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Forecasting Capacity of ARIMA Models; A Study on Croatian Industrial Production and its Sub-sectors *

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Abstract: *As one of the most important indicator for monitoring the production in industry as well as for directing investment decisions, industrial production plays important role within growth perspectives. Not only does the composition and/or fluctuation of the goods produced indicate the course of economic activity but it also reflects the changes in cyclical development of the economy thereby providing opportunity to macro-manage with early signs of (short-term) turning-points and (long-term) trend variations. In this paper, we compare univariate autoregressive integrated moving average (ARIMA) models of the Croatian industrial production and its subsectors in order to evaluate their forecasting features within short and long-term data evolution. The aim of this study is not to forecast industrial production but to analyze the out-of-sample predictive performance of ARIMA models on aggregated and disaggregated level inside different forecasting horizons. Our results suggest that ARIMA models do perform very well over the whole rage of the prediction horizons. It is mainly because univariate models often improve the predictive ability of their single component over the short horizons. In that manner ARIMA modelling could be used at least as a benchmark for more complex forecasting methods in predicting the movements of industrial production in Croatia.*

Keywords: industrial production; industrial sub-sectors; cycles; ARIMA; forecasting; Croatia

JEL Classification: C22, E23, E61

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Introduction

Generally, industrial production is considered as one of the most important variable indicating the expansion or compression of economic activity in a country. It is a variable in a form of an index used for measuring the growth of (real production output) various sectors of industry in an economy. It has become inevitable indicator for monitoring the production in industry as well as valuable standpoint for directing investment decisions. Not only does the composition and/or fluctuation of the goods produced indicate the course of economic activity but it also reflects the changes in cyclical development of the economy. It can thus provide ground for macroeconomic management with early signs of (short-term) turning-points and (long-term) trend variations. The goal of generating, monitoring and publishing industrial production measurement is to see the movements of production in time, to follow the changes between terms and the cyclical characteristics of the economy and to meet decision making bodies and scientists in this area (Kaynar, 2012). Though, most business cycle analyses are based on real gross output movements, we can also use variables such as employment or industrial production within turning points identification process. In fact, despite growing importance of the service sector in many countries, nowadays, industrial production is still important in explaining aggregate business cycle fluctuations. Forecasts of industrial production can also be used as an additional input in larger models, which are often criticized for their (in)ability in tracking business cycle turning points. As Bulligan, Golinelli and Parigi (2010) rightly conclude, the index of industrial is probably the most important and widely analyzed high-frequency indicator, given the relevance of the manufacturing activity as a driver of a whole business cycle which is experienced by the extensive comments and reactions of the business analysts as soon as the index is published. Therefore, the index of industrial production is a crucial variable in the forecasting process of the short-term evolution of national output in most countries.

Industrial production does play very important role in Croatian economic growth path as this indicator is often used is some studies as an approximation for the national output measurement. Registered average rate of change of industrial production between 2000 and 2007 was 4.50%. Then, till 2009, the index dropped by 15 percentage points to experience a relatively steady decline till 2012 with an average annual rate of more than 2.60%. Croatia's average industrial production index for the first months of 2013 was comparable to the level in 2003 (Jaegers, 2013), however till then index grew steadily as the EU markets were in the process of healing. Growth of the industrial production in Croatia took off during 2015 and increased by 2.7% with the rise in the labour productivity. Figuratively, crisis '*took its toll*', as the average annual growth in the period 1998-2015 was only 1.17%. Fluctuations in industrial production index are often influenced by seasonal volatility, trend fluctuations and crisis appearances, as well as calendar and trading day effects, which cover relevant short and long-term movements of time series. It is therefore important to evaluate movements in the aggregate industrial production as in its disaggregated parts. Industrial production index in Croatia is composed of 5 basic sub-sectors i.e. main industrial groupings; energy, intermediate goods, capital goods, durable consumer goods and non-durable consumer goods which enables us also to tackle the industrial production forecasting on a more disaggregated level, by specifying different equations for different manufacturing sub-sectors as well as for the aggregated measurement. This deduction brings us to the core of our study.

In this paper, we will compare univariate autoregressive integrated moving average (ARIMA) models of the Croatian industrial production and its subsectors in order to evaluate their forecasting features within short and long-term data evolution. Hence, the aim of this study is not to directly forecast industrial production but to analyze the out-of-sample predictive performance of ARIMA models on aggregated and disaggregated level inside different forecasting horizons. Finally, it should give us a clearer perspective on whether ARIMA modelling (of industrial production) is in fact a reliable approach for providing forecasting signals and interpretations. Section 2 surveys theoretical and empirical literature. Section 3 gives a full perspective to the analytical part by providing used methodology, data and results whereas Section 4 evaluates the results trough brief discussion and some concluding remarks.

Theoretical Background and Empirical Validation

This section presents a short review of the papers dealing with the topic i.e. ARIMA forecasting performance and in addition offers an empirical background on related studies dealing with the forecasting of the Croatian industrial production.

Theoretical Framework and Related Empirics

Forecasting of industrial production is either based on raw data of real production output in industry (direct approach/quantitative predictors) or business surveys data (indirect approach/qualitative predictors). Though our research will be based on a direct approach, we have to emphasize that qualitative business surveys also represent valuable information about the industrial sector since they provide early statements about variable that has quantitative counterparts (e.g. recent production trends) as well as information which are not directly observed (such as expectation). Many researchers do include these quantitative counterparts in their analysis for the fact that empirical parts are not available at all or they are published with too much delay (Bruno and Lupi, 2004). In next few lines we will present papers that are relevant for our analysis, at least in the part of industrial production forecasting.

