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The Relationship between the Purchasing Managers' Index (PMI) and Economic Growth: The Case for Poland

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Abstract:

Purpose: *The article aims to analyze and evaluate the relationship between the Purchasing Managers' Index PMI (economic sentiment indicator) and GDP dynamics in the Polish economy. The subject of detailed research was the possibility of forecasting Poland's economic situation using a model built based on the PMI sentiment indicator.*
Approach/Methodology/Design: *The study used data on GDP dynamics, EUR/PLN and USD/PLN exchange rates, as well as two indicators of economic sentiment prepared by independent institutions for Poland: the PMI and ESI indicator. The analysis was based on quarterly data for the period from the third quarter of 1998 to the second quarter of 2019 (84 observations). PMI data came from the bankier.pl website, ESI data from the European Commission database, GDP dynamics data from the World Bank database, and exchange rate information was taken from the stooq.pl website. The analysis contained in the article was performed using the ARDL and ECM models.*
Findings: *The analysis showed that the model based on PMI indicator and the model based on ESI indicator is too inaccurate to be considered a tool for forecasting the economic situation in Poland. It also turned out that extension of the model with other explanatory variables increased its accuracy of fitting to real data.*
Practical Implications: *Even though the estimated models were significantly unreliable, it turned out that in periods of greater economic instability, the PMI model showed better forecasting properties. This indicates the possibility of using the PMI model, e.g., in times of recession or economic crisis.*
Originality/Value: *The article broadened the research perspective for forecasting the Polish economy. The results set the directions for further development of research in this aspect. It turned out that probably the optimal solution would be to create different models for different phases of the business cycle, or a different rate of economic growth.*

Keywords: *GDP, PMI, ESI, relationship, forecasting, ECM.*

JEL classification: *A10, C01, C12, C32, C50, E23, E27.*

Paper Type: *Research study.*

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1. Introduction

To decide on a micro and macroeconomics are necessary key information about current and future economic situation in the country. Various measures are used to evaluate it, and one of the most popular is GDP dynamics (Gajewski, 2014). How important is GDP dynamics indicated by, among others strong link between the measure and the stock market, which is particularly sensitive to economic fluctuations (Kim and In, 2002; Hayo and Kutan, 2005; Engelberg and Parson, 2011; Milgrom, 1981; Brenner, Pasquariello, and Subrahmanyam, 2009; Kuiper, 2017). Quick access to key data on the economic condition of the economy, such as the GDP growth rate, from a macro perspective, allows, among others for conducting more effective monetary and fiscal policy, preventing, or minimizing the economic slowdown, or using economic information to make decisions supporting faster recovery of the economy from such a state. In addition, the appropriate use of economic data enables more efficient use of resources in the recovery phase, ultimately leading to higher GDP growth.

However, the collection of specific information from the economy, its processing and publication, requires appropriate work and time from the relevant institutions. In practice, this means that GDP data are published with a significant delay on a quarterly or annual basis. For example, in the US, the first accurate (not estimated) data on GDP growth for the current quarter is only published at the end of the first month of the following quarter (D'Agostino and Schnatz, 2012). With a similar, two-month delay, official data on quarterly GDP changes for euro area countries are published (Gajewski, 2014), while a much higher frequency is desirable-depending on the needs from monthly to even weekly.

A clear delay in the publication of economic data over time has forced the search for alternative (to GDP dynamics) measures allowing for publication with a higher frequency and the least delay possible in time (Siliverstovs, 2018). Research conducted in this direction has proved that the expected criteria can be met by indicators based on the sentiments of specific social groups. A group of indicators has been identified in the literature, the so-called sentiments indicators of economic, which are intended to be the first information made available to the public about the economic situation in the nearest future (D'Agostino and Schnatz, 2012). Their advantage is the relatively simple structure and freedom of modification, which allows adjusting the meters to specific expectations and goals. Sentiment indicators are most often built based on cyclically repeated survey surveys (questions e.g., to managers of specific entrepreneurs about the demand for employees, inventories, the volume of production or the number of new orders from customers), whose results after applying appropriate transformations show a specific empirical value (e.g., value less than 1 means potential negative phenomena in the economy). The role of sentiment indicators seems invaluable, because on their basis, the institution of the state and all market entities can prepare, for example, for an economic slowdown before it occurs, or react to a recovery that is only just to come (Schroeder, Huefner, and Felix 2002).

Therefore, it is not surprising that researchers interested in this issue were looking for relationships between sentiment indicators and GDP dynamics to possibly use these measures for economic forecasting. The existence of a statistically significant relationship between some sentiment indicators and the level of GDP has been proven many times, which allowed to start economic modelling. Models created for this need, such as DFM (dynamic factor model) (Giannone, Reichlin, and Simonelli 2009), bridge models (Irac and Sedillot, 2008), or also DSGE (Dynamic stochastic general equilibrium) (Cerveba and Schneider, 2010) showed that the implication of sentiment indicators for forecasting methods increases the accuracy of results, especially for the period of the beginning of quarters, when official data are not yet published (Antipa, Barhoumi, Brunhes-Lesange, and Darne 2012; Mitchell, Buraimo, and Montanta 2010; Keeney, Kennedy, and Liebermann 2012).

Stating the actual possibility of using certain sentiment indicators to forecast, e.g., GDP dynamics, should open completely new perspectives, e.g., for central banks and governments of individual countries, which could make better decisions in the field of, among others monetary and fiscal policy. However, the desired increase in forecast accuracy is not so obvious (Lombardi and Maier, 2011), because since the middle of the 20th century there has been a debate on aggregation and disaggregation in economic modelling (Theil 1954; Grunfeld and Griliches, 1960). On the one hand, researchers say that disaggregation allows for a higher level of accuracy in modelling individual dynamic properties with less forecast errors. On the other hand, they point out that it is difficult to model economic data without certain specification errors, which is why aggregation may increase the accuracy of forecasts despite relatively larger errors (Barker and Pesaran, 1990; Clements and Hendry, 2011).

