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LABOUR PRODUCTIVITY ANALYSIS OF MANUFACTURING SECTOR IN TURKEY AGAINST EU

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Abstract. This study offers an in-depth analysis of labour productivity of manufacturing sector in Turkey and provides a comparison with EU27 and EA19 countries utilizing Eurostat time series data of 63 quarters covering 2005/first quarter-2020/third quarter time interval. Productivity trends are identified and interpreted by relating them with the key macroeconomic events and factors. Multiple linear and non-linear regression equations, and ARIMA model with different parameters are applied to the time series data considering the periods with and without covid effect. Future projections are made for the periods 2020–2023 for Turkey manufacturing sector based on the best fitting regression and ARIMA solutions and they are compared. Findings revealed that extreme covid conditions of even two quarters of data have significant impact on the forecasted values for Turkey, EU27 and EA19 countries. ARIMA analysis with 12 different parameter settings provided accurate results, supported by Thiel's inequality coefficients and standard error measures. Analysis has shown consistent patterns between EA19 and EU27 countries. ARIMA results represent better compatibility with the regression results for Turkey. Study is valuable by providing comprehensive and comparative analysis, revealing future forecasts and covid effect and degree of recovery from the pandemic.

Keywords: labour productivity, manufacturing, linear regression, ARIMA, Turkey, EU.

JEL Classification: D24, C22, J24, L6.

Introduction

As a multi-factor concept, labour productivity is one of the most critical determinants of performance in manufacturing sector, and it is considered as a major factor in economy's stability, long-run rate of economic growth, tax revenues, inflation and long-term prosperity (Erber et al., 2017; Pettinger, 2019; Holman et al., 2008; Kılıçaslan et al., 2007; Office for National Statistics [ONS], 2007). Productivity growth is considered as the key to increase

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per capita GDP, wages, and living standards (Manyika et al., 2017; OECD, 2023), and labour productivity growth is highlighted as the major determinant of sustained growth of per capita income, which is the main factor to reduce poverty (Dieppe, 2020; OECD, 2023). It is supported that greater portion of cross-country differences in per capita income can be associated with the differences in labour productivity (Dieppe, 2020; Beugelsdijk, 2018). Significant differences in the levels of economic development across EU country subnational regions are explained by variations in factor productivity (Beugelsdijk et al., 2018). In literature, labour productivity appears as a multi-factor concept (ONS, 2007). The issue is also related with the concepts of technology-intensiveness and specialization (Kılıçaslan et al., 2007). There is empirical support that there are sectoral as well as country-based differences (Manyika et al., 2017; Roson, 2019). Hence, the issue deserves attention at sectoral-level, country-level and global level, requiring both micro and macro perspectives.

Major economic disruptions, deep recessions, wars, financial crises and natural disasters are well-supported to go along with significant and elongated decline in labour productivity (Dieppe, 2020). Severe pandemic conditions that the world is going through can cause insistent damage to productivity, resulting in unemployment, negatively effecting labour reallocation, having adverse effects in investments, and resulting in retreats from foreign trade and heavy debt burdens (Dieppe et al., 2020; Dieppe, 2020). It is supported that epidemics are reducing labour productivity and hence the transition of underdeveloped industries to developed industries may be weakened by decreased productivity due to covid (Dieppe, 2020; Casola et al., 2020). It is argued that impact of covid on productivity may be significantly worse than the effects of other natural disasters since its adverse impacts will be amplified in a global and integrated economy. Due to covid, disruptions to employment are being experienced and overall compounded financial stress is created. Hence, in today's VUCA (volatile, uncertainty, complexity and ambiguity) business world, these dimensions are further intensified by covid conditions. Dramatically increasing diffusion and assimilation of disruptive automation and IT technologies are also in action, changing the scene (Lishchuk & Kapelyuk, 2020; Woltjer et al., 2021; Mecik, 2015; Feder, 2018). Consequently, the topic of labour productivity deserves further attention under these extreme conditions.

This study focuses on the labour productivity at macro level in manufacturing sector. The aim of the paper is to analyze the general trends and to obtain forecasts for labour productivity in Turkey, and to provide a comparison with EU27 and EA19 while revealing and analyzing the effects of covid. The comparative study is designed as a Turkey-EU area comparison to reveal the situation and the performance gap between Turkey and developed EU countries. It is important to highlight that Turkey is also a European country, therefore obtaining a meaningful benchmarking is valuable. Performing comparison against similar developing countries would not provide the necessary differentiation and benchmarking, and it would create data availability problems. Hence, EU area was selected for comparison. Based on comprehensive time series data, the paper provides linear, non-linear regression and ARIMA analysis. Forecasting is performed until the end of 2023/3rd quarter for Turkey, EU27, EA19. Since the time series data includes very recent 2 quarters of data under covid conditions, analysis is performed including as well as excluding the covid affected data.

This study answers the following research questions:

a) what are the general trends in labour productivity for Turkey in manufacturing sector, and what can be their possible causes?

b) how do these trends differ when compared with the trends in EU27 and EA19 countries?

c) how are these trends effected by covid pandemic conditions?

d) how can these trends be converted into meaningful forecasts?

The originalities of this paper are as follows: a country-based general trend analysis is provided for Turkey in relation to extreme economic conditions; comparative forecasting analysis is provided for Turkey, EU27 and EA19; and effects of on-going covid on the productivity figures in manufacturing sector are revealed and discussed.

This study differs from the others by providing a comparative perspective, and by revealing the covid effects. Hence, the paper provides an empirical contribution.

It addresses a broad range of academic, business, and governmental audiences interested in macroeconomic indicators and trends, as well as researchers working on the productivity topic from operations and production management field.

Section structure for the rest of the article is as follows: After offering the literature review in Section 1, methodology is given in Section 2. Section 3 offers analysis and forecasting for Turkey. General trends are identified and discussed using regression and ARIMA for Turkey. Section 4 offers analysis and forecasting using regression for EU 27 & EA19, providing a comparison against Turkey for both regression and ARIMA. Section 5 includes the discussion, and the last Section provides conclusion and further research.

1. Literature review

1.1. Multi-dimensional and variable character of labour productivity

Since 1990s, labour productivity is majorly induced by manufacturing industries. Productivity has shown a decelerating trend in developed countries since 1990s, trend starting later in underdeveloped economies. This trend happens while value chains are created and dramatical technological changes take place, which are directly related with higher productivity levels (OECD, 2023).

In the literature, there appears a large degree of variation in labour productivity across countries and regions, variations becoming noticeable at sectoral level. Therefore, the concept represents challenges in terms of compatible comparisons and measurement across countries (OECD, 2023). In this regard, under EU KLEMS Projects by European Union, a standardized database is developed using the input measures including the categories of capital (K), labour (L), energy (E), material (M) and service inputs (S) (ONS, 2007). KLEMS is designed to ensure consistency and a standard base of comparison across countries. In the same direction, another effort of standardization for the measurement of productivity can be mentioned as the matrix development by the Asian Productivity Organization (Nomura & Kimura, 2020).

It is witnessed that a variety of country-based, regional, and multi-country studies are performed by a variety of methods to investigate multiple aspects related with labour productivity. A multitude of research try to show these differences and determine the factors effecting the labour productivity. In this regard, Oosterhaven and Broersma (2007) decomposes regional differences in labor productivity into sector structure, cluster economy and a residual regional component. Beugelsdijk et al. (2018) investigate the role of total factor productivity in explaining significant diversities among European Union countries in terms of economic development. Lishchuk and Kapelyuk (2020) support that labour productivity in the Russion Federation is substantially lower than in the US and European countries; and Vertakova et al. (2019) mention that labour productivity in Russia is about two times lower than the developed countries. In Asada (2020), a comparative six-country East Asia study is offered to analyze the impact of sector-specific labour productivity on the overall labour productivity. Margaritis et al. (2007) put forwards that in the OECD area average gaps in productivity or income levels are reduced, but convergence is not evidenced. Van Biesebroeck (2009) supports industry-based convergence except few industries in 14 OECD countries.

It is well supported that labour productivity has a multi-factor character. Undoubtedly there are a multitude of factors trying to explain variability of the concept in the literature. In this direction, Elshennawy and Bouaddi (2021) identifies average wage, size, manager quality, capital intensity, formality, age, ratio of female labour to total labour and sectoral average wage as the sources of heterogeneity. Dua and Garg (2019) identify technology, macroeconomic variables, capital deepening, institutional quality, and human capital as the significant determinants of labour productivity for both developed and developing economies.

