteroscedasticity or autocorrelation, t-statistics and p-values were computed using heteroscedasticity and autocorrelation consistent residual standard error (s.e.) estimates. All calculations were performed using R statistical software.

4.1. Administered and quasi-administered prices

Administered and quasi-administered prices, defined as prices to a large extent determined by exogenous decisions, (these prices constitute 17.4% of consumer basket weights in 2013) are not modelled in our framework. In some cases (e.g. heating, gas prices), administered prices could essentially be predicted, as we have some information about their determinants. However, due to changes in price setting mechanisms and peculiarities of these mechanisms, formalization of the forecasting process proved to be a difficult task. In other cases (e.g. post services, water supply) timing and extent of price changes is purely determined by exogenous decisions and would be impossible to forecast. In our framework, the forecasts of administered and quasi-administered prices are included into the model separately specifying their future paths, which makes it easy to incorporate information, available from the media and government institutions.

4.2. Unprocessed food

Unprocessed food (composed of meat, fish, fruits and vegetables price indices) is a rather volatile part of HICP which is found difficult to forecast due to its dependence on fluctuations in supply, which in turn depend on climatic conditions in different parts of the world. As a result, unprocessed food components are usually modelled employing ARIMA models, either aggregated into one index, or separately.

In our case, we find that changes of meat price in Lithuania can be partly explained by changes in international price of meat and changes in wages. Due to this reason, meat price was chosen to be modelled separately from the rest of processed food. Regarding the remaining three unprocessed food subindices, since no tested exogenous variables were found to be helpful in forecasting, we do not expect, there would be much difference in forecasting accuracy, whether we predicted indices aggregated or separately. For reasons of convenience, the three unprocessed food subindices were
forecast using separate ARIMA models. The estimates for unprocessed food equations are presented in the Table 1.

The determination coefficients of unprocessed food equations in Table 1 are rather low, illustrating high level of unpredictability, however, it should be noted that much of the month-on-month variation in fruit and vegetable prices can be explained by seasonality, which is not reflected in presented $R^2$.

The transmission of international meat prices to Lithuanian HICP in our findings is rather fast, 5 months being the maximum international meat price lag included in the equation for Lithuanian meat prices. Although we find the coefficient for $pdl_t(\Delta WP_{t-1}^{meat}, 1, 4)$ to be statistically insignificant, the regressor is still included into the equation, as it improves the forecasting accuracy and tells a convincing story of diminishing importance of the regressor with an increase of observation lag. The graph of the resulting coefficients for $\Delta WP_{t-1}^{meat}, ..., \Delta WP_{t-5}^{meat}$ can be found in the Appendix B, Figure 1.

### Table 1: Estimates of unprocessed food equations

<table>
<thead>
<tr>
<th>Food</th>
<th>Equation</th>
<th>Determination Coefficient</th>
<th>Additional Information</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meat</td>
<td>$\Delta p_t^{meat} = -0.0002 + 0.44 \cdot AR(1) + 0.2 \cdot \Delta wages_{t-1}$ + $0.05 \cdot pdl_t(\Delta WP_{t-1}^{meat}, 1, 4) - 0.008 \cdot pdl_t(\Delta WP_{t-1}^{meat}, 1, 4)$</td>
<td>$R^2 = 0.37$, p(BG) = 0.5, p(BP) = 0.5, sample: 1996 m1 – 2013 m9.</td>
<td>s.e. were corrected for heteroscedasticity, sample: 1996 m1 – 2013 m9.</td>
</tr>
<tr>
<td>Fish</td>
<td>$\Delta p_t^{fish} = -0.0009 + 0.47 \cdot AR(1) - 0.005 \cdot AR(2) + 0.21 \cdot AR(3)$</td>
<td>$R^2 = 0.34$, p(BG) = 0.9, p(BP) = 0.02.</td>
<td></td>
</tr>
<tr>
<td>Fruit</td>
<td>$\Delta p_t^{fruit} = -0.003 + 0.48 \cdot AR(1) - 0.29 \cdot MA(1)$.</td>
<td>p(BG) = 0.8, p(ARCH, 4) = 0.99, sample: 1996 m1 – 2013 m9.</td>
<td>Data was seasonally adjusted and seasonal component forecast applying arima x-12.</td>
</tr>
<tr>
<td>Vegetables</td>
<td>$\Delta p_t^{vegetables} = 0.002 - 0.17 \cdot AR(1)$.</td>
<td>$R^2 = 0.03$, p(BG) = 0.37, p(BP) = 0.19, sample: 1996 m1 – 2013 m9.</td>
<td>Data was seasonally adjusted and seasonal component forecast applying arima x-12.</td>
</tr>
</tbody>
</table>

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*Here and further in the text, the estimated equations should be read as follows: numbers in parentheses below the estimated coefficients are t-statistics; p(BG) and p(BP) are p-values for Breusch-Godfrey and Breusch-Pagan tests, testing null hypotheses of no residual 1-st order autocorrelation and heteroscedasticity; p(ARCH, n) is a p-value for a Li-McLeod test for ARCH effects in a model with n lags;*  
*Here and further in the text, weights represent consumer basket weights in 2013.*
4.3. Processed food

There are 11 disaggregate processed food price series, classified according to classification of individual consumption by purpose (COICOP) and published by Statistics Lithuania. Processed food time series were chosen to be modelled using separate equations, as there is a considerable amount of information on food prices available from the media and international markets, which we believe, may help to identify determinants of individual price series. The specifications and estimation results for processed food equations are presented in Table 2 and Table 3.