Interesting time series analysis of the index of industrial production in India was given by Singh, Devi and Deb Roy (2016) as they investigated the effects of seasonal and trend variations on industrial production with the help of ARIMA models. Their findings suggests that both seasonal and trend effects were present in India's industrial production so that the future forecasts could be made by this approach after adjusting the effects of short-term and long-term variations. Next, Bulligan, Golinelli and Parigi (2010) analyzed the performance of alternative forecasting methods to predict the index of industrial production of Italy as they used 12 different models, from simple (univariate) ARIMA to dynamic factors models exploiting the timely information of up to 110 short-term indicators, both qualitative and quantitative. They conclude, that though most of the factor based models outperform ARIMA model (by the sheer fact that short-run indicator signal always dominates the noise component), still this model can be used as a benchmark since it provides rather robust results in term of forecasting performance which do not deviate too much from the results of other methods. Another interesting research is that from Kaynar (2012) who besides using soft computing techniques (Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS)) in forecasting Turkish industrial production index, also used ARIMA and its seasonal type (SARIMA) to attest his initial approach. Sjöberg (2010) has tried to predict the movements of industrial production in Sweden on the basis of non-linear time series modeling. He compares ARIMA models with the non-linear models logistic smooth transition autoregressive (LSTAR) and self exiting threshold autoregressive (SETAR) as judged by the mean square errors in their predictions. The results in general suggest that ARIMA models always outperformed both LSTAR and SETAR models and that ARIMA models performed better over a whole range of the forecasting horizon, but other two models did better when the results were analyzed by the industrial branch. Hassani, Heravi and Zhigljavsky (2009) approached forecasting of UK's industrial production with multivariate singular spectrum analysis (MSSA). The performance of the single spectrum analysis (SSA) was assessed by applying it to eight series measuring the monthly seasonally unadjusted industrial production in main sectors of the UK economy and then the results were compared to those obtained using ARIMA and Vector Autoregression Models (VAR). The comparison of forecasting results showed that SSA is more accurate that ARIMA model, whereas MSSA showed better prediction characteristics in comparison to VAR model in predicting values and the direction of the production series according to the root means square error criterion and the direction of change results In the end we also need to reflect upon some results from indirect approach (see also 2.2.). Bruno and Lupi (2004) proposed a relatively simple procedure to predict Euro-zone industrial production using mostly data derived from the business cycle survey of the three major economies in the European Monetary Union (Germany, France and Italy). Their approach provided results i.e. predictions that are on average more accurate than those stemming from the ARIMA model.

Nevertheless, they concluded that root mean square error and mean absolute error of the ARIMA model with larger sample decreased drastically (in respect to small forecast sample) which confirms its status as a good benchmark model.

What Empirics in Croatia Say?

We find relatively heterogeneous research patterns associated with industrial production forecasting in Croatia. Bačić and Vizek (2006, 2008) evaluated composite leading indicator of the Croatian economy (CROLEI)[1] whose purpose was to forecast classical business and growth cycles (in a form of its derivative CROLEI forecasting index). Authors conclude that the original CROLEI has by far the greatest forecasting power, but also that it predicts the turning points in economic cycle with highest probability. On the other hand, Cerovac (2005) developed some new composite indicators so as to identify and predict cyclical expansions and contractions. An engaging paper was that of Čižmešija and Bahovec (2009) that tested empirical relevance of two leading indicators, CROLEI and Industrial confidence indicator. Authors found a weakening of a correlation between the indicators and a reference series (industrial production) leading them to a conclusion that these indicators should undergo some moderations for improving their predictive features.

Regarding ARIMA modelling we find less empirical validation. We can find Croatia's industrial production forecasts formulated through ARIMA model which is calibrated on specific expectations within 'Trading Economics' statistics. In their approach they model the past behaviour of industrial production using vast amounts of historical data which are then adjusted by taking into account the assessment and expectations of their own analysts. There is no audacity in stating that such assessments could be served as deflection plates. Čižmešija and Knežević (2012) also used ARIMA model to forecast total energy consumption in Croatia by following two different approaches. They allure that predictive values of the total energy consumption calculated using indirect method (forecast values calculated indirectly) is smaller than those obtained by the direct method, which is in line with Croatian economic situation. They also point out that such conclusion is based primarily on their subjective expectations and judgements, thus should be considered with caution. Eventually, they suggest that a successful forecasting should follow an amalgamation i.e. a combination of qualitative and quantitative criteria in selection of convenient forecasting models.

Methodological Issues and the Results

This section consists of three parts, each a conceptual continuation of the previous. First we will clarify some methodological issues, then evaluate the dataset and in the end interpret the results[2].

Methodology

Since the main goal of the paper is to evaluate out-of-sample forecasting performance of ARIMA models in the analysis of Croatian industrial production, in this part we will shortly describe why this kind of modelling provides us with relatively reliable and stable forecasting features and signals. ARIMA models are a useful tool for relatively short term analysis, because their flexibility and adaptive behaviour contribute to their good short-term forecasting. However they also offer interesting mid and long-term interpretations (for example see Škare and Tomić (2014) who evaluated long-term properties of technological progress with ARIMA models) and predictive capabilities for any kind of pattern in the series with autocorrelations between the successive values (for it is the most valuable information for future values in the series). This is especially true for univariate modelling.

