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DEMAND FORECAST WITH BUSINESS CLIMATE INDEX FOR A STEEL AND IRON INDUSTRY REPRESENTATIVE

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Abstract: The steel and iron industry production is dedicated to serve other industries mainly. This makes the exercise of demand forecasting different than for consumer goods. The common sense says that demand fluctuations are influenced by general economic soundness. An attempt was made to address the question of improving forecast's accuracy by adding a business cycle indicator as an input variable. The SARIMAX model was applied. Including a business climate indicator improved model's performance, however no co-integration is observed between the two series.

Keywords: demand forecasting, SARIMAX, business climate indicator

INTRODUCTION

Demand planning is a very important matter in companies' operations. It is an integral part of goods manufacturing and distribution process. Both excessive production that cannot be sold and demand exceeding production levels – despite having adequate production capabilities – are disadvantageous. Estimation of future demand for goods and services is also crucial when determining resources that are used in the production process.

Demand forecasting requires specific tools. Intuitive predictions may turn out to be insufficient due to the number and complexity of influence factors. A belief that the intuitive approach is more advantageous happens to win in some cases as it is based on experience and familiarity with the industry. Not always is this approach advisable as companies' external environment may be unstable.

A lot of attention was paid to demand forecasting for the fast moving consumer goods and energy industries where the data of a high frequency are analysed. In this article the focus is on iron and steel products. The industry is characterized by the following features: long production process, long planning horizon, high value and weight of produced goods. This makes the exercise of demand forecasting different than for consumer goods. Iron and steel products are dedicated to serve other industries rather than individual agents. The common sense says that demand fluctuations are related to general economic soundness. Moreover, the price and quality of goods are believed to impact demand to a greater extent than individual preferences or fashion do. Political and environmental factors are important as companies need to respect restrictions on technologies in use, minimising the harmful impact on the environment. This results in low elasticity in adjusting to demand fluctuations in a short-term as well as in additional costs of technology improvement. Demand for the heavy industry was analysed among others by [Rippe et al. 1976]. [Lallement and Briffaut 2010] analyse demand volatility in the construction industry using the French construction cost index. To analyse demand in the automotive industry, [Klug 2011] employs the Monte Carlo simulation that controls for uncertainty when measuring random demand levels.

The goal of this article is to verify if a demand forecast for the iron and steel industry in Poland can be improved by adding a business climate index. Empirical analysis was carried out for a representative agent. The company is one of the key players in this market. In Section “FACTORS SHAPING DEMAND …” the factors influencing demand levels in the iron and steel industry as well as sector’s characteristics are discussed. Section “RESEARCH METHODS” describes the research approach. In Section “EMPIRICAL ANALYSIS” the SARIMAX model with a business climate indicator added as an input variable is applied to the sample data. Results are compared with SARIMA. Section “CONCLUDING REMARKS” summarizes the main findings.

FACTORS SHAPING DEMAND IN THE STEEL AND IRON INDUSTRY IN POLAND

The environment in which enterprises operate is volatile. Demand levels are impacted by many factors. Economic transformation in Poland posed a challenge for state-owned companies. In the 1990´s they had to undergo a long process of restructuring to adjust to the new market conditions. Nowadays they need to obey some political and environmental restrictions on technologies in use or accept constraints imposed on production levels to reduce emissions of greenhouse gases. Infrastructural investments and the EU policies promoting renewable energy are both an opportunity for the sector. The latter triggers an interest in wind and nuclear energy or ship transport while the industry is a supplier of windmill and ship engines components. At the same time the sector is affected by constantly increasing energy costs. Entrepreneurs face strong competition from Asia and

Europe. Some unfair actions as dumping or tax settlement fraud on steel sales are observed [Forbes 2013].