Table 2: Estimates of processed food equations: food and non-alcoholic beverages

<table>
<thead>
<tr>
<th>Equation</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>p-value</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δp&lt;sub&gt;bread&lt;/sub&gt;</td>
<td>−0.18 + 0.14 · AR(1) − 0.057 · p&lt;sub&gt;bread&lt;/sub&gt;−1 + 0.05 · wages&lt;sub&gt;t−1&lt;/sub&gt;</td>
<td>(−5.9)</td>
<td>2.2</td>
<td>0.0000</td>
</tr>
<tr>
<td>+0.01 · EU&lt;sup&gt;Wheat&lt;/sup&gt;&lt;sub&gt;t−1&lt;/sub&gt; + 0.03 · pd&lt;sub&gt;l&lt;/sub&gt;&lt;sub&gt;t&lt;/sub&gt; (ΔEU&lt;sup&gt;Wheat&lt;/sup&gt;&lt;sub&gt;t−1&lt;/sub&gt;, 2, 7)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Bread &amp; Cereals)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4.5 % HICP)</td>
<td></td>
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<tr>
<td>Δp&lt;sub&gt;milk&lt;/sub&gt;</td>
<td>0.003 + 0.37 · AR(1) + 0.09 · AR(2) − 0.2 · AR(3)</td>
<td>(2)</td>
<td>(5.3)</td>
<td>0.0000</td>
</tr>
<tr>
<td>+ 0.03 · pd&lt;sub&gt;l&lt;/sub&gt;&lt;sub&gt;t&lt;/sub&gt; (ΔEU&lt;sup&gt;milk&lt;/sup&gt;&lt;sub&gt;t−1&lt;/sub&gt;, 0, 6)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Milk, cheese and eggs)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3.6 % HICP)</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Δp&lt;sub&gt;oils&lt;/sub&gt;</td>
<td>0.001 + 0.42 · AR(1) + 0.026 · pd&lt;sub&gt;l&lt;/sub&gt;&lt;sub&gt;t&lt;/sub&gt; (ΔWP&lt;sup&gt;oils&lt;/sup&gt;&lt;sub&gt;t−1&lt;/sub&gt;, 1, 11)</td>
<td>(1.8)</td>
<td>(4.5)</td>
<td>0.0000</td>
</tr>
<tr>
<td>−0.002 · pd&lt;sub&gt;l&lt;/sub&gt;&lt;sub&gt;t&lt;/sub&gt; (ΔWP&lt;sup&gt;oils&lt;/sup&gt;&lt;sub&gt;t−1&lt;/sub&gt;, 1, 11)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>(Oils)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1 % HICP)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δp&lt;sub&gt;sugar&lt;/sub&gt;</td>
<td>0.003 + 0.004 · pd&lt;sub&gt;l&lt;/sub&gt;&lt;sub&gt;t&lt;/sub&gt; (ΔEU&lt;sup&gt;Wheat&lt;/sup&gt;&lt;sub&gt;t−1&lt;/sub&gt;, 0, 12)</td>
<td>(3.3)</td>
<td>(2.1)</td>
<td>0.0000</td>
</tr>
<tr>
<td>(Sugar, jam, chocolate, etc.)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1.8 % HICP)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δp&lt;sub&gt;food, nec&lt;/sub&gt;</td>
<td>0.002 + 0.68 · AR(1) + 0.25 · AR(2) − 0.78 · MA(1),</td>
<td>(1.7)</td>
<td>(6.5)</td>
<td>0.0000</td>
</tr>
<tr>
<td>p&lt;sub&gt;(BG)&lt;/sub&gt; = 0.99, p&lt;sub&gt;(ARCH, 4)&lt;/sub&gt; = 0.9, sample: 2002 m1 – 2013 m9.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
\[
\begin{align*}
\Delta p_t^{\text{coffee}} &= 0.0005 - 0.15 \cdot AR(1) + 0.15 \cdot AR(2) + 0.14 \cdot AR(3) + \\
&\quad + 0.003 \cdot pdl_1(\Delta WPI_{t-1}^{\text{coffee}}, 2, 7) + 0.02 \cdot pdl_2(\Delta WPI_{t-1}^{\text{coffee}}, 2, 7) \\
&\quad + 0.002 \cdot pdl_3(\Delta WPI_{t-1}^{\text{coffee}}, 2, 7).
\end{align*}
\]

\(R^2 = 0.26, p(BG) = 0.8, p(BP) = 0.4, \text{ sample: } 1996 \text{m1} - 2013 \text{m9}.

\[
\begin{align*}
\Delta p_t^{\text{beverages}} &= 0.008 - 0.06 \cdot p_t^{\text{beverages}} + 0.04 \cdot wages_{t-1} + 0.21 \cdot \Delta wages_{t-1},
\end{align*}
\]

\(R^2 = 0.2, p(BG) = 0.67, p(BP) = 0.46, \text{ sample: } 2001 \text{m1} - 2013 \text{m9}.

The shapes of functions, applied to restrict coefficients of commodity price lags, differ in processed food equations and sometimes are not easy to interpret (some of the estimated coefficients are presented in the Appendix B Figures 2 - 4). The strongest restriction – equalization of all lag coefficients, was employed in “milk, cheese and eggs” equation, indicating that response to prices in European market was either varying in different historical periods, or is very gradual in nature. We used the same restriction also in the equation for price of sugar, though the rationale is a bit different. As the market of sugar is highly regulated in EU, it was difficult to find fitting regressors for the equation – movements in global price of sugar seem unrelated to sugar prices in Lithuania. The price of wheat enters the equation to model the relation of sugar beet purchase prices and global prices of alternative cultures (these are positively related to deter sugar beet growers from cultivating alternative cultures).

The estimated coefficient values for \(\Delta EU_{t-1}^{\text{wheat}}\) variable in “bread & cereals” equation, actually, look rather puzzling: firstly, the coefficients of \(\Delta EU_{t-1}^{\text{wheat}}\) are declining with the increase of lag (see Figure 2 in the Appendix B), but from the 5-th lag they are starting to rise again. As all three “pdl” coefficients in the equation are statistically significant, one can only speculate, if such results reflect some specific processes in the bread-making industry, or they should be treated as spurious, perhaps influenced by the high volatility of global wheat market.

The contrasting shape of \(\Delta WPI_{t-1}^{\text{coffee}}\) coefficients (see Figure 4 in the Appendix B) seems more fitting for interpretations: possibly due to existing contracts and stock, the highest impact of a shock in global coffee prices is observed 5 months after the shock and then starts to decline. It should be pointed out, that the statistically insignificant coefficient of \(pdl_1(\Delta WPI_{t-1}^{\text{coffee}}, 2, 7)\) does not signal the need to reduce the degree of the restricting polynomial – the degree of polynomial should be reduced in the presence of insignificant \(pdl_3(\Delta WPI_{t-1}^{\text{coffee}}, 2, 7)\) (see Equation (17) for the details of regressors’ construction).

Only two cointegrating relations were included into processed food equations. Such outcome summarizes the difficulty of specifying cointegrating relations for disaggregate prices, as apparently, there are many diverse and perhaps quite specific factors,
influencing disaggregate price changes. Also, to accommodate for trend changes exhibited in some processed food price series (these changes could be attributed to changes in duty taxes and regulations), the equations were estimated using shorter data samples.

One of the most significant causes of variation in prices of alcoholic beverages is changes in excise duties. After removing the effects of tax changes (the previously described iterative method was applied), not much can be said about determinants of alcoholic beverages price inflation, and therefore, ARMA models were employed for forecasting. The estimates of alcoholic beverages equations are presented in Table 3.

### Table 3: Estimates of alcoholic beverages equations

<table>
<thead>
<tr>
<th>Product</th>
<th>Equation</th>
<th>$R^2$</th>
<th>$p(BG)$</th>
<th>$p(BP)$</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spirits</td>
<td>$\Delta p_t^{spirits} = 0.001 - 0.21 \cdot AR(3)$</td>
<td>0.05</td>
<td>0.42</td>
<td>0.24</td>
<td>2001 m1 – 2013 m9</td>
</tr>
<tr>
<td>Wine</td>
<td>$\Delta p_t^{spirits} = 0.0001 - 0.15 \cdot MA(1)$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beer</td>
<td>$\Delta p_t^{spirits} = 0.001 - 0.15 \cdot AR(1) - 0.14 \cdot AR(2)$</td>
<td>0.04</td>
<td>0.99</td>
<td>0.72</td>
<td>2001 m1 – 2013 m9</td>
</tr>
</tbody>
</table>

4.4. Non-energy industrial goods

We consider the general understanding about DGP of individual NEIG price series to be too scarce and price formation mechanisms too diverse, to employ separate specifications for disaggregate NEIG price series, therefore, the majority of NEIG price inflation is modelled using aggregated price index. Nevertheless, after careful examination of individual NEIG price series, we find it useful to exclude several price series to be modelled separately. These excluded prices, constituting 3.2 % of total HICP weights are depicted in the Appendix B, Figure 5.