Forecasting in periods of relative economic stability seems to be much easier than in others, including by the fact that possible errors do not have such drastic economic effects. In the unstable period 2008-2009, de facto biggest economic crisis in the 21st century, in the opinion of Lombardi and Maier (2014) not only questioned the reliability of the indicators and forecasting methods used so far (in various respects, e.g., construction), but also forced their modification, because have failed in many aspects. With this opinion agreed, among others. Siliverstovs (2018), paying special attention to the need to make changes in economic modelling. Analyzing the subject and direction of scientific research, a certain trend is observed, which is manifested in the fact that on the one hand the role of sentiment indicators in economic forecasting is strengthened, and on the other hand, new possibilities to improve those indicators (Siliverstovs, 2018), that seem to be currently the most developmental are constantly being sought tools created for forecasting in economics.

One of the most popular measures of economic sentiment among economists and governments, which is published for many countries, is the Purchasing Managers' Index (PMI) (D'Agostino and Schnatz, 2012). This indicator is developed by the Institute for Supply Management of Financial Activity based on the results of monthly surveys completed by managers of private sector companies (PMI depending on the country, it can be calculated only for the production sector or the production and services sector). According to Lombardi and Maier (2011), PMI reveals the most current economic data of all available indicators and allows making extremely important economic decisions before official GDP data appear. The PMI is especially observed by central banks, governments, economic agencies, economists, and the private sector. An additional advantage of this measure is its accessibility for anyone interested, and the only condition for obtaining data is Internet access (Habanabakize and Meyer, 2017; Schroeder, Huefner, and Felix, 2002; Gajewski, 2014; Kim and In, 2002; Chudik, Grossman, and Pesaran 2014). PMI it has universal application, because it is not limited to relations with GDP, but also has relationships with other economic measures, such as e.g., export value (Hanslin, Grossmann, and Schuefele, 2015).

Despite many advantages, PMI is also criticized, among others because in some countries is based solely on data from the manufacturing sector. Because the economies of individual countries are diverse in aspects such as the structure of GDP (Chien and Morris, 2016; Lahiri and Monokroussos, 2012), therefore, the relationship with economic growth in different countries is different. However, Ryan Barnes (2015) points out that it is in the production sector that the signs of impending recession and recovery may be the fastest, which is why even PMI limited only by data from the production sector is currently the best indicator of forecasting GDP changes. Similarly claims are from Lombardi and Maier (2011), recognizing the manufacturing sector as "the heart of the economy". Other authors present a similar position, pointing to the key importance of production for economic growth or the unemployment rate (Zalk, 2014), and according to Rodseth (2016), the production sector is so important that it can be called the flywheel of the whole economy.

Knowledge of current and future GDP growth is one of the most important issues for the entire economy. The sentiment indicators created for this purpose, such as PMI, despite some disadvantages, seem to be the best relatively effective tool for forecasting the economic situation, which has been proven for various countries, but there are relatively few studies on the Polish economy. Therefore, due to empirically verified evidence of the relationship between PMI and GDP in many economies around the world, the article fills the existing gap in research on the use of PMI to assess the economic situation in Poland.

The aim of the study was to analyze and evaluate the relationship between the PMI economic sentiment indicator and GDP dynamics in the Polish economy. The subject of detailed research was the prognostic possibilities of Poland's economic situation using a model using the PMI sentiment indicator. Using the method of back forecasting, the hypothesis that both the model built on PMI and economic sentiment indicator ESI is too inaccurate to consider it as a tool to predict the economic situation in Poland was verified. The study used data on GDP dynamics, EUR / PLN and USD / PLN exchange rates as well as two indicators of economic sentiment prepared by independent institutions for Poland, the PMI indicator and ESI. The analysis was based on quarterly data for the period from the third quarter of 1998 to the second quarter of 2019 (84 observations). PMI data came from the bankier.pl website, ESI data from the European Commission database, GDP growth data from the World Bank database, and exchange rate information was taken from the stooq.pl website.

2. Literature Review

The Purchasing Managers' Index (PMI) can be defined as the monthly economic activity index developed by the Institute for Supply Management (ISM) for over 40 countries (Kuepper, 2016; Soni, 2014; Buro of Economic Research, 2015; Chien and Morris, 2016). This measure is based on the results of surveys conducted among selected managers answering questions about new sales orders, employment of employees, orders from suppliers and inventory. Depending on the country, PMI is calculated for the production sector, services or both categories simultaneously (Buro of Economic Research, 2015). The measure ranges from 0 to 100. A score of 50 means that business activity will remain unchanged. A value less than 50 indicates a potential decrease in activity, and a PMI greater than 50 indicates a possible increase in economic activity in each sector or the entire economy (Khundrakpam and George, 2012).

In the light of the literature, Purchasing Managers' Index is an indicator willingly used by authors to determine the current or future economic situation long before the publication of official GDP data (Koenig and Evan, 2002; Godbout and Jacob, 2010; Rossiter, 2010; Lombardi and Maier, 2011; Lahiri and Monokroussos, 2012; Chien and Morris, 2016; Iselin and Siliverstovs, 2016; Kilinc and Yucel, 2016). PMI can be used to analyze growth in the manufacturing sector as well as growth in general in the economy (Koenig and Evan, 2002; Lahiri and Monokroussos, 2012). In the current achievements of research on the use of PMI to assess the condition of the economy, American scientists have the greatest contribution, because the USA was the first country in which this indicator was developed and applied (1948). Based on the analyses, it has been shown that PMI is an important indicator of the current situation of the manufacturing sector activity in the United States (Harris, 1991; Laubscher, 2003) and general economic activity in the form of GDP dynamics (Chien and Morris, 2016; Koenig and Evan, 2002; Soni, 2014; Harris, Owens, and Sarte, 2004; Lahiri and Monokroussoss, 2012; Harris, 1991).

