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TÜRKIYE'S EXPORT COMPETITIVENESS BY PROVINCE: FORECASTING WITH MACHINE LEARNING

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TÜRKIYE'S EXPORT COMPETITIVENESS BY PROVINCE: FORECASTING WITH MACHINE LEARNING

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ABSTRACT

TÜRKİYE'S EXPORT COMPETITIVENESS BY PROVINCE: FORECASTING WITH MACHINE LEARNING

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The importance of export competitiveness for development has increased. The efficiency of the strategies, policies, and incentives should be carefully considered for export competitiveness. Within the scope of this study, the export competitiveness of Türkiye was analyzed by province and manufacturing sector. İstanbul, İzmir, and Kocaeli stand out regarding Türkiye's exports, which were determined as pilot provinces for the competitiveness analysis. Also, traditional and machine learning techniques for forecasting were examined and the export of provinces was forecasted by arima, boosting, and neural network. Comparing the accuracy of the models, arima was selected for competitiveness analysis. Competitiveness analyses were conducted with RCA index. The data at 2-digit levels according to ISIC Rev.4 were used from TurkStat. Accordingly, while İstanbul was competitive in 12 sectors, 2 high, 4

medium-high, 2 medium-low, and 4 low technology, in 2021, it is estimated that İstanbul will be competitive in 9 manufacturing sectors in 2024. İzmir was competitive in 2 medium-high, 3 medium-low, and 6 low technology sectors, and it is predicted that it would be competitive in 8 sectors in 2024. Kocaeli was an export competitor in 1 high, 2 medium-high, and 4 medium-low-technology manufacturing sectors in 2021 while it would be competitive in 6 sectors in 2024. It is suggested that this study, which is carried out by sector, should be expanded with analyses on the basis of product/product groups for all provinces in Türkiye. Hence, especially incentives and strategies should be evaluated in line with the findings.

Keywords: Export competitiveness, regional development, forecasting with machine learning, ARIMA, RCA

ÖZET

TÜRKİYE'NİN İL BAZINDA REKABETÇİLİĞİ: MAKİNE ÖĞRENMESİ İLE TAHMİN

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Kalkınma açısından ihracat rekabetçiliğinin önemi giderek artmaktadır. İhracat rekabetçiliği açısından stratejilerin, politikaların ve teşviklerin verimliliği dikkatle ele alınmalıdır. Bu çalışma kapsamında Türkiye'nin il bazında imalat sektörleri, ihracat rekabetçiliği açısından değerlendirilmiş ve gelecekleri tahmin edilmiştir. İstanbul, İzmir, Kocaeli, Türkiye ihracatı açısından öne çıkmaktadır. Bu iller, çalışma kapsamında rekabetçilik analizleri için pilot iller olarak belirlenmiş ve imalat sektörleri rekabetçilikleri incelenmiştir. Bunun yanında, geleneksel ve makine öğrenmesi ile tahmin yöntemleri araştırılmış ve ihracat projeksiyonları için arima, boosting ve neural network modelleri kullanılmıştır. Tahmin güçleri karşılaştırılarak arima, rekabetçilik analizleri için seçilmiştir. İllerin ihracat projeksiyonları üzerinden ise RCA indeks ile rekabetçilik analizleri gerçekleştirilmiştir. Çalışmada ISIC Rev.4

sınıflamasına göre iki basamak seviyede TÜİK verileri kullanılmıştır. İstanbul 2021'de 2 yüksek, 4 orta-yüksek, 2 orta-düşük ve 4 düşük teknoloji olmak üzere 12 sektörde rekabetçi iken 2024 yılında 9 imalat sektöründe rekabetçi olacağı tahmin edilmektedir. İzmir ise 2 orta-yüksek, 3 orta-düşük ve 6 düşük teknoloji sektörde rekabetçidir ve 2024 yılında 8 sektörde rekabetçi olacağı öngörülmektedir. Kocaeli, 1 yüksek, 2 orta-yüksek ve 4 orta-düşük-teknoloji imalat sektöründe ihracat rekabetçisi iken 2024 yılında 6 sektörde rekabetçi olması beklenmektedir. Sektör bazında yapılan bu çalışmanın tüm iller için ürün/ürün grubu bazında analizler ile genişletilmesi ve özellikle teşviklerin, stratejilerin bulgular doğrultusunda değerlendirilmesi önerilmektedir.

Anahtar Kelimeler: İhracat rekabetçiliği, bölgesel kalkınma, makine öğrenmesi ile tahmin, ARIMA, RCA

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To My Family…

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LIST OF ABBREVIATIONS

ACF	Autocorrelation Function
AI	Artificial Intelligence
ANN	Artificial Neural Network
AR	Autoregression
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
CAGR	Compound Annual Growth Rate
EC	European Commission
EU	European Union
GRU	Gated recurrent unit networks
HWES	Holt's Winter Exponential Smoothening
ISIC Rev.4	International Standard Industrial Classification of All Economic Activities Revision 4
LSTM	Long Short-term Memory Networks
MA	Moving Average
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
NAR	Nonlinear Autoregressive
OECD	Organization for Economic Co-operation and Development
PACF	Partial Autocorrelation Function

RCA	Revealed Compared Advantage
RNN	Recurrent Neural Network
SARIMA	Seasonal Autoregressive Integrated Moving Average
SARIMAX	Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors
SES	Simple Exponential Smoothening
TurkStat	Turkish Statistical Institute
VAR	Vector Autoregression
VARMA	Vector Autoregression Moving Average
VARMAX	Vector Autoregression Moving Average with Exogenous Regressors

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CHAPTER 1

INTRODUCTION

Nowadays, the continuous development of technology and production techniques increases the importance of following trends and being competitive in terms of sustainability. In addition, in terms of socioeconomic development, export is crucial for countries, which is directly related to competitiveness. Moreover, regional development is also significant and necessary for countries. With regard to this, export competitiveness is an essential topic for Türkiye in terms of socioeconomic and regional development, and sustainability. When these are considered, it is expected that especially supporting the areas in which provinces are/can be competitive would positively impact Türkiye's overall competitiveness and development. Therefore, in this study, competitiveness analyses in the manufacturing sectors of Türkiye on a provincial basis were carried out and predictions for the future were conducted. The paper aims to determine the manufacturing sectors in which provinces were/are/will be competitive and highlight the importance of competitiveness in designing regional and sectoral incentives, strategies, and policies.

What is competitiveness? There are several definitions for competitiveness. At its most basic, competitiveness means outperforming competitors in a subject. Although the competitiveness of countries is a result, welfare level, development, and socioeconomic effects can be improved by increasing competitiveness. Nowadays, competitiveness has become dramatically significant, especially for policymakers. Identifying the areas where countries are competitive and designing strategies and policies within this scope are of great importance in terms of the effect to be created. Therefore, when competitiveness is evaluated at the country level, it can be considered as the topics and areas in which the country is ahead compared to its competitors in target markets.

The competitiveness of countries has started to be developed not only with the strategies designed for the country but also by considering the competitiveness of regions/provinces. It is essential to prioritize areas already competitive in the region or potentially competitive by considering several factors specific to the region for

specialization and hence the expected impact. This situation is called "smart specialization". According to OECD (2013), smart specialization is an industrial and innovation framework for regional economies that aims to illustrate how public policies, framework conditions, and especially R&D and innovation investment policies can influence the economic, scientific, and technological specialization of a region and consequently its productivity, competitiveness, and economic growth path. According to the European Commission (2023), the smart specialization strategy is a strategy that will allow public resources to differentiate the region from other regions and focus on a limited number of activity areas where it has a comparative advantage.

Smart specialization differs from the traditional development approach in many ways. In particular, the field of activity and the governance structure contain differences from the traditional approach. In terms of the field of activity, the emergence and support of specific areas with high evidence-based potential, especially for the product/product groups of the region, is crucial for smart specialization. Comparative advantages of the regions are compared with a systematic approach and include benchmark analyses considering national/international best cases. In addition, it aims to identify and focus on the areas of activity of the region where not only technology but also all kinds of innovations. Owing to it, regions that are not technology leaders can gain a comparative advantage. This situation can provide equal development throughout the country instead of making certain regions stand out too much. Regarding the governance structure, the smart specialization strategy adds the society to private, public, education and research institutions and ensures that all stakeholders are united around a common vision.

The research question in this thesis is, "How will the export competitiveness levels of manufacturing sectors change in İstanbul, İzmir, and Kocaeli, which stand out in Turkish exports, in 2024?". Encouraging production and increasing productivity in these provinces, which are essential for the country's trade balance, are also crucial for the country's strategy and development. In terms of socioeconomic impact, it is also necessary to understand the current situation in these provinces, determine future strategies, and design policies considering these strategies.

Within the scope of this study, the prominent manufacturing sectors and their competitiveness in İstanbul, İzmir, and Kocaeli were estimated. While analyzing the competitiveness of these provinces, training periods and forecasting methods are also compared to discuss the accuracy of different models that are arima, boosting, and neural network. The most important motivation here is to set an example for the strategy design regarding the welfare and development of the country. This study is designed as a pilot study and it is recommended that the analyses conducted here should be carried out at the product level and specific to all provinces, and also incentives and policies should be designed accordingly.

In this thesis, literature related to competitiveness and forecasting methods with machine learning has been reviewed and presented in Chapter 2. In addition, Chapter 3 explains the methodology and gives information about the data and forecasting methods. Afterward, in Chapter 4, the current situations of the manufacturing sectors in İstanbul, İzmir and Kocaeli were analyzed, different forecasting methods were compared for time series forecasting, and the forecast results were presented in detail with the best performing method. Then, using these estimates, the competitiveness of the provinces was predicted for 2024. Besides, errors related to the estimation methods are also presented in this section, and the error rates and comparison analyses of methods are also given in the appendix. Finally, in chapter 5, all of these are summarized, and the conclusion is presented.

CHAPTER 2

LITERATURE REVIEW

In the literature, many studies have been published by academic and international organizations on competitiveness, the competitiveness of countries, sectoral competitiveness, and competitiveness by region. However, at the same time, data science has attracted attention as a field that has increased in importance in recent years, which provides input to many fields. In this regard, especially with technology development, data collection, data processing, and analysis methods are constantly being developed. Besides, artificial intelligence and machine learning methods are the most prominent topics. Recently, machine learning methods have been used for various purposes in the field of international trade.

The concept of competitiveness has been developed by different economists and discussed with different methods. For competitiveness, first of all, dealing with the theory of "absolute advantage" developed by Adam Smith is necessary. Smith (1776) argues that a country has an absolute advantage over another country in producing a certain good if it can produce the good more efficiently at a lower cost than the other country, as shown in his book The Wealth of Nations. One of the oldest contributions to the literature on international trade is the theory of absolute advantage which is still a key idea in modern economics. The theory states that both countries can profit from trade if they focus on manufacturing items with a comparative advantage, even if one country has an absolute advantage in producing all goods. If a country can manufacture a good at a lower opportunity cost than another, it has a comparative advantage. In addition, David Ricardo stated that a country does not need to have an absolute advantage over another country in order to carry out international trade in his work titled "On the Principles of Political Economy and Taxation" published in 1817 (Miral, 2006).

Compared to the other country, the country makes fewer resource uses to create that good. Both countries may boost their total economic efficiency and prosperity by focusing on industries where they have a comparative advantage and engaging in trade with other countries. Many years after David Ricardo, Balassa (1965), in his article

"Trade Liberalization and Revealed Comparative Advantage", determined an index to explain the revealed comparative advantages (RCA) of countries. Balassa's revealed comparative advantage index is a measure in international trade that quantifies a country's comparative advantage in producing a particular good compared to other countries, which is widely used as a tool to analyze the comparative advantage of countries in international trade and to provide input to trade policy decisions.