Basic (2020) clearly puts forward that political stability of a country has a serious impact on labour productivity. Country cultures and mentalities are also addressed in literature in relation to labour productivity. The study in Lishchuk and Kapelyuk (2020) highlights national mentalities and cultures of countries to have a significant role in country-based variations and distinctive results. In the same direction, Bakas et al. (2020) supports a significant positive relationship between labour productivity and culture. Effect of Russian mentality is also supported in Vertakova et al. (2019).

Technology in relation to labour productivity is another key aspect that stands out in literature. Lishchuk and Kapelyuk (2020) support that main factor of labour productivity growth is the technology effect, referring to the renewal of the fixed assets and introduction of advanced technologies. Regarding the technology dimension, Kılıçaslan et al. (2007) investigate the relationship among technology, specialization, and manufacturing industry productivity in their cross-country study. They reveal that countries specializing in low technology-intensive production and trade have lower labour productivity and focusing on medium and high-tech industries enhances productivity. It is addressed that managing the low productivity issue has direct relevance to intensifying the technology (Palazuelos & Fernandez, 2009). In this regard, Lishchuk and Kapelyuk (2020) argue that introduction and assimilation of disruptive technologies such as robotics, 3D printing, new materials and production technologies create giant leaps in productivity by reengineering the processes as well as methods, redefining the roles and requirements of labour. Grenčíková and Berkovic (2020) highlight that Industry 4.0 concept significantly affects the labour productivity in countries, leading to productivity improvements. Kılıçaslan et al. (2017) investigate into the relationship with ICT and labor productivity, supporting that ICT investments increase labor productivity. Legros and Galia (2011) provide the evidence that innovation positively affects firm productivity. In the same direction, innovation related with both products and processes increase labour productivity (Woltjer et al., 2021). Coccia (2009) and Castellani et al. (2019) support that R&D investments act as one of the main drivers of productivity improvements. Medda and Piga (2014) put forward that research and development positively affects productivity. It is also well-supported that IT technologies are positively affect labour productivity in OECD countries (Liu et al., 2014; Mecik, 2015; Shahnazi, 2021). Consequently, this section revealed the multi-dimensional and variable character of labour productivity in relation to multiple constructs.

1.2. Turkey perspective

After the trade liberalization efforts of 1980, growth rate of Turkish economy has increased significantly (Mihçi & Akkoyunlu-Wigley, 2009), and fluctuations in total labour productivity are mentioned as the main determinants of ups and downs in the growth rate of Turkish economy. Balkan and Suicmez (2017) provide a comprehensive and comparative study to offer a comparison of Turkey with OECD countries and 121 global countries, including different counties at different levels of development, income groups, continents, and regions of the world. Findings reveal the following: a) during the years 2007–2008, Turkey experienced a drop in labour productivity similar to many other countries in the world; b) for the years 2005–2014, Turkey has experienced an average of 1.65% increase in annual average labour productivity in manufacturing sector; and c) Turkey appears to be 36th in the list of 121 countries in 2005, showing a dropdown of its 43rd position of year 2017. Balkan and Suicmez (2017) revealed that, labour productivity of Turkey in 2012 is approximately 1.5 times above the global average when compared against developed countries, whereas high income countries appear to have labour productivity approximately 2 times higher than Turkey. When compared against EU countries, labour productivity in Turkey appears to be at 68% of EU productivity values.

Türker and İnel (2013) reveal that for Turkey, the contribution of SME s to total value added is 57%, and its contribution is 81.3% to employment, the value being much higher than the OECD countries' average and showing a significantly low level of labour productivity. Besides these studies in Turkey manufacturing sector, Yurtsizoğlu and Kilicaslan (2017) offer a study in Turkish service sector showing that productivity in the service sector of Turkey decreased significantly in 2003–2012 period. The effect of structural change on total labour productivity turned out to be positive, especially for the periods of 2003–2008.

Yildirim (2015) studies three-way relation among real wages, inflation, and productivity in Turkish manufacturing industry, and reveals that effect of inflation on labour productivity is greater than the effect of real wages. Ozcan et al. (2001) also supports that rapid productivity gains in the post-1980 era are not reflected as gains in wages. The study supports that during 2002–2012, labour productivity has shown a sharp increase in Turkish manufacturing industry, majorly caused by a remarkable decrease in both inflation and interest rates. Trend of continual disinflation is mentioned to make an important contribution to powerful productivity growth. Erzan and Filiztekin (2005) also find that decrease in interest rates had an important role in boosting labour productivity in Turkey. Therefore, this section pictured a general Turkey perspective in terms of productivity.

1.3. A variety of methodologies used in productivity-related research

Literature review shows that the following modest classification can provide a general picture regarding the methodologies used in productivity-related research:

Regression-based approaches are frequently used in literature with various forms (linear and nonlinear). Settsu and Takashima (2020) examine the long-term productivity change in Japan using non-linear regression. Dua and Garg (2019) provide a comparative study between developing and developed countries of Asia-Pacific using panel congestion and group-mean fully modified ordinary least squares estimation. In another Asia-Pacific study, Jangam (2021) utilizes dynamic ordinary least squares to estimate long-run elasticities. Bhattacharya and Rath (2020) apply simple ordinary least squares regression to reveal the innovation influence on labour productivity in the comparative study of China and India. Mawejje and Okumu (2018) again use ordinary least square estimation to investigate into skills labour productivity relationship among manufacturing firms in Africa. Hammouda et al. (2010) offers a regression-based study to investigate the relationship among diversification, economic growth and productivity. Herman (2020) uses correlation and regression analysis to investigate the relationship of wages and labour productivity in Romanian manufacturing sector. Cobb-Douglas function is utilized in Brondino (2019), and Calcagnini et al. (2021) analyzed the productivity growth in China and Italy, respectively.

Time-series based approaches are frequently used in literature to analyze various aspects of labour productivity (Singh et al., 2020). Evans (2020) analyses the cyclicality of labour productivity for Australia using a multivariate unobserved components model. Yıldırım (2005) investigates the interrelationships among productivity, real wages, and inflation via quarterly seasonal adjusted data for productivity, real wages and the rate of inflation in Turkey manufacturing industry. Mihçi and Akkoyunlu-Wigley (2009) use fixed effect specification of panel data of 12 manufacturing industries in Turkey to investigate the effect of trade between EU countries and Turkey on the productivity of Turkish manufacturing sector. Under time series analysis, frequent utilization of Autoregressive Integrated Moving Average (ARIMA) method is also well-supported in productivity context to handle the non-stationarity of data (Paul et al., 2013; Samavati, 2013; Perone, 2020; Razak et al., 2017).

Econometric approaches are also frequently used in the literature. Various econometric approaches related with productivity in different contexts are utilized (Melchor-Ferrer, 2020; Ahmed & Kailashaki, 2023; Kim & Patel, 2019; Woltjerv et al., 2021; Roth, 2020; Moussir & Chatri, 2020; Kılıçaslan et al., 2007; Xu et al., 2020; Coccia, 2009). Fatima (2016) is an example of the studies using an econometric approach to study the effects of foreign direct investment on productivity spillovers in Turkey. Mebratie and Bedi (2013) utilized meta-analysis and panel data analysis to investigate the relationship of foreign direct investment with labour productivity in South African context. Labour productivity is considered one of the key variables in the econometric approach of Giordano and Lopez-Garcia (2021).

Structural equation modelling is used in Liu et al. (2021) to investigate the mediating role of labour productivity between absorptive capacity and firm performance. Cristea et al. (2020) again uses SME for analyzing the relationship among economic welfare, ageing and labour productivity in the European Union. Structural decomposition is used in Yurtsizoğlu and Kilicaslan (2017) in a Turkey study.

Various other methods are also utilized in labour productivity studies. Ganau and Rodríguez-Pose (2019) uses a nonlinear time-dynamic model to investigate the degree to which labour productivity is shaped by regional institutional quality in Western Europe manufacturing. Nasirzadeh et al. (2020) propose the use of Artificial Neural Network-based prediction interval to forecast labour productivity using historical data. Based on gravitational growth model, Chugaievska et al. (2020) provide labour productivity simulations for in Ukrainian regions. Balk (2014) and Diewert (2015) utilize a decomposition approach. Essletzbichler and Kadokawa (2010) apply Markov chain analysis, variance shift–share analysis, and analysis of variance, in their study evaluating Japanese manufacturing productivity. Karadağ et al. (2010) employ DEA (Data envelopment analysis) to analyze the improvements in total factor productivity in Turkey. Probabilistic Bayesian networks are also used in various productivity-related contexts. Ko and Han (2015), Khan and Kim (2022) and Hazrati (2016) are three examples utilizing this approach in construction productivity.