Similar conclusions were obtained from research conducted on the ground of economy in other countries in the world, e.g., in Switzerland (Hanslin, Grossmann, and Schuefele, 2015), Japan (Godbout and Lombardi, 2012), South Africa (Habanabakize and Meyer, 2017), Germany (Schroeder and Huefner, 2002) or in the euro area (Gajewski, 2014; Liedo and Munoz, 2010; Godbout and Jacob, 2010; Rossiter, 2010; Lombardi and Maier, 2011; De Bondt, 2012). The PMI is considered to be one of the most universal sentiment indicators, as evidenced by the fact that it can be an effective tool used to forecast not only GDP dynamics, but also, among others, the unemployment rate (Soni, 2014; Habanabakize and Meyer, 2017), or exports, relatively often increasing the accuracy of forecasts to a level higher than models built on the basis of other sentiment measures (Hanslin, Grossmann, and Schuefele, 2015). The relationship between the PMI and the stock exchange was also proven (Habanabakize and Meyer, 2017), in the light of research results so far depended on the characteristics of economies and the specificity of stock exchanges of individual countries (for example, in countries such as Poland, the Czech Republic and Hungary, PMI's impact on equity returns was lower than originally assumed (Hanousek and Kocenda, 2011).

These relationships can have two meanings. On the one hand, a model predicting changes on the stock market can be created based on PMI. On the other hand, stock market investors can respond to published PMI values and make specific decisions on this basis, thereby assigning PMI measures to determinants that shape, among others, investor baskets. Previous studies have shown that the PMI index significantly affect commodity futures for raw materials, S&P 500 index and treasury bonds (Hess, Huang, and Niessen, 2008; Simpson, Ramchander, and Chaundhry, 2005). In addition, it was noticed that PMI had a relatively stronger impact on the shares of smaller companies capitalizing the market and companies from the precious metals, IT, textile and automotive industries (Cevik, Korkmaz, and Atukeren 2012; Johnson and Watson, 2011). Interesting conclusions were brought by the analysis of the impact of PMI on returns on shares in China. It was found that if the PMI increased compared to the previous month and the measure exceeded 50, there was a positive one-day effect of returns on shares. In addition, it was noticed that over the next three days the stock exchange situation normalized (Wang and Yang, 2018).

It should be noted that the existing analyses of the relationship between PMI and the economic situation of selected countries have been varied in many respects. Some authors focused solely on demonstrating the existence of dependencies, while others developed the topic of forecasts in various scenarios, nowcasting, back casting forecasting. In addition, long and short-run forecasting were considered depending on the possibilities. Researchers, looking for answers to the relationship between PMI and the economic situation, created a variety of models from the simplest, in which the only explanatory variable was the PMI sentiment indicator, to much more complex and advanced indicators' factor. In the light of the existing literature, most authors indicate that the added value of forecasts built based on PMI decreases quite quickly with the time horizon of the forecast itself (Chudik, Grossman, and Pesaran, 2014). This means that the PMI can indeed be used to model the current and future economic situation, but only in the short term. Much less frequently, studies showed long-term PMI prognostic potential. One example of the possibility of long-term economic modeling based on PMI is the analysis of the relationship between PMI and South Africa's economic growth. Based on the results, it was found that a statistical relationship was only found in the case of long-run analysis (Habanabakize and Meyer, 2017).

Research on the relationships between the PMI indicator and measures characterizing the economic situation, such as GDP dynamics, were relatively often built on models enriched with other indicators, including indicators of economic sentiments. Thanks to this, the authors could compare the direction and strength of the relationship between selected indicators and e.g., GDP dynamics, or verify the quality of forecasts between these categories. When selecting additional indicators, the most important aspect was the availability of data, as there are many types of indicators of economic sentiment that are calculated and published only for selected countries, or a smaller or larger group of countries –this is one of the reasons for the popularity of PMI is emerging, which is being prepared is for over 40 national economies, thanks to this the measure is considered to be one of the most universal indicators of sentiments in the world. To forecast US GDP dynamics, D'Agostino and Schnatz (2012) put together a model built based on PMI and a model created using a quarterly indicator intended to be a forecasting tool– SPF (Survey of Professional Forecasters) (European Central Bank, 2020; Federal Reserve Bank of Philadelphia, 2020). The results indicated that the PMI model less accurately predicted GDP changes and was less effective in all respects than the SPF model. But it was noticed that the PMI-based model was much more effective when forecasting changes in production (D'Agostino and Schnatz, 2012).

One of the most important indicators of economic sentiment in Europe is the measure prepared by the European Commission– ESI (European Economic Sentiment Indicator) (Eurostat, 2020). The authors relatively often use ESI to study the economic situation of European Union countries, but also willingly compare the prognostic possibilities of models based on ESI with PMI models. Current scientific achievements indicate that ESI models perform much better in the accuracy of predicting annual changes in GDP, while PMI models are characterized by a relatively greater degree of adjustment to the quarterly dynamics of GDP (European Commission, 2012; Insee, 2008). Identical conclusions in forecasting quarterly changes in GDP in the euro area were made by Gajewski (2014), who proved the greater accuracy of the PMI-based model than the model built on ESI.

The relatively high effectiveness of PMI-based models in forecasting quarterly GDP growth has also been confirmed by Gabe de Bondt (2012) in relation to the euro area. It turned out that this method allowed to predict the real values of changes even better than the initial estimates of the European Commission. Relatively high accuracy of PMI model forecasts for quarterly GDP dynamics is also indicated by Lombardi and Maier (2011). At the same time, the authors considered whether predicting GDP changes using PMI models is effective for economies of varying economic instability. It has been found that forecasting quarterly GDP dynamics using the PMI model is effective in both, low and high volatility economic growth countries.