An ARIMA model is appropriate for this kind of analysis since it predicts a value in a response time series as a linear combination of its own past values, past errors (shock or innovations) and current and past values of other time series (in terms of multivariate analysis). Besides, ARIMA procedure also provides a comprehensive set of tools for univariate time series model identification, parameter estimation and forecasting and in that way it offers great flexibility. To identify appropriate ARIMA models we have to recognize its elements *p*, *d* and *q*. Lags of the differenced series in the forecasting equation are called auto-regressive terms (*p*), lags of the forecast errors are called moving average terms (*q*), and a time series which needs to be differenced to be made stationary is said to be an integrated version (*d*) of a stationary series. Based on those elements we can estimate proper ARIMA model. We must stress that basically an ARIMA model is derived from widely used group of parametric models in time series analysis called autoregressive moving average models or ARMA. We can define general ARMA process as Sjöberg (2010) were $\{X_t\}$ is an ARMA (p,q) process if $\{X_t\}$ is weakly stationary and it holds for every t that:

$$X_t - \phi_1 X_{t-1} - \dots - \phi_p X_{t-p} = Z_t + \theta_1 Z_{t-1} + \dots \theta_q Z_{t-q} \tag{1}$$

and the polynomials $(1- \phi_1 z - \dots \phi_p z^p)$ and $(1- \theta_1 z - \dots \theta_q z^q)$ have no common factors. Then $\{Z_t\}$ is white noise, i.e. a sequence of uncorrelated stochastic variables with the same expected value (in this case 0) and variance σ^2, which will be denoted as $\{Z_t\} \sim WN(0, \sigma^2)$. A process $\{X_t\}$ is therefore an autoregressive integrated moving average ARIMA (p,d,q) process if (Brockwell and Davis, 2002):

$$\boldsymbol{Yt = (1 - B)^d X_t} \text{ is an ARMA process.} \tag{2}$$

The operator B is the backward shift operator and its application gives $BX_t = X_{t-1}$, d as a non-negative integer. The case $d = 0$ gives directly X_t is an ARMA process. We can conclude from the preceding that ARIMA models can be used to model non-stationary time series as long as the transformation of the original series according to equation (2) gives a series that can be modelled as a stationary ARMA process.

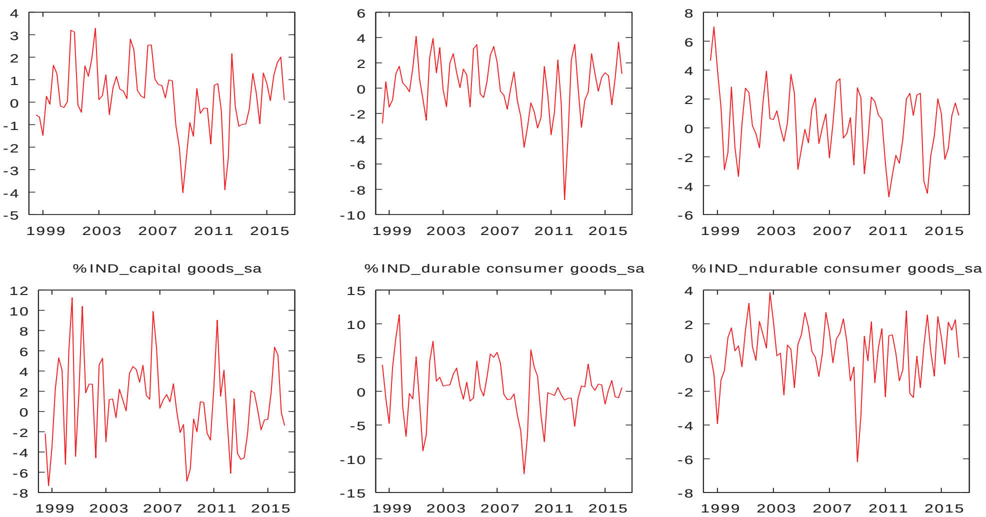
Dataset

Quarterly data on industrial production index covering the period 1998Q1 – 2016Q2 were taken from Croatian National Bank database with 2010 as a base year. This database also provides time series for industrial production sub-sectors which enabled us to evaluate forecasting features of ARIMA modelling on aggregated and disaggregated level. Data were seasonally adjusted using the ARIMA X12 seasonal adjustment procedure due to a fact that it facilitates the comparison of short-term and long-term movements among series. Namely, Croatian industrial production is strongly exposed to seasonality. Therefore, seasonal adjustment allows us to see the real movements and turning points in the variable (if we want to track long-term perspective) and to compare series from quarter to quarter (if we want to track short-run developments). Hence, fluctuations due to exceptional strong or weak seasonal influences (such as consequences of economic policy, strikes and etc.) will continue to be visible in the seasonally adjusted series.

Another dimension of our objective was to compare univariate ARIMA models of the Croatian industrial production and its subsectors in order to evaluate their forecasting features within short and long-term data evolution. To part time frequency we opted for the twofold analysis i.e. we assess (1) long-run forecasting ability by considering basic seasonally adjusted real time series and (2) short-run forecasting feature by including quarterly growth rates in estimation process. Since growth rates represent relative movements, the same are also an adequate tool for identification of the turning points in the variable. For each time frequency appropriate ARIMA model is assessed. Thereby, our analysis is based on the univariate evaluation of the basic indexes; variable industrial production (**IND_sa**) and variables that represent main industrial groupings: industrial production of capital goods (**IND_capital goods_sa**), energy (**IND_energy_sa),** intermediate goods (**IND_intermediate goods_sa**), durable consumer goods (**IND_durable consumer goods_sa**) and non-durable consumer goods (**IND_ndurable consumer goods_sa**) where *_sa* stands for seasonally adjusted series. Series presented as quarterly growth rates will be marked with %.