Consequently, our literature review supported the multi-dimensional character and variability of labour productivity with a wide range of country-based and region-based studies. Regression and ARIMA appeared as very frequently used methods in productivity-related research. It is striking to note that studies analyzing labour productivity in relation to covid is quite rare due to the recency of the pandemic conditions. Hence, this study contributes to literature by providing a comparative perspective as well as revealing the effect of covid.

2. Methodology

This study utilizes regression analysis and ARIMA methods based on the Eurostat (2021) data of volume index of manufacturing and employment (number of persons employed). These indicators are selected as macro indicators for the manufacturing sector. Both volume index of manufacturing and employment data are seasonally, and calendar adjusted. The data set covers the time interval of 2005/first quarter – 2020/third quarter, corresponding to a 63-period quarterly data in the form of time series for Turkey, EU27 and EA19 countries. In the available data set, volume index of production started from 1986/first quarter whereas labour data set started from since 2005/first quarter. Hence, the analysis period has been selected to start from 2005 first quarter. Summary of the data sets utilized is given in Table 1.

Table 1. Summary of the data sets used in the study

Dataset	Production	Labour	Productivity
Time frequency	Quarterly	Quarterly	Quarterly
Business trend indicator	Volume index of production	Employment (number of persons employed)	Productivity index = (Volume index of production / Employment)
Classification of economic activities – NACE Rev.2	Manufacturing	Manufacturing	Manufacturing
Seasonal adjustment	Seasonally and calendar adjusted data	Seasonally and calendar adjusted data	Seasonally and calendar adjusted data
Unit of measure	Index, 2015 = 100	Index, 2015 = 100	Index, 2015 = 100

As has been highlighted in the review section, regression and ARIMA are well-supported as proven and frequently used methodologies in different contexts.

Various forms of regression are preferrable due to their practicality and ease of use. Regression typically assesses the net effect of a variable on an outcome, allowing for formal estimation of the impact of a cause (Vis, 2012). Regression stands out as a manageable and easily implemented approach providing a robust solution (Schroeder et al., 2016).

Being a mathematically valid and formal forecasting methodology, ARIMA is a widely used and popular forecasting model for univariate time series data (Padhan, 2012). ARIMA is supported to be a generalized approach useful in explaining the dynamics of changes in time for various economical parameters and interruptions (Jarrett & Kyper, 2011; Kohlrausch & Brin, 2020). ARIMA has the autoregressive character with the advantage of handling non-stationarity in the data, hence being more flexible (Paul et al., 2013; Samavati, 2013; Perone, 2020; Razak et al., 2017; Sabry et al., 2007; Mandrikova et al., 2021; Singh, 2013). The systematic and phases of the study followed are depicted in Figure 1.

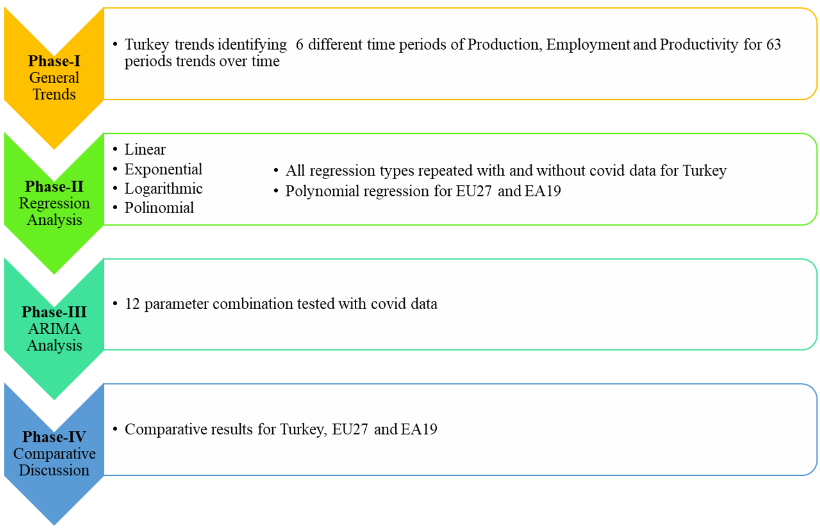

Figure 1. Systematic and phases of the study

As can be seen in this figure, general trends are described in Phase I. Then linear, exponential, logarithmic and polynomial regressions are applied in Phase II. Afterwards, ARIMA is applied to dataset to better handle the non-stationarity. ARIMA approach is repeated with different parameter sets for the following combinations: ARIMA(0,0,1); ARIMA(0,1,1); ARIMA(0,1,2); ARIMA(1,1,0); ARIMA(1,1,1); ARIMA(1,1,2); ARIMA(1,2,1); ARIMA(1,2,2); ARIMA(2,1,0); ARIMA(2,1,1); ARIMA(2,1,2); ARIMA(2,2,2). In this way, results are obtained for Turkey, EU27 and EA19 countries, process being repeated twice (with and without covid affected data) for each regression type and for each ARIMA parameter combination. Forecasting results are discussed across different methods and parameters, and comparisons across Turkey, EU27 and EA19 countries are provided.

3. Analysis and forecasting for Turkey

3.1. General trends for Turkey

Before performing regression and ARIMA analyses, overall picture of the dataset is to be observed for Turkey. For this purpose, plot of seasonally and calendar-adjusted quarterly data for production, employment and productivity indices are obtained using the dataset to identify their individual trends in Figure 2 on the same graph.

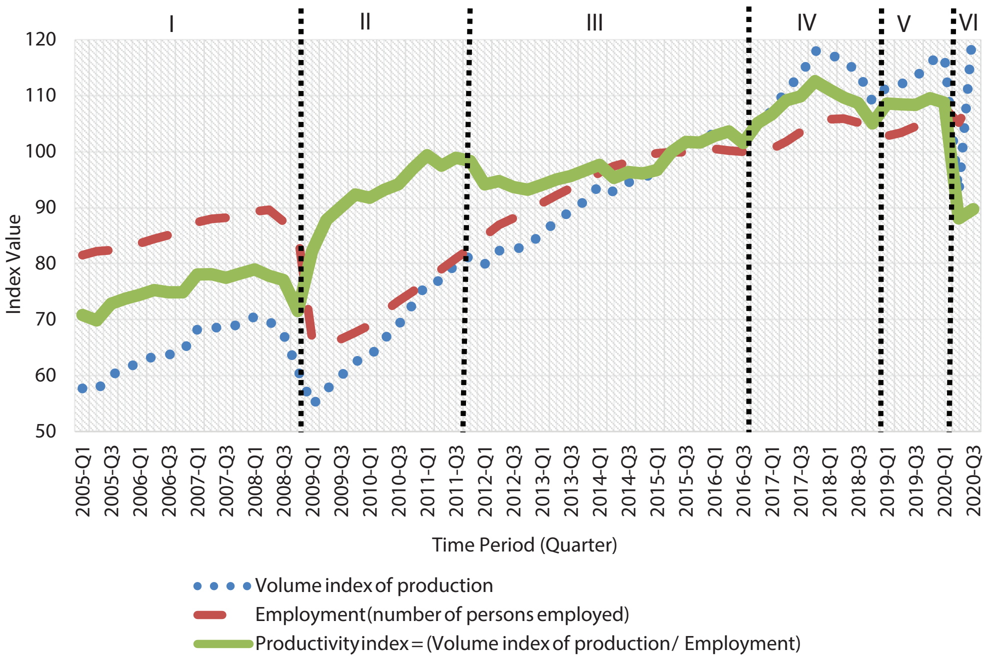

Figure 2. Trend over time for production, employment and productivity for Turkey

This graph can be analyzed in six different regions. Lines separating the regions represent the quarters at which there exist critical trend changes of productivity index. Region-1 exhibits a linear trend with a steady rise. Region-2 shows a convex behavior with a recovery after a sudden drop. This drop can easily be related with the September 2008 Global Economic Crisis, which is well known to have negative effects on various industries in different countries. Region-3 again shows a linear trend behavior with no significant outlier. In this region, an increase is observed in production quite parallel to the increase in employment. It can be argued that production increase is attributable to labour increase. Region-4 reveals a sudden increase followed by a dropdown. It can be highlighted that increase in production and productivity indices are much more dramatic when compared with the increase in employment in this region. This behavior is quite different from the behavior observed in Region-3. Machine intensiveness level appears to increase in manufacturing sector. Presence of new technologies, increasing levels of automation and computerization and more widespread usage of a variety of IT tools and technologies can be effective in manufacturing industry. In Region-5 although a downswing is observed in employment, manufacturing continues to increase. This resulted in a smoothing effect in the productivity line. It can again be argued that impact of decreased labour is tolerated and continued to increase. On the overall, in Regions 4 & 5 dependence on the labour is somewhat reduced for production and productivity. In region-6 a totally different behavior is observed, exhibiting a drastic dropdown. It is evident that this region corresponds to the starting period of covid. Hence, this can be considered as general effect of pandemic, resulting in a significant shrinkage in manufacturing industry.