Schroeder and Huefner (2002) came to different conclusions, they compared the results of economic forecasts using two models for this purpose, the first built on the basis of PMI and the second, built on the basis of the sentiment indexIFO (IFO business expectations, the so-called business climate index in Germany prepared and published byIfo Institut fur Wirtschaftsforschung in Munich (2020). The study proved that the accuracy of forecasting based on the PMI model depends on the relative stability of economic growth. Therefore, it was found that for such economies as the relatively stable German, the effectiveness of forecasting with models built based on PMI is unsatisfactory. The lower effectiveness of PMI models in relation to economic forecasting in more stable economies was also confirmed by Gajewski (2014), who pointed out that in a stable macroeconomic environment there is a tendency to decrease the advantage of PMI over alternative sentiment indicators.

However, from a macroeconomic point of view, the greater challenge is to predict the economic situation in economies with less regularity, which is why Godbout and Jacob (2010) argue that PMI is the best sentiment indicator in the study of GDP dynamics in the eurozone countries, as it enables the creation of relatively accurate forecasts in periods economic instability (for example, such as the crisis in 2008-2009), i.e., in the most difficult moments of the business cycle. Ultimately, as demonstrated by the work of Lombardi and Maier (2011), even PMI models during the 2008-2009 recession could have been characterized by relatively large errors, which in the euro area pointed to faster than real recovery, but also to a more severe slowdown in economic activity in 2009. In addition, the literature indicates that the effectiveness of forecasts built on selected sentiment indicators may also vary depending on the characteristics of a particular economy, and not only because of its stability. When analyzing the relationship between PMI and quarterly GDP growth in the euro area, Gajewski (2014) proved that PMI models perform less efficiently in countries such as Spain, where capital-intensive construction sector is the dominant sector of the economy, which makes the capital-intensive production sector relatively less important. By the way, the author showed that PMI models relatively accurately forecast the beginning of quarters and periods in which there is a high rate of GDP growth.

The widespread use of PMI as an economic indicator has made it the most important sentiment indicator for 40 years (Rodseth, 2016). The authors prove its importance for economic forecasting (Kuepper, 2016; Tsuchiya, 2012; Banerjee and Marcelino, 2006; Lindsey and Pavur, 2005), whereas the forecast accuracy is relatively high (Rossiter, 2010; Godbout and Jacob, 2010; Liedo and Munoz, 2010). However, the 2008-2009 crisis proved that models built based on PMI can fail (Lombardi and Maier 2011). Therefore, there were allegations that the algorithm for calculating PMI is already outdated and not adapted to the operating conditions in the 21st century (Siliverstovs, 2018). Some authors argue that the methodology for calculating PMI should vary depending on individual countries (Pelaez, 2003; Cho and Ogwang, 2006). Siliverstovs (2018) proposes that PMI should be built using additional subindices, which would allow for more reliable results. At the same time, empirical research indicates that measurable effects that increase the accuracy of economic forecasts follow creation of models based on several sentiment measures (PMI, SPF) (D'Agostino and Schnatz, 2012) or creating relatively advanced econometric models using PMI (Godbout and Lombardi, 2012), because these models can generate smaller errors than e.g., the extensive factor models (Lombardi and Maier, 2011).

3. Materials and Methods

3.1 The Scope of Data

PMI (Purchasing Managers' Index) is an indicator of economic sentiment developed and published by the Institute for Supply Management (ISM) for over 40 countries (Kuepper, 2016; Soni, 2014; Buro of Economic Research, 2015; Chien and Morris, 2016). Depending on the country, PMI is prepared exclusively for the production sector, services or both fields at the same time. The value of the indicator is between 0-100, where a score of 50 shows the maintenance of economic activity, a score greater than 50 means a potential increase in activity, and a score less than 50 may indicate a possible decrease in economic activity in the sector or the entire economy (Khundrakpam and George, 2012). In turn, ESI (European Economic Sentiment Indicator) is an indicator of economic sentiment calculated and published by the European Commission for European Union countries. It is composed of five sectoral partial indicators of various weights: industrial, service and consumer indicators as well as the index of retail trade and construction. Specific surveys are prepared for each sector to obtain the necessary information to determine the current situation of the industry. ESI is calculated as an index with an average of 100 and a standard deviation of 10 over a set and normalized sampling period (Eurostat, 2020).

Statistical data with the highest possible frequency were used to study the relationship, while increasing the sample to the maximum size, which was to contribute to greater reliability and accuracy of the resulting model. The main problem, however, was the lack of compatibility, as exchange rate measures as well as PMI and ESI are published monthly, and information on GDP changes in a quarterly. Unfortunately, there is no tool that would perfectly synchronize data at different frequencies. Researchers use various transformation methods, among which more complex ones can be distinguished, such as mixed-data sampling regression (MIDAS), which allows to study the relationship between incompatible data. MIDAS was relatively often used by the authors when analyzing the relationship of PMI with GDP (Siliverstovs, 2018; D'Agostino and Schnatz, 2012; Chudik, Grossman, and Pesaran, 2014), however, at work it was decided on a different, relatively easy, and effective way to match the data by reducing the readings from monthly to quarterly based on the calculated average of three months per quarter. Based on the possibility of access to historical data of individual indicators, the study used quarterly data, starting from the third quarter of 1998 (1998Q3) to the second quarter of 2019, i.e., 84 observations.

To perform a more complete analysis of the relationship between PMI and GDP dynamics, it was decided to build three dependency models. The first considered the relationship between GDP dynamics and the PMI indicator, the second the relationship between GDP growth and ESI indicator, consecutively, the third was to model GDP dynamics based on the PMI indicator, ESI indicator and the EUR / PLN and USD / PLN exchange rates. The creation of three independent models forecasting GDP changes enabled the verification of the existing literature on these issues. It was decided to confront the possibilities of predicting the economic situation in Poland based on the most popular index of economic sentiment in the world (PMI) and the second most popular index of economic sentiment in Europe (ESI).