The RCA index is frequently used, especially when analyzing the competitiveness of the entire country or the country level of a sector/product group. For example, Büyükbağrıaçık (2021) has examined the development of Türkiye's revealed comparative advantages for the years 1990-2017 and it has been determined that the products or product groups that Türkiye has a competitive advantage in are generally labor-intensive products with low value-added or product groups that can be produced with low or medium technology. In addition, in the study by Ardıç, it has been determined that Türkiye has a comparative advantage in exports of herbal products, food industry products, textile products, glass and glassware, metals, and vehicles (Ardıç, 2017). Moreover, in Halife (2022), it is aimed to analyze the Turkish textile industry by using the RCA approach. As a result of the study, it has been determined that Türkiye's textile industry has a positive competitiveness trend.

In addition, machine learning methods have recently attracted attention in the literature regarding international trade and forecasting methods. The World Bank (Breinlich et al., 2021) is an example that shows the importance of data science in evaluating the effects of trade agreements, especially in the fields of impact and forecasting, along with other disciplines. Within the scope of this study, machine learning and time series forecasting methods are especially focused. "In statistics, the primary goal of forecasting is to provide valuable information for decision making, economic and business planning, inventory and production control, control and optimization of industrial process." (Boukary, 2016). In addition to that, there are important issues for time series analysis, which are;

- Complicated or statistically sophisticated methods do not always result in more precise projections than less complex ones.

- Depending on the accuracy metric being utilized, different approaches perform differently relative to one another.
- On average, accuracy, when different approaches are combined, outperforms the individual methods being combined and performs quite well in contrast to other ways.
- The length of the forecasting horizon involved determines how accurate the various methods are (Bharatpur, 2022).

Time series models can be especially preferred due to their simplicity. Indeed, the variable tried to be estimated can also be affected by many other factors. In time series forecasting models, determining, and analyzing trends is essential. Trends can change for many reasons. However, external factors or unpredictable events, such as the COVID-19 pandemic, can make trend analysis particularly difficult. In addition, machine learning has many advantages for time series forecasting, the development of automated algorithms (Boukary, 2016), accuracy control with train & test methods, and more accurate results are the main ones. With machine learning, automated algorithms can be developed that can be considered more traditional methods, and various new methods are being developed as an alternative. Especially recently, alternatives that are easier to use have been created for the benefit of different disciplines. An example of this is The Prophet Forecasting Model, which is "a practical approach to forecasting at scale that combines configurable models with analyst-in-the-loop performance analysis" (Taylar & Letham, 2017, p.1).

With these developments, the comparison of the models and the determination of the methods that give the most accurate results is a subject of particular interest. In this context, various studies are carried out and prediction models, especially machine learning methods and traditional methods are compared. Moreover, machine learning methods are also compared among themselves. In the paper (Duenas et al., 2021), different machine learning techniques in forecasting the trade status of firms were investigated in terms of effectiveness and the ML techniques were compared. They compared six models, which are Logit, Logit-Lasso, Classification Tree, Random Forest, Support Vector Machine, and Extreme Gradient Boosting. They concluded that Logit-Lasso is the best option within the list by comparing the R2, area under the

receiver operating curve, precision-recall, balanced accuracy, and F1-score for the positive class (Duenas et al., 2021). In addition to that, in the paper (Batarseh et al., 2019), the importance of forecasting for trade was emphasized and the machine learning techniques were considered in order to allow more accurate predictions to inform policy decisions. Machine learning models including ARIMA, GBoosting, XGBoosting, and LightGBM for estimating the future trade patterns were performed as well as K-Means clustering of countries considering the economic factors (Batarseh et al., 2019). It is concluded that "The experimental work in this article indicates the high relevance of ML for predicting a range of trade patterns with a greater accuracy than traditional approaches." (Batarseh et al., 2019, p.4).

Research discussed so far shows that machine learning methods are especially powerful in terms of their performance and prediction power while revealing that their importance in different fields is gradually increasing. Machine learning methods provide an opportunity for policymakers to forecast international trade and design strategies, develop policies, and predict their effects.

As well as the competitiveness and forecasting with machine learning, COVID-19 is a significant issue. The COVID-19 pandemic is a global health crisis that began in late 2019 and continues to impact today's world. The pandemic has caused considerable disruptions to daily life, including school closings, business closures, and travel restrictions, in addition to widespread illness, hospitalization, and death. Lockdowns, mandatory mask use, and vaccine campaigns are just a few of the strategies that governments have used to limit the virus's spread. A significant effect of the pandemic on the world economy has been widespread job losses and financial difficulties. Therefore, the COVID-19 pandemic, which is a significant issue in terms of international trade, has led to changes in the trends of countries and sectors. Hence, it is a situation that should be considered especially for 2020.

Considering export competitiveness, machine learning and forecasting methods, and the COVID-19 pandemic, it has been observed that there is a need for competitiveness analyses that will be necessary for determining Türkiye's forward-looking strategies and developing policies/incentives. Furthermore, these analyses are important in terms of the steps to be taken to give an idea about the future. The fact

that the research on competition analyses is specific to the country or a sector shows that there is a gap in the competitiveness analysis by province and sector. Due to that, it is thought that export competitiveness analysis is needed considering the current situation and forecasts at the provincial and sectoral level, considering innovative methods. This study aims to fill the gap at the provincial and sector level analysis in the literature with data science methods. In addition, it is hoped that the study will contribute to Türkiye's export competitiveness as well as development and sustainability at the provincial level, and thus to competitiveness and economic development at the country level.

CHAPTER 3

METHODOLOGY

Within the scope of this thesis, the current situation and future projections of the export competitiveness of the provinces in the manufacturing sectors were analyzed. In the study, time series forecasting models and machine learning methods were also examined, and competitiveness analyses were carried out on the basis of province and sector in terms of exports. İstanbul, İzmir, and Kocaeli, which are crucial for Türkiye's export, were selected as pilot provinces, and analyses were conducted for these provinces.

First of all, the data to be used within the scope of the study was decided and were collected from TurkStat and were prepared for analysis. Subsequently, the study started with the research of time series forecasting models. Afterward, time series forecasting models with machine learning were examined. In addition, arima (autoregressive integrated moving average), boosting, and neural network models are examined in detail, which are used to compare difference methods in terms of predictive power. In addition to the models, training period was also examined by taking care of the COVID-19 period in order to assess the predicting power in shocks periods and the trends after. Due to that, the training periods of 2013-2018 and 2013-2021 were compared by considering the in-sample and out-of-sample performances of each model. With regard to this, the training period of 2013-2018 was examined by using 2013-2018 as in-sample and 2019-2022 as out-of-sample and compared with mean absolute percentage error (MAPE) considering the actual and forecasted values. In addition, for the training period of 2013-2021, the performances of models were tested considering the 2013-2021 as in-sample and 2022 as out-of-sample by using MAPE. İstanbul’s manufacturing export by sector is used to perform these analyses. With regards to these comparisons, the training period of 2013-2021 was selected due to the relatively better accuracy level and the performance for catching the trends after COVID-19 pandemic. Furthermore, since it is selected for the detailed analyses considering the comparison with boosting and neural network in terms of out-of-sample performance, future projections for the manufacturing sectors of İstanbul, İzmir, and Kocaeli were analyzed using the arima model with machine learning

techniques. In addition, the accuracy of the forecasts using arima was tested with MAPE (mean absolute percentage error) by comparing the forecast results with actual data for 2022 for each province and each sector. Finally, the export competitive manufacturing sectors in İstanbul, İzmir, and Kocaeli were determined by RCA (revealed comparative advantage) analysis, and future predictions were conducted. The details of the methodology are demonstrated below.

3.1. Data

Within the scope of this thesis, export data of Türkiye on a provincial basis and according to the International Standard Industrial Classification of all Economic Activities Revision 4 (ISIC Rev.4) were used from the Turkish Statistical Institute (TurkStat). The data is published on a monthly basis and in TL, USD, and EURO for the years 2013-2021.

The export data is publicly available in the TurkStat as foreign trade statistics (General Trade System), which covers cross-border trade in goods between Türkiye and other countries. According to TurkStat, it is defined as follows "within the scope of foreign trade statistics according to the general trade system; the flow of goods (export-import), reference period, customs, product code and name, country (country of origin for import, last known country for export), nationality of the carrier, mode of transport, customs regime, statistical value (export FOB, import CIF), net weight (kg), supplementary unit (pieces, square meter, cubic meter, etc.), delivery terms, type of payment information are presented.".

In addition, the coverage of the data is presented below as in TurkStat.

Table 3.1 The Coverage of the Data from TurkStat

Items included	Items excluded
• Normal export and import procedures • Under customs inward and outward processing procedures • Border trade	• Transit trade • Shuttle trade • Temporary import and export • Commodities not crossed the border

• Imports by financial leasing • Non-monetary gold • Re-export/re-import • Returned goods	• Monetary gold, means of payment which are legal tender, securities (HS 710820, 4907) • Goods for repair and maintenance • Goods imported/exported by operational leasing

The example of the data is also illustrated below.

Table 3.2 Example Data Used from TurkStat

Yıl	Ay İsmi	İl Adı Detaylı	ISIC Rev4 (2 Digit) Adı Detaylı	İhracat Dolar	İhracat Euro	İhracat TL
2022	12-Aralık	41 - KOCAELİ	32 - DIğer Imalatlar	3577232	3383432	66802561
2022	12-Aralık	35 - İZMİR	32 - DIğer Imalatlar	21804627	20658064	406984632
2022	12-Aralık	34 - İSTANBUL	32 - DIğer Imalatlar	577792004	547402375	10782481594
2022	11-Kasım	41 - KOCAELİ	32 - DIğer Imalatlar	5521609	5371771	102873092
2022	11-Kasım	35 - İZMİR	32 - DIğer Imalatlar	21109344	20847370	393128704
2022	11-Kasım	34 - İSTANBUL	32 - DIğer Imalatlar	659084160	648755466	12274413944
2022	10-Ekim	41 - KOCAELİ	32 - DIğer Imalatlar	2785751	2839526	51803264

The analyses were conducted at 2-digit level for İstanbul, İzmir, and Kocaeli, which are the prominent provinces in terms of the total export in Türkiye, on a monthly basis for 2013-2021. Furthermore, in order to test the accuracy of the forecasts, MAPE is used and presented in the appendix.

3.2. Time Series Forecasting

Evaluating the current situation and making predictions based on the past is a situation that will always be needed in every field. It is important and makes a serious contribution in terms of predicting the future, determining strategies, policy design, and actions to be taken. Regarding the estimation of future trends, forecasting is a technique that makes trained assumptions using historical data as inputs. There are two ways to forecast, which are the qualitative and quantitative methods. Intuition, expert opinions, stakeholder reflection, and discussion are the examples for the qualitative forecasting approaches. In addition, univariate, bivariate and multivariate forecasting approaches are covered under the quantitative approach in which one variable appears in a univariate time series, two appear in a bivariate time series, and more than two appear in a multivariate time series.

There are several advantages of time series forecasting although there are some disadvantages. One of the most important advantages of time series forecasting is its high accuracy and simplicity. It can be used to examine the relationships between changes in the selected data point and changes in other variables over the same period. It can give useful output with fewer variables. As regression models fail with fewer variables, time series models would work better and more effectively (Bharatpur, 2022). However, one of the situations to be careful of for time series forecasting is that overfitting. In addition, the period of forecasting also affects the performance of the model.

Briefly, time series forecasting is based on the notion that one can predict the future by knowing the past. The primary concept of time series analysis typically involves interpreting the future in light of the past. In connection with this, there are serious developments in accessing and using data today. Big data's importance has increased, affecting the models and methods used in time series predictions.

3.3. Machine Learning Forecasting Models

Today, with the development of technology and alternative data collection methods, access to data is becoming easier and easier. This situation increases the size of the data to be analyzed, which is called "big data". With the increase in data size and diversity, there are also developments/improvements in analysis methods.