RESEARCH METHODS

General Considerations

[Cieślak et al. 1997] present an overview of forecasting methods and its applications in the economic context. There are several statistical techniques that can be used to build a forecast based on macroeconomic variables. Traditional methods are criticised for basing solely on past observations. It is justified providing that the external environment is stable and customers' behaviour is not a subject to significant changes. It is rarely the case though. It would be advisable to include some external factors that shape demand. One difficulty here would be that they may not be easy to identify or their value remains unknown. To address that [Crane and Crotty 1967] use exponential smoothing. The authors analyse past trends in banking data. They measure the demand for financial products using outputs of exponential smoothing in a multiple regression. They take benefit from both approaches, building a prediction based on historical data and other explanatory variables. Alternatively, ARIMA described by [Box et al. 1994] can be a foundation for the ARIMAX approach. ARIMA specifies a relation between a variable in the period *t* and its values in previous periods. In ARIMAX, another time series is added as an input variable. Hence, it allows for including a business cycle indicator that provides with early information on agents´ future activity. [Ďurka and Pastoreková 2012] compare results of ARIMA and ARIMAX to model the GDP. In this case ARIMA turns out to be more accurate than ARIMAX where an unemployment rate is added as an input variable. [Bielak 2010] compares ARIMA and ARIMAX when forecasting unemployment. Adding the economic mood index improves model´s accuracy in terms of errors and information criteria. The improvement is slight but applying the index can be justified by its property to signal changes in advance as well as by its strong correlation with fluctuations observed in the market.

Business Climate Indicators

Macroeconomic indicators show trends in social and economic development of a country. In our model a leading or a business climate index would be required as they measure future activity. For price or production indices this assumption is not fulfilled as they reflect past values of a variable (i.e. how much was sold, at what price). Moreover, prices may adjust in the long term; therefore some trends will be presented with a delay. Leading indices show changes in economic performance a few months ahead of the GDP. Using them in a model may increase the forecasting horizon as well as help obtain better parameters [Szeplewicz 2011]. A variable reflecting general economic conditions serves the following purposes:

- Controls for the variability of factors influencing demand;
- Controls for performance of various sectors that purchase steel goods;
- Increases model's reliability and extends the forecasting horizon;
- Allows for early identification of fluctuations owing to its leading properties.

A relevant indicator was sought for among those that measure the activity of various industries. Both domestic and international databases were considered. Given the nature of demand in the steel and iron industry, business climate index for the processing industry published by the Central Statistical Office (GUS - Główny Urząd Statystyczny) was selected for further research. It refers to the Polish market where the major part of transactions for the sample data is conducted. The indicator comprises of respondents´ current assessment on: order backlog, financial soundness, expected delays in settling payments by contractors, selling prices and employment. Such tests are successfully used to diagnose economic conditions in a short term and are distributed as questionnaires [GUS 2013]. They should be considered as CEO´s subjective opinions. They enrich the knowledge about markets. Subjectivity can be regarded as a weakness but we assume that predictions of entrepreneurs will be translated into action, i.e. they will be more prone to invest when economic conditions are favourable. Selecting the index for the processing industry is explained by the fact that it measures performance of industries producing metals, metal products, machinery and equipment while the industry´s production is addressed to entities operating in the iron and steel or metallurgical industry. On the top of that, the indicator is easily accessible and published with a monthly delay. It replaces subjective opinions of experts in a company. That covers the question of a trade-off between statistical methods and intuition when determining future demand levels. We expect that experts´ assessment is based on monitoring such indicators or tracking information in trade magazines or through participation in trade fairs. Business climate indicators measure the condition of a number of related industries and may provide additional information that an expert does not possess. There are some interesting findings from [Franses and Legerstee 2013] who consider the inclusion of a variable reflecting opinions of people involved in sales and marketing activities. They assume that the final forecast is a weighted average of an expert´s and model´s forecasts. Adding the variable did not improve the forecast significantly. Its accuracy increased only in the event of an expert having very specific knowledge.

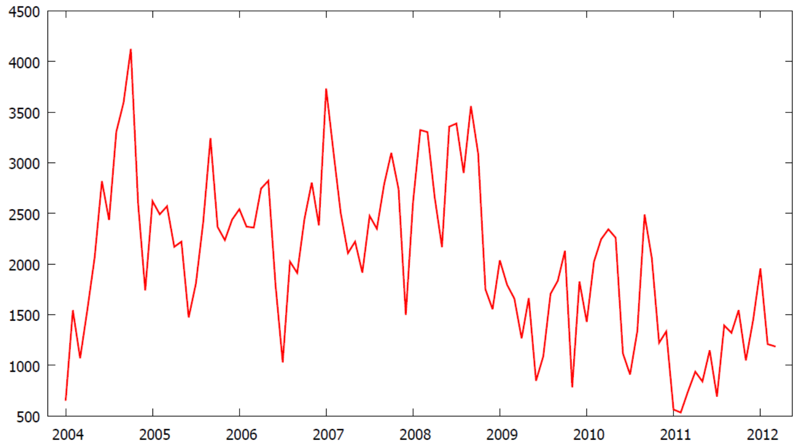
In this sense adding the business climate indicator is a way to include an average opinion of various agents acting in the market instead of CEO's predictions solely.