Considering the opinions of some authors that economic forecasting models should be built based on a larger number of exogenous variables, an optional attempt was made to create a model in which the predictors were EUR / PLN and USD / PLN exchange rates, as well as ESI and PMI (Godbout and Lombardi, 2012; D'Agostino and Schnatz, 2012; Lombardi and Maier, 2011). The implication of the most significant exchange rates for the Polish economy to the widest model was reinforced by the fact that exchange rates are an indicator with a relatively the fastest response time to any macroeconomic changes, which should translate into more accurate parameters and greater empirical effectiveness of the model's forecast.

3.2 Model Specification

Each time the econometric model is built, it must be preceded by a thorough analysis of the variables that are necessary to create it. This is due to both axioms of general modelling and detailed, mandatory guidelines for specific econometric methods. Data verification in the search for stationarity, normality, autocorrelation, heteroscedasticity, collinearity and cointegration was performed using popular statistical tests is presented in Table 1 (Pesaran, Shin, and Smith 1999; Pesaran and Smith, 1995; Rao, Hadri, and Bu, 2010). It should also be noted that before these activities a decision about transforming all measures towards stabilization of variance (logarithm) had been made. Thanks to this, the effect of series stabilization, their normalization, smoothing, transformation into a linear form, removal of unwanted collinearity, heteroscedasticity and autocorrelation was obtained (Shrestha and Bhatta 2018).

Table 1. *The scope of variables testing*

Research criterion	Statistical test	H0:	H1:	H0 testing based on value
Integration level	ADF test	The series is not integrated	The series is integrated to a certain extent	P(x)
Normal distribution of residues	Doornik-Hansen test	The random component has a normal distribution	The random component has no normal distribution	P(x)
Autocorrelation of residue distribution	Durbin-Watson test	The random component has not a correlation	There is an autocorrelation of the random component	P(x)
Autocorrelation of residue distribution	Breusch-Godfrey test	The random component has not a correlation	There is an autocorrelation of the random component	P(x)

Heteroskedasticity of residues	Breusch-Pegan test	Hetereskastasticity of residues does not occur	Heteroskedasticity of residues occurs	P(x)
Collinearity of variables	VIF variation factor	VIF values = <10: no collinearity	VIF values> 10: possible collinearity problem	VIF value
Cointegration of variables	Johansen trace test	No cointegrating vectors	There are cointegrating equations	P(x)

Source: *Own study.*

Based on the pre-estimated OLS (ordinary least squares) regression model, created to test specific statistics (Hertel, Klimkowski, and Stańko, 2014) and taking into account the lack of cointegration of the studied categories and the fact that GDP dynamics was the only one characterized by stationary at level (Table 2), it was decided to conduct a dependency analysis based on the ARDL method (autoregressive distributed lag) (Pesaran, Shin, and Smith, 1999; Usman and Elsalih, 2018; Abubakar and Shehu, 2015).

Table 2. *Characteristics of variables used for modelling*

Criterion \ Variable	PMI	ESI	EUR/PLN	USD/PLN	ΔPKB
Integration level	I(1)	I(1)	I(1)	I(1)	I(0)
Normal distribution of residues	The random component of the initial model has a normal distribution				
Autocorrelation of residue distribution (Durbin-Watson)	The random component of the initial model is not autocorrelated				
Autocorrelation of residue distribution (Breusch-Godfrey)	The random component of the initial model is not autocorrelated				
Heteroskedasticity of residues	The random component of the initial model is not heteroscedastic				
Collinearity of variables	In the initial model, there is no distension				
Cointegration of variables	No integrating vectors = I(0)				

Source: *Own study.*

The ARDL model (1) consists of two elements determining the short-run (2) and long-run (3) relationships, which can occur between variables despite the lack of cointegrating vectors. After estimation, it is extremely important to verify the optimal number of delays (lags) and potentially occurring undesirable phenomena such as serial correlation and dynamic model instability (dynamically unstable). The use of ARDL allows verification of the existence of a long-term relationship based on Wald test extended with a Bound test (Pesaran, Shin, and Smith 2001). If such a phenomenon is detected, the long-run condition can be replaced by its lagged residuals (4) and thus transform the ARDL model into an ECM model (5). The advantage of the ECM model is that it extends the analysis with information on the speed of regulation towards long-term equilibrium.

$$ARDL: \Delta Y_t = \beta_0 + \sum_{i=1}^{n} \beta_i \Delta y_{t-i} + \sum_{i=0}^{n} \delta_i \Delta x_{t-1} + \varphi_1 y_{t-1} + \varphi_2 x_{t-1} + \mu_t \quad (1)$$

$$Short-runmodel: y_t = \beta_0 + \sum_{i=1}^{n} \beta_i \Delta y_{t-i} + \sum_{i=0}^{n} \delta_i \Delta x_{t-1} \quad (2)$$

$$Long-runmodel: y_t = \beta_0 + \beta_1 x_t + \varepsilon_t \quad (3)$$

$$Laggedresiduals: z_{t-1} = y_{t-1} - b_0 - b_1 x_{t-1} \quad (4)$$

$$ECM: \Delta Y_t = \beta_0 + \sum_{i=1}^{n} \beta_i \Delta y_{t-i} + \sum_{i=0}^{n} \delta_i \Delta x_{t-1} + \varphi z_{t-1} + \mu_t \quad (5)$$

4. Research Results

Based on the information criteria of Akaike, Schwartz-Beyesian and Hannah-Quinn, the creation of 1 lagged ARDL models was started. Three models were estimated (Table 3), ARDL1 (Y=ΔPKB, X=PMI, EUR / PLN exchange rate, USD / PLN exchange rate, ESI), ARDL2 (Y=ΔPKB, X=PMI) oraz ARDL3 (Y=ΔPKB, X=ESI). The Breusch-Godfrey Serial Correlation LM Test performed did not show the undesirable phenomenon of serial correlation, and the Cusum stability test proved that each of the models is stable (Figure 1) (Levin, Lin, and Chu, 2002; Choi, 2001; Pesaran, 2006). Based on the results, it was found that none of the models showed a statistically significant short-run relationship between variables (except autoregression of GDP dynamics). In addition, it turned out as expected that the ARDL1 model, due to the use of more explanatory variables, had the best adjustment to GDP growth (R^2= 36 precent), whereas the worst in this aspect was the ARDL2 model, which explained the Y changes to a lesser extent than the ARDL3 model by about 3 percentage points (R^2= 29 precent). From the perspective of further analysis, it is worth noting that each of the models was statistically significant.