In order to estimate adequate ARMA i.e. ARIMA model we have to identify whether the variable, which is being forecasted, is stationary in time series or not. To test the integration properties we analyze graphical displays of the variables and apply three unit root tests; Augmented Dickey Fuller test, Phillips-Perron test and Kwiatkowski-Phillips-Schmidt-Shin test (see *Appendix*). Generally, graphs (see *Figure 1*) and tests confirmed the absence of unit root in the observed variables when we observed quarterly growth rates which is to be expected since calculation of growth rates is imminent to differentiation. We can conclude that the series are stationary in its mean and variance, thus there is no need for further differencing the time series and we can adopt $d = 0$ for our ARIMA (p,0,q) or to be exact ARMA (p,q) model in the short-run analysis. On the other hand, when we considered basic seasonally adjusted variables (see *Figure 2*) as the part of the long-run analysis we found the presence of unit roots so we made first order differencing ($d = 1$) in order to generate a table of differenced data of current and immediate previous one ($\Delta X_t = X_t - X_{t-1}$). Caution must be taken in this stage of ARIMA model building as over-differencing will tend to increase the standard deviation, rather than a reduction. Again, we conclude that we are dealing with series that are stationary in its mean and variance (first order differenced) so we adopt $d = 1$ for our ARIMA (p,d,q) model. Next step is model identification and the results.

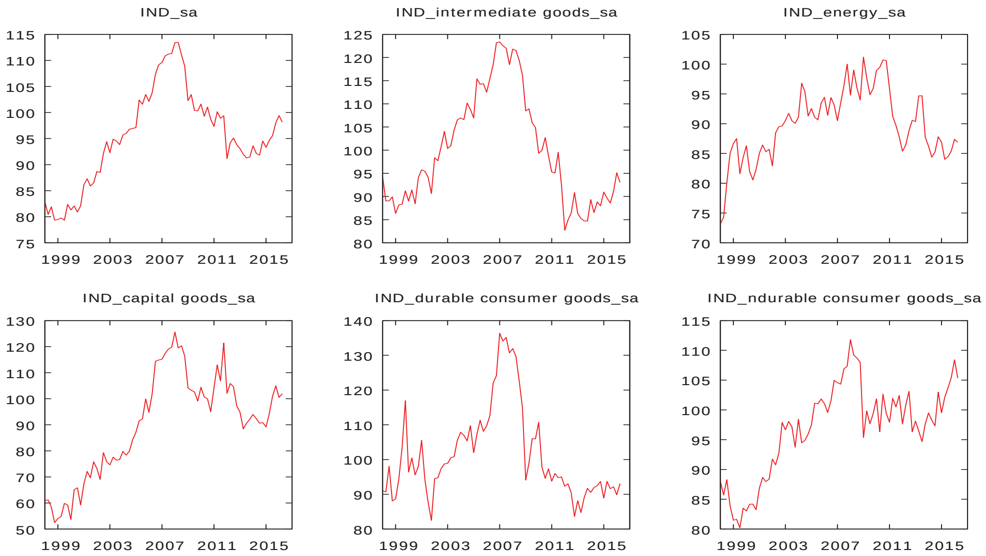
Figure 1: Quarterly Growth Rates of Selected Variables (seasonally adjusted)



* *2quarters moving average*

Source: Authors' calculation (from CNB, 2016).

Figure 2: Real Time Indexes (seasonally adjusted)



Source: Authors' calculation (from CNB, 2016).

Model Identification and Results

Following the deductions from the previous part, next step is the model identification in which we must select the number *p* (AR) and *q* (MA) lags[3]. In the process of selecting the best suitable models for forecasting we have chosen the models with lowest BIC (Bayesian Information Criterion), however we also wanted to identify models that would satisfy the lowest AIC (Akaike Information Criterion) in order to achieve robustness. Before we applied BIC and AIC, we checked the series correlogram to see whether *p* lags are likely to be important in the data. Trough such examination we have discovered that most series are likely to have *p* lags of at least 1. Thus, for each ARIMA model we tested the statistical properties of models with combination of 1 to 4 *p* lags and 0 to 4 *q* lags. Further, we have examined the BIC (plus AIC) results for each set of models to come to next deduction. After selecting the ARIMA parameters by using the principle of parsimony we reached the conclusion that ARMA (*p*,*q*) or ARIMA (*p*,0,*q*) are best candidate models for the short-term dynamics in which we will evaluate quarterly growth rates of selected variables and that ARIMA (*p*,1,*q*) specifications must be used within long-term forecasting perspective in which we evaluate real time variables (due to their initial non-stationarity).

To check the quality of selected models we have investigated various line and Q-Q plots as well as histogram of standard residuals and found that standard errors are mostly constant in its mean and variance over the observed time. This is confirmed by plots of correlogram and partial correlogram in which we find no evidence of the autocorrelation between lag 1 and 16. Furthermore, we have checked for series correlation on the basis of autoregressive conditional heteroscedasticity (ARCH) and Ljung-Box p-values test up to 4 lags. In this part of the analysis it is also important to compare forecasting errors such as Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Percent Error (MAPE) and Mean Absolute Error (MAE). Most of these indicators suggested the smallest values of errors compared to other model specifications. One indicator *per se* is important for our analysis because on the basis of this parameter we will test the forecasting capacity and dynamics of ARIMA models over the different periods of forecasting. This indicator is RMSE.

