SHORT-RUN FORECASTING OF CORE INFLATION IN UKRAINE: A DISSAGGREGATED APPROACH

by

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Kyiv School of Economics

Abstract

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The ability to produce high-quality inflations forecasts, including those of inflation, is of crucial importance to modern central banks. Good nowcasts and short-run forecasts are important to keep a finger on the pulse of current economic situation, to evaluate previous actions and policy decisions in terms of how their actual and expected effects differ from each other, as well as to enhance credibility of a Central Bank in the eyes of the society. The purpose of the paper is to build and evaluate a data-driven model for forecasting core inflation in Ukraine. The main model is based on the disaggregation approach and ARMA process with data-based dummies that controls for fluctuations with exogenous nature. The model considerably outperforms standard structural model and models simple ARMA models, in particular in terms of forecasting performance in 6 months ahead horizon.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Number *Page*

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Finally, I want to say "Thank you" to my parents and friends for on my side during this long path.

Chapter 1

INTRODUCTION

A high-quality forecast is a must-have for a central bank since it provides a foundation for most of its decision-making activities. This is the reason why most Central Banks develop and use a wide range of models, starting from small data-driven models for certain macroeconomic measures such as inflation or unemployment, to some big and structural models, which contain many relationships between parts of the economy and focus on an economy as a whole.

There are two broad types of models that central banks use for forecasting: data-driven and structural. Data-driven models appear to do a good job in short-term forecasting. The reason for that is their ability to work with a huge amount of data, squeeze all the information possible without a necessity to set a strong relationship between an explained variable and other variables from different parts of economies. On the other hand, theoretical models are based on microfoundations, which help them to explain the general macroeconomic framework. They work well in describing the economic structure but have limited use for short-run predictions. Despite a huge variety of macroeconomic series, which could help to understand the building blocks and fundamental of an economy to make a strategy of monetary policy much better, setting these relationships altogether could be cumbersome and not necessarily helpful in terms of the forecasting quality.

Nowcasting (prediction of the present, the very near future and the very recent past) and short-run forecasting models belong to the class of data-driven models and are important tools to understand the dynamics of inflation in the nearest future and to adjust monetary policy accordingly. In general, monetary policy actions affect inflation only with at least a half-year lag, which is the reason for inflation to be "already determined for the next 6 months". At the same time, the level of inflation at any point of time is not known and will only be revealed with some significant lag. Therefore, a central bank is very interested in getting constant updates on where the economy is heading and whether its current strategy is still in line with the set targets.

Also, it is quite important to build the credibility of a central bank. If society pays attention to the forecast quality, correct macroeconomic forecasts of a central bank will increase its credibility as a powerful analytical center and a force to reckon with, which in turn could help to build society's expectations, which is one of the fundamental determinants of the economic behavior.

In the National Bank of Ukraine, there is a demand for improvement of the forecasting toolbox, particularly in terms of enhancing its capacity for short term inflation forecasting. Core inflation is one of the fundamental indicators of economic dynamics. Its high accuracy predictions could support two important goals: help adjust the monetary policy via a better understanding of the present state of the economy; improve its credibility through enhancing forecasting performance.

This paper will attempt to fill this gap by building several data-driven inflation forecasting models with different additions, based on disaggregated components of the core inflation. The aim is to forecast core inflation in Ukraine in the short-run. The disaggregation approach gives a possibility to use a rich structure of information from the economy and capture the overall tendency of various inflation components.

The key model used in this thesis is ARMA-based model with dummy variables. These dummy variables are designed in a way to capture excessive volatility that has exogenous nature and thus help to increase forecasting quality of the model.

This study would contribute to the existing literature in several ways. First, the object of the paper, ARMA-based modeling is a still field with some potentially interesting additions, that might support to the model performance in a way, where it becomes even better than more sophisticated models. Moreover, to the best of my knowledge, the literature does not cover too much the issue of building such models specifically for emerging economies, which is an important condition in terms of the design. Such a data-driven approach is a universal and powerful tool that should not be underestimated even with a fashion for other forecasting tools.

Second, there will be results and discussion about the effect of crises on the components dynamics, which could be quite unobvious, come with lags or does not come at all. Third, it will contribute to the existing literature about data disaggregation methods and their relative performance.

Here is a more detailed discussion of the points mentioned above. Naturally, every economy suffers from shocks and shifts (instability) in history, so the good model must be able to deal with them and forecast correctly. Since Ukraine is an emerging economy with relatively high inflation, high volatility of main macroeconomic series, few changes in methodology of data collecting and some crises, there is a necessity to adjust the structure of the simple data-driven ARMA-type model to capture the peculiarities of the Ukrainian economic data, which is the main object of the paper. In addition, the relationship between different components of the core inflation, some causality effect, which is based on the complementarity and the substitution effects, are a good justification of a disaggregated approach usage. A good example, however for the closed economy, is tea, sugar, and coffee, that have a link between each other and increase in the price of tea would increase the price for its complementary sugar and decrease for a substitute coffee. However, a decrease in coffee price would also support a decrease in the sugar price. Aggregating all these effects would compensate them. In simpler terms, there is a mistake in each series prediction, which could disappear after aggregating all these errors together. There are a number of other issues associated with this type of models, but they are rather technical and will be discussed further.

Another point of the paper is about building a better understanding of crises effect on the core inflation components and other breaks effect throughout Ukrainian history. In the period of 2007-2018, the points of the high core inflation volatility are the Global Financial Crisis (2007-2009) and an economic crisis (2014-2015). Moreover, there was a change in the methodology of the data collection at the beginning of 2014, allowing the seasonality of clothes (which is based on the huge sales at the end of the season that was not counted previously), so it has to be counted in the model and would be discussed in the corresponding section. While total core inflation reached its peak in 2015m03 and the biggest contribution was from the exchange rate side, it is not actually true for every component of the core inflation, so the nature of the rapid increase in different goods is also an interesting topic for investigation using the tool described above.

The last purpose of this paper is to contribute to the discussion about the increased performance of disaggregated models in comparison to their simpler counterparts. Since the literature contains papers with contradictory empirical results and there are no strict mathematical proofs about improvement, it is important to check whether the disaggregation helps to increase the prediction quality of the model empirically.

The paper will be structured as follows. The second part describes the existing literature, discusses the peculiarities and issues that various authors focus on and some additional objects of interest, that are tangible to the topic of the paper. The third part contains the data description. In the fourth part, the model will be built. The fifth part will contain the total results and sixth part will conclude all of the above.

Chapter 2

LITERATURE REVIEW

The main focus of this paper is on the short-term forecasting and nowcasting models. They are important for monetary policymaking since they give a better understanding of the economy and its future dynamics, can handle the problems with lags in the data and a secondary benefits such as increase of the Central Bank credibility (correct predictions gives a numerical reason to the society for its level of trust increase).

As Banbura et al. (2013) explain, the idea of the nowcasting is to use the high-frequency data to approximate the series that become available at much lower frequencies and often with considerable lags. For example, quarterly GDP data is typically released with a lag of several weeks, while it can probably be approximated using disaggregated data much earlier and already be used by policymakers and other economic agents. In addition, such lags with data can limit the usefulness of structural models as long as they have to "wait" for new data releases.

Nowadays, nowcasting is an essential activity for many Central Banks. For example, Antipa et al. (2012) show that in Germany the early and accurate GDP forecast is crucial for the efficiency of policy decisions as long as there is some extensive volatility in GDP components, which requires corresponding policy actions by Central Bank and other government structures with the goal of achieving sustainable growth.

A part of the nowcasting toolbox is a survey-based judgment about the future state, the results of which are then aggregated into indexes. It might be a useful extension to the forecasting and policy analysis system (FPAS) and possible early approximation of the data, which could improve a nowcasting performance as long as these surveys represent expectations of economic agents. Lahiri and Monokroussos (2011) in their paper suggests that even with a large amount of other data, diffusion indices by the Institute for Supply Management improve the quality of quarterly US GDP forecasts. In addition, these indices become available way earlier than other indicators, which helps to develop an early understanding of the economy state. The authors worked with the data from 1965m03 to 2011m11 to construct an earlier version of the index, which has a very long history and from 1997m07 to 2011m11 for the more modern index. It means enough amount of data for the conclusions to be justified.

One of the most important tools to perform nowcasting of inflation is based on the web-scraping of prices. The idea behind it is to look at the real-time prices, obtained from e-commerce or other sources. Faryna, Talavera and Yukhymenko (2018) did this for Ukraine and found that this technique gives an opportunity to obtain the approximation of the price level for different components of the CPI basket for Ukraine in the period 2016m1-2017m12. This research was done on 75,000 goods in 130 CPI components with over 3 million of weekly observations. They have also shown that this approach gives a marginally different result than the official statistics for most of the sub-components. In the minor part of them, the difference is rather significant. It is important to notice that with the development of e-commerce, the data from it could be even better than official as long as it reacts fast to the new economic conditions.