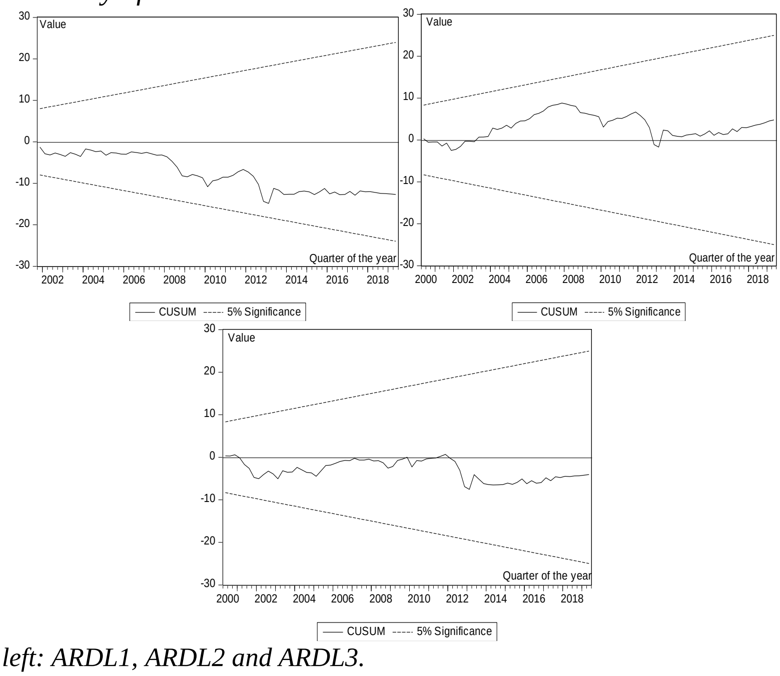
Table 3. *Estimation of ARDL models*

Type of equation	Variable	Coefficient	Std. Error	t-Statistic	Prob.
Model ARDL1					
Short-run	C	-8.248014	5.100649	-1.617052	0.1103
	D(L_PKB(-1))	0.420483	0.117269	3.585626	0.0006***
	D(L_PMI(-1))	1.924569	1.284999	1.497720	0.1386
	D(L_USDPLN(-1))	0.687661	0.850562	0.808479	0.4215
	D(L_EURPLN(-1))	-0.581809	1.082702	-0.537367	0.5927
	D(L_ESI(-1))	1.760161	1.565583	1.124285	0.2647
Long-run	L_PKB(-1)	-0.359959	0.088616	-4.062021	0.0001***
	L_PMI(-1)	-0.701520	0.978932	-0.716618	0.4760
	L_USDPLN(-1)	0.185720	0.323459	0.574167	0.5677
	L_EURPLN(-1)	0.367443	0.660461	0.556343	0.5797
	L_ESI(-1)	1.971346	0.969160	2.034078	0.0457
Adjustment	R-squared = 0,356658				
Prob.	P = 0.000273***				
Model ARDL2					
Short-run	C	-2.418888	3.329503	-0.726501	0.4697

	D(L_PKB(-1))	0.391911	0.110419	3.549314	0.0007***
	D(L_PMI(-1))	1.307101	1.152346	1.134295	0.2602
Long-run	L_PKB(-1)	-0.245414	0.069616	-3.525261	0.0007***
	L_PMI(-1)	0.400669	0.811263	0.493884	0.6228
Adjustment	R-squared = 0.291461				
Prob.	P = 0.000021***				
Model ARDL3					
Short-run	C	-6.059927	3.475017	-1.743855	0.0852
	D(L_PKB(-1))	0.471256	0.109999	4.284185	0.0001***
	D(L_ESI(-1))	1.624311	1.156757	1.404194	0.1643
Long-run	L_PKB(-1)	-0.340259	0.082269	-4.135949	0.0001***
	L_ESI(-1)	1.068305	0.713779	1.496689	0.1386
Adjustment	R-squared = 0.317109				
Prob.	P = 0.000006***				

Note: **** statistically significant at significance level of 1 percent.*
Source: *Own study.*

***Figure 1**. Stability of ARDL models*



From the left: ARDL1, ARDL2 and ARDL3.
Source: *Own study.*

Next, the long-run relationship between variables using Wald test was verified. Based on the obtained values of F statistics, a Bound test was carried out, which revealed the existence of a statistically significant long-run relationship in all three ARDL models. With certainty about the long-run relationship, it was possible to transform the models into ECM models (ARDL1 was transformed into ECM1, ARDL2-ECM2 and ARDL3-ECM3). The Breusch-Godfrey Serial Correlation LM test did not show the undesirable phenomenon of serial correlation, and the Cusum stability test proved that each of the ECM models is stable. Models obtained through the ARDL transformation lost an average of 4 percentage points of the level of adjustment to changes in Y but remained statistically significant (Table 4). Most importantly, ECM estimation allowed verification of the adjustment rate towards long-term equilibrium because the ECT coefficient in each of the three models was negative and statistically significant. On this basis, it was found that the rate of adjustment of deviations from the long-run balance of the system is: in ECM1 36 percent, ECM2 25 percent and in ECM3 34 percent. This confirms the conclusions to date that the empirically the weakest model was built solely based on PMI.