3.2. Regression analysis and forecasting for Turkey

Based on the employment index, linear regression is performed to reveal the behavior of production and productivity indices. Regression line equations and R^2 values for each of them are depicted in Figure 3.

In regression analysis, R^2 values are indicators of goodness of fit, and values higher than 0,70 are generally considered as highly acceptable (Zikmund et al., 2013). Hence, R^2 values for both regression lines exhibit acceptable goodness of fit. In employment-production graph, a better curve fit is obtained. It can be noted that both regression lines are displaying similar behavior. When the deviations from the regression lines are observed, employment-production graph displays a significant deviation corresponding to Region-2 in Figure 2. Dropdown in Region-2 is reflected as a significant deviation of curve fitting.

Afterwards, linear, exponential, logarithmic and polynomial equations are fitted to the quarterly time series data for productivity. The extreme points observed in 2020 second and the third quarters in the graphs are undoubtedly attributable to the extreme conditions of covid. To reveal the impact of covid, these four types of regression are performed with and without covid effected quarters.

Summary regression results (best equation fitted and R^2 values obtained for each case) are given in Table 2 each case.

Since the last two periods' data represent extreme conditions, a radical increase is observed in the R^2 values for all equations when these periods are included in the analysis. It can be seen that parameters defining the curves are also differentiated.

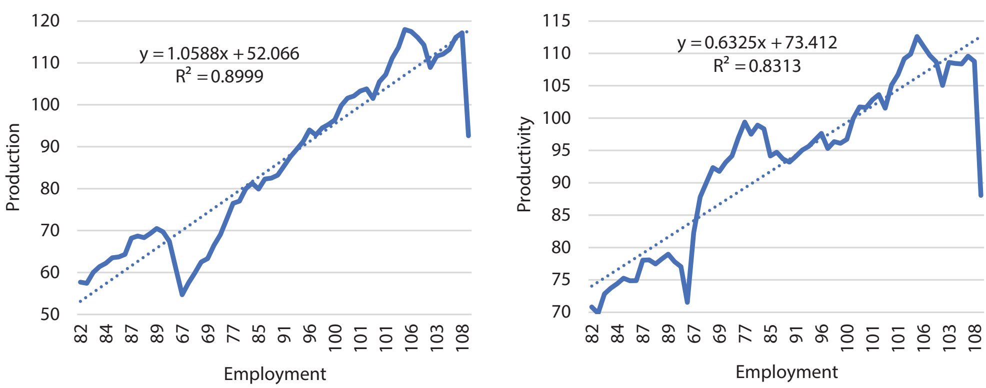

Figure 3. Regression lines for employment-production and employment-productivity indices for Turkey

Table 2. Summary results for the regression analysis for productivity

	Including covid effect		Excluding covid effect	
	Best-fit equation	R^2 value obtained	Best-fit equation	R^2 value obtained
Linear regression	y = 0.5975x + 74.159	0.7772	y = 0.6728x + 72.566	0.8985
Exponential regression	$y = 74.774e^{0.0066x}$	0.7695	$y = 73.515e^{0.0074x}$	0.8807
Logarithmic regression	y = 12.028ln(x) + 54.902	0.7656	y = 12.658ln(x) + 53.428	0.8206
Polynomial regression	y =12.658ln(x) + 53.428	0.8206	$y = -0.0065x^2 + 1.075x + 68.343$	0.9192

When the R^2 values are considered, polynomial equation appears to provide the best fit for both with and without-covid cases. Graph for the best-fitting polynomial regression is given below:

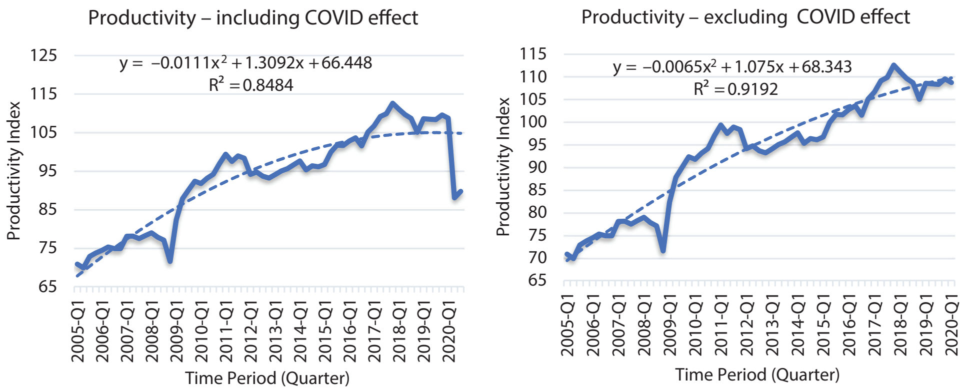

Figure 4. Polynomial regression for productivity with and without covid effect for Turkey (quarters versus productivity index)

It is important to highlight that when compared with the second quarter of 2020 (first period with covid), third quarter of 2020 shows a significant increase, which indicates that dramatic effects of covid in the second quarter are somewhat tolerated in the third quarter. The effect of this recovery can easily be seen in Figure 4. Undoubtedly, the magnitude of the recovery experienced in the manufacturing sector will become clearer as new data becomes available under covid conditions.

Since the regression analysis revealed that polynomial equation provided a better fit, future forecast values are calculated until year 2023/2nd quarter basing on the fitted polynomial curve. In forecasting literature, it is generally supported that 20 percent of the total sample is appropriate to use as the forecast horizon (Otext, 2021; Frost, 2013). Hence, 20% of 63 quarterly periods (12 quarters) is selected to be included in the forecasting horizon. After extending the regression curve to cover 75 quarters. To exclude the covid effect, last two quarters are eliminated from the data set, and regression is reperformed. Actual productivity values and the two regression lines- with and without the covid effect- are plotted on the same graph for Turkey in Figure 5.

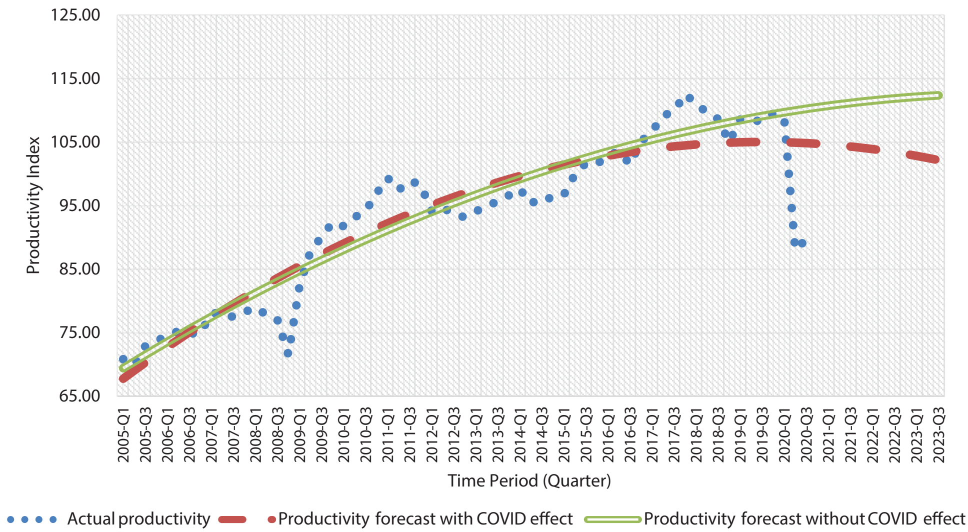

Figure 5. Actual productivity figures and forecasts with and without the COVİD-19 effect plotted on the same graph for Turkey

3.3. ARIMA analysis and forecasting for Turkey

This section offers the forecasting results for Turkey using ARIMA. Considering the non-stationary character of the data set observed from the graph ARIMA methodology is applied. Table 3 offers the compact summary of ARIMA results obtained with different parameter sets. Table 2 shows that based on SSE, MSE, RMSE and WN variance, ARIMA (0,1,1) provided the best result, whereas AIC, AICC and SBC criteria indicate ARIMA (1,2,1) as the best ARIMA solution.

In Table 3, Thiel's Inequality coefficient (TIC) is calculated based on the formula:

$$TIC = \frac{\sqrt{\frac{1}{n}\sum_i^n (x_i - y_i)^2}}{\sqrt{\frac{1}{n}\sum_i^n x_i^2} + \sqrt{\frac{1}{n}\sum_i^n y_i^2}}, \tag{1}$$

where x_i is actual value of the time series and y_i is forecasted value of the time series.