At the same time, this tool could be used even to challenge the credibility of the official data. Cavallo (2012) made a research over a few Latin America countries for the period 2007m10-2011m03, aggregating individual price series of 28.5% to 48.5% of items entering the total official consumption basket. He found that

Argentina`s annual inflation via web-scrapping is 2-3 times higher than in the official statistics. Several different methods were used to make results more robust, including checking of both monthly and quarterly series. The inflation dynamics in all cases was quite similar in both the official and estimated series, the only difference was in the level which contributes to the idea that government simply divided the real inflation by 2 and reported it. Strictly speaking, although this paper is about inflation, Cavallo had found a similar picture in the GDP and poverty reports. That gives an additional tool to justify criticism of the official data, which seems to be falsified. Concluding these papers, it is important and useful addition to the early (data) stage of the model building.

There is a huge variety of models that could be used to calculate the prediction in the nowcasting round. However, as long as the data frequency or other parameters might differ in countries or in objects of study, various approaches can be used. For example, Giannone, Reichlin, and Small (2008) developed a factor model (also called as a "bridge" equations model), which connects different economic channels by corresponding equations. The resulting small structural model is used to make a prediction.

A more popular approach to nowcasting is based on small data-driven models with an autoregressive component such as Factor-Augmented VAR with a Principal Component Analysis (see Grui and Lysenko, 2017) or different kinds of regularized and factorized OLS (see Kucharcukova and Bruha, 2016). Strictly speaking, the last approach gives more freedom for data usage in terms of mixed-frequency and high-disaggregation case. They are also better in terms of capturing the short-run volatility and dynamics of the predicted measure.

One of the main purposes of the model in this study is short-term forecasting (about a half-year ahead), When the inflation targeting became one the most popular monetary policy frameworks in the world, public's understanding of the policy and state of the economy became essential, (). Faust and Wright (2012) explain this by a necessity for transparency and credibility increase of the Central Bank activity. In its turn, the issue of credibility may be partially solved by the high-quality forecast in the short-run.

A great number of different models could be used in the short-run forecasting exercise. For example, Faust and Wright (2012) analyze 17 different types of models, where a big chunk of them are data-driven and used for quarterly inflation forecasting in the period of 1985q1 to 2011q4. There are AR and VAR-type models, DSGE, Bayesian Averaging, Factor models and Philips Curve type models are present, evaluated and compared with each other in different categories. Another good example is the paper by D'Agostino, Gambetti and Giannone (2010) where they have built a Time-Varying VAR model to investigate inflation, unemployment rate, and interest rate and count for a structural change during the Great Moderation Period in US 1980s.

The question is if data-driven models mostly outperform in terms of prediction small structural models, why it is not convenient to take a large and main structural model instead? Big structural models are built in order to investigate the whole economy and capture its total peculiarity, but their architecture is not well for the forecasting purposes (see Grui, Lepushynskyi, 2016). There is no consensus in the literature about nowcasting performance of the models, built on micro-foundations such as DSGE. One part of the literature shows that forecasting experience with such models is good (see Yau, Hueng, 2011) while others found that it is quite poor (see Edge, Gurkaynak, 2010). With all this in mind, it is not clear whether to pay attention to the structural models and the best solution is to develop a data-driven and compare its performance.

Nevertheless, in the case of emerging economies, it becomes even more difficult to use simple data-driven models. However, it does not mean that these models can be considered as useless. If a model is built carefully, it could have decent conduct and outperform other (more structural) models despite their data-driven nature and related problems. In Kaufmann and Huwiler (2013) it is shown that the correct combination of data-driven models (VECM for oil and Disaggregated ARMA for everything else) could outperform structural models and experts judgment. This paper would be discussed further in details. However, the model development becomes much pickier, requires more sophisticated additions (rather than universal seasonality or disaggregation additions) that could be calibrated for some country, like in the paper of Stelmasiak and Szafranski (2016). They have made two BVAR approaches for inflation forecasting that counts seasonality pretty well due to the nature of the Villani approach for priors. This issue is quite important for the case of Poland as long as they have got a shifting seasonality pattern which could not be predicted by the simple seasonal adjustment well. In addition, benefits from these extensions become very tangible contrary to the case of developed economies. In some sense, it means that models in emerging countries must be more refined to have comparable performance with simple ones in developed countries.

From another angle, it is not necessarily the truth as long as developed countries have their own problems that require a solution which emerging economies does not face. An awesome example would be a society aging in Japan that is investigated by the number of authors, for example by Muto, Oda, and Sudo (2016). They have found an influence of the drop in the fertility rate, increase in life longevity and, as a consequence, an increase of the average age on the economic situation in the country. Using an overlapping generation model over 1982-2010 years, they have found that this situation has a negative effect on GNP. A very important moment is that emerging economies suffer from such a problem that deep rarely.

Data-driven approaches suffer from a variety of problems, however, they have some benefits. One of them is an unprecedented ability to use a low-level, highly disaggregated data. In other words, it means forecasting of components of some series and then summing them up (aggregating) to represent the forecast of the series. They are able to squeeze information that structural models could not use as long as they would become too complex to be solved. Nonetheless, literature has no agreement about the usefulness of this approach both from the theoretical and empirical side. There are two main camps of authors: one of them strongly support the effectiveness of disaggregation in obtaining a higher quality forecast (see; Hendry and Hubrich, 2010; Zellner and Tobias, 1999).

Bermingham and D'Agostino (2011) conclude that if a correct model is taken, disaggregation technique would improve forecasting performance. These conclusions are based on the very deep and fundamental research about the different model, such as AR, FAVAR, BVAR, AO models, performance on the datasets from the US and EU. Also, some data manipulation approaches were used too and at the end, the disaggregated approach performed much better than the aggregated one for all cases. Another camp has an opposite opinion, as there is also evidence that disaggregation has limited usefulness (see Benalal et al., 2004). This ambiguity in the literature indicates that further investigation of this question is required. This thesis will contribute to this discussion further.

Sometimes, aggregation is just the feature that might be added into the model to improve the forecast. However, there are even models, the core of which is based on the idea of disaggregation such as Large BVAR based on disaggregated components of the inflation (see Carrera, Ledesma, 2015). The basket of goods was divided by some economic reasoning into 18 groups which are made an opportunity to build the model. So this approach even broadened the field of study. All of the above gives a flavour about its usefulness, an opportunity to be the case of the interest for forecasting purposes.

The model that will be used in this paper is based on the Combined ARMA model used by the Swiss Central Bank (see Kaufmann, Huwiler, 2013) with some adjustments. The authors made such a model for the forecasting Switzerland inflation except for oil, which was modeled by the VECM as the most volatile part. There were 217 components of inflation from 2004m01 to 2011m12. ARMA specification will be used to make the prediction for inflation components, which will then be combined into the aggregated variable. An important difference is that in the case of Ukraine this model is used only for core inflation rather than for the whole inflation due to the issues with higher volatility than in the Swiss case. Also, the authors faced a number of problems, that are similar to those that would be described in the paper, which means that their experience is very valuable for future discussions.

To extend the model and improve its performance, the approach with some exogenous addition to the formula was chosen. It is, so-called, ARMAX model. The literature about this type of models for the forecasting economic measures purposes, to my best knowledge, is not quite rich. However, there are still a number of papers that use such an approach and it shows decent results. Kongcharoen and Kruangpradit (2013) in their paper used data about exports from Thailand, which constitutes a significant share of GDP (about a half). As an exogenous variable, the Composite Leading Indicator was chosen as long as it explains GDP well, especially in turning points. The results of the estimation exercise showed that ARIMAX significantly outperforms simple ARIMA approach in many cases, however, in some of them, this outperformance was insignificant.

Bos, Franses, and Ooms (2001) used ARIMAX and ARFIMAX to forecast US post-war core inflation, which really close to the main topic of the paper and means that literature is not absolutely empty in terms of such an approach for such goals. Also, this type of models is used in the wide range of non-economic forecasting, starting from medical (see Kaewkungwal, 2010) and engineering area (see Newsham and Birt, 2010) to the social behavior (see Williams, 2001; Tsui et al., 2014), which shows its usefulness.

Of course, it does not mean that the only way to predict inflation with the univariate model is a bottom-up approach. Even if numerous authors have used this method (see Duarte, Rua, 2007; Kaufmann, Huwiler, 2013; Bermingham, D'Agostino, 2011; Benalal et al., 2004), there are many other methods, starting from straightforward ARMA with seasonal adjustment (see Suleman, Sarpong, 2012) or even without it (see Meyler, Kenny, Quinn, 1998) to the way more sophisticated ARMA with exogenous variable (see Bos, Franses, Ooms, 2002) and adjusted by neural networks approach (see Zhang, 2001). All of the papers mentioned above, except the last one, are concentrated on the inflation forecasting. In the last case, the model is used to forecast exchange rate, predict sunspots etc. which shows how broad the areas of use for such a model could be. Papers are done for the Ghana, Ireland and US inflations correspondingly, which also suggests the universality of such a method as long as economies are quite different.