The rationale behind the exclusion of some NEIG prices is that they are considered to be mostly determined outside the Lithuanian economy, often as a result of technological progress in specific markets. Such technological progress is reflected by downwards sloping HICP price indices in Figure 5, which also appears to depict slope coefficients varying in time. Due to possible parameter variation, we chose not to use AR models to forecast the selected indices, as they would potentially transform to AR models with time-varying intercepts. Selected indices were forecast using exponential smoothing and our rather naïve 12 month moving average method, defined in equation (2). The moving average method is expected to capture not only time-varying trend, but also to smooth out any remaining seasonal effects.
The main part of NEIG prices (denoted “NEIG_main”), constituting 20.3% of consumer basket weights, is modelled aggregated into a single index and is considered to be determined by both foreign and domestic pressures. We use unit labour costs (ULC) and import deflator ($P_{\text{import}}$) to measure production cost changes coming from the inside and outside of Lithuanian economy. The graph of seasonally adjusted and standardized values of the NEIG_main index, ULC and $P_{\text{import}}$ can be found in the Appendix B, Figure 6.

The graph in Figure 6 tells a rather convincing story regarding the determinants of the NEIG_main inflation, though the sharp drop of import deflator in 2008 – 2009 also shows a possible shortcoming of using import deflator. While Lithuanian import deflator is very dependent on fluctuations in oil prices, it seems that NEIG_main prices are less sensitive to oil price shock, or at least the effect comes with a considerable lag (as illustrated in the period of 2009 – 2011). Such differences might lead to inaccurate NEIG_main inflation forecasts in the presence of large oil shock, as the pressure coming from the import deflator would be overstated.

Other, perhaps more theoretically appropriate production cost measures, such as ULC, computed only for manufacturing sector, and import price index of manufactured goods, were also tested for the NEIG_main index modelling. However, due to these alternative series being available only for considerably shorter time periods (starting in years 2005 – 2006), they could not be properly tested in the out-of-sample forecasting exercise, and therefore, we opted to use ULC and import prices of the whole economy. The indicators of the whole economy are also a convenient choice regarding the actual forecasting process, as the future projections of the indicators are readily available from the solutions of the Lithuanian multi-country model (LT-MCM) (see Vetlov (2004)), used in Bank of Lithuania.

The estimated NEIG_main equation (presented in Table 4) confirms our assumption that the index is governed by import deflator and ULC – indeed, the series are cointegrated. A somewhat worrying sign, however, is that the sum of cointegrating series coefficients is, actually, far from zero. The result can be again explained, considering the large influence rising oil prices had on Lithuanian import deflator, during the period examined, leading to smaller than expected cointegrating coefficient for import deflator. Despite this shortcoming, and lacking alternatives for cointegrating relation, we continue with the “NEIG_main” equation presented in Table 4.

Table 4: Estimated NEIG_main equation

| $\Delta p_t^{\text{NEIG_main}} = 0.45 + 0.23 \cdot AR(1) - 0.09 \cdot p_{t-1}^{\text{NEIG_main}}$ | $\begin{array}{c} +0.007 \cdot P_{t-1}^{\text{import}} + 0.011 \cdot ULC_{t-1}, \\ p_{t-1}^{\text{NEIG_main}} \end{array}$ |
| 0.22, $p(BG) = 0.29$, $p(BP) = 0.1$, sample: 2001 m1 – 2013 m9. |

Data was seasonally adjusted and seasonal component forecast applying arima x-12.
4.5. Services

Our strategy regarding modelling inflation of services was firstly to exclude prices which possess some “atypical” behaviour, and then to decide whether and how the remaining price series should be aggregated, based on our judgement on their common determinants. The excluded services’ prices constitute 4% consumer basket weights and were forecast using either the 12 month moving average method or exponential smoothing. The graph of these excluded series can be found in the Appendix B, Figure 7. The estimates of equations for modelling the remaining (major) part of prices for services are presented in the Table 5.

<table>
<thead>
<tr>
<th>Package</th>
<th>( \Delta p_t^{holidays} = 0.002 + 0.06 \cdot pdl_1(\Delta wages_{t-1}, 0, 4), )</th>
</tr>
</thead>
<tbody>
<tr>
<td>holidays</td>
<td>( R^2 = 0.03, \ p(BG) = 0.9, \ p(BP) = 0.5, \text{ sample: 2001 m1 – 2013 m9}. )</td>
</tr>
<tr>
<td>(1 % HICP)</td>
<td>Data was seasonally adjusted and seasonal component forecast applying arima x-12.</td>
</tr>
</tbody>
</table>

| Accommodation   | \( \Delta p_t^{accom.} = -0.002 + 0.1 \cdot pdl_1(\Delta wages_{t-1}, 0, 4), \) |
| services        | \( R^2 = 0.07, \ p(BG) = 0.6, \ p(BP) = 0.5, \text{ sample: 2001 m1 – 2013 m9}. \) |
| (1.3 % HICP)    | Data was seasonally adjusted and seasonal component forecast applying arima x-12. |

| Transport index | \( \Delta p_t^{transport} = 0.002 + 0.21 \cdot AR(1) + 0.01 \cdot pdl_1(\Delta wp_{t-4}^{brent}, 0, 6) + 0.03 \cdot pdl_1(\Delta wages_{t-1}, 0, 12), \) |
| (1.8 % HICP)    | \( R^2 = 0.2, \ p(BG) = 0.3, \ p(BP) = 0.05, \text{ sample: 1996 m1 – 2013 m9}. \) |

| SERV_main       | \( \Delta p_t^{SERV_main} = 0.0006 + 0.43 \cdot AR(1) + 0.044 \cdot pdl_1(\Delta wages_{t-1}, 0, 6), \) |
| (13.6 % HICP)   | \( R^2 = 0.54, \ p(BG) = 0.96, \ p(BP) = 0.13, \text{ sample: 2001 m1 – 2013 m9}. \) |

We used gross nominal wages as the main regressor in all equations of the Table 5. Although wages variable has an obvious drawback of not accounting for productivity gains, other alternatives – ULC in the whole economy and ULC in the service sector, proved to be either too crude, or lacking longer data series to be used to account for domestic inflationary pressures in prices of services. On the other hand, as can be seen from the Appendix B Figure 8, at least empirically, nominal wages can be considered a fitting variable to forecast inflation of services – the dynamics of wages closely resemble the dynamics of service prices with a certain precedence. Interestingly, we
find the coefficients for $\Delta wages_t$ lags to be equal in the equations of Table 5, which means we are effectively forecasting service price inflation using moving averages of $\Delta wages_t$. While such estimates may be caused by the frequency conversion and inertia in $\Delta wages_t$ variable, it can also be the result of not differentiating the economy sector where the changes of wages originate from. In our mark-up model framework, we interpret wages as a production cost, and therefore, we expect $\Delta wages_t$ to have a decreasing impact with an increase of lag. Different behaviour could be expected when changes of wages are observed in a non-service sector: the impact of $\Delta wages_t$ might be increasing with an increase of lag due to perceived increase of demand or wage spillover effect between sectors. Our estimates in Table 5 potentially reflect the sum of these two cases.