As a summary measure of forecasting accuracy, the use of this coefficient is popular and well-supported in the literature (Leuthold, 1975; Bliemel, 1973; Conceição & Ferreira, 2000), with values closer to zero showing better accuracy. This coefficient is more sophisticated when compared with the standard error measures such as MES or MAPE. The formula uses not only the rooted mean deviations but also utilizes total rooted squares of actual and forecasted values. Hence, it is included in the analysis. For each ARIMA setting, calculated coefficient values are extremely close to zero, which supports the overall consistency and the accuracy of the forecasts. Based on the coefficient values, best value is obtained in ARIMA (1,2,2), which is very slightly different from the best result selected by SSE, MSE, RMSE and WN variance. Therefore, we observe the convergence and accuracy of the results.

Table 3. Summary forecasting results of ARIMA with different parameters for Turkey

Models	ARIMA (0,0,1)	ARIMA (0,1,1)	ARIMA (0,1,2)	ARIMA (1,1,0)	ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (1,2,1)	ARIMA (1,2,2)	ARIMA (2,1,0)	ARIMA (2,1,1)	ARIMA (2,1,2)	ARIMA (2,2,2)
Observations	63	50	50	50	50	50	37	37	50	50	50	37
DF (degrees of freedom)	61	46	44	46	43	41	30	28	44	41	39	26
SSE (sum of squared errors)	3161	569	646	669	626	620	805	516	638	621	621	608
MSE (mean squared errors)	50	11	13	13	13	12	22	14	13	12	12	16
RMSE (root mean ssquare error)	7	3	4	4	4	4	5	4	4	4	4	4
WN (white noice) Variance	50	11	13	13	13	12	22	14	13	12	12	16
MAPE(Diff) (mean absolute percent error- diff)	7	108	124	132	132	131	76	73	132	132	131	73
MAPE (mean absolute percent error)	6.7	1.7	1.8	1.8	1.8	1.8	1.7	1.4	1.8	1.8	1.8	1.5
–2Log(Like.)	427	283	280	280	279	279	243	241	279	279	279	241
FPE (final prediction error)	50	11	13	23	21	21	45	29	40	39	39	94
AIC (Akaike Information Criterion Indicator)	431	291	292	288	293	297	257	259	291	297	301	263
AICC (Corrected Akaike Information Criterion Indicator)	432	292	294	289	295	301	261	265	293	301	308	274
SBC (Schwartz's Bayesian Criteria)	436	299	304	296	306	314	268	273	303	314	322	281
Iterations	24	138	42	8	35	137	111	795	60	70	34	37
Thiel's Inequality coefficient (TIC)	0.0254	0.0107	0.0114	0.0116	0.0112	0.0112	0.0128	0.0102	0.0113	0.0112	0.0112	0.0111

Detailed plots (productivity values, residuals, auto correlograms and partial auto correlograms graphs) are provided for ARIMA (0,1,1) and ARIMA (1,2,1) in Figures 6 and 7. Use of two-periods differencing seemed to result in significantly lower values for lower and upper bound (95%) lines in the graph. Regarding the residual graphs, ARIMA (0,1,1) showed more randomly distributed behavior when compared with ARIMA (1,2,1). The ARIMA process reques reaching stationarity with fast drops in the auto correlogram graph (Sevüktekin & Çınar, 2014). For both ARIMA (0,1,1) and ARIMA (1,2,1) auto correlogram graphs show sudden decrease, therefore supporting that stationarity is reached.

Figure 8 offers a comparative graph of forecasts made by the polynomial regression (best fitting regression obtained in section 5), ARIMA (0,1,1) and ARIMA (1,2,1) results, with and without covid graphs for each. It shows that for the data set containing covid data, both ARIMA (0,1,1) and ARIMA (1,2,1) captures the sudden drop experienced until time period 2020/4th quarter, but after period 2020/1nd quarter a sudden deviation is seen in between the results of ARIMA (0,1,1) and ARIMA (1,2,1) models. On the upper right-side of the curve, two forecast curves obtained by polynomial regression curves (with and without covid data) provide lower and bounds for actual data and ARIMA (1,2,1) without-covid curves, showing the consistency.

When data including covid are considered, it is clear that effect of covid is more amplified with the ARIMA models when compared with the polynomial regression. It seems that deleting the covid-affected data brough the most significant deviation for ARIMA (1,2,1). Consequently, ARIMA (0,1,1) appears to provide a better solution considering the overall picture.