While simple ARMA-type models are relatively easy to build and understand, they do not capture too much of country and data issues, they're not that customizable, more sophisticated in their structure models could be very broad, have a tremendous amount of extensions and could be adjusted to the country case. A good example is an ARMA with an exogenous variable (ARMAX) model and corresponding exogenous variable searching, which represent an area for the so-called blue-sky thinking, which means a possibility to have absolutely new ideas, connections between them. It could also strongly help to capture some additional and country-specific connections

Moreover, there is a vast range of different classical data-driven models that might be used in order to predict some macroeconomic measures. It contains a simple VAR and its Bayesian version, GARCH, VECM, factor models, which were already mentioned above. Another example is Dynamic Model Averaging by Koop and Korobilis (2012), who have made a research about different specifications of DMA model and its forecasting performance in 1, 4 and 8 quarters ahead, their performance comparing to the Greenbook forecasts by the Federal Reserve Board of Governors. For nowcasting purposes, there is a popular MIDAS or other models (see Schorfheide, Song, 2013), which provides an ability to work with a mixed-frequency data as long as it is common to have some data on a quarterly basis and some on a monthly (for example as a result of the web-scrapping). In the corresponding paper, authors used dozens of macroeconomic variables on the quarterly basis mixed with a so-called, real-time data, which leads to the rapid improvement in the short-run forecasts comparing with the simple VAR on macroeconomic variables. However, it does not give a significant improvement in the forecasts for 1-2 years horizon. There is no agreement about the model that serves the best for some specific dataset type. It leads to the necessity of empirical checking whether some model would perform well in the economy.

It is also important to mention the trend to use some more exotic tools, which belongs mostly to the Data Science area, for the work with economic measures. A good example of such a technique which already takes it to place in the economic scientific papers are clustering tools (see Moshiri, Cameron, Scuse, 1999). They could be widely used in a combination with the medium level of disaggregation approach as an analog to logic-driven disaggregation (for example aggregating components of inflation to food, clothes, services instead of purely dynamics driven aggregation). Neural networks are also used for this purpose (see Jung, Patnam, Ter-Martirosyan, 2018; Chen, Racine, Swanson, 2001), despite the canonic problem with a tremendous amount of data necessary, which is the case in the economic data. Another example, where a common statistical tool become popular in economics (and many other areas, such as meteorology, biology) and then become very popular in the Data Science is Principal Component Analysis (see Stock, Watson, 2002; Kunovac, 2007). So, there is some interdependence between areas.

Data-driven models are subject for a Lucas critique, which discussed very well by Del Negro and Schorfheide (2003), due to their nature of reliance on historical data even if there are some changes. Lucas critique says that there is no opportunity to use previous data after some more or less significant change including crises and its consequences, changes in policy and many other. These events might have an effect on the change of behavior, but it is not necessarily true. For example, Blanchard (1984) in his iconic paper found that there is no significant shift of the Philips curve after an apparent policy change. That is one more argument to investigate the model performance empirically and then conclude whether there is an effect of structural changes. An important discussion is about a lag between shift and changes in consumer behavior (see Van Heerde, Dekimpe, Putsis Jr., 2005), which means that society needs some time to adapt for new circumstances. However, it helps only in the rare case when the model faces a break itself.

Naturally, the Lucas Critique suggests that a major contest that data-driven models face in emerging economies are structural breaks. There are many ways to deal with these problems including ignorance, deleting the problematic part and others, but these are rather rude and could lead to additional problems, results might be not robust. However, there are tools that might be claimed as a more scientifically correct way to deal with such a problem. An example is Time-Varying Parameter BVAR (see Heidari, 2008), which gives an opportunity for coefficients to be changed over time if some breaks occur. Another, albeit very close to the previous one, method is a Time-Varying VAR made by the D'Agostino, Gambetti, and Giannone (2010), which was described at the beginning of this chapter. Also, there are plenty of tests for breaks (see Clements, Hendry, 2006) that might be accompanied with "rude" techniques to correct for breaks. This critique and issue will be discussed further in the case of the model, which will be described in the paper.

To conclude this section, a rich part of the history of different views on issues were checked and a number of authors experience was taken. Nevertheless, the literature does not fill all the gaps that must be stuffed. Every country has its own combination of problems and models must be designed to deal with them well. The model itself contributes to the world models pool, means that it has some innovative and unreviewed things. Next sections would shed some light on these issues.

Chapter 3

DATA DESCRIPTION

The data, which is used in this thesis, contains core inflation components with a monthly frequency from the beginning of 2007 (when most of the series become available) to the end of 2018. There are 240 series in total, that are divided into 4 main categories: processed food, services, clothes and other. There are 69, 41, 55 and 75 series in each category respectively. Processed food and clothes include most of the goods, that might be purchased in retail stores, excluding raw food such as meat, fruits, and vegetables, administratively regulated items, such as alcohol and cigarettes and those, that have too low weight in the total basket (extremely exotic food, rare services etc). The usage of data on a monthly instead of a quarterly basis is driven by two considerations: use as much data as possible and have an ability to deal with a monthly-based seasonality.

To have a closer look on the components themselves, consider Figures 1 to 4, which represent inflation for Components 31 (sausage), Component 301 (higher education), Catergory 5 (food) and Category 7 (clothes) respectively. It is clearly seen that sausages have "healthier" dynamics (simple dynamics without much of seasonality, endogenous peaks and drops), while Higher Education has a number of one-time changes in September on annual basis. It gives a flavour of dynamics diversity throughout components. On the other hand, there are food and clothes components, where the first one has a "natural" dynamics, while the second have a strong seasonality pattern after year 2014, but no seasonality before 2014. This could be explained by the change in the methodology of the data collection. In this particular case the change lies in a counting prices with discounts as a real market price.