EMPIRICAL ANALYSIS

Data Description

Demand level data of a Polish enterprise operating in the steel and iron industry constitute a monthly time series for the period 2004-2012. The company is among the leading and mid-range 50 players of the industry. The chart presents significant demand fluctuations (Figure 1). A decrease can be observed in the average demand level starting from 2009. The production is purchased by several industries like metallurgy and machinery and targeted at the Polish market mainly.

Figure 1. Monthly steel products sales of a sample enterprise in 2004 – 2012 (in tons)



Source: author's calculations

The seasonality test was carried out in Demetra[1]. The general evaluation of the model is considered *severe*, which means that results of the seasonality check cannot be trusted. In such instances it is advised to verify the series case by case and modify parameters in the specifications window of Demetra to improve the quality of the adjustment if needed [Grudkowska 2013]. There is a significant drop in the demand level if we compare the period 2009 - 2012 with 2004 - 2008. Therefore the earlier observations may not be relevant. But a time series needs to contain data for at least 5 years so that the procedures used in Demetra can produce a reliable outcome. Eventually an analysis is carried out for the period 1/2007 – 12/2012, which fulfils this requirement. The model turns out to be of a good quality and the analysis carried out in Demetra gives an evidence of seasonality. This

[1] Demetra - a software for seasonal adjustments.

conclusion is based on the results of the F and Kruskal-Wallis tests for stable seasonality. For both tests the null hypothesis of non-seasonality is rejected with *p* value equal to 0.02 and 0.04 respectively. The null hypothesis of the F test assuming the lack of moving seasonality cannot be rejected with *p* value = 0.1. We conclude on the stable seasonality of the narrowed time series.

The Augmented Dickey-Fuller unit root test indicates non-stationarity of the time series. The null hypothesis is not rejected with *p* value equal to 0.84. The same test carried out for variable’s first differences rejects the null hypothesis of non-stationarity, giving an evidence of the first degree integration (*p* = 0.003).

The SARIMAX model

ARIMA (p,d,q) is first built for the period 2007 - 2012. It now has 72 observations, which is sufficient to apply the model. To find the optimal parameters the ACF and PACF are examined. Basing on that and on the results of the unit root test, ARIMA (1,1,1) is chosen. Modification of *p* and *q* does not improve the model, indicating statistical insignificance of both parameters. Residuals correlogram is generated showing autocorrelation at lag 10. We would wish to find a better model. In the next step SARIMA (1,1,1)(0,1,1) is built. *P, D, Q* parameters are chosen based on backward selection. Table 1 presents the specification of the model and information criteria.

Table 1. The SARIMA (1,1,1)(0,1,1) model

	Coefficient	Std. error	z	p-value
phi_1	0.5090	0.1559	3.265	0.0011
theta_1	-0.9232	0.1169	-7.899	0.0000
Theta_1	-0.9999	0.3033	-3.298	0.0010

Log-likelihood	-564.937	Akaike criterion	1137.874
Schwarz criterion	1146.981	Hannan-Quinn	1141.500

Source: author’s calculations

The SARIMA forecast is entirely based on past values, which calls for a variable controlling for the future. The model does not provide with explanation of demand volatility, except for seasonal influences. To address that, the SARIMAX approach is introduced. The processing industry business climate indicator is added as an input variable. It is not seasonally adjusted. The impact of seasonal factors was examined in Demetra with the TRAMO/SEATS procedure. The seasonally adjusted time series was produced to be used in the model with overall evaluation of the model defined as good. The Augmented Dickey-Fuller unit root test indicates non-stationarity of the series. The null hypothesis is not rejected with p value = 0.61. The same test carried out for variable's first differences rejects the null hypothesis of non-stationarity, giving an evidence of the first degree integration (p = 0.03).