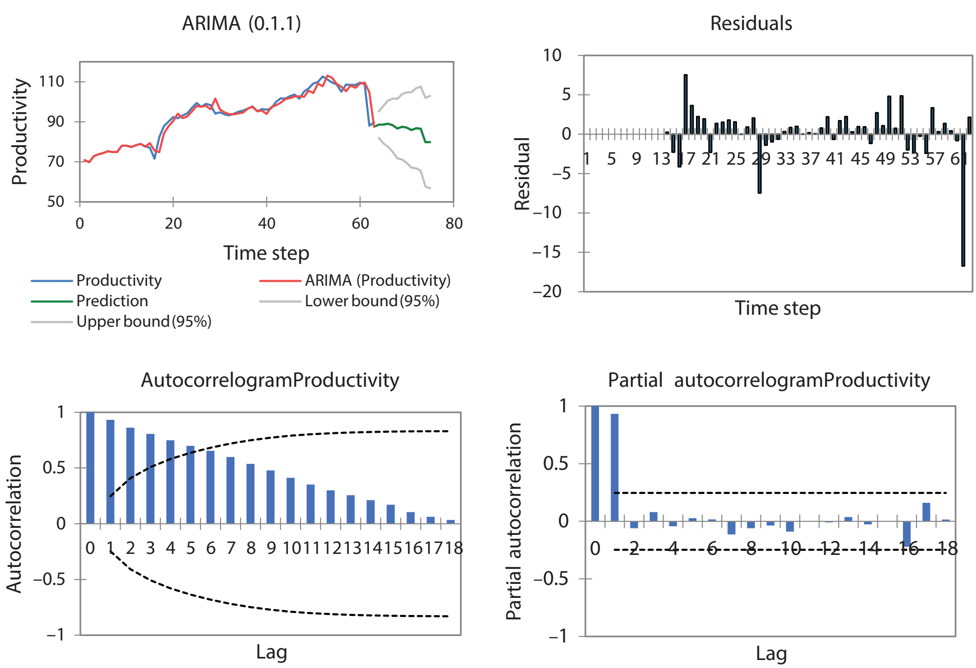

Figure 6. Detailed graphs for ARIMA (0,1,1) for Turkey

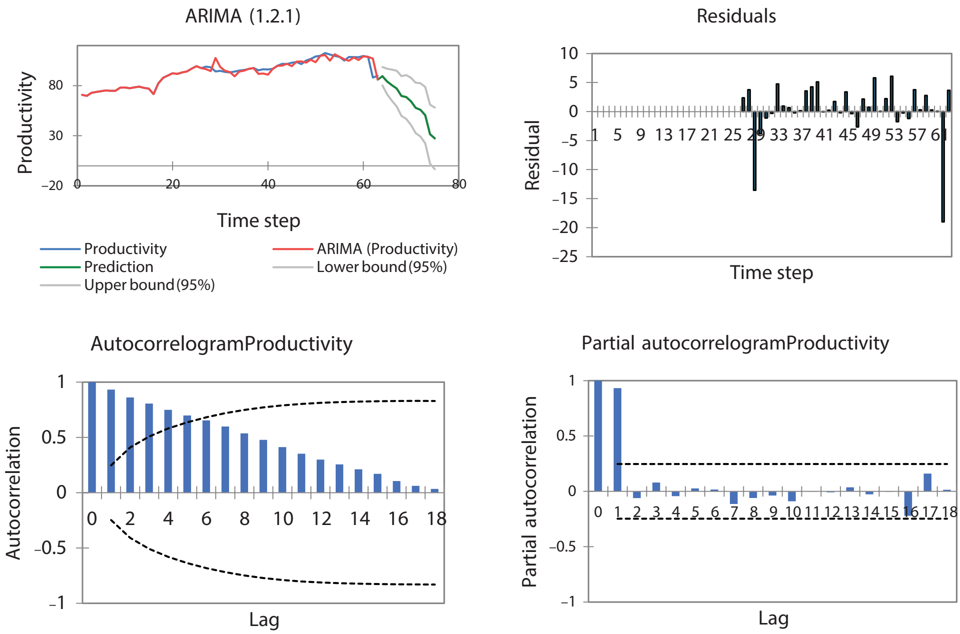

Figure 7. Detailed graphs for ARIMA (1,2,1) for Turkey

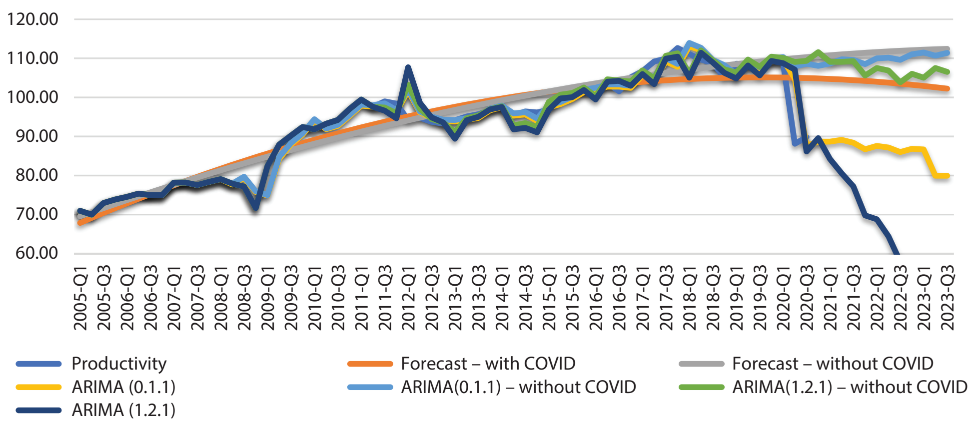

Figure 8. Comparative graph of actual productivity values, polynomial regression forecasts and two ARIMA models of Turkey

4. Forecasting for EU27 & EA19 and comparison with Turkey

In this section of the study, a similar approach is applied to the productivity figures of EU27 (European Union – 27 countries) and EA19 (Euro area-19 countries) countries based on the data from the same EUROSTAT database (European Union, 2021).

4.1. Regression analysis and forecasting for EU27 & EA19

Figure 9 provides the regression results and the forecast (with and without covid effect) on the same graph, again using polynomial regression for EU27.

When Figure 9 is compared with the Turkey graph given in Figure 5, deviation from the regression line is much higher for EU27 for the period 2005 Q1 – 2008 Q3. More sudden and sharper drop down is observed for Turkey in 2008 /Q4, whereas EU27 graph shows decline and recovery during 2008/ Q3 – 2010/ Q3. For the period 2012/Q1 – 2017/ Q1, a better fit is present for EU27 graph. A larger and more dramatic recovery is experienced in period 2020/3 in EU 27 than achieved in Turkey. A better fit in some regions for EU27 can be due to the smoothing effect coming from the accumulation of the data from 27 countries. Furthermore, a much more dramatic drop is experienced in period 2020/2 in productivity figures for EU27, whereas Turkey experienced a drop of smaller degree. Based on the details in the dataset, this can be attributable to the countries Hungary, Slovakia, Portugal, Romania which have experienced decreases above 20%, which is much higher than the EU27 average.

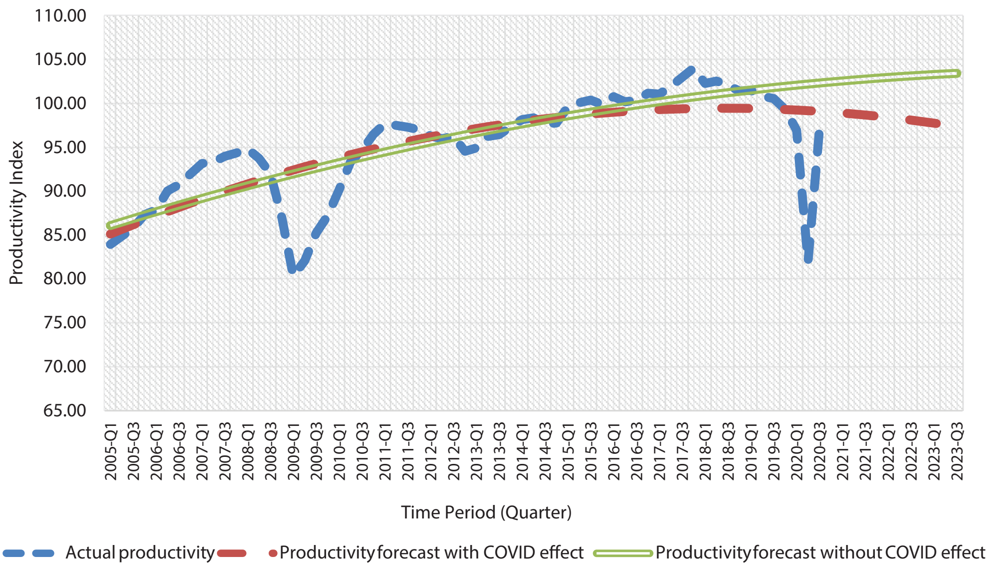

Figure 9. Regression lines with and without the covid effect plotted on the same graph in EU27

An average decrease of 15.48% is observed for EU27 and 15.57% decrease in EA19 countries between 2020/ Q1– Q2 data, whereas Turkey experienced 21.31%. Hence, it appears that Turkey experienced a larger dropdown of productivity due to covid. With the similar logic, Figure 10 provides the regression results and the forecast for EA19 with and without covid effect, on the same graph.

When EU27 and EA19 graphs are compared, a similar trend is observed. A better fit is obtained in 2012 Q1 – 2017 Q1 period for EU27, which appears to be slightly distorted in EA19 graph. Hence, countries not included in EA19 appear to have a smoothing effect for the deviations. Moving towards the right of the graph, deviation between the two forecasts (with and without covid effect) becomes larger especially for EA19 graph.

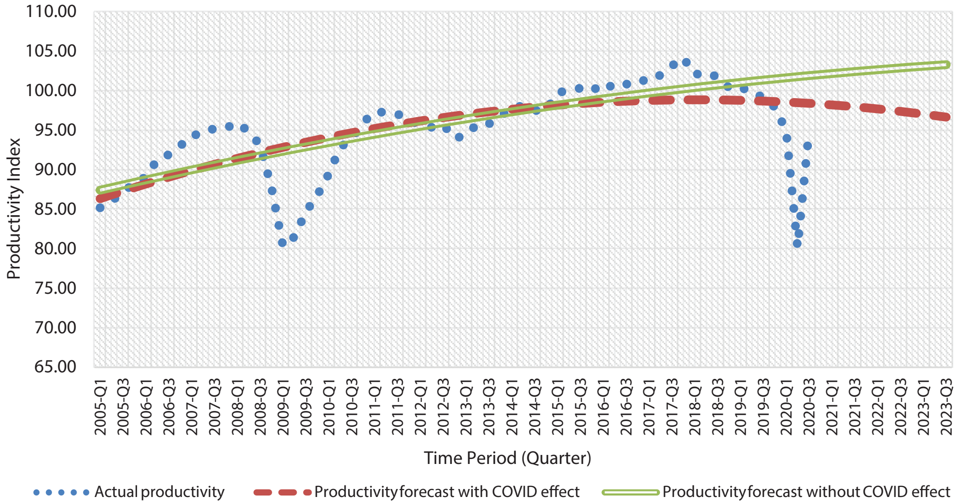

Figure 10. Regression lines with and without the covid effect plotted on the same graph in EA19

Deviations of the forecasted values from two different regression lines are calculated and averaged over the forecast horizon as given the Table 4 for Turkey, EU27 and EA19 countries. Overall mean percent deviation over 12 quarters indicates a 7.07% deviation for Turkey, whereas these values are 4.57 and 5.00 for EU27 and EA19, respectively. It is clear that increased number of countries appears to reduce the overall percent deviation over 12 quarters.

Table 4. Percent deviation of two regression lines (with and without covid effect)

Quarter	Percent deviation of two forecasts – TR	Percent deviation of two forecasts – EA19	Percent deviation of two forecasts – EU 27
2020-Q4	5.20	3.67	3.36
2021-Q1	5.51	3.89	3.56
2021-Q2	5.83	4.12	3.77
2021-Q3	6.16	4.36	3.99
2021-Q4	6.50	4.60	4.20
2022-Q1	6.84	4.85	4.43
2022-Q2	7.20	5.10	4.65
2022-Q3	7.56	5.36	4.89
2022-Q4	7.92	5.62	5.13
2023-Q1	8.30	5.89	5.37
2023-Q2	8.69	6.16	5.62
2023-Q3	9.08	6.44	5.87
Mean Percent Deviation over 12 Quarters	7.07	5.00	4.57

It is important to highlight that these deviations in the forecasted values are created by only two quarters of covid-affected data. Undoubtedly, this deviation can change depending on the length of time period that covid effects will continue. As future data becomes available under covid effect, these regression lines and percentages can easily be refreshed.