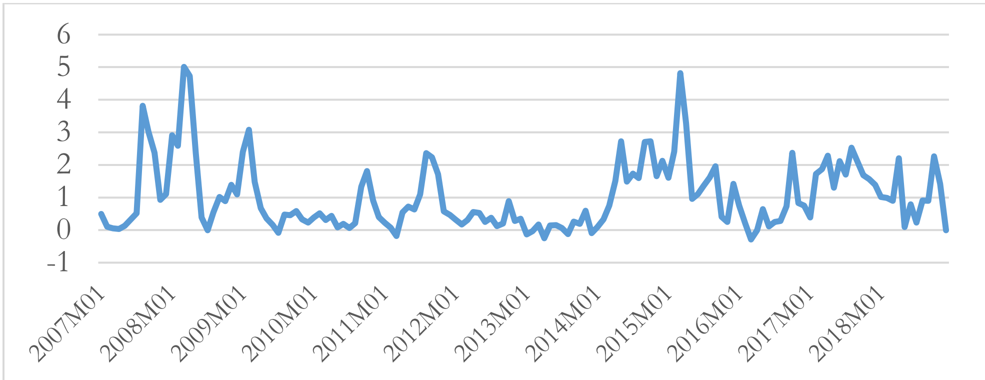

Figure 1. M-o-m inflation for component #31 -
Sausages

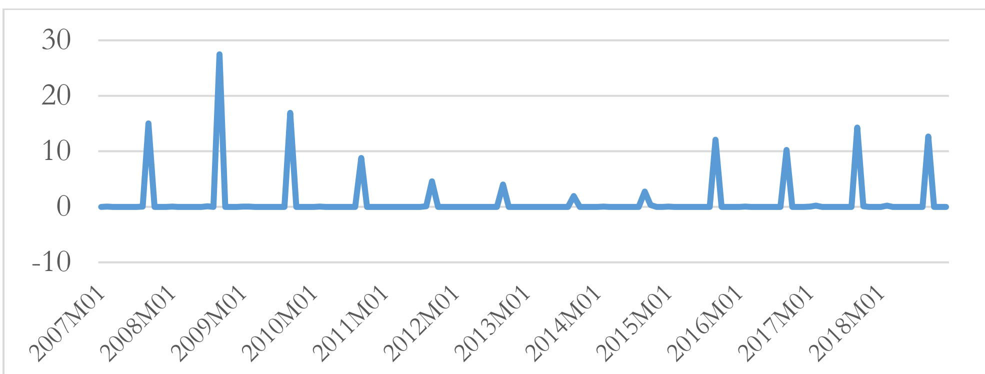

Figure 2. M-o-m inflation for component #301 -
Higher Education

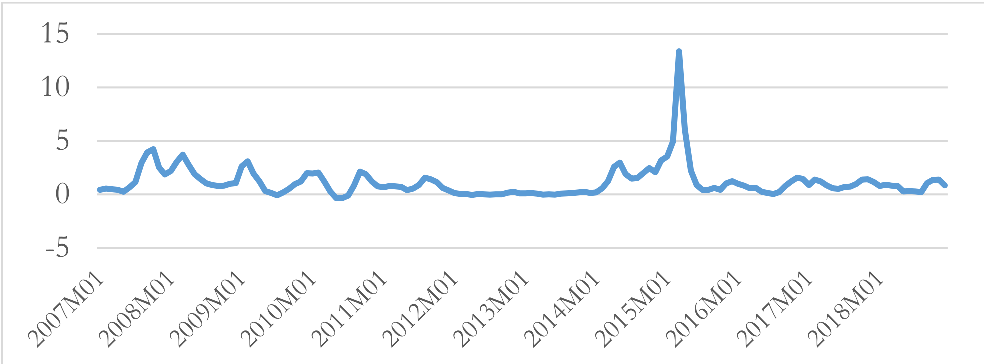

Figure 3. M-o-m inflation for category #5 - Food

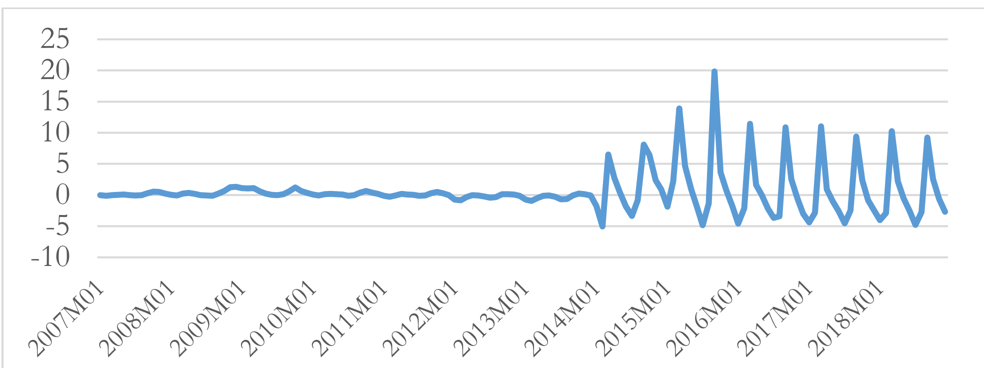

Figure 4. M-o-m inflation for category #7 - Clothes

Since these series will be aggregated to produce a core inflation forecast, some weights must be assigned to each of them in the total basket of core inflation items. The official weights series are available from the National Bank of Ukraine. However, aggregating series with official weights does not result in exact official core inflation. The reason is in different methodologies between National Bank of Ukraine and Ukrstat (static weights vs dynamic weights) which gives this slight gap between series. In Figure 5, it is clearly seen that the gap between two series is negligible overall. Also, it could be showed by an RMSE value, which is about 0.09, however, at this stage of the paper, it can not be compared with other RMSE values to understand whether this value small or not.

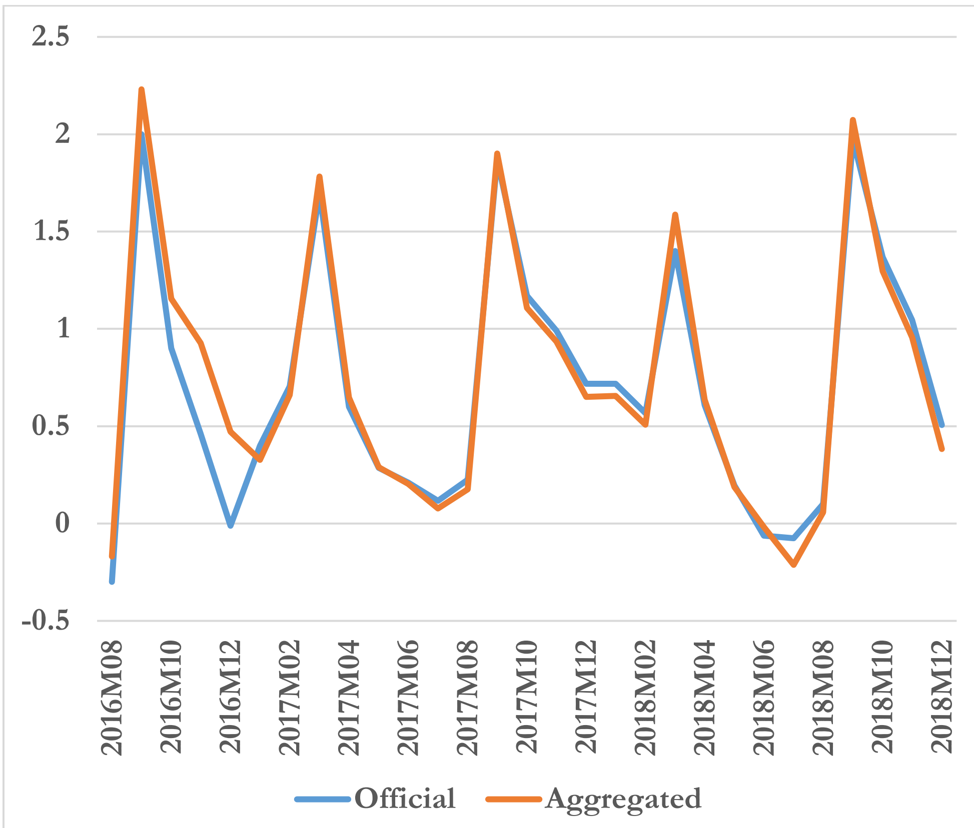

Figure 5. Official vs Aggregated Core Inflation, m-o-m

To give even better flavour of series, there is a table with basic statistical description, however, instead of showing it for all 240 series, I have decided to make statistics for Means and Standard Deviations of these 240 series (so, we have got 240 numbers of both means and standard deviations). Also, there is a pooled data statistics (statistics over all individual component data points) and statistics for core inflation.

There is a number of possible conclusions that could be made from the table. In particular, series of Means is not very volatile with a mean around 0.9, while series of Standard Deviations have relatively huge mean, which is around 2.16. It gives an understanding about how average series looks like. Moreover, the clothes contributes to the deviation strongly via seasonality mechanism (corresponding table might be seen in Appendix). One more interesting finding is in the Pooled column. Mean is way more than Median here which shows the effect of the strong crisis with huge values in 3rd quartile of data (because the 3rd quartile is not that big in comparison with how small 1st quartile is). In short, values in a Pooled section gives an understanding that some crisis happened during the observed period.

Table 1.Descriptive statistics for core inflation and its components

	Means	Stdevs	Pooled	Core Inflation
Min	-0.18	0.34	-22.08	-0.36
1st quartile	0.64	1.27	0.02	0.17
Mean	0.87	2.16	0.88	0.93
Median	0.92	1.77	0.40	0.60
3rd quartile	1.12	2.59	1.19	1.38
Max	1.75	6.89	46.26	10.80
Stdev	0.33	1.30	2.53	1.25

Also, it is informative to consider how important different categories are and how many constituent series they have. As figures 6 and 7 demonstrate, there is almost equal number of series in each category, however, the weight of the food category is much higher in the consumption basket. This is a consistent with the data from other emerging markets, where people tends to spend higher shares of their incomes on food than other goods.