One of the reasons the series of accommodation services and package holidays in Table 5 were modelled separately is that they have tendencies rather distinct from the index of SERV_main. Such differences may be caused by strong influence of foreign prices and growth in competition. In addition, we believe, that strong seasonality patterns, observed in the aforementioned series, (which are not present in the SERV_main index) will be better handled separately. The separate equation for transport index (includes passenger transport by railways and roads), displays our intention to distinguish the link between energy prices and service prices. Although, we expect energy prices to have a certain influence on all service prices, the coefficients of $\Delta WPI_{t-1}^{brent}$ were not significant in the equation for SERV_main.

4.6. Energy

Energy comprises 16.8% of consumer basket weights, however, major part of it is treated as administered prices and is forecast exogenously specifying future inflation values. The estimated equations for the remaining part, constituting 7.9% of consumer expenditure, are presented in Table 6.

**Table 6: Estimated equations for energy prices**

<table>
<thead>
<tr>
<th>Solid and liquid fuels (0.9 % HICP)</th>
<th>$\Delta p_{t}^{fuels} = 0.84 + 0.23 \cdot AR(1) + 0.017 \cdot p_{t}^{fuels} + 0.016 \cdot p_{t}^{fuels}(\Delta WPI_{t-1}^{brent}, 0, 7)$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$+ 0.016 \cdot p_{t}^{fuels}(\Delta WPI_{t-1}^{coal}, 0, 11)$, $R^2 = 0.23, p(BG) = 0.4, p(BP) = 0.3, \text{sample: 2001 m1 – 2013 m9.}$</td>
</tr>
<tr>
<td>Fuels for personal transport (6.9 % HICP)</td>
<td>$\Delta p_{t}^{fuels,trans} = 0.84 + 0.13 \cdot WPI_{t-1}^{brent} - 0.33 \cdot p_{t}^{fuels,trans}$</td>
</tr>
<tr>
<td></td>
<td>$+ 0.2 \cdot \Delta WPI_{t}^{brent} + 0.12 \cdot \Delta WPI_{t-1}^{brent}$, $R^2 = 0.64, p(BG) = 0.93, p(BP) = 0.0002 =&gt; s.e. are HAC, \text{sample: 2001 m1 – 2013 m9.}$</td>
</tr>
</tbody>
</table>
Frequent and substantial changes in fuel taxes may render modelling of energy prices quite a challenging task. In our modelling framework, we eliminate excise changes from the levels of consumer prices, effectively converting them into price levels, that would be observed in a constant tax environment and legitimizing their usage in cointegrating relations. On the other hand, the log-differences (basically percentage changes) appearing on the left-hand side of equations are the actual observed log-differences, except for the periods when the tax changes are implemented. Despite the attempts to account for tax changes, we still may expect some specification problems, as e.g. in Table 6 equation for personal transport fuels, increasing tax share in fuel price imply that $\Delta WPI_{t}^{brent}$ and $\Delta WPI_{t-1}^{brent}$ coefficients should decrease over time. One of the solutions would be to formulate the model for personal transport fuels in simple (non-log) differences, however, in the out-of-sample exercise such specification actually yielded slightly worse results, therefore we stick to the specification in log-differences.

It is widely believed, that oil price transmission to personal transport fuel prices is asymmetric: fuel prices increase faster in the presence of positive oil price shock (than they decrease in case of a negative oil price shock). To measure if such belief has any basis, we also estimated personal transport fuels equation with separate coefficients for positive and negative oil price changes:

$$\begin{align*}
\Delta p_{t}^{fuels\_trans} &= 0.83 + 0.13 \cdot WPI_{t-1}^{brent} - 0.32 \cdot p_{t-1}^{fuels\_trans} \\
&+ 0.24 \cdot \Delta WPI_{t}^{brent} \cdot I_{\Delta WPI_{t}^{brent}>0} + 0.17 \cdot \Delta WPI_{t}^{brent} \cdot I_{\Delta WPI_{t}^{brent}<0} \\
&+ 0.09 \cdot \Delta WPI_{t-1}^{brent} \cdot I_{\Delta WPI_{t-1}^{brent}>0} + 0.15 \cdot \Delta WPI_{t-1}^{brent} \cdot I_{\Delta WPI_{t-1}^{brent}<0}. 
\end{align*}$$

The estimates of equation (18) seem to support the view of asymmetric price transmission, as a positive oil price shock generated greater coefficient for $\Delta WPI_{t}^{brent}$ and lesser for $\Delta WPI_{t-1}^{brent}$ than in the case of negative oil price shock, i.e. fuel price adjustment seems to be slower in the presence of negative oil price shock. However, these differences in parameters were not statistically significant according to the Wald’s test (p-value for $\Delta WPI_{t}^{brent}$ coefficients’ differences equals 0.29, and the corresponding p-value for $\Delta WPI_{t-1}^{brent}$ equals 0.36). Consequently, in our model specification we stayed with the symmetric oil price transmission to the personal transport fuel prices.

5. Out-of-sample forecasting exercise

To measure the performance of the forecasting model presented in Section 4, we employed an out-of-sample forecasting exercise. The following subsection will be devoted to elaborate on the details of the exercise.

---

4 The indicator function is defined as follows: $I_A = \begin{cases} 1, & \text{when } A \text{ is true} \\ 0, & \text{otherwise} \end{cases}$. 

5.1. Setting of the exercise

The out-of-sample forecasting exercise, actually, consists of few separate exercises and is constructed to achieve several different goals. Firstly, we would like to learn how well we could forecast Lithuanian inflation if we knew the actual future paths of the exogenous variables beforehand forecasting. This part of the exercise should reveal which part of Lithuanian inflation in different time periods could have been anticipated by our model, and which part comes from other, unexplained sources. As a step towards more realistic forecasting setting, we also generated exogenous variable assumptions using the vintages of LT_MCM forecasts (in case of macroeconomic variables) and a random walk model (in case of most commodity prices). This part of the exercise resembles actual conditions at the time of forecasting and should answer the question if at all the model can be useful in terms of its forecasting accuracy. In this second part of the forecasting exercise, besides a benchmark model, we also employed several competing forecasting models which should provide clearer view regarding model’s forecasting abilities. Finally, the comparison of model’s outcomes of the two aforementioned parts of the exercise will display the influence inaccurate exogenous variable assumptions have on the forecasts.

The forecasting exercise, with assumptions generated in accordance with the past LT_MCM forecasts, resembles pseudo real-time out-of-sample forecasting exercise, however, we would like to stress that it has a rather specific setting. As the paper is mainly motivated by the need to create a model for forecasting, constant consumer basket weights of the year 2013, representing the last available up-to-date consumer basket structure, are used throughout the paper (we elaborate on the issue of time-varying weights in the subsection 2.5). Hence, in our forecasting exercise we do not account for the effect, time-varying weights have on forecasting errors. This effect cannot be estimated separately from variation in prices, as they are likely to be correlated. One of the alternatives would be to use time-varying weights for different iterations of the exercise, which would be constant in iteration’s sample. Such setting, however, would not eliminate the possibility that, when model’s specification is chosen judging from the root mean square errors (RMSE) of the forecasting exercise, we will choose the specification which works well for past data, though, is not the best for current/future consumer basket structure.