4.2. ARIMA analysis for EU27 & EA19

ARIMA results for EU27 utilizing the same parameter set used in section 3 are offered in Table 5.

Table 5 shows that based on SSE, MSE, RMSE and WN variance, ARIMA (1,1,2) provided the best result, whereas AIC, AICC and SBC criteria indicate ARIMA (1,2,1) as the best ARIMA solution. Thiel's inequality coefficients calculated again shows high accuracy. The lowest value obtained in ARIMA (1,1,2) is totally consistent with the selection based on SSE, MSE, RMSE and WN variance.

Same process is repeated for EA19 and ARIMA results are offered in Table 6.

Table 6 presents that based on SSE, MSE, RMSE, WN variance and MAPE, ARIMA (1,1,2) provided the best result, whereas AIC, AICC and SBC criteria indicate ARIMA (1,2,1) as the best ARIMA solution. Thiel's Inequality values calculated provide consistent results, ARIMA (1,1,2) giving the lowest value. It is important to highlight that these two ARIMA models selected are the same for EU27 and EA19. This provides an overall compatibility and consistency check for the analysis.

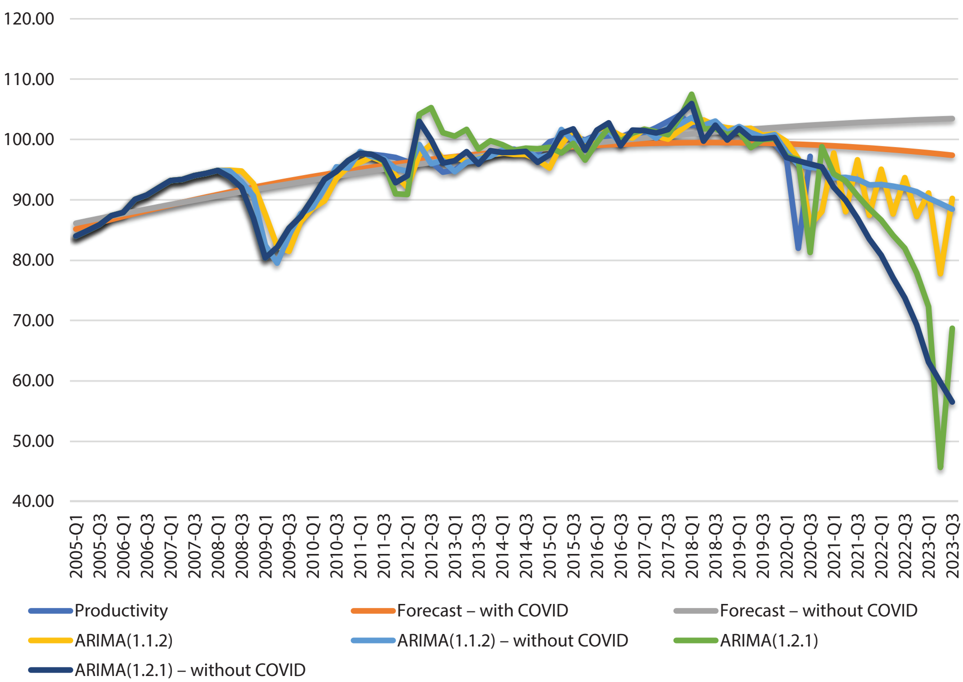

Figure 11. Comparative graph of actual productivity values, polynomial regression forecasts and two ARIMA models of EU27

Table 5. Summary forecasting results of ARIMA with different parameters for EU27

Models	ARIMA (0,0,1)	ARIMA (0,1,1)	ARIMA (0,1,2)	ARIMA (1,1,0)	ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (1,2,1)	ARIMA (1,2,2)	ARIMA (2,1,0)	ARIMA (2,1,1)	ARIMA (2,1,2)	ARIMA (2,2,2)
Observations	63	50	50	50	50	50	37	37	50	50	50	37
DF	61	46	44	46	43	41	30	28	44	41	39	26
SSE	971	637	619	658	603	584	863	807	612	597	596	800
MSE	15	13	12	13	12	12	23	22	12	12	12	22
RMSE	4	4	4	4	3	3	5	5	3	3	3	5
WN Variance	15	13	12	13	12	12	23	22	12	12	12	22
MAPE(Diff)	3	443	1242	811	1079	1226	370	415	1385	1283	1238	335
MAPE	3,01	1,81	1,79	1,88	1,81	1,77	1,86	1,82	1,81	1,78	1,78	1,80
-2Log (Like.)	353	272	271	272	270	270	227	227	270	270	270	226
FPE	15	13	12	22	21	20	49	45	39	38	38	124
AIC	357	280	283	280	284	288	241	245	282	288	292	248
AICC	357	281	284	281	287	292	245	252	284	292	299	259
SBC	361	287	294	288	298	305	253	260	294	305	313	266
Iterations	64	42	33	29	35	37	285	175	57	97	67	56
Thiel's Inequality coefficient	0.0136	0.0431	0.0108	0.0112	0.0107	0.0105	0.0127	0.0123	0.0108	0.0106	0.0106	0.0123

Table 6. Summary forecasting results of ARIMA with different parameters for EA19

Models	ARIMA (0,0,1)	ARIMA (0,1,1)	ARIMA (0,1,2)	ARIMA (1,1,0)	ARIMA (1,1,1)	ARIMA (1,1,2)	ARIMA (1,2,1)	ARIMA (1,2,2)	ARIMA (2,1,0)	ARIMA (2,1,1)	ARIMA (2,1,2)	ARIMA (2,2,2)
Observations	63	50	50	50	50	50	37	37	50	50	50	37
DF	61	46	44	46	43	41	30	30	44	41	39	26
SSE	918	653	641	681	632	618	878	878	639	626	625	825
MSE	15	13	13	14	13	12	24	24	13	13	12	22
RMSE	4	4	4	4	4	4	5	5	4	4	4	5
WN Variance	15	13	13	14	13	12	24	24	13	13	12	22
MAPE(Diff)	3	108	114	111	117	120	185	185	122	120	121	188
MAPE	2,9	1,9	1,9	1,9	1,9	1,9	1,9	1,9	1,9	1,9	1,9	1,9
-2Log(Like.)	349	273	272	274	272	272	228	228	272	272	272	227
FPE	15	13	13	23	22	21	49	49	40	40	40	128
AIC	353	281	284	282	286	290	242	242	284	290	294	249
AICC	353	282	286	283	289	294	246	246	286	294	300	260
SBC	357	288	296	289	299	307	253	253	295	307	315	267
Iterations	4	14	37	31	34	35	259	259	44	59	34	56
Thiel's Inequality coefficient	0.0132	0.0112	0.0110	0.0114	0.0110	0.0108	0.0129	0.0129	0.0110	0.0109	0.0109	0.0125

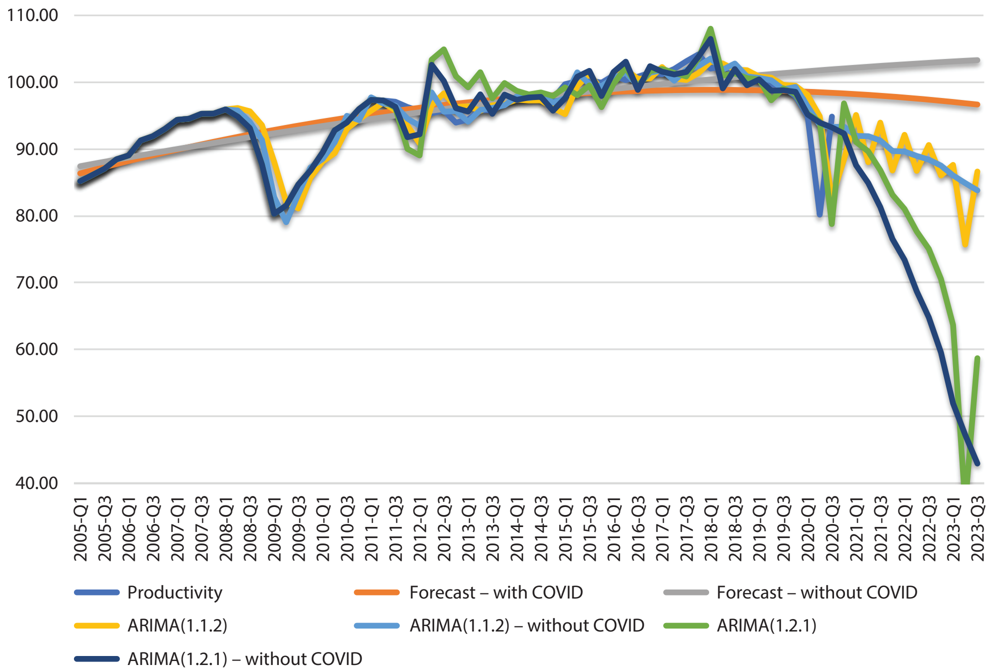

Figure 12. Comparative graph of actual productivity values, polynomial regression forecasts and two ARIMA models of EA19

Comparative graphs of EU27 and EA19 for actual productivity values of polynomial regression forecasts and two ARIMA models are given in the Figures 11 and 12, respectively.