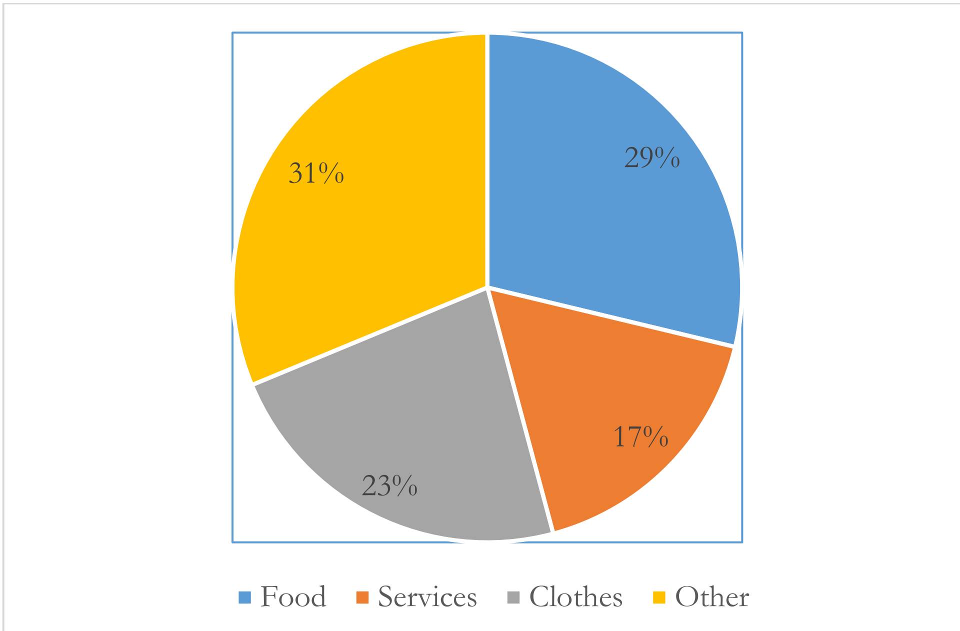

Figure 6. Number of components in categories

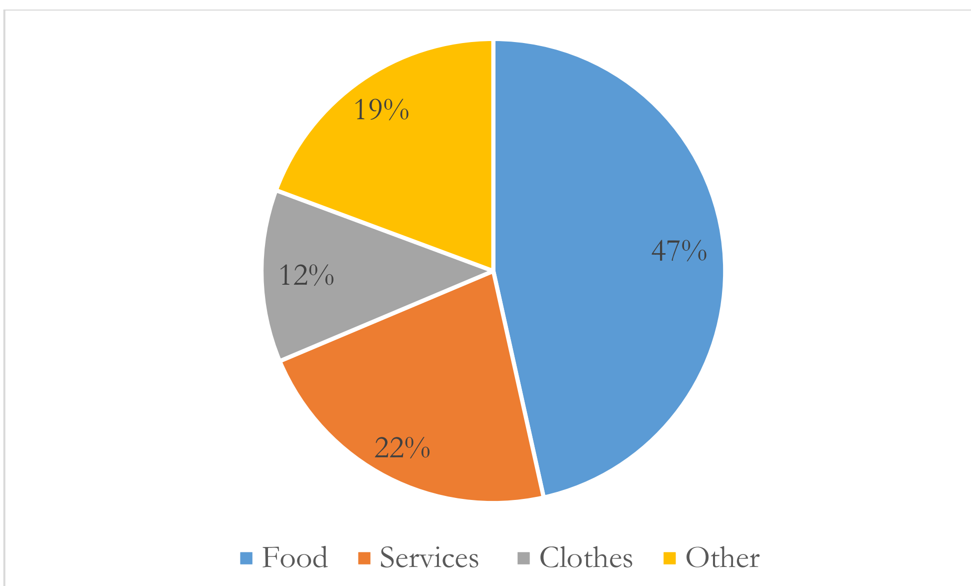

Figure 7. Average weight of categories

There are some other issues with the data that must be discussed. First, some of the series start not from 2007, but from 2012 or 2016. The reason for that is a change in methodology. The good news is that there are only 7 series which start in 2016 and their combined weight in the basket is less than 2%. So, there is an opportunity to drop these series in the performance evaluation exercise (because their length is not appropriate, only 6 observations), but keep them in the real application and future performance evaluations (in this case it would be 36+ observations which is enough).

Other than that, there are some other series that are dropped from the model. The reason for that is their nature of change, which might be not like in a competitive market. Examples are middle and higher education, which prices could be dictated by the government as a socially important service. In addition, prices for education could not change during the existing year, however, due to the different rules, the authorities could announce a change in prices and it would be counted as an actual change in statistics rather than in the September when payments for the next year would begin.

Another example is a mobile network, which is oligopolized by a few companies. Also, these companies expect very high "menu" costs in terms of clients loyalty and some additional issues due to the design of the contracts when trying to change main plans price, which is a core source of income. However, there are not as huge problems for additional service prices such as change of number and other. These series contain many zeroes and the graph looks like a jagged line. But ARMA is pretty smooth and it could not reflect and describe such a movement good enough, also these series would be unstationary and that is why it is better for the total inflation not to count these series and to renormalize weights.

One of the most popular questions about the data is seasonality. In the case of core inflation, there is an apparent seasonal pattern in the clothes components, which could be easily observed on the graph with the official inflation or on the corresponding graph for this category below. The underlying nature is consumer behavior to buy clothes for autumn/winter (and school uniform) at August-September, so prices rise significantly at this time and drop afterward. Once the raw food component is removed from the core basket, there is no obvious seasonality in the food component.

The last point in this section is about weights, which are used in the forecasting exercise. There are several approaches such as taking average weights over some period and use them for forecasts, to take the last know weights, forecast the weight via simple OLS regression. All of them has their own pros and cons. However, I have decided to take the last weights approach for reasons, which will be described in the next paragraph.

There are not many different types of data used, but there is still a wide range of issues arise. Despite the overall data-driven way to deal with problems, this section requires some economic understanding and explanation. Of course, it might be skipped and left as it is, for example, there is no necessity to drop series or to take last weights instead of OLS forecasted. So as there is no agreement about the number of lags and other issues. However, with a view to improving forecast quality, it is good to be guided by results in this and next sections.

Chapter 4

DATA DISCUSSION

There are several reasons for usage of static weights, where the most important is the simplification of the aggregation method. In two words, the official and sophisticated method (by Ukrstat) contains a translation of monthly CPI changes into the CPI index and, after some black box actions, vice versa into the monthly changes. However, the results of the simplified method with multiplication of m-o-m series by static weights deviates from the official one slightly enough, as it was showed in the previous chapter.

Second thing to discuss is the problem with a huge number of lags allowed in the model. It gives a number of benefits with correct dynamics capturing, but a lower quality of specification building comes from the side of short series since it requires a lot of data and short series could be strongly overfitted with far lags. For example, if we build an AR(12) model for series, that contains 1 year of data, every lag coefficient would be univocally defined by corresponding month and previous lags. However, even if the series starts from 2016 there are already two years of data, but some part of the available data might be used in the pseudo-out-of-sample forecasts to estimate the forecasting performance, so it is not appropriate to use these series in the performance evaluation stage.

But how these short series appears in the data? The nature of this process is division of some previous series on more, which means that this data was counted previously, but in an aggregated way. For example, the division of some product by quality on extra and first class (sausages, cream cheese). One more point is that weights are approximated for series which starts from 2012 on the whole history, but those from 2016 are absent. It means that aggregating with these weights would be biased as long as if we take series from 2007 it must include those from 2012 until 2012. So as corresponding weight series of 2007 must include weight series for 2012, but it does not due to the approximation. However, this issue would contribute only to the bias in aggregated series before 2012, which is not the point of interest of the paper so it might be just ignored in particular case, but the discussion overall is important in terms of exercises during the period with division or aggregation of some series.

There are plenty of ways to deal with the seasonality. The first one is to add seasonal dummies into the equation. The second option is to perform widely-used X-12 seasonal adjustment. The third option is to use 12-13 lags ARIMA as lags could capture seasonal patterns. Thirteenth lag could be used in the case when there is some floating seasonal pattern. Third approach is used in the paper.

Average weights (average over some period) are good because they could capture a mean weight during some period, however, it does not capture trend dynamics and does not give a good enough estimate if weights consistently move upward or downward, while other methods are much better in these terms. In this case, taking the most recent weights instead of average weights over the sample period might give better results if the forecasting horizon is relatively short. However, if these most recent weights happen to be outliers, the forecast is going to be very imprecise.

After the test for the statistical significance of the trend via Augmented Dickey-Fuller test in the last 4 years of weights data, we have found that 119 series, which is nearly a half of all, have a statistically significant trend, while others have not. It is not possible to take a different weights approach for the corresponding series, for example average for series without trend and last for series with trend, because the inconsistency of nature would arise. Between these 2 ways, it is better to choose last weights due to the empirical results, so as RMSE in the case of average weights is higher. The last approach is good in capturing dynamics, edge, and trend, of the series, however, it is way more complex, because it requires to take some period where OLS would be evaluated and economically justify it and deal with cases like those, described in the paragraph above. Even if they are dropped, there might be some that have a similar, but not as strong, pattern and their OLS forecasting would give biased results. That is the reasoning for the last weight approach to be in use in the model.

C h a p t e r 5

METHODOLOGY

The model is based on three core elements: ARMA model to predict inflation via its lags; disaggregation to deal with inflation components instead of the inflation index itself; dummy to capture periods with unusually large shocks.

ARMA-type models are widely used in modelling time series data since many economic variables strongly depend on their previous values. For example, GDP in the quarter for a big country would be relatively the same as the GDP in the previous quarter. Similarly, if we have sales on winter boots every April, there would be a big negative spike of inflation on this good every 12 months, so the coefficient with 12th lag would be huge in this process. It is quite common to see an AR or ARMA model as a simple benchmark to compare more complex models with.

An ARMA(m,n) process can be defined as:

$$y_t = \sum_{i=1}^{m} \beta_i * y_{t-i} + \sum_{i=1}^{n} \gamma_i * \varepsilon_{t-i} + \varepsilon_t \qquad (1)$$

To use the most, first we need to identify the number of AR and MA terms, which explain the series dynamic the best. One of the classic methods is a visual analysis of the correlogram, however, due to the large number of series to be analyzed, this approach is barely feasible. An alternative approach is to use a formal information criterion to find the optimal number of lags for each series. The two common information criteria are Schwarz (or Bayesian) Information Criterion (SIC) and Akaike Information Criterion (AIC). The AIC is calculated using the following formula:

$$AIC = 2 * k - 2 * \ln(\hat{L}) \tag{2}$$

where k is the number of parameters, estimated in model and $\hat{L}$ is the value of the maximum likelihood function. The lower the AIC is, the better the model is. As we can see, AIC penalizes for the large number of parameters to prevent overfitting and therefore higher likelihood (a measure of goodness of fit).