"Machine learning", which is heard in many fields today and is a subfield of artificial intelligence (AI), basically refers to the idea that a computer program can pick up new information and adapt without human involvement. Prediction with machine learning allows models to train and test results. In this way, results can be obtained and compared with different algorithms.

Machine learning is divided into two as supervised and unsupervised learning. The use of labeled datasets distinguishes the machine learning strategy known as supervised learning. These datasets are intended to "supervise" or "train" algorithms to correctly classify data or forecast outcomes (Delua, 2021). In addition to supervised learning, machine learning algorithms are used in unsupervised learning to examine and group unlabeled data sets. These algorithms are referred to as "unsupervised"

because they identify hidden patterns in data without human intervention (Delua, 2021). Supervised and unsupervised learning algorithms are used to respond to different problems. As can be seen in the table below, supervised learning is for classification and regression whereas unsupervised learning is used for clustering, association, and dimensionality reduction.

Table 3.3 The Areas of Supervised and Unsupervised Learning

	Supervised Learning	**Unsupervised Learning**
Discrete	Classification	Clustering
Continuous	Regression	Dimensionality reduction

Various algorithms are used to find answers to problems that can be addressed under supervised and unsupervised learning, which are presented in the table below and are not limited to.

Table 3.4 Supervised and Unsupervised Learning Methods

Machine Learning			
Supervised Learning		Unsupervised Learning	
Classification	**Regression**	**Clustering**	**Dimensionality reduction**
Support Vector Machines	Linear Regression	K-Means	Principal Component Analysis
Naive Bayes	Logistic Regression	Hierarchical	Factor Analysis
K-Nearest Neighbor	K- Nearest Neighbors	Artificial Neural Network	
Decision Trees	Decision Trees		
Artificial Neural Network	Artificial Neural Network		
Discriminant Analysis	Ensemble Methods		

In addition to these, the following models have been used for time series forecasting (Bharatpur, 2022).

- Autoregression (AR)
- Moving Average (MA)
- Autoregressive Moving Average (ARMA)
- Autoregressive Integrated Moving Average (ARIMA)
- Seasonal Autoregressive Integrated Moving Average (SARIMA)
- Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX)
- Vector Autoregression (VAR)
- Vector Autoregression Moving Average (VARMA)
- Vector Autoregression Moving Average with Exogenous Regressors (VARMAX)
- Simple Exponential Smoothening (SES)
- Holt's Winter Exponential Smoothening (HWES)

Several machine learning methods have been developed for time series forecasting, and also traditional methods have been used with machine learning techniques. With regard to this, arima, boosting, and neural network were examined in the next sections.

3.4. ARIMA

Time series analysis has several benefits, including spotting trends, cleaning data, finding outliers, and predicting the future. For time series forecasting, it is also essential to analyze trends, seasonality, and heteroscedasticity. The trend is the thing of an increasing or decreasing pattern across time. The occurrence of events in a cyclical pattern is referred to as seasonality. After some time, a pattern starts to emerge (Bharatpur, 2022). Additionally, heteroscedasticity refers to the situation in which the standard deviations of predicted variables are not constant compared to earlier periods or various values of an independent variable. An autoregressive integrated moving average (ARIMA) uses time series data to forecast future trends or to comprehend the

current data collection better. Thus, the export of İstanbul, İzmir, and Kocaeli was predicted using the ARIMA model.

In the ARIMA model, "AR" means autoregression, which is modeling the dependent relationship between observation and a set of lagged observations. "I" refers to integrated and it is used for making the time series stationary by differencing of observations. "MA" is the moving average that forecasts a series based on the past error in the series called error lags. ARIMA models are used on non-stationary series, but by difference-taking to make stationary. Standard notation for ARIMA models would be ARIMA with p, d, and q, where integer values stand in for the parameters to denote the type of ARIMA model being employed.

- p: the number of lag observations in the model; also known as the lag order.
- d: the number of times that the raw observations are differenced; also known as the degree of differencing.
- q: the size of the moving average window; also known as the order of the moving average.

In addition, the mathematical formulas of AR (p), I (d), MA (q) are as follows (Hyndman & Athanasopoulos, 2018).

The formula of autoregressive (AR) is as below in which p is the lag order, ε is the white noise, c is constant and φs are parameters;

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t \quad (1.1)$$

The formula of integrated (I) is as below where d is the degree of differencing and B is a backshift operator;

$$y'_t = (1 - B)^d y_t \quad (1.2)$$

The formula of moving average (MA) is as below where q is the order of the moving average;

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \quad (1.3)$$

At the end, the general formula of ARIMA (p, d, q) model by combining all is as below.

$$y'_t = c + \emptyset_1 y'_{t-1} + \emptyset_2 y'_{t-2} + .. + \emptyset_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + .. + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (1.4)$$

ARIMA model is useful considering the flexibility, catching the trends, handling the missing data. However, it should be considered that deciding the best model for ARIMA by choosing the p, d, q is important as well as the stationarity to get more accurate results. Thus, the autocorrelation function (ACF), partial correlation function (PACF), and Augmented Dickey-Fuller Test were used. The best model by sector for each province is selected by using the auto.arima in Rstudio. In addition, Boz-Ljunt Test was performed for validation. Furthermore, the accuracy was tested for each forecast of province and sector with mean absolute percentage error (MAPE). In addition to that, Rstudio and Tableau were used for the data visualization.

3.5. Boosting

Boosting is a widely used technique in machine learning within ensemble models. This technique is used to combine weak estimators to form a stronger estimator. Boosting is especially preferred for classification and regression, which was developed by Freund and Schapire (Robinzonov et al., 2011).

The basic approach of the boosting method is to train the estimators cumulatively. Predictive models typically use decision trees. After each tree has been trained using a modified version of the original dataset, an efficient classifier is produced. Whereas boosting models are generally used to improve the performance of forecasting models, they are also used for forecasting. Frequently used boosting models are as follows;

- Adaboost,
- Gradient Boosting,
- XGBoost,
- LightGBM.

Gradient boosting models stand out for the successful outcomes they provide in a wide range of regression and classification use cases as the other boosting models.

In recent years have used in the forecasting and proved that they are capable of producing outcomes that are competitive. That's why, it has been chosen to compare with arima and neural network. In addition, one of the main advantages of boosting is including the non-linear relations, which is also important for the time series forecasting. However, there could be overfitting problem for these models, at the same time. Therefore, it could be preferred or not depends on the performance of the model considering the using area and data (Hastie et al., 2017).

The gradient boost algorithm is as follows (Natekin & Knoll, 2013, p. 3).

Inputs:

- Input data $(x, y)_{i=1}^{N}$
- Number of iterations M
- Choice of the loss-function $\Psi(y,\ f)$
- Choice of the base-learner model $h(x, \theta)$

Algorithm:

1. Initialize $\widehat{f_0}$ with a constant
2. For $t = 1$ to M do
3. Compute the negative gradient $g_t(x)$
4. Fit a new base-learner function $h(x, \theta_t)$
5. Find the best gradient descent step-size ρ_t:

$$\rho_t = argmin_\rho \sum_{i=1}^{N} \Psi\left[y_i, \widehat{f_{t-1}}(x_i) + \rho h(x_i, \theta_t)\right] \quad (2.1)$$

6. Update the function estimate:

$$\widehat{f_t} \leftarrow \widehat{f_{t-1}} + \rho_t h(x, \theta_t) \quad (2.2)$$

7. End for

Within the scope of this, gradient boosting model is used to forecast and compare with arima and neural network. The package gbm (gradient boosted models) in R used to establish the model and conduct the analyses.

3.6. Neural Network

While deep learning is a sub-field of machine learning, Neural Network is a deep learning model developed by considering neural networks in the human brain. Artificial neural networks are used for different purposes in many sectors and fields such as image processing, language processing, finance, medicine and manufacturing. Some of the artificial neural networks models are feedforward neural networks, convolutional neural networks, recurrent neural networks, and self-organizing maps. In addition, artificial neural networks are also used for time series forecasting. Some of the artificial neural network models used for time series predictions;

- Recurrent neural network (RNN),
- Long short-term memory networks (LSTM),
- Gated recurrent unit networks (GRU),
- Artificial Neural Network (ANN),
- Nonlinear Autoregressive (NAR).

Models such as artificial neural network and nonlinear autoregressive are used to perform nonlinear modelling as an alternative. Neural networks have a number of advantages, such as requiring less formal statistical training, having access to a variety of training algorithms, and being able to implicitly detect complex nonlinear relationships between dependent and independent variables (Dumitru & Maria, 2013). Although neural networks are strong in terms of accuracy and model selection, there could be over-fitting problem in the forecasting with neural networks.

In addition, the architecture of the nonlinear autoregressive neural network model (NAR) is as follows. As it is shown in the figure below, the model is trained by using past values (Benrhmach et al., 2020).

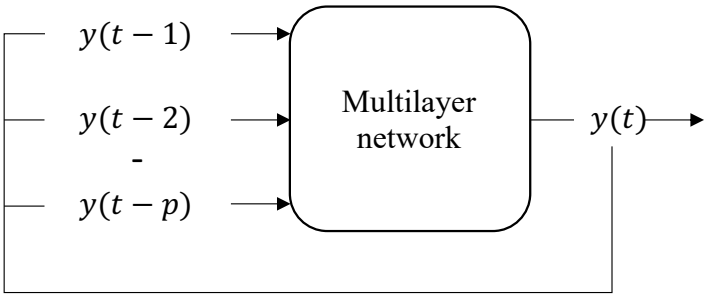


Figure 3.1 Achitecture of the Nonlinear Autoregressive Neural Network

Besides, the general mathematical formula of the NAR is as below in which (Benrhmach et al., 2020);

$$Y_t = \alpha_0 + \sum_{j=1}^{k} \alpha_j \emptyset\left(\sum_{i=1}^{a} \beta_{ij} Y_{t-i} + \beta_{0j}\right) + \varepsilon_t \quad (3.1)$$

- a: the number of entries
- k: the number of hidden layer with activation function $\emptyset$
- β_{ij}: the parameter corresponding to the weight of the connection between the input unit i and hidden unit j
- α_j: the weight of the connection between the hidden unit j and the output unit
- β_{0j} and α_0 are the constants

Within the scope of this work, nonlinear autoregressive (NAR) model was used to predict İstanbul, İzmir and Kocaeli's export in the manufacturing sectors and also compare with arima and boosting models. Nonlinear autoregressive model is an alternative to forecast with nonlinear data comparing the traditional autoregressive models. The "nnetar" function in the forecast library in R was used to establish the model.

3.7. Export Competitiveness: RCA

David Ricardo's theory of comparative advantage states that countries can benefit from trade even if one country is more efficient in producing all goods compared to the other. According to Ricardo, trade should be based on a country's comparative advantage, which is the product they can produce at a lower opportunity cost than other products. David Ricardo's comparative advantage theory is based on

Adam Smith's theory of absolute advantage and underlines the importance of the areas in that countries should specialize. On top of that, Bela Balassa developed the comparative advantage index based on the theory in the 1960s. According to Balassa (1965), a country should possess comparative advantages for a certain commodity if its exports of that product exceed its share at the level of the trade area under consideration (Stellian & Buitrago, 2022).

In addition, at the country level, the comparative advantage of a country in certain sectors or product groups compared to other countries could be due to different reasons such as cost advantage, logistics advantages, quality, etc. The important thing here is first to determine in which areas the country is competitive or has potential. Revealed comparative advantage (RCA) is used to measure export competitiveness, which means that "it is based on Ricardian trade theory, which posits that patterns of trade among countries are governed by their relative differences in productivity." (UNCTAD, 2018). The formula of RCA index is demonstrated below.

$$RCA = \frac{\frac{sp}{tp}}{\frac{ST}{TT}} \tag{4.1}$$

where;

- sp: export of the industry in the province
- tp: total export of the province
- ST: export of the industry in Türkiye
- TT: total export of Türkiye

RCA analysis can be applied at different levels. In this study, RCA was preferred since the export competitiveness of the provinces was tried to be estimated. Theoretically, the universe is considered as Türkiye and the countries as the provinces of Türkiye. With regards to this, RCA analysis has been conducted to determine the competitive sectors specific to the province, and in the analysis, the ratio of the province's exports in the sector to the total exports in the province is the ratio of the sector's exports in Türkiye to Türkiye's total exports. If this ratio is greater than one (RCA≥1), it means that the province is competitive in the sector.