Namely, we compare the forecasting ability of alternative models through RMSE calculated over the observed period 1998Q1 – 20165Q2 (or 74 quarters) and within different (rolling) window sizes (see figures in *Appendix*). We will report forecasting results based on a whole sample (benchmark model), then shortened 33 window size (from 2008Q2 which we can mark as the end of growth period for Croatian economy and which is followed by the crisis; see Krznar (2011) and Tomić (2016)) and 22 window size (from 2011:Q1 in which economy experienced a small peak as a result of modest growth in the EU). In this manner we test out-of-sample forecasting ability of the ARIMA benchmark model and of the other models but with different sample size. It is in fact a forecasting exercise with shorter and longer window sizes. Additionally, we calculate ratios of the RMSE of different window sizes with respect to the benchmark model in order to check the robustness of our conclusion regarding the predictive capacity of such modelling. This approach is applied to both, short-term analysis (with quarterly data) as well as on long-term perspective (with real time variables) as a mean of checking the short- and long-term forecasting perspective of ARIMA models of the Croatian industrial production that can also be described as an assessment of such modelling approach. In next few lines we will present our results and give a brief statistical overview.

Table 1: Short-Term Forecasting Dynamics of Industrial Production

ARIMA estimations - Basic window size: 74; 2008:Q2 (33 window size) and 2011:Q1 (22 window size)								
Models with growth rates	*RMSE*		*33 window*		*ratios*	*22 window*		*ratios*
%IND_sa ARIMA (2,0,1)	**2,1879**		**2,4480**		**1,12**	**2,3568**		**1,08**
	const	0,26	phi_1	0,58***	phi_2	0,25**	theta_1	-0,75***
	ARCH (4)		*p = 0,89*		*LM (4)*		*p = 0,54*	
%IND_capital goods_sa ARIMA (2,0,1)	*RMSE*		*33 window*		*ratios*	*22 window*		*ratios*
	5,7969		**5,7975**		**1,00**	**5,9591**		**1,03**
	const	0,92*	phi_1	-1,08***	phi_2	-0,38***	theta_1	0,93***
	ARCH (4)		*p = 0,41*		*LM (4)*		*p = 0,15*	
%IND_energy_sa ARIMA (1,0,1)	*RMSE*		*33 window RMSE*		*ratios*	*22 window*		*ratios*
	3,1552		**3,0052**		**0,95**	**2,8255**		**0,90**
	const	0,29	phi_1	-0,69***	theta_1	-0,83***	/	/
	ARCH (4)		*p = 0,89*		*LM (4)*		*p = 0,40*	
%IND_intermediate goods_sa ARIMA (2,0,2)	*RMSE*		*33 window*		*ratios*	*22 window*		*ratios*
	3,2060		**3,5394**		**1,10**	**3,6289**		**1,13**
	const	0,07	phi_1	0,99***	phi_2	-0,86***	theta_1	-1,24***
	theta_2	1,00***	/	/	/	/	/	/
	ARCH (4)		*p = 0,86*		*LM (4)*		/	
%IND_durable consumer goods_sa ARIMA (3,0,2)	*RMSE*		*33 window*		*ratios*	*22 window*		*ratios*
	5,4984		**5,1215**		**0,93**	**3,6576**		**0,67**
	const	0,21	phi_1	0,02	phi_2	-0,68***	phi_3	-0,32**
	theta_1	-0,15	theta_2	0,87***	/	/	/	/
	ARCH (4)		*p = 0,43*		*LM (4)*		/	
%IND_ndurable consumer goods_sa ARIMA (2,0,1)	*RMSE*		*33 window*		*ratios*	*22 window*		*ratios*
	2,6579		**2,9345**		**1,10**	**2,3863**		**0,90**
	const	0,33	phi_1	-1,21***	phi_2	-0,52***	theta_1	0,91***
	ARCH (4)		*p = 0,94*		*LM (4)*		*p = 0,10*	

***, **, * *denotes 1%, 5% and 10% significance levels respectively*

- all variables are I(0), therefore appropriate ARIMA (p,0,q) models with stationary series are evaluated

Source: Authors' calculation (Gretl package).

Based on the results from *Table 1*, which considers ARIMA models with quarterly growth rates (short-term analysis), we can evaluate one quarter ahead predictive ability of alternative forecasting windows over the observed period. First, we find a better performance of aggregate indicator of industrial production forecasts over the sectoral forecasts as its RMSE was by far lower than in the other models. As we focus on main industrial groupings we can notice very high RMSE values (in average 2 times higher) in the models that evaluated industrial production of capital goods and durable consumer goods suggesting that predictions on the basic indicator of industrial production should not be based on forecasting features of these industrial sectors.

Such results are not unexpected if know that these type of industries are typical cyclical industries i.e. industries that are sensitive to a business cycle. On the other hand, model that evaluated industrial production of non-durable consumer goods displayed relatively low RMSE in comparison to other sectors which partially confirms general agreement that Croatian economic growth is induced by high consumption. Across the columns, different window sizes imply a worsening of forecasting performance for almost all models. Namely, the average of the forecasts from two window sizes used in this paper is always outperformed in the terms of RMSE by the benchmark variable. General conclusion is that all ARIMA models display stable and relatively close results within a distinct time frame.