Further details of the forecasting exercise are rather typical. During every run of the iteration, endogenous data is seasonally re-adjusted (if needed) and the equations are re-estimated, using the data which should be available at the time of the forecasting. The specification of model’s equations as well as the specification of competing forecasting models was kept constant during the run of the exercise. The whole forecasting exercise procedure is recursive, which results in expanding data sample for the estimation. The time span of the graphs for the out-of-sample forecasts depend on a starting date of estimation sample, leaving at least 4 years for in-sample estimation. For comparability reasons, the RMSE statistics were computed only for the forecasts of the period 2007m1-2013m6, as the data vintages of the LT_MCM are available only from 2007.
5.2. Benchmark model

As it is common in the forecasting literature, we evaluated forecasting performance of the model against a benchmark model. Benchmark model was chosen from the class of univariate models. Following benchmark models were considered: 12 month moving average model (as in equation (2)), single exponential smoothing, state space model with time-varying intercept, and ARMA model, specified using automated AIC minimizing procedure “auto.arima” from the R package “forecast”. The models were tested for the out-of-sample period of 2005m1 – 2013m6. During each run in the period, models were re-estimated recursively and m-o-m forecasts up to 15 months ahead were obtained. Regarding the disaggregation level, we followed the same aggregation/disaggregation structure as presented in Section 4, hence, the results are comparable with the results of our main model. For brevity reasons, in Table 7 only the RMSE of the y-o-y inflation forecasts \(E[100 \cdot \left( \frac{P_{t+12}}{P_t} - 1 \right) | P_t, P_{t-1}, P_{t-2}, \ldots] \) are presented.

Table 7: RMSE of tested models for forecasting y-o-y inflation

<table>
<thead>
<tr>
<th>Predicted HICP component</th>
<th>12 month moving average</th>
<th>Exponential smoothing</th>
<th>State space model</th>
<th>ARMA</th>
</tr>
</thead>
<tbody>
<tr>
<td>UF</td>
<td>8.79%</td>
<td>8.43%</td>
<td>8.48%</td>
<td>8.16%</td>
</tr>
<tr>
<td>PF</td>
<td>7.34%</td>
<td>7.05%</td>
<td>7.12%</td>
<td>6.41%</td>
</tr>
<tr>
<td>NEIG</td>
<td>2.24%</td>
<td>2.19%</td>
<td>2.24%</td>
<td>2.20%</td>
</tr>
<tr>
<td>SERV</td>
<td>5.45%</td>
<td>4.30%</td>
<td>4.50%</td>
<td>4.99%</td>
</tr>
<tr>
<td>ENERGY</td>
<td>20.90%</td>
<td>14.26%</td>
<td>15.94%</td>
<td>13.62%</td>
</tr>
</tbody>
</table>

Although exponential smoothing and 12 month moving average methods worked well for prices with time-varying trends, the results in Table 7 suggest that ARMA model is the best choice for the general case. Based on these results, we have chosen ARMA (minimizing AIC) to be our benchmark model for further analysis.

5.3. Few competing forecasting models

To make a fairer comparison of model’s forecasting abilities, we also generated forecasts of several more elaborate (than the benchmark model) competing forecasting models. We chose a factor augmented autoregressive model (FAAR) and a vector autoregression with exogenous variables (VARX) as competing forecasting models. We employed the following general form of factor augmented autoregression:
\[
\Delta p_t = \alpha_0 + \sum_{i=1}^{N_1} (\alpha_i \Delta p_{t-i}) + \sum_{j=1}^{r} \sum_{k=1}^{N_{j,2}} (\beta_{j,k} f_{j,t-k}) + \epsilon_t,
\]
(19)

\[
Z_t = \Lambda F_t + \xi_t,
\]

where \(Z_t\) is a \(M \times 1\) vector of monthly variables, movement of which is explained by the idiosyncratic component \(\xi_t\) and factors \(F_t = (f_{1,t}, f_{2,t}, \ldots, f_{r,t})',\) orthogonal to the idiosyncratic component.

The factors \(F_t\) were estimated employing principal components estimator for a set of 74 monthly variables (we chose to use 3 factors to model the variation in monthly variables). The dataset included 26 indices of international raw material prices, 19 Lithuanian producer price indices, 12 Lithuanian CPI aggregates as well as some financial, real and business survey variables. The data was also first-differenced and in most cases logarithmically transformed and seasonally adjusted beforehand the extraction of factors. During the run of the forecasting exercise, we also imitated different publication lags of the data, later balancing the “ragged-edge” using univariate ARMA models, automatically specified by the “auto.arima” function.

In order to reduce the number of estimated coefficients we applied polynomial distributed lag function for the lags of factors and the autoregressive part in the same fashion as in our main model. The specifications were selected firstly by determining maximum lag numbers for factors and autoregressive part according to AIC, when parameters are approximated by 3rd degree polynomials. In the second step, we selected number of parameters in “pdl” functions minimizing AIC for the found maximum lag numbers (in the final specification some factors may not even be excluded). Lastly, it should be noted, that we predicted \(\Delta p_{t+h}\) in (19) using direct forecasting (no model was specified for the dynamics of factors), hence, we applied different specification for every \(h = 1, 2, \ldots 15\).

As a second competing forecasting model we used a VAR model for 5 NIPE components, augmented with 2 exogenous variables: ULC and oil prices. The VAR model was specified for month-on-month changes with number of lags determined by AIC and number of cointegrating relations estimated by Johansen test’s trace statistic. The future values of exogenous variables in VAR model were constructed using the same assumptions as in our main model.

5.4. Results of the exercise

The results of the exercise are summarized in Tables 8-9, where models’ RMSE statistics are presented as a ratio to RMSE of the benchmark model. The statistical significance of forecasting accuracy differences was tested using the modified Diebold-Mariano test as in Harvey et al. (1997). The p-values for the test statistics are given in parenthesis next to the RMSE ratios. P-values were computed for the two-sided alternative hypothesis of \(d_t \neq 0\), where \(d_t = \hat{\epsilon}_{\text{model,}t}^2 - \hat{\epsilon}_{\text{benchmark,}t}^2\) and \(\hat{\epsilon}_{\text{model,}t}, \hat{\epsilon}_{\text{benchmark,}t}\) are the forecasting errors of the two models. For reasons of convenience
we denoted the model, presented in Section 4 as a “Mark-up” model (we put the name in quotation marks, as it is only partly based on mark-up pricing). It should be also noticed that FAAR model in Table 9 used the same disaggregation level as the “Mark-up” model.