Within the scope of this, RCA analyses were conducted at 2-digit level according to ISIC Rev.4 classification, and sector definitions and codes are presented in the table below (TurkSTAT, 2023).

Table 3.5 ISIC Rev.4 Sector Codes and Definitions

ISIC Rev. 4	**Definition**	**Short Definition**
C.10	Manufacture of food products	Food
C.11	Manufacture of beverages	Beverages
C.12	Manufacture of tobacco products	Tobacco
C.13	Manufacture of textiles	Textiles
C.14	Manufacture of wearing apparel	Wearing apparel
C.15	Manufacture of leather and related products	Leather
C.16	Manufacture of wood and of prod. of wood and cork except furniture; manuf. of articles of straw and plaiting materials	Wood
C.17	Manufacture of paper and paper products	Paper
C.18	Printing and reproduction of recorded media	Recorded media
C.19	Manufacture of coke and refined petroleum products	Coke and refined petroleum
C.20	Manufacture of chemicals and chemical products	Chemicals
C.21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	Pharma
C.22	Manufacture of rubber and plastics products	Rubber and plastics
C.23	Manufacture of other non-metallic mineral products	Non-metallic mineral
C.24	Manufacture of basic metals	Basic metals
C.25	Manufacture of fabricated metal products except machinery and equipment	Fabricated metal

C.26	Manufacture of computer electronic and optical products	Computer electronic
C.27	Manufacture of electrical equipment	Electrical equipment
C.28	Manufacture of machinery and equipment n.e.c.	Machinery
C.29	Manufacture of motor vehicles trailers and semi-trailers	Motor vehicles
C.30	Manufacture of other transport equipment	Other transport
C.31	Manufacture of furniture	Furniture
C.32	Other manufacturing	Other manufacturing

CHAPTER 4

EXPORT COMPETITIVENESS BY PROVINCE: THE CASE OF İSTANBUL, İZMİR, KOCAELİ

4.1. Rationale

Some provinces/regions stand out in terms of Türkiye's export and also export competitiveness. These provinces, which directly contribute to the development of the country, are the regions where production is intense. In addition, in terms of competitiveness, each province can have an advantage in one area compared to the other. For this reason, although the provinces that attract attention in the total export volume are prioritized, all provinces are also crucial in terms of export competitiveness and therefore the development of the country.

Within the scope of this study, 3 provinces with the highest export value of Türkiye, which are İstanbul, İzmir, and Kocaeli, were examined as cases. As can be seen in the figure below, İstanbul, İzmir, and Kocaeli are the provinces that highest export values in 2021. According to TurkStat, Türkiye exported approximately 225 billion USD in 2021, of which 48% is İstanbul, 7% is İzmir and 5% is Kocaeli. In other words, approximately 60% of Türkiye's exports are made from these 3 provinces. Due to that, especially considering the export competitiveness of İstanbul, İzmir, and Kocaeli while determining the future strategies of Türkiye is necessary for the impact to be created.

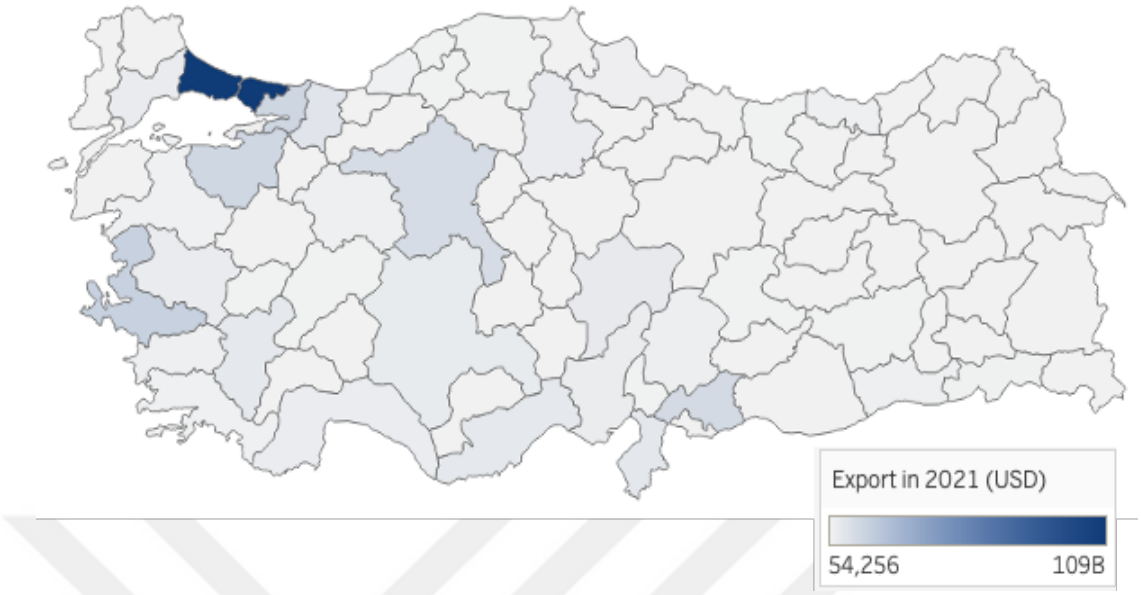


Figure 4.1 Türkiye's Export by Province in 2021 (USD)
Source: TurkStat

In this study, 3 provinces were examined in detail. However, it should not be forgotten that all provinces can be competitive in different sectors. Therefore, although the inclusiveness of this study is high in terms of Türkiye's exports, it is important to evaluate the remaining provinces, especially in terms of the development of provinces and regions.

4.2. Recent Trends in Export

In terms of the total export performances of İstanbul, İzmir, and Kocaeli in the 2013-2021 period, it is observed that there is a stable trend. İstanbul has an export value of approximately 82 billion USD in 2013. Although it decreased to 78 billion USD in 2016, there is an increase in the export performance of İstanbul between 2016-2019. Between 2016 and 2019, it reached 89 billion USD with a compound annual growth rate of 5%. Furthermore, the actual rise took place in 2021 after the COVID-19 pandemic (in 2020), and İstanbul has an export of 109 billion USD in 2021.

When İzmir is examined, while it had an export value of 11 billion USD in 2013, it experienced a decrease in 2015 and 2016 like İstanbul but caught its previous performance with 18 billion USD in 2018. After the COVID-19 pandemic, İzmir experienced a serious increase in 2021 and hosted 15 billion USD of exports in 2021.

In addition, in Kocaeli, the trend between 2013-2021 is similar to İstanbul and İzmir. Kocaeli has an export value of 9 billion USD in 2013 and 10 billion USD in 2019. Exports, which fell to 8 billion USD in 2020, recovered in 2021 and reached 12 billion USD with a performance beyond its previous performance. In the figure below, the total export values (in billion USD) of İstanbul, İzmir, and Kocaeli between the years 2013-2021 are presented.

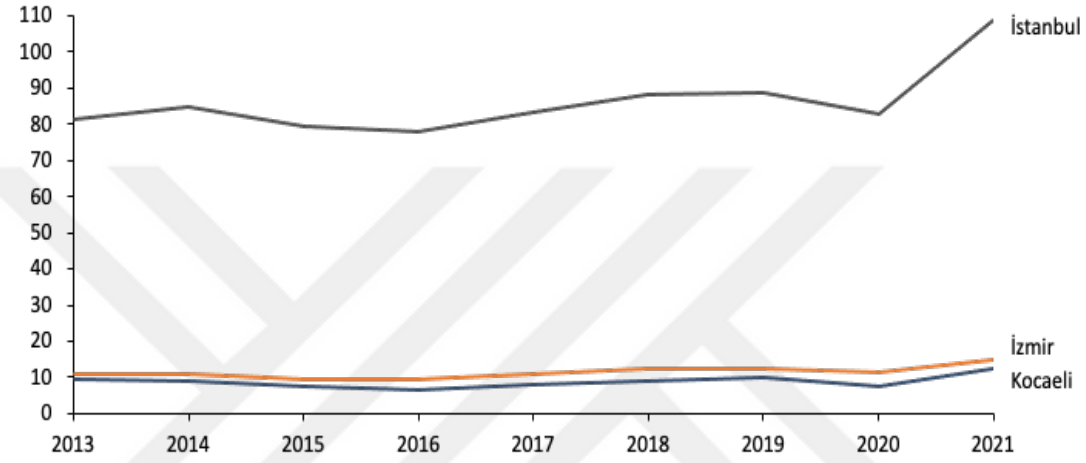


Figure 4.2 İstanbul, İzmir and Kocaeli's Export by Year (2013-2021, bn USD)
Source: TurkStat

İstanbul, İzmir, and Kocaeli are important provinces for Türkiye in terms of export performance in manufacturing sectors as well as their total export performance. In the figures below, İstanbul, İzmir, and Kocaeli are examined separately for the manufacturing sectors.

İstanbul has an export value of ~107 billion USD in manufacturing sectors in 2021. Looking at the breakdown of manufacturing sectors, the manufacture of basic metals comes first with ~16 billion USD in exports. The second most exported sector is the manufacture of wearing appeal with ~15 billion USD, while manufacture of motor vehicles trailers and semi-trailers is the third most exported manufacturing sector with ~14 billion USD. These sectors are followed by the manufacture of electrical equipment, manufacture of chemicals and chemical products, respectively. While the export performances of the sectors over the years generally showed a similar trend, the manufacture of basic metals experienced a significant increase in 2021. İstanbul’s export by sector and year is illustrated in the figure 4.3.

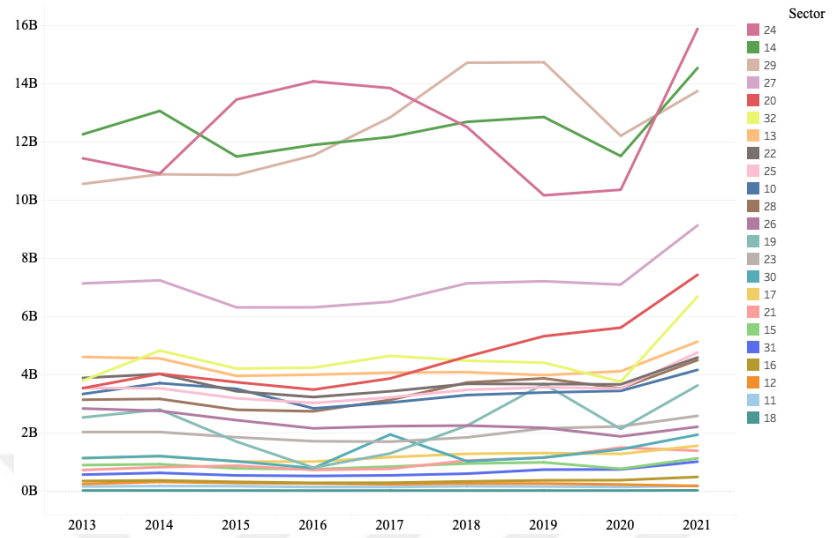


Figure 4.3 İstanbul's Export by Sector and Year (billion USD, 2013-2021)
Source: TurkStat

When the performances of the manufacturing sectors in İstanbul are examined for the years 2013-17-21, it is seen that the 3 prominent sectors are the same over the years, but there is a relatively significant increase in the manufacture of basic metals. On the other hand, the manufacturing sectors with the least exports in İstanbul are printing and reproduction of recorded media, manufacture of tobacco products and manufacture of beverages.