Table 2: Long-Term Forecasting Dynamics of Industrial Production

ARIMA estimations - Basic window size: 74; 2008:Q2 (33window size) and 2011:Q1 (22window size)								
Models with real time data	*RMSE*		*33 window*		*ratios*	*22 window*		*ratios*
IND_sa ARIMA (2,1,1)	**2,1099**		**2,4419**		**1,16**	**2,2977**		**1,09**
	const	0,21	phi_1	0,57***	phi_2	0,24**	theta_1	-0,72***
	ARCH (4)		*p = 0,95*		*LM (4)*		*p = 0,40*	
IND_capital goods_sa ARIMA (2,1,1)	*RMSE*		*33 window*		*ratios*	*22 window*		*ratios*
	5,1840		**6,0336**		**1,16**	**6,2076**		**1,20**
	const	0,57	phi_1	-1,13***	phi_2	-0,33***	theta_1	0,92***
	ARCH (4)		*p = 0,20*		*LM (4)*		*p = 0,08*	
IND_energy_sa ARIMA (1,1,1)	*RMSE*		*33 window*		*ratios*	*22 window*		*ratios*
	2,8494		**2,8944**		**1,02**	**2,8254**		**0,99**
	const	0,15	phi_1	0,68***	theta_1	-0,81***	/	/
	ARCH (4)		*p = 0,98*		*LM (4)*		*p = 0,25*	
IND_intermediate goods_sa ARIMA (2,1,2)	*RMSE*		*33 window*		*ratios*	*22 window*		*ratios*
	3,1242		**3,3854**		**1,08**	**3,2360**		**1,04**
	const	0,01	phi_1	0,96***	phi_2	-0,86***	theta_1	-1,21***
	theta_2	1,00***	/	/	/	/	/	/
	ARCH (4)		*p = 0,91*		*LM (4)*		/	
IND_durable consumer goods_sa ARIMA (3,1,2)	*RMSE*		*33 window*		*ratios*	*22 window*		*ratios*
	5,7388		**5,3892**		**0,94**	**3,5455**		**0,62**
	const	0,21	phi_1	0,02	phi_2	-0,67***	phi_3	-0,31**
	theta_1	-0,13*	theta_2	0,90***	/	/	/	/
	ARCH (4)		*p = 0,48*		*LM (4)*		/	
IND_ndurable consumer goods_sa ARIMA (2,1,1)	*RMSE*		*33 window*		*ratios*	*22 window*		*ratios*
	2,6328		**3,0354**		**1,15**	**2,4016**		**0,91**
	const	0,26	phi_1	-1,21***	phi_2	-0,52***	theta_1	0,92***
	ARCH (4)		*p = 0,94*		*LM (4)*		*p = 0,08*	

****, **, * denotes 1%, 5% and 10% significance levels respectively*

- all variables are I(1), therefore appropriate ARIMA (p,1,q) integrated models are evaluated

Source: Authors' calculation (Gretl package).

Next, *Table 2* presents results from ARIMA models with real time indexes (long-term analysis) as we also evaluate their one quarter predictive capacity through different window sizes. The results in the long-run were quite similar to those in the short-run. In explanation, the ARIMA model with basic industrial production index showed better predictive performance with RMSE value that was perceivably smaller than in the rest of the models that evaluated main industrial groupings. As in the short-run, industrial production of energy, intermediate goods and non-durable consumer goods displayed relatively low values of RMSE indicating that their predictive capacity based on adequate ARIMA modelling could be useful in forecasting assessments of the industrial production in Croatia. Again, cyclical industries that are represented by industrial production of capital goods and durable consumer goods suggest their poor position within forecasting capacity, even in the long-run. Across different window sizes we can once more conclude that a reduction in sample size worsens forecasting ability in almost all models, however it damages more the sectoral forecasts that the aggregate indicator forecasts. Both in the short- and long-term analysis, consistently with the reduction of the sample size, RSME of the sub-sector forecasts worsens in average, but again, generally speaking, all models provided analogous and comparable results suggesting in that manner pragmatism of our ARIMA models.

An Epilogue: Discussion and Conclusion

There is no doubt that industrial production holds an irreplaceable position within growth and development prospect of each county, therefore an inquiry into historical movements, fluctuations and trends, correlation to business cycles, volatility features as well as future developments as a part of a predicting process, becomes a crucial part of economic planning. Trough this paper we wanted to evaluate predicting capacity of ARIMA model in order to answer the question could this kind of relatively simple approach offer us reliable short- and long-term forecasts of industrial production in Croatia. We have to point out that distinction between two time dynamics is just an analytical separation and not by all mean methodological question. The end goal of this study was not to directly forecast industrial production but to analyze the out-of-sample predictive performance of univariate ARIMA models on aggregated (industrial production *per se*) and disaggregated (industrial production sub-sectors) level inside different forecasting horizons (short-term analysis based on quarterly growth rates and long-term analysis based on real time variables). ARIMA models were used for the reason of it capability to make predictions using a time series with any kind of pattern and with autocorrelations between the successive values in the time series, not to mention that ARIMA single-equation models can be easily calculated. To add, ARIMA models have theoretically desirable properties, as they better account for short-term dynamics and provide a more reliable basis for forecasting where indexes are currently above or below trend.

Our ARIMA models forecast horizon was limited to one quarter ahead whereas forecasting ability of each equation has been evaluated over the whole interval (a benchmark ARIMA model) and reduced length (2 shortened samples) of the out-of-sample forecast period. In this way, we reduced possible uncertainty in estimating forecasting values at very end of the series, which is fundamental issue in short-term economic analysis. The relative performance of each model has been assessed by looking at RMSE. In spite of the model simplicity, the results appear to be stable and robust stressing the strong forecasting ability of each model.