The starting point is the model with 12 lags for the independent variable. Backward selection is used to determine the longest lag. The lag order 4, 5 and 6 are significant and the lowest values of information criteria are observed for the lag order 6, hence it is chosen solely. The Doornik-Hansen normality test does not allow for rejecting the null hypothesis that residuals are multivariate normal with p value equal to 0.50. Table 2 shows parameters of the model. SARIMAX turns out to be better when log-likelihood, Akaike and Hannan-Quinn criteria are compared.

Table 2. The SARIMAX (1,1,1)(0,1,1) model with business climate index

	Coefficient	Std. error	z	p-value
phi_1	0.4794	0.1060	4.524	0.0000
pheta_1	-1.0000	0.0751	-13.32	0.0000
Theta_1	-0.9999	0.2944	-3.396	0.0007
index_6	-1.4273	0.6955	-2.052	0.0401

Log-likelihood	-563.3111	Akaike criterion	1136.622
Schwarz criterion	1148.006	Hannan-Quinn	1141.154

Source: author's calculations

Co-integration between the two series was tested using the Engle and Granger approach [Engle and Granger 1987]. The sample series shows no evidence of co-integration with the business climate indicator, therefore we cannot conclude on their long-term relationship. This result is confirmed by the Johansen approach. For the Johansen test we fail to reject the null hypothesis that there is no co-integration vector with p = 0.58 for the eigenvalue test and p = 0.66 for the trace test. We expect such a result as due to a high volatility of market conditions. Factors influencing demand change constantly which does not allow for a long-term relationship to prevail. This could be verified with longer time series, both are relatively short however. There are two reasons for that: gathering information on business climate indices is quite a recent activity and it is not advisable to analyse the company´s sales in the transition period, in the 1990´s, as market conditions were extremely different.

Results Comparison

Table 3 presents a comparison of forecast accuracy measures for SARIMA (1,1,1)(0,1,1) and SARIMAX (1,1,1)(0,1,1) with the business climate indicator for the last 9 observations excluded[2]. Better *ex post* accuracy measures are observed for SARIMAX. An improvement from SARIMA to SARIMAX is slight but noticeable when comparing mean errors and Theil's U which are lower for the latter.

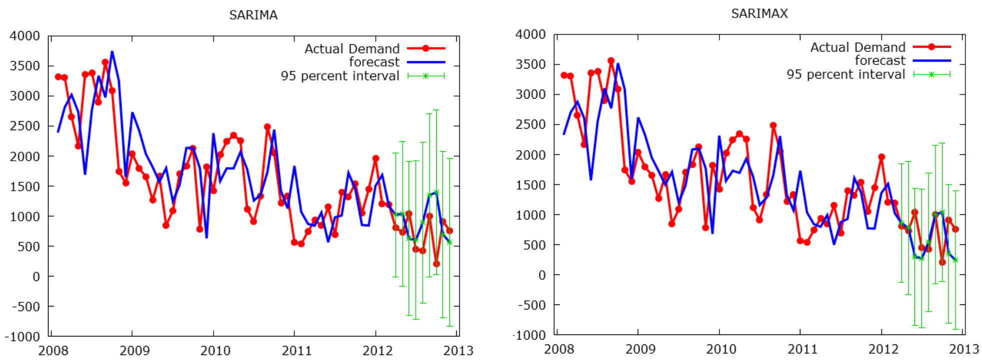
Table 3. *Ex post* forecast accuracy measures

Forecast Evaluation Statistics	**SARIMA**	**SARIMAX**
Mean Error	-204.95t	106.29t
Mean Squared Error	2.41e+005	2.08e+005
Root Mean Squared Error	491t	456.36t
Mean Absolute Error	389.87t	338.14t
Mean Percentage Error	-80.163	-21.52
Mean Absolute Percentage Error	100.13	75.04
Theil's U	0.84	0.70
- Bias Proportion, UM	0.50	0.17
- Regression Proportion, UR	0.36	0.59
- Disturbance Proportion, UD	0.14	0.24

Source: author´s calculations

Figure 2 presents forecasts based on SARIMA and SARIMAX[3]. For ARIMAX the accuracy of an interval forecast is increased. The average confidence interval set at the 95% level shrank by about 13% for SARIMAX (Table 4).