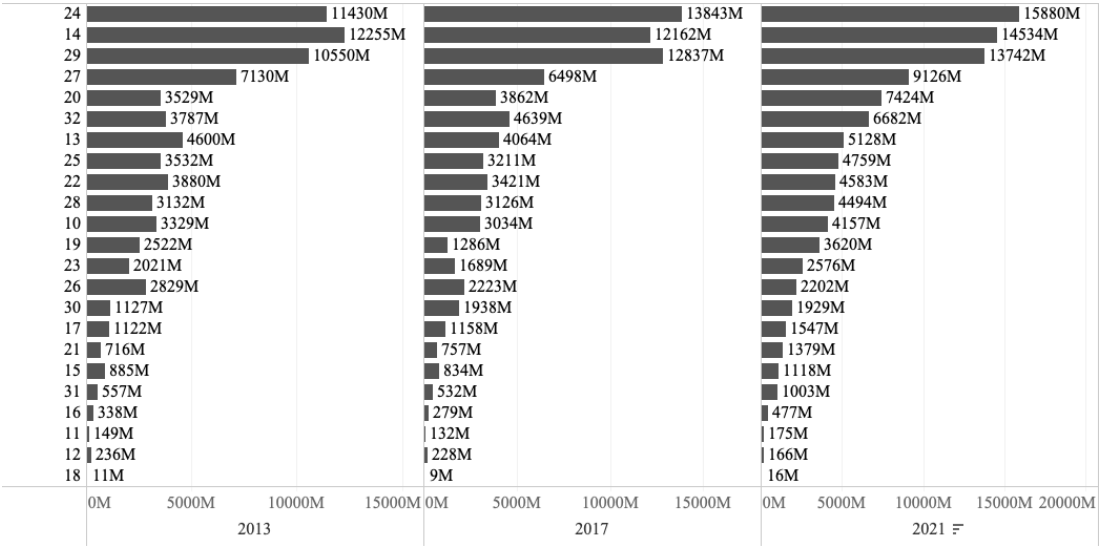


Figure 4.4 İstanbul's Export by Sector (million USD, 2013-17-21)
Source: TurkStat

Manufacturing sectors in İstanbul have a positive compound annual growth rate (CAGR) in 2013-2021, excluding the manufacture of tobacco products and the manufacture of computer electronic and optical products sectors. The manufacture of chemicals and chemical products is the manufacturing sector that has grown the most in terms of exports in the 2013-2021 period, with a CAGR of 10%. Following this, the manufacture of basic pharmaceutical products and pharmaceutical preparations with 9% CAGR, and the manufacture of furniture with 8% CAGR were the manufacturing sectors that grew the most. In addition, in 2021, the manufacture of basic metals, which has the highest export value, grew with an average of 4% CAGR in the manufacturing sectors.

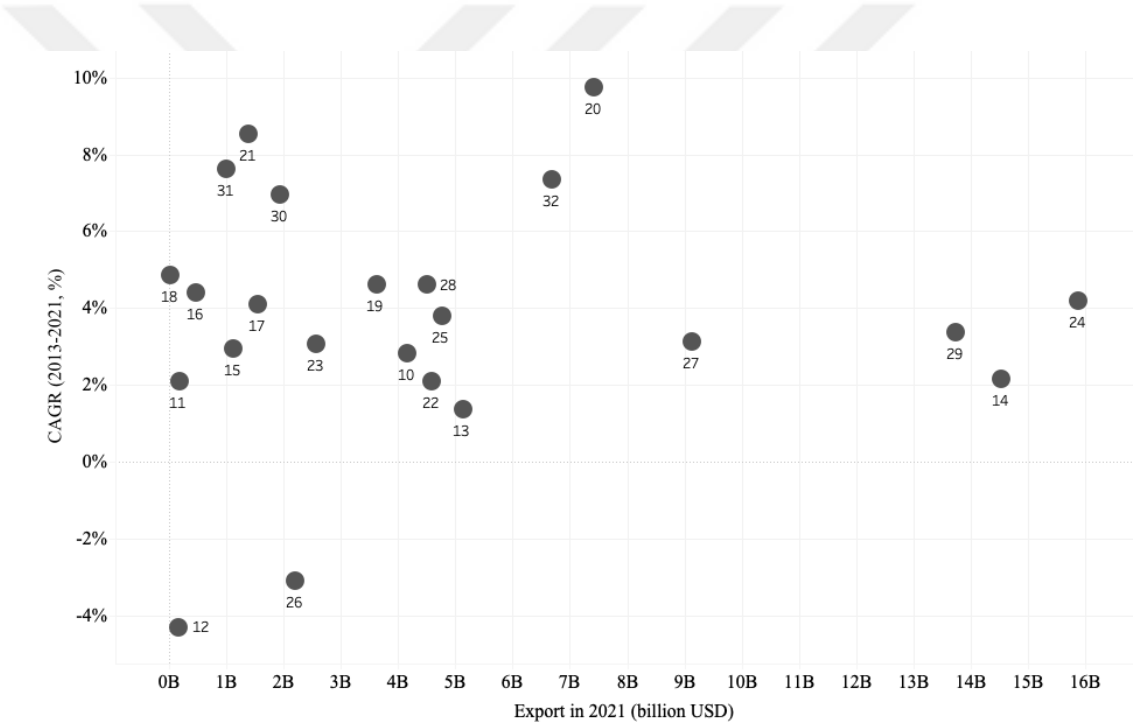


Figure 4.5 İstanbul's Export by Sector (billion USD, 2021) and Compound Annual Growth Rate (%, 2013-2021)
Source: TurkStat

The export of manufacturing sectors in İzmir is ~13.5 billion USD in 2021. In terms of the breakdown of the manufacturing sectors, with ~1.9 billion USD export value, the manufacture of food products is the prominent sector. The manufacturing sectors with an export value of more than 1 billion USD are as follows, from the largest to the smallest;

- Manufacture of wearing apparel,

- Manufacture of machinery and equipment,
- Manufacture of motor vehicles trailers and semi-trailers,
- Manufacture of chemicals and chemical products.

In addition, the least exported sectors are printing and reproduction of recorded media, manufacture of basic pharmaceutical products and pharmaceutical preparations and manufacture of beverages.

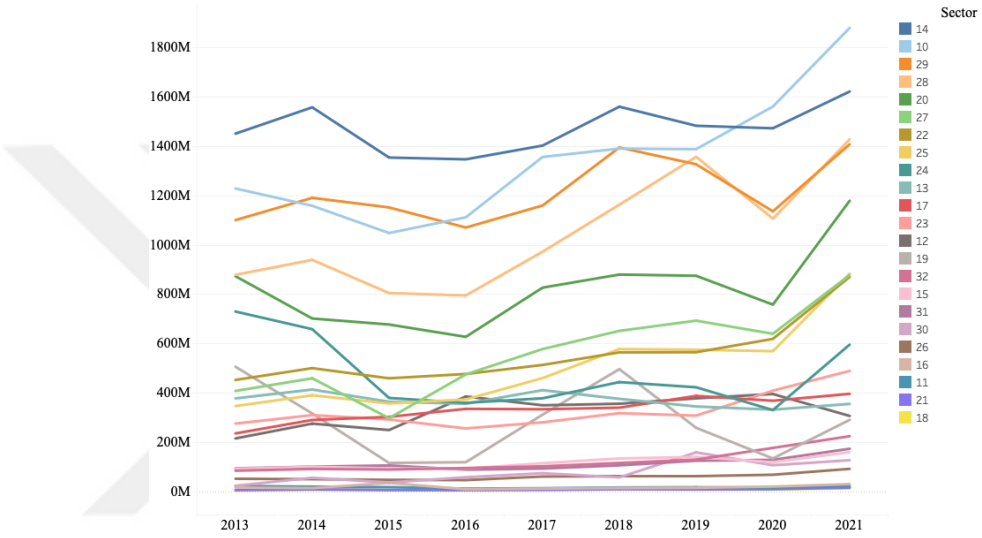


Figure 4.6 İzmir's Export by Sector and Year (million USD, 2013-2021)
Source: TurkStat

In terms of the performances of the sectors for the years 2013-17-21, it is seen that the manufacture of food products has a relatively better performance in İzmir. Although there is no significant change in the prominent sectors, it can be seen that there is an increase in general, but some sectors have increased more. İzmir's export by sector for the years 2013, 2017 and 2021 is demonstrated in the figure 4.7.

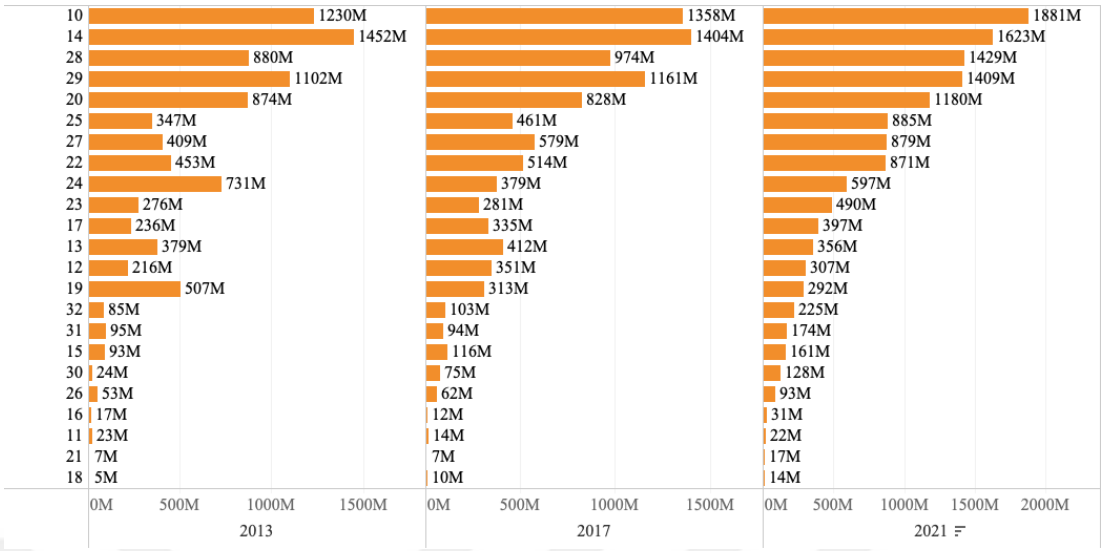


Figure 4.7 İzmir's Export by Sector (million USD, 2013-17-21)
Source: TurkStat

Between 2013-2021, the manufacture of other non-metallic mineral products was the sector that grew the most with a CAGR of 23%, while the manufacture of food products, which had the highest nominal export value, showed a below-average performance and grew with a CAGR of 5%. While the manufacturing sectors average 7% CAGR, the sectors with the highest growth are those with a nominally lower export value. However, the manufacture of coke and refined petroleum products shrank by 7% CAGR. The manufacture of basic metals, the manufacture of textiles, and the manufacture of beverages are the other manufacturing sectors with negative CAGR values.