Results from the short- and long-run analysis provide rather similar conclusions meaning that ARIMA models *de facto* mimic the cyclical movements (around the trend) of industrial production and its sub-sectors quite good as well as the trend itself. General conclusions may be drawn from next few facts. Namely, we found a better performance of aggregate indicator of industrial production forecasts over the sub-sectors forecasts as its RMSE was by far lower than in the other models; meaning that cyclical movements of Croatian economy could have feasible motive in industrial production fluctuations that can be forecasted relatively successfully. All fluctuations in industrial production (for example in 2008:Q2) have been followed by strong movements in national output. Strong build-up in industrial production since 2013 certainly had some positive effects in the annulling of negative gross domestic product growth rates. We did not find any significant worsening of RMSE (seen as ratios) across different window sizes, proving once again good forecasting ability of ARIMA models in the case of aggregate industrial production variable. Next, when observing disaggregated variables, the so-called cyclical industries in the likes of industrial production of capital goods and durable consumer goods displayed relatively poor results as their RMSE values were significantly higher (though stable trough different window sizes) suggesting their low predictive capacity. It would be interesting to see whether these industries are lagging, leading or are coincident with the aggregate variable or do some sub-sectors become more/less cyclical over time or even change from lagging to leading. This information could help in multivariate modelling approach and bear some additional information to forecasting perspective. Yet figures reveal their volatile behaviour meaning that they would certainly elude short-term forecasting capacity (even the long-run projections) if they are to be included in the multiple-equation forecasting models. Other sub-sectors i.e. industrial production of energy, intermediate goods and non-durable consumer goods displayed relatively low values of RMSE indicating that their predictive capacity based on adequate ARIMA modelling could be useful in forecasting assessments of the industrial production in Croatia. They are less cyclically sensitive, therefore a good choice for both short- and long-run assessments. This raises another interesting issue i.e. Croatia has relatively proved manufacturing industry that produces goods with low or no additional value (for example intermediate goods) suggesting that an employment in those sectors could become more sensitive to a business cycle movements over time. Warning fact, surely! Again we can conclude that a reduction in sample size in average worsens forecasting ability in almost all models, however it damages more the sub-sector forecasts that the aggregate indicator forecasts.

As this paper implies, forecasting performance of ARIMA models based on a study of Croatian industrial production can be proclaimed as quite stable and reliable, though limited. However, some empirical literature (for example see Bulligan, Golinelli and Parigi (2010)) suggests that usage of alternative forecasting methods could assure statistically significant accuracy gains, without relevant differences between static and dynamic approaches. This brings us to two major shortcomings of the paper that we as authors would like to emphasize. First is relatively short time series and second is the partiality of some conclusions. Both can impose scantiness in economic reasoning (since we cannot comprehend a larger picture); however, we find this argument as an incentive for further research that might include more complex forecasting methods. These methods should be based on both simple- and multiple-equation modelling, all which would assure greater stability and accuracy of industrial production forecasts. Non-the-less, we believe that our conclusions could bear important implications and raise awareness of Croatian macroeconomic management in answering as to what should economic policy plans encompass within their future prospects, especially in context to industrial production perspective.

APPENDIX

Table A.1: Unit Root Tests for Quarterly Growth Rates

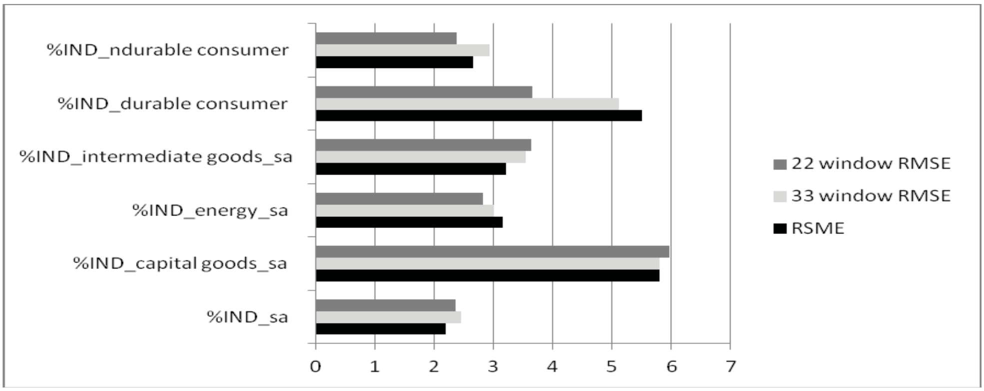
Augmented Dickey-Fuller test (ADF)				
Variables	**In level**		**In first difference**	
	constant	*constant + trend*	*constant*	*constant + trend*
%IND_sa	-9,93***	-10,08***	-17,06***	-16,93***
%IND_capital goods_sa	-10,71***	-10,76***	-15,75***	-15,64***
%IND_energy_sa	-8,22***	-8,42***	-12,89***	-12,82***
%IND_intermediate goods_sa	-9,44***	-9,50***	-14,51***	-14,41***
%IND_durable consumer goods_sa	-9,56***	-9,59***	-15,76***	-15,65***
%IND_ndurable consumer goods_sa	-12,46***	-12,36***	-18,31***	-18,18***

Phillips-Perron test (PP)				
Variables	**In level**		**In first difference**	
	constant	*constant + trend*	*constant*	*constant + trend*
%IND_sa	-9,83***	-10,04***	-74,62***	-74,22***
%IND_capital goods_sa	10,66***	-10,80***	-23,80***	-23,67***
%IND_energy_sa	-8,29***	-8,69***	-29,25***	-33,43***
%IND_intermediate goods_sa	-9,40***	-9,50***	-33,85***	-33,26***
%IND_durable consumer goods_sa	-9,70***	-10,08***	-44,26***	-47,38***
%IND_ndurable consumer goods_sa	-12,38***	-12,29***	-21,66***	-21,50***
Kwiatkowski-Phillips-Schmidt-Shin test (KPSS)				
Variables	**In level**		**In first difference**	
	constant	*constant + trend*	*constant*	*constant + trend*
%IND_sa	0,27	0,13*	0,15	0,09
%IND_capital goods_sa	0,19	0,07	0,05	0,05
%IND_energy_sa	0,30	0,05	0,09	0,09
%IND_intermediate goods_sa	0,19	0,11*	0,22	0,13*
%IND_durable consumer goods_sa	0,18	0,08	0,50**	0,50***
%IND_ndurable consumer goods_sa	0,07	0,08	0,10	0,06

****, **, * denotes 1%, 5% and 10% significance levels respectively. The lag length used to estimate the ADF test is based on Schwarz Bayesian criterion (SBC) and the lag length (‘) used to compute the PP and KPSS tests is based on the Newey-West Bandwidth. KPSS test is based on inverse H_0 and H_1 relation in comparison to ADF and PP.*

Source: Authors’ calculation (EViews 9 package).