Table 8: Relative RMSE of the “Mark-up” model’s forecasts with exogenous variable assumptions formed using their actual historical values (out-of-sample period 2007m1 – 2013m6)

<table>
<thead>
<tr>
<th>Predicted HICP component</th>
<th>Forecasting horizon (months)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>h=3</td>
</tr>
<tr>
<td><strong>UF</strong></td>
<td>0.75 (0.04)</td>
</tr>
<tr>
<td><strong>PF</strong></td>
<td>0.72 (0.25)</td>
</tr>
<tr>
<td><strong>NEIG</strong></td>
<td>0.90 (0.88)</td>
</tr>
<tr>
<td><strong>SERV</strong></td>
<td>0.79 (0.66)</td>
</tr>
<tr>
<td><strong>ENERGY</strong></td>
<td>0.58 (0.19)</td>
</tr>
</tbody>
</table>

Table 9: Relative RMSE of models’ forecasts with exogenous variable assumptions based on random walk models and vintage LT_MCM forecasts (out-of-sample period 2007m1 – 2013m6)

<table>
<thead>
<tr>
<th>Predicted HICP component</th>
<th>Model</th>
<th>Forecasting horizon (months)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>h=3</td>
</tr>
<tr>
<td><strong>UF</strong></td>
<td>“Mark-up”</td>
<td>0.84 (0.15)</td>
</tr>
<tr>
<td></td>
<td>FAAR</td>
<td>1.02 (0.88)</td>
</tr>
<tr>
<td></td>
<td>VARX</td>
<td>1.00 (0.98)</td>
</tr>
<tr>
<td><strong>PF</strong></td>
<td>“Mark-up”</td>
<td>0.73 (0.27)</td>
</tr>
<tr>
<td></td>
<td>FAAR</td>
<td>1.09 (0.66)</td>
</tr>
<tr>
<td></td>
<td>VARX</td>
<td>1.22 (0.32)</td>
</tr>
<tr>
<td><strong>NEIG</strong></td>
<td>“Mark-up”</td>
<td>0.88 (0.86)</td>
</tr>
<tr>
<td></td>
<td>FAAR</td>
<td>0.98 (0.97)</td>
</tr>
<tr>
<td></td>
<td>VARX</td>
<td>1.08 (0.90)</td>
</tr>
<tr>
<td><strong>SERV</strong></td>
<td>“Mark-up”</td>
<td>0.83 (0.71)</td>
</tr>
<tr>
<td></td>
<td>FAAR</td>
<td>0.75 (0.61)</td>
</tr>
<tr>
<td></td>
<td>VARX</td>
<td>1.01 (0.99)</td>
</tr>
<tr>
<td><strong>ENERGY</strong></td>
<td>“Mark-up”</td>
<td>0.83 (0.18)</td>
</tr>
<tr>
<td></td>
<td>FAAR</td>
<td>1.06 (0.39)</td>
</tr>
<tr>
<td></td>
<td>VARX</td>
<td>0.83 (0.24)</td>
</tr>
</tbody>
</table>
The first and most important thing which should be taken from the results presented in the Tables 8-9, is that the forecasts of the suggested “Mark-up” model were more accurate than the forecasts of the benchmark model regardless how exogenous variable assumptions were formed. This result should provide us with some confidence that the model is applicable to the real time forecasting.

The “Mark-up” model performed relatively well against the competing forecasting models – the forecasts of the “Mark-up” model were better or at least more or less equally accurate as those of the competing models (see Table 9). The advantage of “Mark-up” model is especially visible in the forecasts of NEIG and PF components, where high level of disaggregation was used. On the other hand, FAAR model also had some success in forecasting NEIG and especially SERV components, pointing that factor models in some cases can be a viable alternative in short-term inflation forecasting.

The comparison of the results in Tables 8-9 reveals in which HICP categories forecasting accuracy suffers the most due to inaccurate exogenous variable assumptions. Unsurprisingly, the biggest changes in RMSE ratios are observed in UF, PF and ENERGY groups, which heavily depend on commodity price assumptions. The loss of accuracy in SERV group is less severe due to reliance on assumptions based on vintage LT_MCM forecasts (which are likely to be more accurate than the random walk model for commodity prices), while in NEIG group, interestingly, the forecasting accuracy seems not to decrease at all.

Although the forecasts of our model, in the “more realistic” out-of-sample forecasting framework, are always more accurate than the forecasts of the benchmark model, Diebold-Mariano test finds them to be statistically significantly different (with the significance level $\alpha = 0.05$) only for UF and NEIG groups in several forecasting horizons (Table 9). As always, longer out-of-sample period is desirable and might lead to more rejections of the null hypothesis, however, in our case we are limited by the availability of the vintage LT_MCM forecast data. On the other hand, if we were interested in the one-sided alternative hypothesis of our model forecasts being more accurate than the benchmark forecasts, at least with $\alpha = 0.1$, we would get some null hypothesis rejections for PF and SERV groups as well.

While Tables 8-9 serve well quantifying the forecasting accuracy of the model, the out-of-sample forecasting graphs should be much more informative regarding properties of the forecasts and sources of the forecasting errors. The graphs, presented in the Appendix C, compare two annual out-of-sample forecasts with the actual observed annual inflation for all 5 HICP subgroups. The forecast labelled “best forecast”, denotes forecast with actual exogenous variable data taken for the exogenous variable assumptions, and thus represents best possible forecast made by our model. On the other hand “Pseudo real forecast” represents a more realistic forecast, with exogenous variable assumptions produced by random walk models or vintage MCM forecast data.

The large forecasting errors, produced by “best forecast” during certain time periods (Figures 10-14 in the Appendix C), could be interpreted as a shortcoming of the mark-up model in general. An example of such period is the high NEIG, and especially SERV
inflation during the peak of economic boom in 2007-2008, which could be mainly attributed to the demand-pull, and not cost-push factors as suggested by our mark-up model.

The forecasting errors of UF inflation during the period of 2005-2009 seem to be more difficult to explain. It is commonly agreed that UF inflation is mostly determined by supply shocks. In our case, as we have not included fruit and vegetable farm gate prices into the equations of UF inflation (these are hard to include due to sheer number of fruit and vegetable species), we may as well conclude that the UF forecasting errors in 2006-2009 were caused by the rise of producer prices. After examining the graph of Lithuanian and eurozone unprocessed food annual inflation (see Figure 9 in the Appendix B), such interpretation is put in a bit different perspective. As it is seen from Figure 9, Lithuanian UF inflation in 2005-2009 was considerably larger than the UF inflation in the eurozone (UF inflation for Germany is included to illustrate that smaller fluctuations in the eurozone UF inflation can be only partly explained by the aggregation of cross country data). Hence, we infer that high Lithuanian UF inflation in 2005-2009 cannot be fully explained by common tendencies in the eurozone UF market, which leads us to believe that demand-pull inflation and price convergence were also significant factors in determining Lithuanian UF inflation in the period examined. Such view is also partly supported by the out-of-sample meat price inflation forecasts in Figure 15, which also exhibits large forecasting errors in 2006-2008, although, we suppose, we have accounted for changes in international meat price, using lags of WPI_meat in the equation for meat price inflation.

While “best forecast” in some periods produces large forecasting errors for SERV, NEIG and UF groups, the model seems to explain PF and ENERGY inflation rather well. For ENERGY group, the quality of the forecast hinges mostly on the accuracy of oil price assumption, and the forecast rapidly deteriorates after introduction of pseudo real-time assumptions. Interestingly, after the switch to pseudo real-time assumptions, forecast deterioration in the PF case is not as large as in the ENERGY case. Such difference should be attributed to the richer lag structure, utilised in modelling commodity price transmission mechanism in the PF case. For a more detailed study of PF forecasts, the out-of-sample forecasts for selected PF group components can be found in Figures 16-19, which also depicts how the forecasts change due to introduction of pseudo real-time assumptions for exogenous variables.