The SIC is calculated as:

$$SIC = \ln(n) * k - 2 * \ln(\hat{L}) \tag{3}$$

where n is the number of observations. The more data we have, the higher the penalty for additional parameters, which is a core difference between SIC and AIC. The SIC approach is chosen for the model development, because it gives more strength to get rid of last lags if the seasonality pattern absent or unexpressed.

The key feature of our forecasting model is the use of disaggregated series, which means that instead of forecasting the core inflation, its components will be forecasted first and then they will be aggregated into the core inflation. Such an approach gives the ability to use much more available information than otherwise. Also, it captures causality between components, which is based on the complementarity and the substitution effects. For example, tea, sugar, and coffee have a link between each other, and an increase in the price of tea would increase the price for its complementary sugar and decrease for a substitute coffee. However, a decrease in coffee price would also support a decrease in the sugar price.

The predicted inflation in period t+1 would be as follows:

$$y_{t+1} = \sum_{k=1}^{p} w_k * \Big(\sum_{i=0}^{m_k - 1} \beta_i^k * y_{t-i}^k + \sum_{i=0}^{n_k - 1} \gamma_i^k * \varepsilon_{t-i}^k + \varepsilon_t^k \Big) \tag{4}$$

where *k* is the index for a component, w_k – its weight in the total basket, *p* – total number of components, y_{t-i}^k – inflation of the component *k* in the moment t-i, ε_{t-i}^k – error term of the component *k* in the moment t-i, m_k and n_k are AR and MA term of the component *k* correspondingly. Of course, this model will face the problem with aggregation error (deviation of aggregated series from real), however, as it was described in the data chapter, this problem is rather minor and ignoring it would not worsen results much.

We can extend the standard ARMA model by adding a dummy that captures volatility in some manner:

$$y_t = \sum_{i=1}^{m} \beta_i * y_{t-i} + \sum_{i=1}^{n} \gamma_i * \varepsilon_{t-i} + \gamma D_t + \varepsilon_t \qquad (5)$$

where D_t is a dummy variable, which has the value of 0 when there are no huge deviations from the mean, and 1 otherwise. There are two main definitions of "a huge deviation from the mean" used in this thesis. Both of these definitions support the idea that crises (or huge deviations) effectively result in jumps in inflation levels without affecting other coefficients in the equation. However, neither of these dummy variables is predicted inside the model.

The first approach to defining the dummy is to assign it the value of one in periods when the value of inflation exceeds its mean by the 3 and 4 standard deviations (which is 2 different designs). So different series have got different number of ones in the dummy variable which gives an ability to support series with low number of huge deviations (which are unnatural for the time series) and don't affect series with relatively uniform deviations, without any matter how big they are (for example, persistent seasonal factor wouldn't be affected by dummy in this approach).

The second approach gives an opportunity to "get rid" of the one, two and three outliers in every series (it gives three different designs). It serves the same purposes as the first approach, however, it affects even smooth series and does not affect too much those series, whose graph looks like a jagged line (higher education, for example).

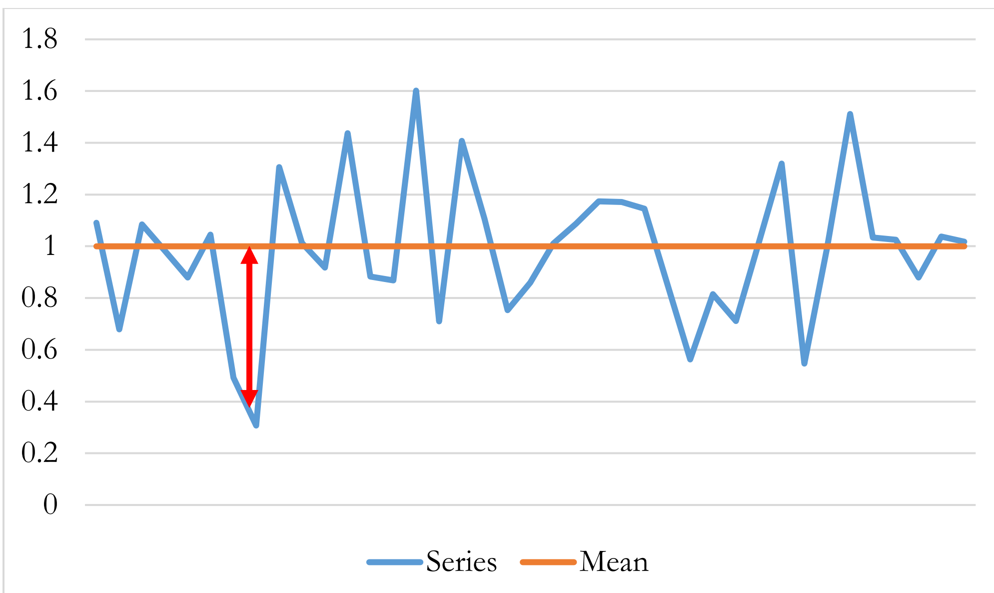

Figure 8. Dummy with deviation from mean, architecture example

However, both of these two approaches might be criticized since their core idea is to put a dummy into the model to explain deviations that could not be explained by the model itself. To deal with this issue, we can also look at the deviations of the dependent variable fitted values from its actual values. In other words, we will use model residuals as the design of a dummy. It is possible to remake approaches that were described above, in this case, so to take a series of residuals find 1-3 largest deviations from the mean of the residual series. A standard assumption here is that residuals are Gaussian noise and they would have a normal distribution around zero.

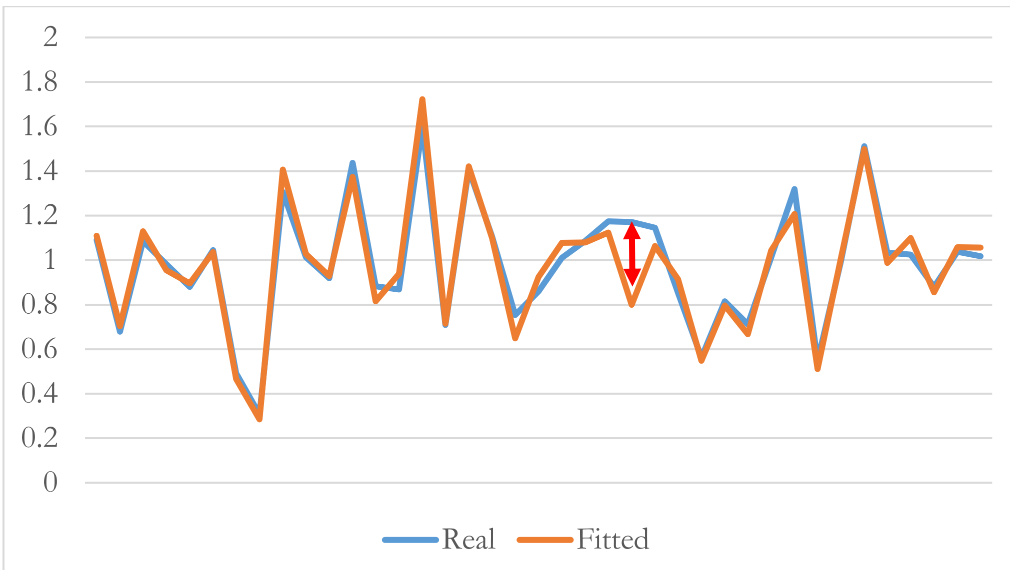

Figure 9. Dummy with deviation in residuals, architecture example

A nice sub-product of the model is a graphical tool for observing where variables deviate from the mean or from the expected value the strongest. It is great to understand where something goes wrong from the point of view of the model, this point would be very suspicious to be a structural break. Example of how it looks like on figures below (from the mean there are first two and last two are from the residuals):