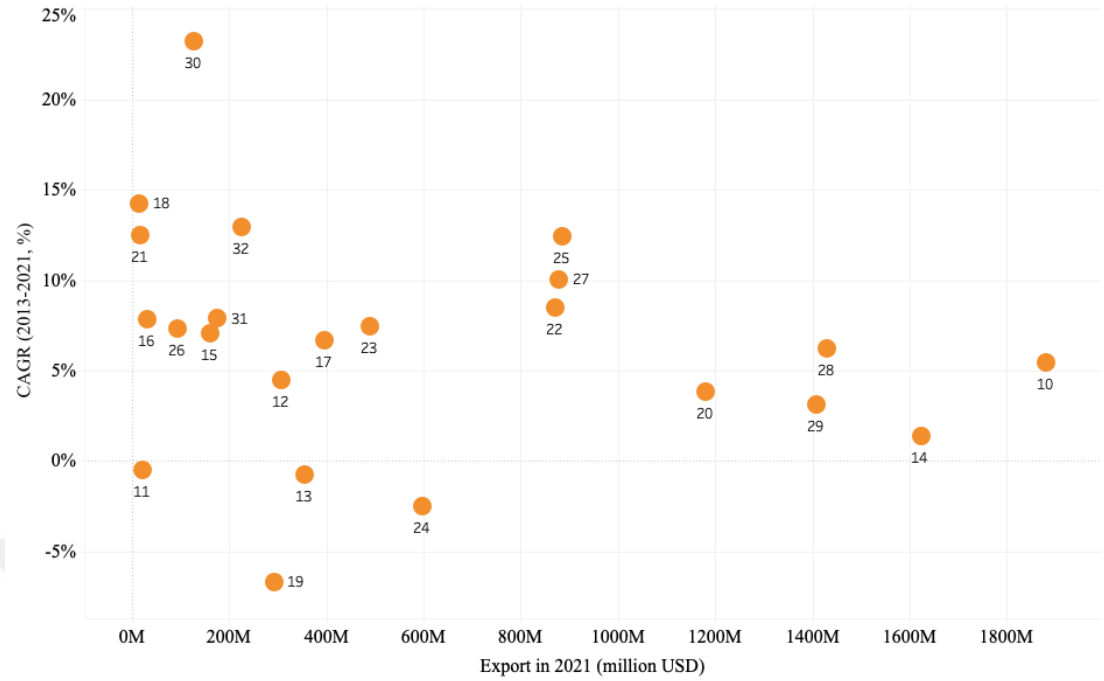


Figure 4.8 İzmir's Export by Sector (million USD, 2021) and Compound Annual Growth Rate (%, 2013-2021)
Source: TurkStat

In addition, Kocaeli has a total export value of ~12 billion USD in the manufacturing sectors in 2021. It is seen that the manufacture of coke and refined petroleum products stands out among manufacturing sectors. It is observed that the performance of the manufacture of basic metals increased in 2021 and has an export value close to the manufacture of coke and refined petroleum products. However, it can be said that other sectors have export performances close to each other and there has been no significant change over the years. Kocaeli's export by sector and year is shown in the figure 4.9.

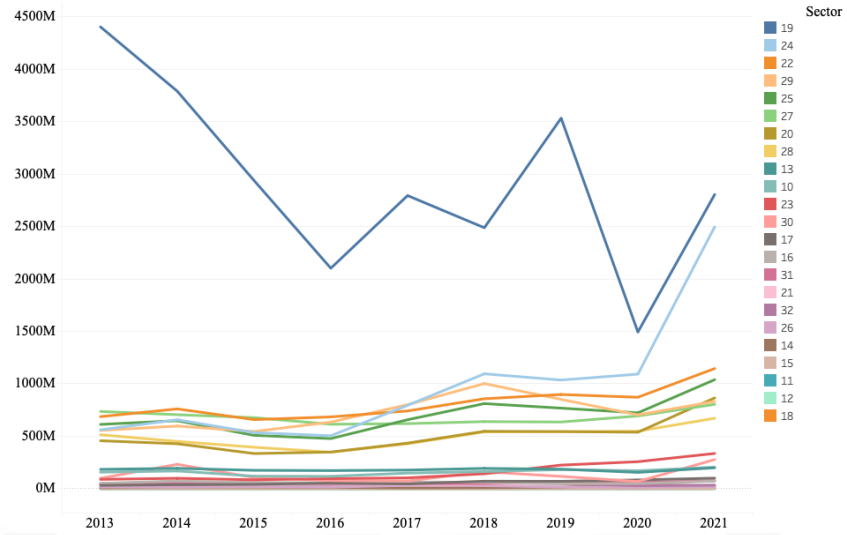


Figure 4.9 Kocaeli's Export by Sector and Year (million USD, 2013-2021)
Source: TurkStat

When the performance of the sectors for the years 2013-17-21 is compared, it is seen that the manufacture of coke and refined petroleum products is dominant, but there is a significant increase in the performance of the manufacture of basic metals.

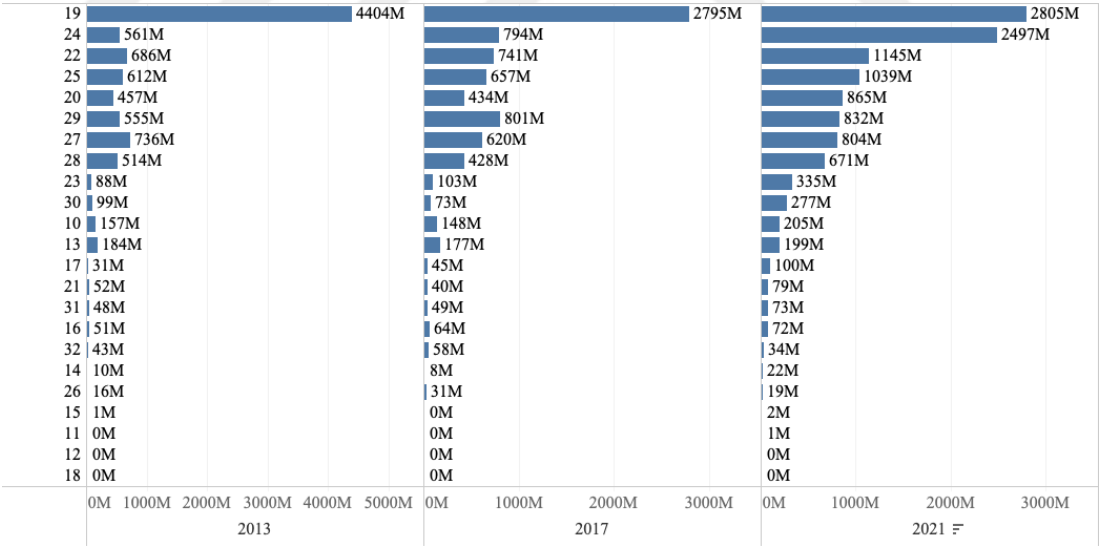


Figure 4.10 Kocaeli's Export by Sector (million USD, 2013-17-21)
Source: TurkStat

In terms of the growth performances of the manufacturing sectors in Kocaeli between the years 2013-2021, the manufacture of tobacco products, which has a much lower nominal value, showed an outlier performance of 76% CAGR. In addition, as can be seen in the graphs above, the manufacture of basic metals is the second largest

manufacturing sector with 21% CAGR, which is the second sector in terms of nominal export value in 2021. Moreover, it draws attention as the manufacturing sector with the lowest growth performance with the highest export value of manufacture of coke and refined petroleum products -5% CAGR.

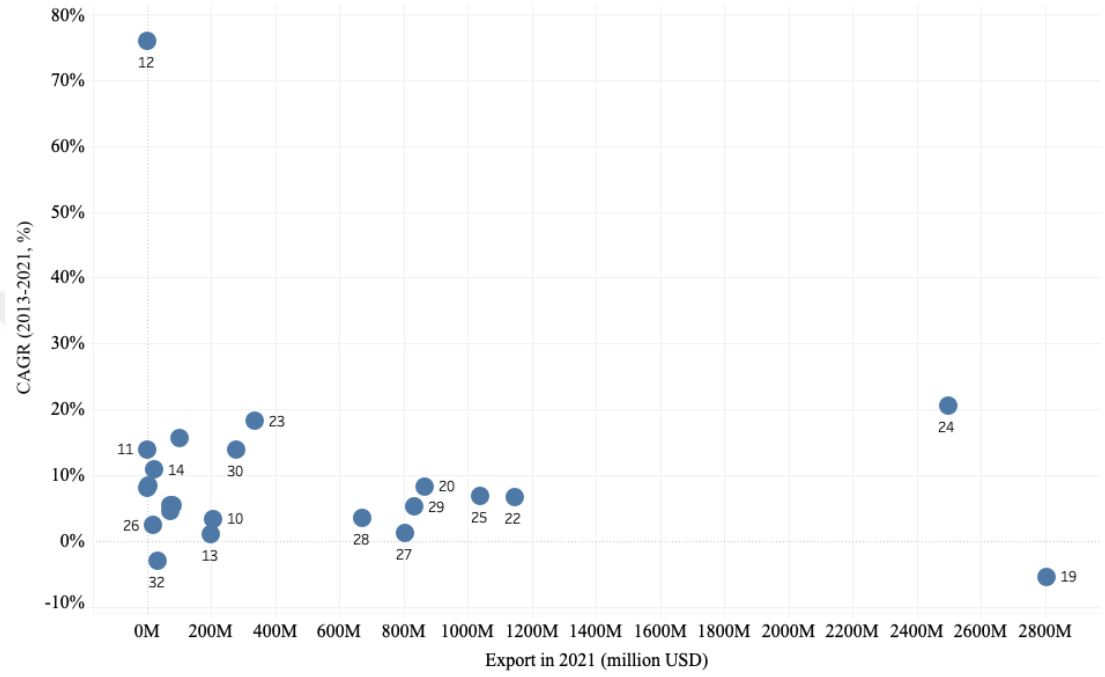


Figure 4.11 Kocaeli's Export by Sector (million USD, 2021) and Compound Annual Growth Rate (%, 2013-2021)
Source: TurkStat

It is seen that the sectors that stand out in terms of export performance in İstanbul, İzmir, and Kocaeli manufacturing sectors vary, and there are also changes in the prominent sectors.

4.3. Forecast Model Comparison: Arima, Boosting, Neural Network

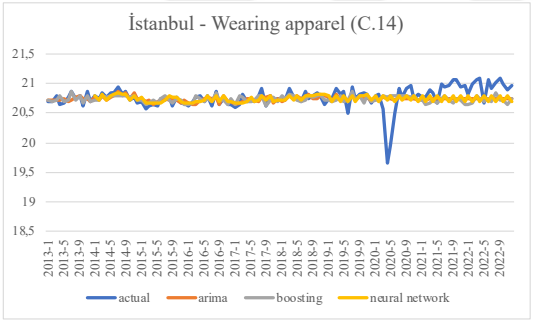
In this section, the results of time series forecasting with arima, boosting and neural network for İstanbul manufacturing sectors were compared for different training periods. With regard to this, the model to be used for competitiveness analyses was selected. In addition, the predictability of crises that would affect foreign trade, such as COVID-19, and their reflection on forecasts were also examined. For this reason, models were trained for the manufacturing sectors of İstanbul according to the 2013-2018 and 2013-2021 periods and the results are presented below. In addition, the error

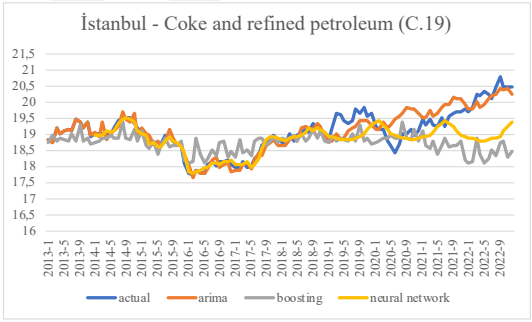
rates of the models were examined as in-sample and out-of-sample. The error rates of İzmir and Kocaeli for the selected training period and model are also presented in the appendix.

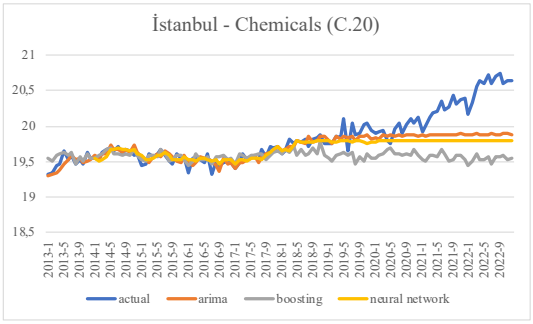
4.3.1. Training Period: 2013-2018

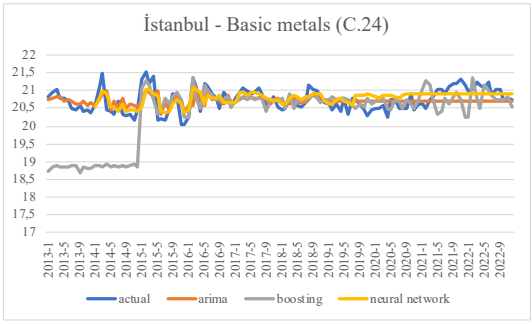
Using 2013-2018 data for the exports of İstanbul manufacturing sectors, the period of 2019-2022 was estimated with arima, boosting and neural network models. Analyzes were performed by taking the logarithm of the data on a monthly basis. Here, the results of the six manufacturing sectors with the highest exports in 2022 in İstanbul are given, and the results for other sectors are presented in the appendix.