5.5. Impact of disaggregation on service and goods indices

As a separate out-of-sample exercise, we once again approach the issue of data aggregation/ disaggregation, discussed in Section 2. For this purpose, we examine the differences in forecasting the aggregate vs. aggregating the forecasts of disaggregates, only this time from an empirical perspective. As we had certain reasoning to choose model’s current level of disaggregation, we do not consider reducing the number of forecast indices and only further disaggregation of indices “NEIG_main” and “SERV_main” is considered. These indices are composed of (respectively) 23 and 26
more detailed indices and thus, we would like to examine if there is a reason to expect that further disaggregation would lead to more accurate overall forecasts.

The forecasts for aggregated indices were computed employing the specifications presented in Tables 4-5, whereas the specifications for disaggregates, coincide with the corresponding aggregate specifications. As in the previous out-of-sample exercise, the specifications for ARMA model were chosen based on AIC criterion. The results of the exercise are summarized in Table 10, which depicts RMSE ratios of aggregated forecasts and forecasts of an aggregate, value smaller than 1 indicating that disaggregate forecasts produced smaller RMSE for that specification. For testing equality of forecasting accuracy, the p-values of the Diebold-Mariano test can be found in parenthesis, beneath the figure of a relative RMSE.

Table 10: RMSE of aggregated-disaggregate forecasts vs. RMSE of forecasts of an aggregate (relative RMSE = \( \frac{RMSE\ (\text{disaggregate})}{RMSE\ (\text{aggregate})} \)); out-of-sample period 2007m1 – 2013m6).

<table>
<thead>
<tr>
<th>Predicted index</th>
<th>Model specification (Pseudo real-time assumptions)</th>
<th>Forecasting horizon (months)</th>
<th>h=3</th>
<th>h=6</th>
<th>h=9</th>
<th>h=12</th>
<th>h=15</th>
</tr>
</thead>
<tbody>
<tr>
<td>NEIG_main</td>
<td>ARMA specification</td>
<td></td>
<td>0.87</td>
<td>0.90</td>
<td>0.90</td>
<td>0.94</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>Model specification</td>
<td></td>
<td>1.04</td>
<td>1.33</td>
<td>1.62</td>
<td>2.05</td>
<td>2.30</td>
</tr>
<tr>
<td></td>
<td>Model specification (Pseudo real-time assumptions)</td>
<td></td>
<td>1.07</td>
<td>1.35</td>
<td>1.58</td>
<td>1.97</td>
<td>2.14</td>
</tr>
<tr>
<td>SERV_main</td>
<td>ARMA specification</td>
<td></td>
<td>1.25</td>
<td>1.31</td>
<td>1.42</td>
<td>1.51</td>
<td>1.60</td>
</tr>
<tr>
<td></td>
<td>Model specification</td>
<td></td>
<td>1.14</td>
<td>1.08</td>
<td>1.05</td>
<td>1.03</td>
<td>1.03</td>
</tr>
<tr>
<td></td>
<td>Model specification (Pseudo real-time assumptions)</td>
<td></td>
<td>0.92</td>
<td>0.98</td>
<td>1.13</td>
<td>1.30</td>
<td>1.58</td>
</tr>
</tbody>
</table>

Judging from the results in Table 10, further disaggregation of “NEIG_main” and “SERV_main” indices, probably, is not going to produce more accurate forecasts (at least for “Mark-up” model’s specifications). The specification of “NEIG_main” equation, incorporating a cointegrating relation with ULC and import deflator, was clearly not appropriate for forecasting separate “NEIG_main” components and generated RMSE considerably higher than 1. On the other hand, results for ARMA model specification, which, contrary to the previous case, we do not have reason to believe could be a priori favourable to aggregated forecasting, signal that there might be some gain in using more disaggregated “NEIG_main” index forecasting. As for “SERV_main” forecasting, the results seem to be less contradicting, as the forecasts of the aggregate index were more accurate for all cases, except for forecasting with pseudo real-time assumptions up to the horizon of 6 months.

Interpreting Table 10 results in the context of Section 2, “NEIG_main” components are likely to be less interrelated than the elements of “SERV_main” index, and
therefore, have more potential to produce more accurate forecasts when modelled separately. The reasons behind such supposed weaker interrelationship of “NEIG_main” elements might be explained by the variety of inflation influencing factors: we expect ULC/ wages to be the main factor for inflation of service prices, while the inflation of goods prices might be thought to have factors of larger variety.

6. Conclusions

In this paper, we presented short-term forecasting model, suitable to predict Lithuanian inflation of 5 HICP price groups: unprocessed food, processed food, non-energy industrial goods, energy, and services. The focus on short-term horizon is embedded in the choice of the forecasting method, as the model consists of separate univariate equations, mainly based on mark-up pricing, and thus, any spillover effects between HICP groups are neglected. On the other hand, operating the dataset of 92 disaggregate HICP price series, a lot of attention was paid to understanding dynamics of disaggregate series, considering possible gains and losses in using disaggregate forecasting vs. aggregate forecasting. The latter issue was approached in the framework of forecast error decomposition, which gave us some background to choose the current disaggregation scheme.

Food prices, always receiving much attention in the society, were modelled in a fully disaggregated way, attempting to capture the influence international food prices have on Lithuanian food prices. The price transmission mechanism was implemented employing a distributed lag model and restricting coefficient values to lie on a polynomial of a small degree. In some cases, the dynamics in estimated transmission coefficients, however, was only minimal, resulting, probably, from changes in transmission mechanism over time, or impact of other, unaccounted factors. The maximum lag used for international prices, varies across the equations, with maximum 5 month WPI_meat lag included in the meat price equation, and 12 month WPI_oils lag included in the oils and fats price equation. These maximum lags could be interpreted as showing speed of price transmission, and in most cases also indicate forecasting horizon, for which the forecast remains more or less informative, before reverting to series long term mean (granted that our commodity price assumptions commonly resemble forecasts of a random walk model).

The forecasting performance of our model was tested using the out-of-sample exercise, involving two types of exogenous variable assumptions: assumptions, based on information which was available at the time of forecasting (pseudo real-time assumptions), and assumptions matching historical exogenous variable data (model’s best possible forecast). The principal result, obtained from the out-of-sample exercise, is that our model produced forecasts with smaller RMSE than benchmark ARMA models for all 5 HICP price groups, and for both types of assumptions. Model’s forecasts were also more accurate, or at least as accurate as the forecasts of the competing forecasting models.
The results of the paper, we believe, contribute to better understanding short-term inflation dynamics of Lithuanian HICP components, leading to more accurate inflation forecasting. The future research on Lithuanian inflation forecasting should also encompass the inflation spillover between groups effect, omitted in this study, which might be an important factor in longer term forecasting.
References