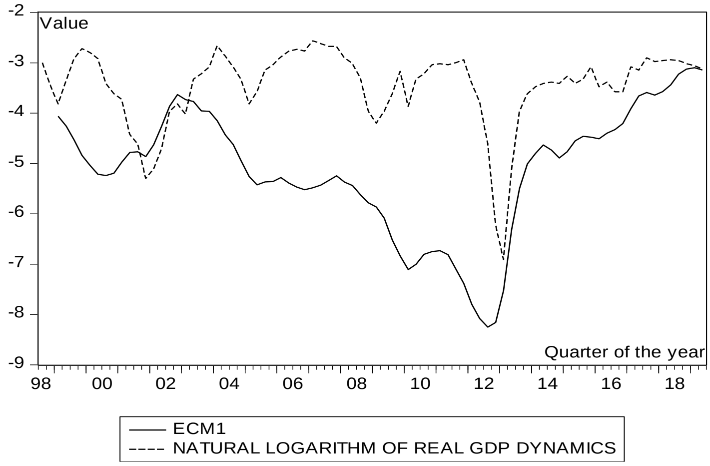
Table 4. *Estimation of ECM models*

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ECM1				
C	0.002972	0.041778	0.071135	0.9435
D(L_PKB(-1))	0.420623	0.117603	3.576632	0.0006***
D(L_PMI(-1))	1.596962	1.134362	1.407806	0.1633
D(L_USDPLN(-1))	0.826629	0.829214	0.996882	0.3220
D(L_EURPLN(-1))	-0.366050	1.028158	-0.356025	0.7228
D(L_ESI(-1))	0.506909	1.461175	0.346918	0.7296
ECT(-1)	-0.357307	0.089218	-4.004871	0.0001***
Adjustment	R-squared = 0.305014			
Prob.	P = 0.000094***			
ECM2				
C	0.001786	0.042129	0.042387	0.9663
D(L_PKB(-1))	0.376928	0.111445	3.382184	0.0011***
D(L_PMI(-1))	0.776885	1.124131	0.691098	0.4916
ECT(-1)	-0.250244	0.070425	-3.553317	0.0006***
Adjustment	R-squared = 0.264269			
Prob.	P = 0.000024***			
ECM3				
C	0.002075	0.041690	0.049767	0.9604
D(L_PKB(-1))	0.501326	0.111306	4.504053	0.0000***
D(L_ESI(-1))	0.994426	1.139236	0.872888	0.3854
ECT(-1)	-0.344836	0.083952	-4.107549	0.0001***
Adjustment	R-squared = 0.279128			
Prob.	P = 0.000011***			

Note: **** statistically significant at significance level of 1 percent*
Source: *Own study.*

In the last phase of the analysis, it was decided to make a back casting forecast to confront three ECM models. According to empirical results, the ECM1 model was most suited to real GDP changes, but its relatively best fit in the entire period was in the period 2001Q3 to 2003Q2 and 2013Q3 to 2019Q2 (Figure 2). In the surveyed time series, the forecast indicated more optimistic changes in GDP dynamics than it was in the four quarters (2001Q3-2003Q2). In addition, it was found that the forecast was five times ahead of the actual change in GDP growth. The model predicted the economic slowdown 2008-2009 relatively well but pointed to a much stronger decline in GDP growth than in reality. The situation was similar in the case of the slowdown in 2012, where the model forecasted a much stronger weakening of the GDP dynamics than the actual one.

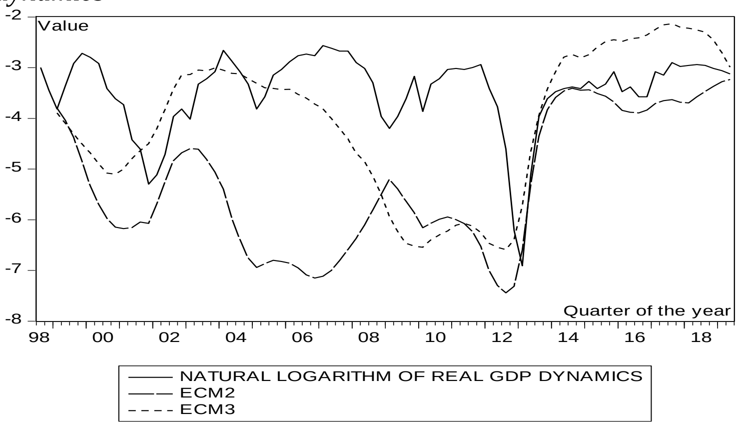
Figure 2. *ECM1 model back casting forecast against the background of real GDP dynamics*



Source: *Own study.*

The model forecast based on PMI was relatively best suited to real GDP changes in the periods between 2001Q2 and 2005Q2 and 2013Q2 to 2019Q2 (Fig. 3). The model pointed to more optimistic changes in GDP than it was in 30 quarters (2001Q2-2004Q1 and 2012Q4-2019Q2). In addition, it was found that the empirical values of the ECM2 forecast were three times ahead of real GDP dynamics. Interestingly, the model built based on PMI already from the second quarter of 2006 pointed to the economic slowdown in 2008-2009 and relatively accurately estimated the moment of recovery in 2010. The model also anticipated the slowdown in 2012 and the faster recovery of GDP dynamics in advance than it was in advance (the model showed less weakening of the GDP dynamics than the actual one). In turn, the ECM3 model was most suited to real GDP changes, like ECM1, in the quarters 2001Q3 to 2003Q2 and 2013Q3 to 2019Q2 (Figure 3). This model pointed to more optimistic changes in GDP than it was in two quarters, i.e., 2013Q1 and 2013Q2. ECM3 was relatively worst of all when forecasting the crisis in 2008-2009, however it was the best in forecasting the slowdown in 2012 (even though it showed a greater decline in dynamics than it was in the reality). What is more, the ECM3 model well predicted the recovery after the recent strong economic slowdown, i.e., after 2012. A relatively good adjustment of both the ECM2 and ECM3 models to the actual GDP dynamics in 2013 is noticeable, i.e. at a time of relatively rapid GDP growth. Importantly, the model built based on ESI relatively well predicted the deceleration of "accelerated" dynamics from 2013, while the ECM2 model pointed to further relatively strong growth (overestimation).