Figure 2. Forecast demand in tons for the period 4/2012 – 12/2012



Source: author´s calculations

[2] This number was chosen to build a forecast for at least 10% of observation and to keep enough cases in the learning set for the relatively short sample time series. On the other hand, the forecast must be for at least 6 months ahead for the company to be useful.

[3] Forecast carried out in a continuous manner, without re-estimating model's parameters.

Table 4. Comparison of SARIMA and SARIMAX average interval forecast

	SARIMA	SARIMAX	% Difference
Average Confidence Interval Width	2598.38	2254.22	-13.25%

Source: author´s calculations

The comparison of mean errors and the confidence interval reduction prove that SARIMAX is a slightly better fit. Choosing SARIMAX serves the purpose of building a relatively simple model, but of a good quality and with good predictive properties.

CONCLUDING REMARKS

The achieved result and verification of SARIMA and SARIMAX quality measures lead to the conclusion that the business climate indicator can be a good predictor of future demand levels. SARIMAX' forecast accuracy slightly improved when compared to SARIMA. The indicator controls for general economic conditions in companies´ external environment therefore not only is the forecast based on past values but a component informing about the future is added. It proves correct to forecast the demand for products dedicated for the metallurgy, engineering and steel industry. As this is a business climate indicator, it may provide with a subjective evaluation, but we assume that entrepreneurs' opinions will be translated into action. As no co-integration with the analysed series is observed, we cannot conclude on the long-term relationship.

REFERENCES

Briffaut, J.P., Lallement, P. (2010) Volatility Forecasting of Market Demand as Aids for Planning Manufacturing Activities. Service Science & Management, 3, pp. 383-389.

Bielak, J. (2010) Prognozowanie ryku pracy woj. Lubelskiego z wykorzystaniem modeli ARIMA i ARIMAX. Barometr Regionalny, nr 1(19), pp. 27-44.

Box, G. E. P., Jenkins, G., Reinsel, G. C. (1994) Time Series Analysis: Forecasting and Control, third edition. Prentice-Hall.

Cieślak, M. et al. (1997) Prognozowanie gospodarcze. Metody i zastosowania. Wydawnictwo Naukowe PWN, Warszawa.

Crane, D. B., Crotty, J. R. (1967) A two-stage forecasting model: Exponential smoothing and multiple regression. Management Science, Vol. 13 (8), Series B, pp. 501-507.

Ďurka, P., Pastoreková, S. (2012) ARIMA vs. ARIMAX – which approach is better to analyze and forecast macroeconomic time series? Proceedings of 30th International Conference Mathematical Methods in Economics, Karviná, Czech Repubic.

Engle, R. F., Granger, C. W. J. (1987) Co-integration and error correction: Representation, estimation and testing. Econometrica, 55(2), pp. 251–276.

Franses, P.H., Legerstee, R. (2013) Do statistical models for SKU level data benefit from including past expert knowledge? International Journal of Forecasting 29, pp. 80–87.

Forbes (2013) W Europie znika stal. Dowód na wyłudzanie VAT? http://www.forbes.pl/artykuly/sekcje/wydarzenia/w-europie-znika-stal--dowod-na-wyludzanie-vat,26826,1

Główny Urząd Statystyczny (2013) Wskaźniki makroekonomiczne. http://www.stat.gov.pl/gus/wskazniki_makroekon_PLK_HTML.htm

Główny Urząd Statystyczny (2013) Uwagi metodyczne. http://www.stat.gov.pl/gus/5840_2794_PLK_HTML.htm

Grudkowska, S. (2013) JDemetra+. User Manual. National Bank of Poland.

Klug, F. (2011) Automotive Supply Chain Logistics: Container Demand Planning using Monte Carlo Simulation. International Journal Automotive Technology and Management, Vol. 11, No. 3, pp. 254-268.

Rippe, R., Wilkinson, W., Morrison, D. (1976) Industrial Market Forecasting with Anticipations Data. Management Science, Vol. 22, No. 6 (Feb., 1976), pp. 639-651.

Szeplewicz, K. (2011) Wskaźniki wyprzedzające koniunktury - analiza ekonometryczna. Prace i materiały Instytutu Rozwoju Gospodarczego, IRG SGH, Warszawa, nr 87, pp. 33-63.