Appendix A. Variables used in the study

Table 11: Variables used in the study

<table>
<thead>
<tr>
<th>Variable</th>
<th>Source/ description</th>
<th>Suggested basis for assumptions in real time forecasting</th>
<th>Frequency</th>
<th>Transformations</th>
</tr>
</thead>
<tbody>
<tr>
<td>92 price indices</td>
<td>Statistics Lithuania</td>
<td>–</td>
<td>Monthly</td>
<td>Log; seasonal adjustment, if needed[^5]</td>
</tr>
<tr>
<td>92 weight series</td>
<td>Statistics Lithuania</td>
<td>–</td>
<td>Monthly</td>
<td>Weights set to equal to weights, observed in 2013</td>
</tr>
<tr>
<td>wages</td>
<td>Statistics Lithuania, average gross monthly wage</td>
<td>Forecasts of compensation per employee in LT_MCM</td>
<td>Quarterly</td>
<td>Log; seasonal adjustment</td>
</tr>
<tr>
<td>pimport</td>
<td>Statistics Lithuania, import deflator</td>
<td>Forecasts in LT_MCM</td>
<td>Quarterly</td>
<td>Log; seasonal adjustment</td>
</tr>
<tr>
<td>ULC</td>
<td>(Total compensation to employees)/(real GDP)</td>
<td>Forecasts in LT_MCM</td>
<td>Quarterly</td>
<td>Log; seasonal adjustment</td>
</tr>
<tr>
<td>EUwheat</td>
<td>European Commission; wheat prices in EU</td>
<td>Bloomberg, median of analysts’ survey</td>
<td>Monthly</td>
<td>Log</td>
</tr>
<tr>
<td>EUmilk</td>
<td>European Commission; prices of milk powder in EU</td>
<td>Random walk</td>
<td>Monthly</td>
<td>Log</td>
</tr>
<tr>
<td>WPIoils</td>
<td>United Nations FAO index of vegetable oil prices</td>
<td>Bloomberg, median of analysts’ survey</td>
<td>Monthly</td>
<td>Log</td>
</tr>
<tr>
<td>WPIcoffee</td>
<td>Bloomberg; S&amp;P coffee price index</td>
<td>Bloomberg, median of analysts’ survey</td>
<td>Monthly</td>
<td>Log</td>
</tr>
<tr>
<td>WPImeat</td>
<td>United Nations FAO index of meat prices</td>
<td>Random walk</td>
<td>Monthly</td>
<td>Log</td>
</tr>
<tr>
<td>WPIcoal</td>
<td>IMF; price of Australian coal</td>
<td>Bloomberg, median of analysts’ survey</td>
<td>Monthly</td>
<td>Log</td>
</tr>
<tr>
<td>WPIbrent</td>
<td>Bloomberg, world price index of “Brent” oil</td>
<td>Oil futures price</td>
<td>Monthly</td>
<td>Log</td>
</tr>
<tr>
<td>EXRUSD</td>
<td>LTL/ USD exchange rate</td>
<td>Random walk</td>
<td>Monthly</td>
<td>–</td>
</tr>
</tbody>
</table>

[^5] In case of aggregation of several price series, seasonal adjustment performed for the aggregated series.
Table 12: P-values of augmented Dickey-Fuller tests ($H_0$: $\Delta$(*variable*) has a unit root).\(^6\)

<table>
<thead>
<tr>
<th>Variable</th>
<th>P-value</th>
<th>Variable</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>wages</td>
<td>0.0586</td>
<td>Meat (HICP)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$p^{import}$</td>
<td>&lt;0.0001</td>
<td>Fish (HICP)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>ULC</td>
<td>&lt;0.0001</td>
<td>Dairy products (HICP)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$E^{wheat}$</td>
<td>&lt;0.0001</td>
<td>Oils (HICP)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$E^{milk}$</td>
<td>&lt;0.0001</td>
<td>Coffee (HICP)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$WPI^{oils}$</td>
<td>&lt;0.0001</td>
<td>Fruit (HICP)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$WPI^{coffee}$</td>
<td>&lt;0.0001</td>
<td>Vegetables (HICP)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$WPI^{meat}$</td>
<td>&lt;0.0001</td>
<td>NEIG_main (HICP)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>$WPI^{coal}$</td>
<td>&lt;0.0001</td>
<td>SERV_main (HICP)</td>
<td>0.0178</td>
</tr>
<tr>
<td>$WPI^{brent}$</td>
<td>&lt;0.0001</td>
<td>Transport (HICP)</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Bread &amp; Cereals (HICP)</td>
<td>&lt;0.0001</td>
<td>Fuel for cars (HICP)</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

\(^6\) Tests performed for logarithmically transformed, seasonally adjusted data in its original frequency (quarterly series were not interpolated). Lag length has been selected, based on Schwartz information criterion. Depending on a series, sample starts between January 1995 and January 1997, and ends in September 2013.
Appendix B. Various graphs

Figure 1. $\Delta WPI_{t-l}^{meat}$ coefficients in the HICP meat eq.

Figure 2. $\Delta EU_{t-l}^{wheat}$ coefficients in the HICP bread eq.

Figure 3. $\Delta WPI_{t-l}^{oils}$ coefficients in the HICP oils equation

Figure 4. $\Delta WPI_{t-l}^{coffee}$ coefficients in the HICP coffee eq.

Figure 5. NEIG prices modelled separately

Figure 6. Evolution of NEIG_main index, ULC and import deflator in 1996 – 2013

Variables were seasonally adjusted and standardized to have zero mean and variance equal to 1.
As in the previous cases, variables were standardized and seasonally adjusted.
Appendix C. Annual inflation graphs generated by the out-of-sample exercise

Figure 10. Annual UF inflation and its recursive out-of-sample forecasts

Figure 11. Annual PF inflation and its recursive out-of-sample forecasts

Figure 12. Annual NEIG inflation and its recursive out-of-sample forecasts

9 Here and in the subsequent graphs “best forecast” denotes model’s forecast with actual historical values taken for exogenous variable assumptions and “Pseudo real forecast” denotes model’s forecast with exogenous variable assumptions based on vintage LT_MCM forecast data or random walk model. Both out-of-sample forecasts have a 12-month forecasting horizon, i.e. they were produced as if were possessing information about HICP data which was available 12 months before the depiction of a predicted point in the graph.

10 Jump in annual NEIG inflation in January 2009 mark the changes in excise taxes, which are treated as if they could have been forecasted beforehand.
Figure 13. Annual SERV inflation and its recursive out-of-sample forecasts

Figure 14. Annual ENERGY inflation and its recursive out-of-sample forecasts

Figure 15. Annual meat price inflation and its recursive out-of-sample forecasts
Figure 16. Annual bread & cereals price inflation and the recursive out-of-sample forecasts

![Graph showing annual bread & cereals price inflation and the recursive out-of-sample forecasts.](image1)

Sources: Statistics Lithuania, Bank of Lithuania computations

Figure 17. Annual milk, cheese and eggs price inflation and the recursive out-of-sample forecasts

![Graph showing annual milk, cheese and eggs price inflation and the recursive out-of-sample forecasts.](image2)

Sources: Statistics Lithuania, Bank of Lithuania computations

Figure 18. Annual oils & fats price inflation and the recursive out-of-sample forecasts

![Graph showing annual oils & fats price inflation and the recursive out-of-sample forecasts.](image3)

Sources: Statistics Lithuania, Bank of Lithuania computations

Figure 19. Annual coffee & tea price inflation and the recursive out-of-sample forecasts

![Graph showing annual coffee & tea price inflation and the recursive out-of-sample forecasts.](image4)

Sources: Statistics Lithuania, Bank of Lithuania computations