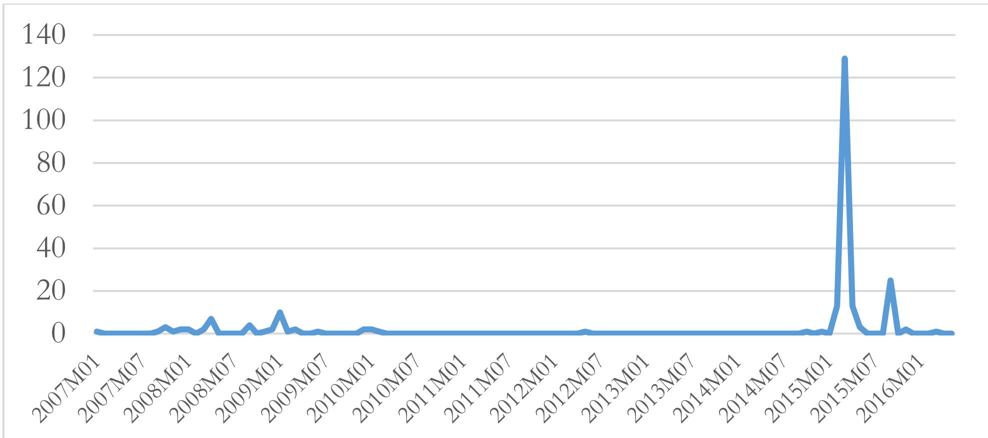

Figure 10. Dummy with 1 Highest Deviation from mean. Values for all components

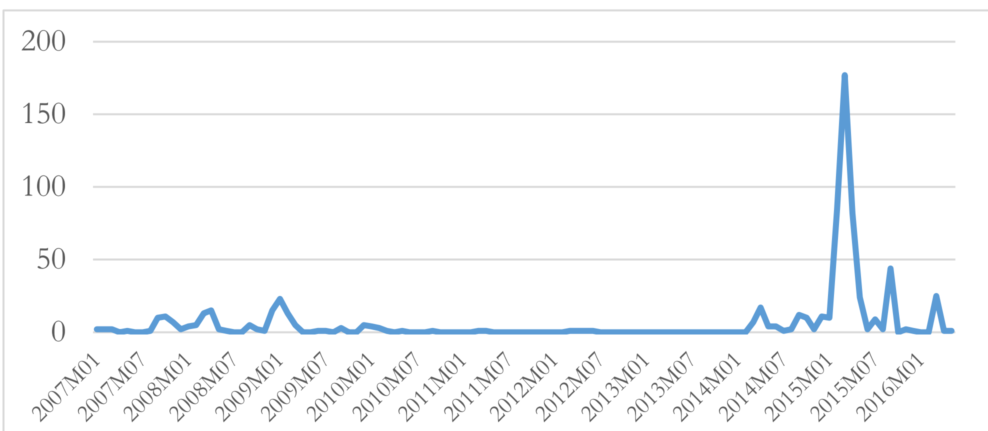

Figure 11. Dummy with 3 Highest Deviations from mean. Values for all components

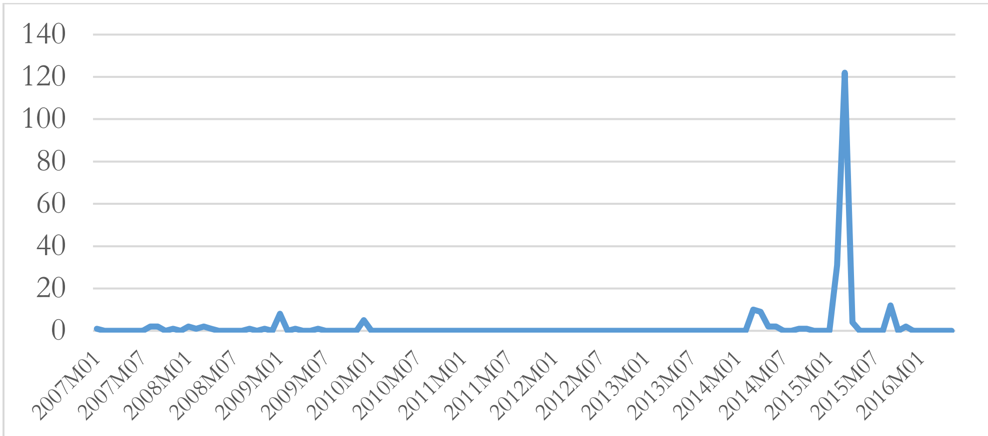

Figure 12. Dummy with 1 Highest Deviation from modelled, residuals. Values for all components

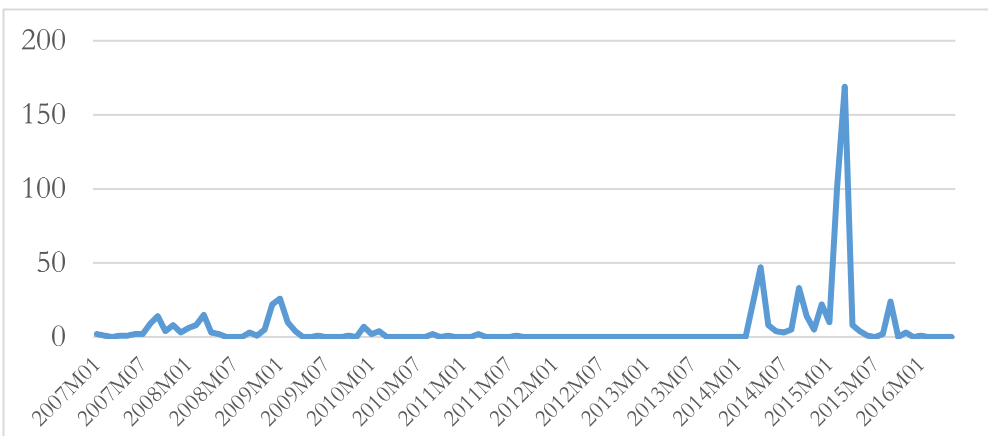

Figure 13. Dummy with 3 Highest Deviation from modelled, residuals. Values for all components

The next issue is about the changes in statistical methodology. The biggest one was in 2014, when the State Statistics Service of Ukraine started to incorporate the data on sales, which is a source of the huge price variations, especially in clothing. To be more precise, before 2014 all prices were taken as they were officially reported, but in real life, the official price without sales might not reflect the real price level in the market. It was a common to observe price hikes just before sales started, so the real change in price could be lower than indicated in the sale price. In any case, for statistical purposes the officially recorded prices were much higher than the actual ones. After 2014 the new methodology with the inclusion of discounts brought a visible seasonality pattern to inflation, with the source being mostly in the clothes category.

There are several ways to deal with this issue, with most of them leading to some kind of division between clothes before 2014 and clothes after 2014. The data before 2014 has only two uses in the model: to evaluate the number of ARMA coefficients and to evaluate the coefficients itself. Since there is enough data to evaluate all model coefficients in the post-break period, we will disregard the pre-break data and work only with the post-break data samples for clothing. Another way is to seasonally adjust clothes series, then evaluate and, after the forecasting round, return seasonality pattern back to the series, but this way is inconsistent with the previous choice of using 13 lags for seasonality capturing. So, the first approach is used in the paper.

There is a number of purely technical issues which arise during the model building and evaluating. First of them is a problem with calculating the number of AR and MA coefficients. As long as the method straightforwardly takes different processes, evaluate them, calculate SIC and pick the best, it becomes very bulky from the point of view of the computational resources. However, there is a nice and theoretically interesting way to omit this problem. It is to simply take the ARMA(13,13) process for all series, instead of calculating AR and MA coefficient for each series. In the evaluation process, however, it might be that high and significant coefficients would still be with those lags, which were picked by the SIC-based algorithm. But this method is left for the further investigation.

Another problem with computational power is that in the best case we need to evaluate SIC for the final specification and use it for forecasting purposes. However, we have found the best dummy for the series with the specification, that was found without the dummy. So this dummy might be not the best for other specification (when we are talking about dummies based on residuals). So there should be an endless iterative process of finding the best specifications with a dummy and finding a new the best dummy for the specification until it converges (if it ever does this). The best decision is to omit this problem or stop after 2-3 iterations. In the paper it's omitted to do not overcomplicate technical side of research. But it might be used in the pure forecasting exercise because of much lower number of calculations than on the research stage.

C h a p t e r   6

RESULTS

First of all, we present the results of the simple disaggregated ARMA-based model (let's call it CARMA, which is Combined ARMA), which is the very basis of this thesis. Its results are compared between CARMA for all series, for four main components (food, clothes, services, other) which would be aggregated from the series and for official core inflation, reported by Ukrstat. The results are in form of the RMSE, which represent a magnitude of the deviation for the forecasted series (a series, which include point forecast 1-6 months ahead). This form would be used for all tables with forecasting exercise results. Also, the nice graph with the most important results might be found further.