Figure A.1: RMSE From Short-Term Forecasting Dynamics of Industrial Production



Source: Authors’ calculation.

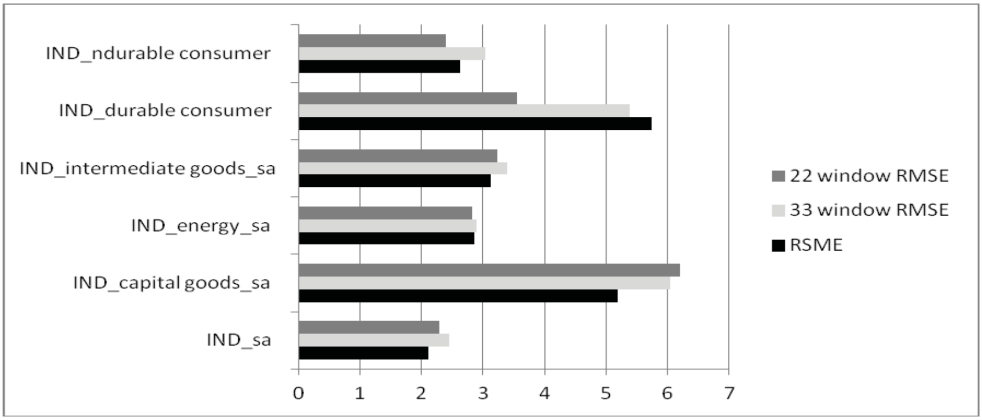
Table A.2: Unit Root Tests for Real Time Indexes

Augmented Dickey-Fuller test (ADF)				
Variables	**In level**		**In first difference**	
	constant	*constant + trend*	*constant*	*constant + trend*
IND_sa	-1,47	-1,16	-9,65***	-9,78***
IND_capital goods_sa	-1,59	-1,62	-10,77***	-10,78***
IND_energy_sa	-3,20**	-2,85	-8,46***	-8.62***
IND_intermediate goods_sa	-1,19	-1,27	-9,13***	-9,21***
IND_durable consumer goods_sa	-2,09	-2,19	-9,34***	-9,34***
IND_ndurable consumer goods_sa	-1,80	-2,56	-12,36***	-12,26***
Phillips-Perron test (PP)				
Variables	**In level**		**In first difference**	
	constant	*constant + trend*	*constant*	*constant + trend*
IND_sa	-1,47	-1,15	-9,57 ***	-9,70 ***
IND_capital goods_sa	-1,53	-1,57	-10,59***	-10,63***
IND_energy_sa	-3,21**	-2,85	-8,50***	-8,97***
IND_intermediate goods_sa	-1,11	-1,19	-9,16***	-9,19***
IND_durable consumer goods_sa	-2,07	-2,13	-9,43***	-9,44***
IND_ndurable consumer goods_sa	-1,57	-2,50	-12,25***	-12,16***
Kwiatkowski-Phillips-Schmidt-Shin test (KPSS)				
Variables	**In level**		**In first difference**	
	constant	*constant + trend*	*constant*	*constant + trend*
IND_sa	0,47**	0,26***	0,26	0,12*
IND_capital goods_sa	0,74**	0,24***	0,15	0,08
IND_energy_sa	0,41**	0,27***	0,27	0,05
IND_intermediate goods_sa	0,27	0,25***	0,25	0,12*
IND_durable consumer goods_sa	0,23	0,21**	0,13	0,06
IND_ndurable consumer goods_sa	0,73**	0,22***	0,07	0,08

****, **, * denotes 1%, 5% and 10% significance levels respectively. The lag length used to estimate the ADF test is based on Schwarz Bayesian criterion (SBC) and the lag length (‘) used to compute the PP and KPSS tests is based on the Newey-West Bandwidth. KPSS test is based on inverse H_0 and H_1 relation in comparison to ADF and PP.*

Source: Authors’ calculation (EViews 9 package).

Figure A.2: RMSE From Long-Term Forecasting Dynamics of Industrial Production



Source: Authors' calculation.

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NOTES

1 CROLEI is a composite leading indicator constructed of eleven indicators with the main purpose of forecasting the direction of the Croatian economy's movement six month ahead (for more see Bačić and Vizek, 2006).

2 Before we determine research framework we should clarify here some methodological vagueness i.e. the difference between the terms forecasting and predicting, which is very important for our analysis as it explains the motivation in choosing the method of the analysis. There is only one difference between these two in time series. Forecasting pertains to out-of-sample observations, whereas prediction pertains to in-sample observations. Predicted values (or Ordinary Least Square (OLS) predicted values) are calculated for observations in the sample used to estimate the regression. However, forecast is made for the some dates beyond the data used to estimate the regression, so the data on the actual value of the forecasted variable are not in the sample used to estimate the regression.

3 Results related to model identification and the quality of selected ARIMA models is available upon request.