Figures 11 and 12 indicate totally compatible behavior for both regression and ARIMA results. Hence, it can be argued that eight countries excluded from EU27 to EA19 do not seem to have a significant effect on the results. ARIMA (1,1,2) without covid line represented a perfect fit the actual productivity pattern. ARIMA (1,1,2) values for both with and without covid show total compatibility, which was not the case for Turkey.

When compared with the Turkey graph in Figure 8, it is important to highlight that for European countries ARIMA results do not fall into the regression lines with and without covid. Hence, compatibility of the regression results with ARIMA results can be said to be higher for Turkey when compared with EU27 and EA19 countries. When auto correlograms graphs of EA19 and EU27 are considered, analysis shows faster decrease towards stationarity for Turkey.

Discussion

This study of 63 quarters have shown that production, employment, and productivity data trends of Turkey exhibit a steady rise, except for 2008 global economic crisis and 2020 covid pandemic. Regression analysis has shown that polynomial type of equation represented the actual data set better. A similar pattern is also observed for EU27 and EA19 countries. Detailed ARIMA analysis performed for Turkey, EU27 and EA19 with 12 different parameter settings provided very accurate results, supported by Thiel's inequality coefficients calculated in addition to the standard error measures. ARIMA analysis supported consistent patterns between EA19 and EU27 countries. ARIMA (1,1,2) giving the lowest value. This scenario is providing a very low Thiel's inequality coefficient value for Turkey too, surpassed by a very slight improvement by the scenario ARIMA (0,1,1). It can also be highlighted that ARIMA results represents better compatibility with the regression results for Turkey.

During the analysis, effect of covid pandemic became apparent, resulting in a dramatic decrease in productivity figures for Turkey, EU27 and EA19 countries alike.

Analysis has shown that pandemic has resulted in larger deviations in the forecasted values for Turkey when compared with EU27 and EA19 countries. It seems that all countries are trying to recover from the effects of pandemics in terms of productivity by increasing their industrial production. In the literature there is strong support that in case of dramatic crises, output does not recover to its pre-crisis trend, and in the medium run it may remain well below pre-crisis trends (Balakrishnan et al., 2009). Our analysis also supported this, and it can be argued that countries still need some time for full recovery.

Our analysis revealed that Turkey has demonstrated significant recovery for all these indices. During the pandemic conditions, Turkey has successfully demonstrated its ability to provide rapid response to dynamically changing crisis conditions with its qualified human capital. In this regard, Turkey appears to have an advantage with a strong health infrastructure when compared with European counterparts. This can be justified by significant investment in the establishment of 19 huge city hospitals with 1.1 million health care workers, 246.000 hospital beds and 40.000 intensive care bed capacity in various cities (Primepropertyturkey.com, 2022). This fact has enabled Turkey to handle the covid pandemic with rapid response. The presence of these hospitals can change the picture in terms of further recovery of the productivity values. Thus, the recovery observed in Turkey can be easily attributable to our prior health investments.

However, by looking at the deviations between the forecast values with and without pandemic, it can be argued that both EU27 and EA19 countries showed a faster recovery when compared to Turkey. This significant variation in the speed of recovery across different countries and uneven effects of the pandemics are also supported in OECD Compendium (2021) and ILO (International Labor Organization [ILO], 2021). Balakrishnan et al. (2009) and OECD Compendium (2023) highlight that proactive domestic macroeconomic policies and structural policy reforms may mitigate the losses in the medium run. During the pandemic conditions, Turkey has taken significant macro-economic measures concurrently with the EU countries to minimize the economic effects of pandemics. Unrequited financial supports are provided to especially SME's and most covid-affected sectors such as tourism and all other service sectors, and legal bans have been imposed for firing the workers to protect the employment. In principle, these macro-economic measures taken in Turkey are similar with the ones in EU countries. Nevertheless, magnitudes of these supports and budget availabilities are undoubtedly different, which can explain different recovery rates. It is also the fact that based on OECD Health Report health expenditure per capita for 2022 in Turkey is 908 euro, whereas this value is 3.159 euro in EU average (OECD, 2022). This significant difference of more than three times can be the reason for the Turkey's slower recovery identified during the analysis in Section 4.1.

Undoubtedly, pandemic conditions are still in effect and vaccination efforts are still undergoing all through the world. Further tough financial measures to support firms and debt restructuring may still be needed for the countries. Consequently, it can be argued that many countries may be forced to apply such structural changes and measures.

Conclusions and further research suggestions

This study has revealed the trends in productivity in Turkey, EU27 and EA19 countries, put forward forecasts and related them with general macroeconomic conditions. 2008 global economic crisis and covid pandemic appeared to be the main events that have radically affected the productivity figures. The comparison has shown that all countries are affected by the pandemics, showed similar declining patterns but different recovery rates.

The paper is valuable in providing both Turkey perspective and a comparative study with the Eurozone, enabling forecasting under covid conditions, and showing the covid effect on the forecasted figures. A country-based analysis and a comprehensive general trend analysis are offered by relating the changes to key macroeconomic conditions for Turkey. Comparative forecasting analysis is also provided for Turkey, EU27 and EA19 until the end of 2023/quarter 3. Effects of on-going covid on the productivity figures in manufacturing sector are revealed and discussed. It is useful in showing the productivity gaps, and positioning Turkey with respect to Eurozone, as well as offering suggestions to policy makers in Turkey.

The following can be offered as the suggestions to guide the policy makers:

Further policies (income, monetary and fiscal) should be designed with an SME-focus, considering the dominance of SME's (99% of the enterprises) in Turkey.

Turkey has to increase the health expenditure per capita values to the EU levels.

Sound policies towards less protected labor force (such as people working in service sector, especially women, very young and old people, freelancers, increasingly employed immigrants) and job retention policies will also be effective in mitigating the covid effects.

Consistent and sound digitalization policies for the workforce to support work from distance are needed.

With the overall trend of shifting towards more technological manufacturing systems, investments in IoT related technological components undoubtedly will gain importance. The correct balance between the use of labour resources and technology intensive resources will be determining the competitiveness among countries. In this context, investment in IT infrastructure and various recent technologies such as; computerization, automated warehouse systems, robotics, blockchain, and any consistent country based strategy towards these technologies will surely change the picture.

In a more technological context, policies towards improving the technological skills of the labour, their education and training will be affecting the productivity figures.

Policy and strategy development, planning and resource allocation should take into consideration the general shift from manufacturing to service sector, which is a more labour-intensive sector.

Country based differences of labour productivity values and different recovery rates identified in this study can be eliminated by cross collaboration across countries as well as sharing knowledge and innovation. In this regard, policies towards enabling cross-border collaboration will be valuable.

Evidently, covid pandemic has intensified the VUCA world conditions. The world is passing through extreme conditions (covid, war conditions, high inflation, and earthquakes). These may significantly affect the future data that will be upcoming. Hence, productivity figures can be subject to further variation in the near term. Upon ending of the pandemic conditions, significant recovery of the production and employment index values may be expected in the medium term. Undoubtedly, pandemic conditions still prevail. Therefore, further impact of covid on the productivity are to be observed.

The main limitations of the study are data availability and non-existence of comparable data before 2005. Data availability is restricted with Euro Zone Countries, not allowing for a global analysis.

The authors believe that this study opens up the following further research avenues: a) depending on the data availability, further comparative studies can be performed comparing Turkey and other developed countries outside the eurozone, b) comparisons can also be based on other different country groupings, c) the study focused on manufacturing sector, further similar studies can be performed in other sectors such as service, and d) as new data under covid effect becomes available, similar approaches can be followed to further analyze and reveal the covid effect, e) further data availability may lead to longitudinal studies.

Author contributions

The authors collaborated in all the sections of the paper, and both authors participated in the conceptualization, analysis, writing, revising and finalizing the paper.

Disclosure statement

There is no conflict of interest.

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