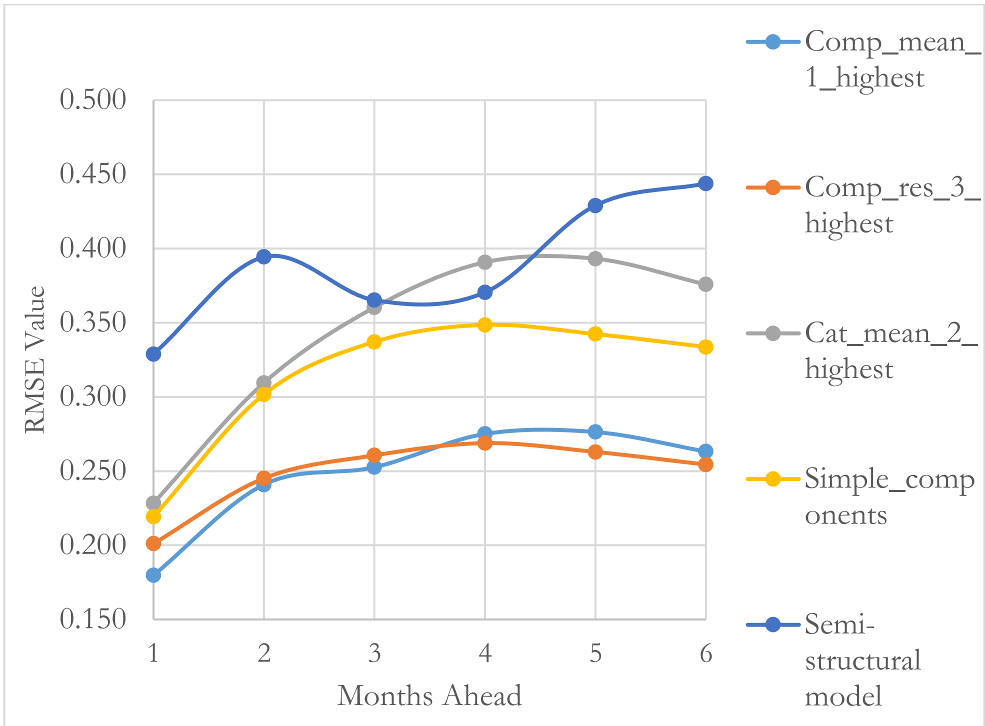

Figure 14. Comparison of best models and semi-structural model

Table 2. Results of different models, RMSE

	Benchmarks		CARMA without dummies			CARMA with different dummies					
						Components		Categories		Core	
RMSE to Official	NBU semi-structural model	RW	Components	Categories	Core	1 highest deviation, mean	3 highest deviations, residuals	2 highest deviations, mean	2 highest deviations, residuals	1 highest deviation, mean	2 highest deviations, mean
1	0.329	0.541	0.332	0.249	0.332	0.180	0.201	0.228	0.229	0.337	0.334
2	0.394	0.783	0.448	0.340	0.448	0.241	0.245	0.310	0.319	0.450	0.436
3	0.365	1.017	0.515	0.409	0.515	0.253	0.261	0.360	0.369	0.500	0.503
4	0.370	0.978	0.521	0.445	0.521	0.275	0.269	0.391	0.402	0.505	0.520
5	0.429	0.960	0.507	0.439	0.507	0.276	0.263	0.393	0.403	0.493	0.518
6	0.444	0.892	0.495	0.414	0.495	0.263	0.254	0.376	0.388	0.481	0.500

Table 2 clearly shown that the disaggregated approach outperforms the other two since the this model's RMSE for every forecasting horizon is lower. Also, it is nice to notice that the forecast of aggregated series includes aggregation bias and RMSE to the aggregated rather than the official core inflation is even smaller. The approach with seasonal adjustment for components looks better, however, it has poorer performance on other horizons which might be explained by the rather insignificant difference in the first few periods or by the fact, that seasonality would drive the performance in a next manner. Even if the forecasting of seasonally adjusted series has a poorer performance itself, the magnitude of the seasonal factor could be big enough and quite accurate to make a total deviation lesser than in the regular case without seasonal adjustment. That is why for simple Combined ARMA without extensions it is good to take a model without seasonal adjustment as a benchmark.

Now we will repeat this exercise, but for a new set of models with different dummies. It will be 10 different dummies, 5 of them are related to the deviations from the mean, and 5 – to the deviations of residuals. These 5 are 1, 2 and 3 highest deviations and all values that are at 3+ and 4+ standard deviation away from mean or expected value. Also, this exercise will be repeated for components version and for the official CPI.

Table XXX contains some representative results, while all other could be seen in the Appendix. Ton make this table easier to read, we highlighted the cells with the lowest RMSE (relative to official inflation series) plus/minus 0.01 for each type of the model. Simple ARMA approach slightly outperforms the categories approach, however the best among them are the highest disaggregation (component) approach, which outperforms very clearly. It is quite hard to choose the best approach since for different horizons the best specification would differs, for example for longer horizons the models, in which the dummies are defined by two highest deviations from the mean and for residuals, strongly outperform the other approaches, while for 1-month horizon the winner is the model with the dummy defined by one highest deviation from the mean. As we can see, the residuals approach does not outperform the deviation for the mean approach, which suggests that this difference might be insignificant and the model is already on the peak of its performance. In other words, any improvement would be just a random as long as the unexplained deviations have an exogenous nature and might not be explained by the data anymore.

One more interesting finding is that one-two highest deviations approach is better in most of the cases (between both the mean deviations and residuals deviations). This might be explained by the dummy overfitting of the seasonality in the case of three-four standard deviations and that in the history most of the variables experience one or two, but not three huge deviations that could not be explained at all.

There is a slightly updated results on the graph, where only the best models were taken out of 10 for components-based models. It's clearly seen that "gray" and "yellow" models together outperform any another on any interval ahead, which might give as the best solution one of those models or their combination for different forecasting horizon.

The most interesting part is the comparison with the National Bank of Ukraine's semi-structural model. Frankly speaking, these results are adjusted by some expert judgement. Also, in the comparison a simple Random Walk model is used as a canonic benchmark that helps to evaluate models forecasting performance. As a representative of the Combined ARMA with extensions the models with 2 highest deviations from the mean and in residuals are taken.

The question is whether it is correct to compare with official results rather than with the model results. The first point is that, as it was shown in one of the papers from literature review, expert judgements tends to improve forecasting performance. Another point lies in the purposes of the short-run forecasts. Its idea to give a monthly estimation, while QPM gives a quarterly which is adjusted to the monthly by mathematical means. However, even if the result of the QPM might be worsened by such a manipulation, it is the only way to obtain a monthly data from this channel so it is correct to compare these results. Another way is to obtain pure QPM results and translate CARMA results from m-o-m to q-o-q, however, the problem here lies in the tremendously low number of observations (about 10 observations), which makes it impossible to make a comparison meaningful.

One last point is how the forecast will looks like, just to give a flavour of the forecasting experience here:

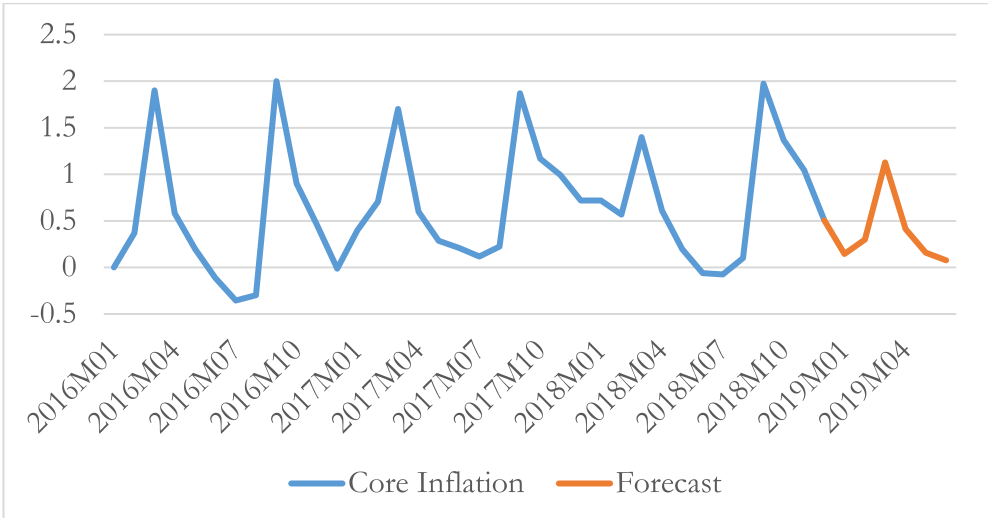

Figure 15. Forecast from 2019m01 to 2019m06

Chapter 7

CONCLUSIONS

The existing demand for well-performing short-run forecasting data-driven models is partially satisfied by the model, developed in this paper. It performs well on the Ukrainian data, showing better results than the National Bank of Ukraine semi-structural QPM model with expert judgments and other benchmarks such as RW and Combined ARMA for components. Therefore, the purely data-driven approach might survive even in emerging economies and give a comparable result. Such an approach might be used not only for the inflation forecasting but it also possible to use whenever there are many subcomponents. Also, the results showed that disaggregation improves the model performance in all the cases. So, this paper contributes to this discussion as well.

The model has faced a number of issues, because the economy is not developed yet and there are a number of changes, starting from the methodology changes. However, it is possible to solve such problems. Also, it is possible for the model to work well even after the crisis, which could affect components differently, with a lag, happens.

There is an ability for a further investigations. A good example is to use a clustering such as a K-means approach to capture a dynamics and try to make a model simpler in terms of calculations (closer to categories approach) but doesn't lose the information that might be taken from the data.

Using of the exogenous variable (ARIMAX model) might be also useful to improve the prediction quality as long as inflation could be explained by other processes well, however the problem with preliminary prediction of that exogenous variables arise.

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