Figure 3. *ECM2 and ECM3 model back casting forecast against the background of real GDP dynamics*



Source: *Own study.*

5. Summary and Discussion

The analysis made it possible to achieve the research objective in the field of analyzing and assessing the relationship between the PMI economic sentiment indicator and the GDP dynamics in the Polish economy. Based on the estimation of ARDL models, it was found that there was not statistically significant short-run relationship between the PMI measure and GDP dynamics. No such relationship was found for another sentiment indicator – ESI. On the other hand, using the Wald test and the Bound test, a statistically significant relationship was demonstrated in the long-run relationship. This agrees with research carried out in South Africa, where the relationship between PMI and GDP dynamics has been proven only from the long-run perspective (Habanabakize and Meyer, 2017). Due to the transformation of ARDL models into ECM models, the prognostic possibilities of Poland's economic situation were verified based on the PMI indicator. This made it possible to positively consider the research hypothesis according to which both the model built based on PMI and the model based on ESI is too inaccurate to be considered as a tool for predicting the economic situation in Poland. Although back casting forecasts have opened prospects for a relatively quick prediction of potential economic slowdown, however the models estimate the value of GDP changes with a relatively high inaccuracy, which can certainly not be called reliable. In addition, the results proved that in the Polish economic reality, forecasting of quarterly GDP dynamics using the PMI model is less accurate than modelling based on ESI (the difference R^2 is 2 percentage points).

The superiority of the model using the ESI indicator was also manifested in the speed of matching its deviations from the equilibrium level (34 percent compared to 25 percent of the model based on the PMI indicator), i.e., unlike in the euro area countries for which the superiority of the PMI-based model over the model using with ESI (European Comission, 2012; Insee, 2008; Gajewski, 2014).

Conclusions from the work on the Polish economy were confirmed in relation to the achievements of Lombardi and Maier (2011) devoted to the analysis of the eurozone countries. In both cases, relatively large model errors based on PMI during the recession have been proven, mainly due to an overestimation of the economic slowdown in relation to real data. In addition, the PMI-based model showed relatively often too optimistic forecasts of GDP changes (overestimated). Based on the results, it was found that the PMI model relatively accurately forecasts the beginning of quarters and entire periods in which there is a high rate of GDP growth. Paweł Gajewski (2014) came to the same conclusion when analyzing the eurozone countries, due to this fact a kind of correctness of the PMI model in this matter can be assumed.

Opinions put forward by Lombardi and Maier (2011) as well as Godbout and Lombardi (2012) that in the eurozone countries measurable effects of increasing the accuracy of economic forecasts occurred after creating models where are together PMI and others explanatory variables were also confirmed in Polish conditions. It was proved that the most extensive ECM1 model (created using the PMI, ESI indicator and EUR / PLN and USD / PLN exchange rates) most predicted changes in GDP dynamics, i.e., combining several sentiment indicators and other measures in one model affects the efficiency of dynamics forecasting GDP in Polish economic reality.

However, it is worth noting that, despite the average better fit level and the smallest level of error, the most complex model may not be considered the best in every aspect. Empirical analysis proved that at certain intervals the most accurate model was the one based on PMI or the one based on ESI. Such a conclusion in some sense undermines the opinion of D'Agostino and Schnatz (2012), who argue that increasing the number of explanatory variables in econometric models (e.g., sentiment indicators) each time leads to greater forecast reliability. As an example, the ECM2 and ECM3 forecasts can be cited in the period 2006Q4 to 2009Q1, as well as 2014Q4 to 2019Q2 (Figure 3). The model built on the basis of ESI, and the model created on the basis of PMI showed quite the opposite direction of changes in GDP dynamics, which, as a consequence of using both measures in one model, can cause strong distortions of the empirical forecast.

An important issue for choosing the best model among those created in the paper was the answer whether more perfect mapping of the Y variable is more important, or maybe the method that predicts the upcoming economic slowdown is more important (in this aspect the superiority of the model built on the basis of PMI was observed). This issue was left unanswered in the analysis. The research results contained in the article are of an application nature, because they showed the inaccuracy and unreliability of models built on the most popular indicators of economic moods to predict the economic situation in Poland. The model based on PMI can be called moderately overestimated (too optimistic), while the ESI model – moderately underestimated (too pessimistic). It should be noted that during periods of relatively stronger economic slowdown, the PMI model forecasted a decline in GDP growth before it appeared, i.e., it was ahead of economic reality and could prepare market entities, government, or state institutions for the future economic downturn. This is of crucial importance because anticipating crises at the right time could effectively offset the adverse effects of the slowdown for the economy and could also be the basis for flattening the business cycles (variability at a minimal level). However, the analysis also showed that the PMI-based model has some disadvantages and unfortunately cannot be used as an effective and reliable method of forecasting Poland's economic situation.

The research results leave a wide spectrum of further analysis of the possibility of using measures such as indicators of economic sentiment to forecast, e.g., changes in GDP dynamics. The direction of further considerations can be very extensive. Analyses can be focused on building models based on a much larger number of variables, including sentiment indicators. They can also use the knowledge from the article in such a way that the ESI indicator is implied for large forecasting models (due to better adjustment of empirical forecast values to changes in GDP dynamics), and the PMI indicator is implied only for periods of greater economic instability.

According to this line of reasoning, it is possible to create different models for other phases of the business cycle, or for a different level of economic fluctuation or a different rate of economic growth. Being also aware of the burden of any analyses with specific weaknesses (e.g., selection of a sample, variables, or methods), it can be assumed that in the article a certain weakness, reducing the accuracy of the analysis, was the forced transformation of monthly data into quarterly data, the lack of decomposition of time series and the fact that PMI is calculated only for the production sector for the Polish economy. It also opens opportunities for further research in which the elimination of these aspects can show results that may shed new light on verified issues.

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