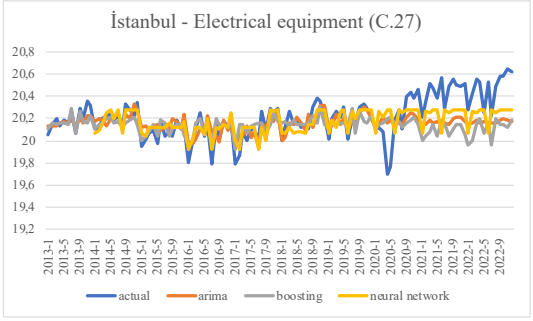
The results of arima, boosting and neural network for the wearing apparel, coke and refined petroleum, chemicals, basic metals, electrical equipment, and motor vehicles export in İstanbul are demonstrated below.











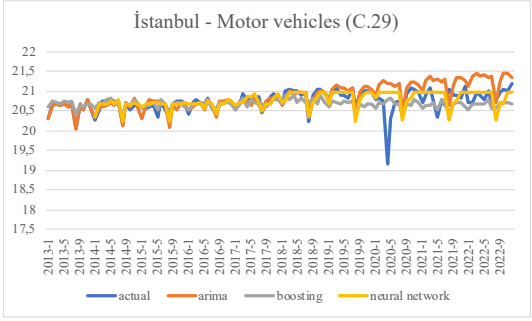


Figure 4.12 Comparison of Forecast Methods for İstanbul for the Period of 2013-2018
Note: Training period is 2013-2018 and test period is 2019-2022 that is compared with actual data.
Source: TurkStat

As depicted in the aforementioned graphs, three models showed a notable weakness in estimating the duration of the COVID-19 pandemic. It is also seen that it would be difficult to predict the evolving trends and patterns after this time.

4.3.1.1. Error Rates for The Period of 2013-2018

The period of 2019-2022 was forecasted using Arima, boosting and neural network models and 2013-2018 monthly and logarithmic data. In-sample (2013-2018) and out-of-sample (2019-2022) error rates were compared for the actual and forecasted values based on these estimates.

MAPE is used to compare the models. MAPE, which is mean absolute percentage error, has been used to measure the predictive power of forecasting models. The mathematical formula of MAPE is as follows.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|\widehat{y_t}-yt|}{y_t} \times 100 \quad (5.1)$$

where;

- n: the size of the sample
- $\hat{y}$: forecasted value
- y: actual value

In addition to this, the thresholds of the MAPE values for interpretation were examined by Lewis (1982), which has been still used in the literature. According to it, the interpretation for each threshold is demonstrated in the table below (Moreno et al., 2013).

Table 4.1 Interpretation of MAPE

MAPE	Interpretation
<10	Highly accurate forecasting
10-20	Good forecasting
20-50	Reasonable forecasting
>50	Inaccurate forecasting

The table below demonstrates the MAPE values calculated by using the forecasted and actual values for 2019-2022, which is for out-of-sample.

Table 4.2 MAPE Values for 2019-2022 Considering the Training Period of 2013-2018

Sector Code	Sector	MAPE		
		Arima	Boosting	Neural Network
10	Food	15	21	17
11	Beverages	22	26	26
12	Tobacco	53	65	53
13	Textiles	19	19	18
14	Wearing apparel	20	22	21
15	Leather	24	33	27
16	Wood	25	28	33
17	Paper	16	25	18
18	Recorded media	38	40	44
19	Coke and refined petroleum	43	53	43
20	Chemicals	25	42	29
21	Pharma	25	39	31

22	Rubber and plastics	17	20	23
23	Non-metallic mineral	22	26	32
24	Basic metals	23	28	26
25	Fabricated metal	22	24	20
26	Computer electronic	15	23	15
27	Electrical equipment	18	22	17
28	Machinery	20	29	15
29	Motor vehicles	55	29	31
30	Other transport	45	47	55
31	Furniture	37	38	37
32	Other manufacturing	54	54	59
Average		28	33	30

According to the MAPE results, the most successful model on average is the arima model, although there is no significant difference between the models. However, it is seen that the prediction power of the estimations in the tobacco, motor vehicles and other manufacturing sectors is weak and the results would be misleading.

In addition, the in-sample (2013-2018) performances of the models constructed using the 2013-2018 data below were examined with MAPE.

Table 4.3 MAPE Values for 2013-2018 Considering the Training Period of 2013-2018

Sector Code	Sector	MAPE		
		Arima	Boosting	Neural Network
10	Food	7	8	7
11	Beverages	10	11	11
12	Tobacco	19	12	14
13	Textiles	6	5	5
14	Wearing apparel	6	5	5
15	Leather	7	8	9
16	Wood	15	11	5
17	Paper	6	6	5
18	Recorded media	26	21	5
19	Coke and refined petroleum	11	30	8
20	Chemicals	6	6	5
21	Pharma	19	16	0.3
22	Rubber and plastics	6	5	4
23	Non-metallic mineral	5	6	3
24	Basic metals	24	39	23
25	Fabricated metal	6	5	3
26	Computer electronic	10	14	11
27	Electrical equipment	8	6	6

28	Machinery	7	7	7
29	Motor vehicles	9	11	8
30	Other transport	45	32	35
31	Furniture	9	8	8
32	Other manufacturing	13	11	0.5
Average		12	12	8

It is observed that the in-sample performances of the models are generally superior than the out-of-sample performances. However, although there is no significant difference in the predictive power among the models, the neural network model demonstrates the highest accuracy on the average considering in-sample performance. The discrepancy between the in-sample and out-of-sample predictive powers of the models can be attributed to the changing trends brought about by the COVID-19 pandemic, as evident in the accompanying graphs. Due to that, in the next section, estimations were conducted as training period 2013-2021 and the models were compared.

4.3.2. Training Period: 2013-2021

Arima, boosting, and neural network models were used to estimate the period of 2022–2024 using data for the exports of the manufacturing sectors in İstanbul from 2013–2021. On a monthly basis, analyses were carried out by taking the logarithm of the data. The six manufacturing sectors in İstanbul that have the highest exports in 2022 are listed here, and the results for the remaining sectors are listed in the appendix.

The results of arima, boosting and neural network for the wearing apparel, coke and refined petroleum, chemicals, basic metals, electrical equipment, and motor vehicles export in İstanbul are demonstrated below.

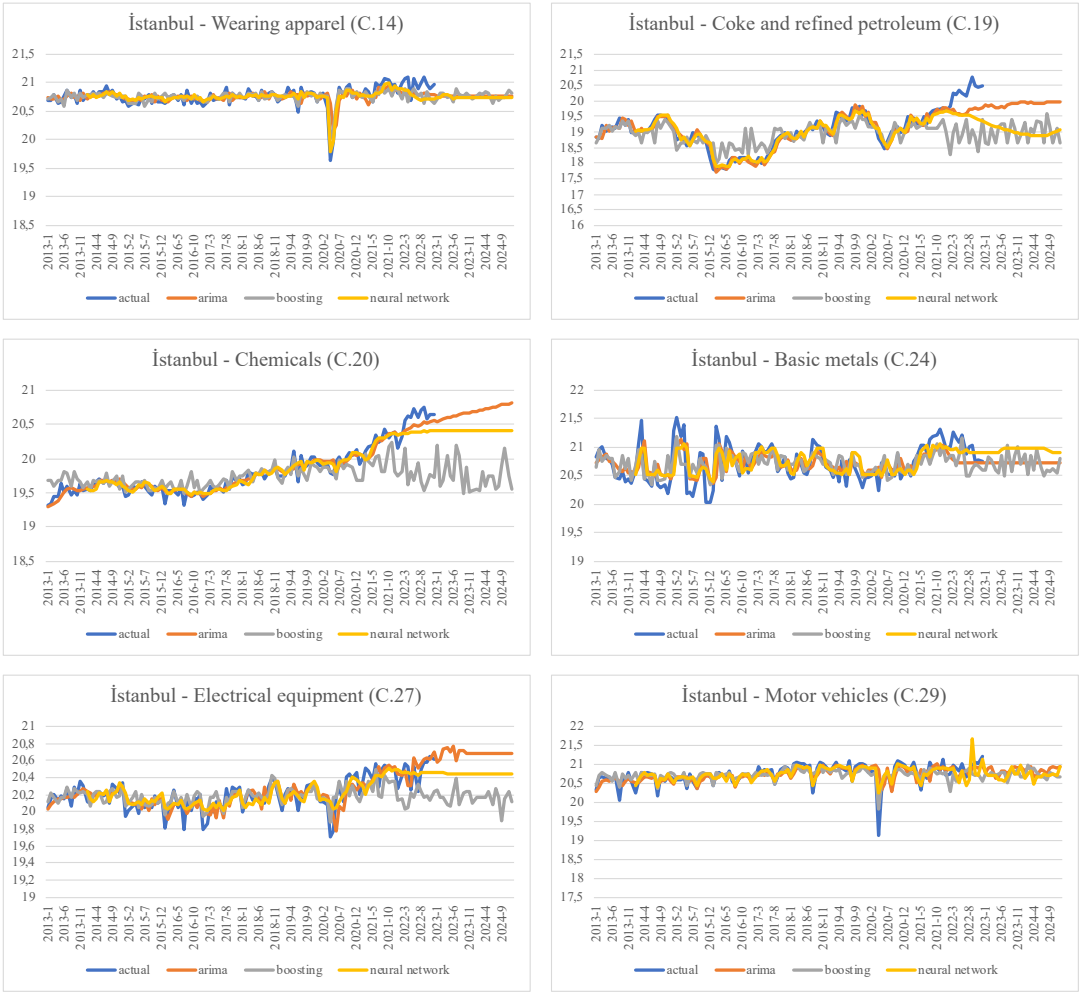


Figure 4.13 Comparison of Forecast Methods for İstanbul for the Period of 2013-2021
Note: Training period is 2013-2021 and test period is 2022 that is compared with actual data.
Source: TurkStat

Upon examining the results of the six manufacturing sectors that stand out for İstanbul, it can be seen that utilizing the data from 2013–2021 allows the models to better identify trends. Additionally, the comparative analyses for the out-of-sample and in-sample performances of the models were presented in the next.

4.3.2.1. Error Rates for The Period of 2013-2021

Arima, boosting, and neural network models were used to predict the years 2022-2024 utilizing monthly and logarithmic data from 2013-2021. The actual and forecasted values based on these estimations were compared to the out-of-sample (2022) and the in-sample (2013-2021) error rates.

The table below shows the MAPE values calculated by using the forecasted and actual values for 2022, which is for out-of-sample.

Table 4.4 MAPE Values for 2022 Considering the Training Period of 2013-2021

Sector Code	**Sector**	**MAPE**		
		Arima	**Boosting**	**Neural Network**
10	Food	7	33	20
11	Beverages	34	40	34
12	Tobacco	46	101	42
13	Textiles	14	18	12
14	Wearing apparel	16	20	19
15	Leather	23	35	28
16	Wood	15	41	12
17	Paper	13	42	14
18	Recorded media	18	58	23
19	Coke and refined petroleum	44	72	50
20	Chemicals	14	54	21
21	Pharma	25	37	31
22	Rubber and plastics	7	22	11
23	Non-metallic mineral	14	36	22
24	Basic metals	20	22	14
25	Fabricated metal	7	41	9
26	Computer electronic	13	31	13

27	Electrical equipment	10	27	12
28	Machinery	13	37	16
29	Motor vehicles	14	23	25
30	Other transport	38	45	39
31	Furniture	9	44	17
32	Other manufacturing	39	41	31
Average		20	40	22

Based on the MAPE values calculated using the predictions and actual values for the year 2022 based on the data from 2013-2021, it can be concluded that the ARIMA model exhibits the highest average predictive power. In addition, it is worth noting that the neural network model demonstrates a comparable level of predictive capability to ARIMA, while the boosting model falls behind the other models in terms of predictive power but still maintaining an acceptable level of accuracy.

In addition, the in-sample (2013-2021) performances of the models constructed using the 2013-2021 data were examined with MAPE, which is shown in the table below.

Table 4.5 MAPE Values for 2013-2021 Considering the Training Period of 2013-2021

Sector Code	**Sector**	**MAPE**		
		Arima	**Boosting**	**Neural Network**
10	Food	8	8	3
11	Beverages	13	10	12
12	Tobacco	20	15	16
13	Textiles	9	7	5

14	Wearing apparel	10	6	6
15	Leather	14	11	14
16	Wood	14	12	13
17	Paper	7	7	7
18	Recorded media	25	19	23
19	Coke and refined petroleum	14	26	14
20	Chemicals	7	12	7
21	Pharma	18	18	2
22	Rubber and plastics	7	6	7
23	Non-metallic mineral	8	7	7
24	Basic metals	22	17	21
25	Fabricated metal	8	7	8
26	Computer electronic	10	11	12
27	Electrical equipment	9	8	9
28	Machinery	9	9	8
29	Motor vehicles	16	12	10
30	Other transport	42	27	35
31	Furniture	11	13	11
32	Other manufacturing	21	19	11
Average		14	12	11

According to the in-sample performances of the models, the most successful model was the neural network, while all the models showed a close performance and on average, all of them had values in the range considered as good forecasting.

4.3.3. Training Period and Model Selection

On the basis of past data, time series forecasting techniques are used to forecast future values. The selection of the training period, which reflects the previous data range utilized in the training of model, has a substantial impact on the performance of forecast since it allows the model to comprehend future trends and patterns.

Firstly, the length of the training period holds significant importance as it allows the model to encompass a greater volume of historical data and trends. Additionally, the incorporation of crucial events and crises within the training period is another crucial aspect. Instances such as the COVID-19 pandemic can significantly impact the model's ability to forecast similar events in the future or to gain insights into the evolving trends beyond that period. Consequently, both the duration of the training period and the inclusion of crisis periods have substantial importance so as to estimate future values.

Owing to these reasons, two different training periods, 2013-2018 and 2013-2021, were analyzed in the study. Whereas the 2013-2018 training period was tested with the data realized in 2019-2022, the 2013-2021 training period was tested with the values realized in 2022. Considering model results, detailed in 4.3.1 and 4.3.2 sections, it is observed that including the crisis period for arima, boosting and neural network gives better results. For this reason, the period 2013-2021 was selected as the training period within the scope of the study.

In addition to the training period selection, the performance of the models was examined both in-sample and out-of-sample for both training periods. According to these, the prediction powers of the models differ in the in-sample and out-of-sample forecasting. Although the models demonstrated comparable performances with each other, arima and neural network models have better accuracy compared to boosting model. While arima exhibits superior performance in the out-of-sample context, neural network has lower error rates in the in-sample forecasting. However, both models fall

within the range of good forecasting accuracy in terms of MAPE regarding the average performances in all sectors. As detailed in the previous sections, arima yields average MAPE values of 20 for out-of-sample and 14 for in-sample, while neural network has values of 22 and 11, respectively. Considering the importance of out-of-sample performance, especially for forecasting future, the arima model was selected as the model for forecasting exports in 2022-23-24 and conducting competitiveness analyses in the manufacturing sectors of the provinces.

As a result of the comparison of training period and the arima, boosting, and neural network models, 2013-2021 training period and arima model are selected to forecast and discuss the competitiveness of İstanbul, İzmir, and Kocaeli in the manufacturing sectors in the next 3 years. Therefore, by starting from the next section, the results of export value prediction and RCA analyses have been conducted by using the training period of 2013-2021 and the arima model.

4.4. Export Value Prediction

It is important to make forecasts for İstanbul, İzmir, and Kocaeli, which are the leading provinces for Turkish exports, in terms of increasing the efficiency of strategies and hence policies. Moreover, it is necessary to conduct forecasts of the manufacturing sectors in the provinces, especially to predict competitiveness. In this context, competitiveness analyses were conducted for the manufacturing sectors of İstanbul, İzmir, and Kocaeli for the years 2022-23-24. In addition to these, the performance of Türkiye in the manufacturing sectors was also estimated for the same years and then the RCA analysis was carried out by province and sector. In order to analyze the competitiveness, the export value predictions in İstanbul, İzmir, Kocaeli, and Türkiye for 2022-23-24 were conducted by using arima model. The monthly data for 2013-2021 is used to predict 2022-23-24, which means out-of-sample forecasting. These are conducted by sector and province for monthly results and then aggregated as yearly results. The results of forecast analyses for Türkiye, İstanbul, İzmir, and Kocaeli are demonstrated as follows.

First of all, Türkiye's exports in the manufacturing sectors are predicted for 2022-23-24. Türkiye has the highest export value in the manufacture of basic metals in 2021. While exports of approximately 29 billion USD were made in the manufacture

of basic metals in 2021, export value of 27 billion USD in 2024 is forecasted. Considering the performance of basic metals, it is predicted that the manufacture of motor vehicles trailers and semi-trailers would be the sector that has the highest export in 2024. In addition to these, manufacture of food products, manufacture of chemicals and chemical products, manufacture of electrical equipment, manufacture of machinery and equipment, manufacture of wearing apparel, and manufacture of fabricated metal products also draw attention compared to other sectors with their export values.

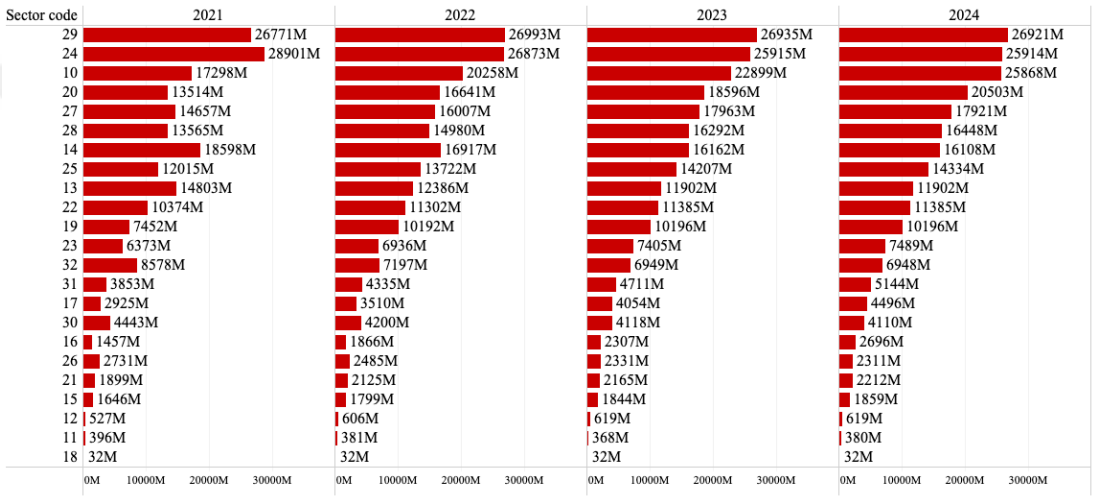


Figure 4.14 Türkiye's Export Forecast by Sector (million USD, 2021-22-23-24)
Source: TurkStat

In addition, it is observed that the export performances of some manufacturing sectors were positively affected during and after the COVID-19 period and this trend continued. It is estimated that this situation is due to the effects of the COVID-19 pandemic, such as changes in the supply chain and consumer behavior. One of the sectors affected by the COVID-19 pandemic is food. COVID-19 has an impact on the whole process from the field to the consumer, which means food production, processing, distribution, and demand (Aday & Aday, 2020). Considering the Turkish food sector exports, it is expected to increase due to reasons such as increasing demand, richness of the natural product, and the development of e-commerce. Besides, the chemical industry is among the sectors that have been positively affected by this process in terms of exports, especially with the increase in demand and the changes in the supply chain (Gomez & Elser, 2021). Also, the demand for the automotive sector

is expected to increase due to changes in consumer behavior and individual automobile demand (TOSB, 2020). While there were also sectors that were negatively affected, there are sectors in which exports were positively affected during the COVID-19 period. This positive effect is expected to continue in some sectors. Therefore, the importance of predicting trends and determining strategies/policies accordingly is emphasized and seems essential.

In terms of manufacturing sectors in İstanbul, the manufacture of basic metals performed beyond other sectors in 2021. The sector has an export of ~15.9 billion USD in 2021. In addition, the manufacture of motor vehicles trailers and semi-trailers is another prominent manufacturing sector in İstanbul with its export performance. In addition, although the manufacture of basic metals sector was the most exported in 2021, the manufacture of motor vehicles trailers and semi-trailers is the sector that is expected to have highest export value in 2024. The sectors with the highest percentage increase in exports in İstanbul are the manufacture of chemicals and chemical products, furniture, coke and refined petroleum products, food products, whereas the sectors that are expected to decrease the most are the manufacture of other transport equipment, basic metals, computer electronic and optical products and textiles.

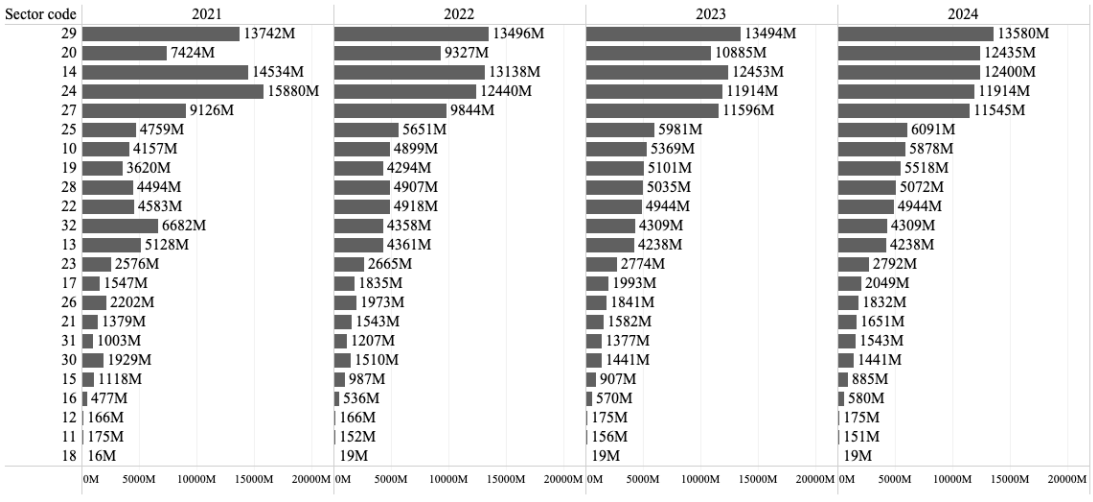


Figure 4.15 İstanbul's Export Forecast by Sector (million USD, 2021-22-23-24)
Source: TurkStat

Nominal differences between sectors in terms of exports are less in İzmir compared to İstanbul. In 2021, the most exports were made in the manufacture of food

products with approximately 1.9 billion USD in İzmir. In addition, in 2021, the manufacture of wearing apparel, the manufacture of machinery and equipment, and the manufacture of motor vehicles trailers and semi-trailers sectors stand out with their export values. Considering the performance of the manufacture of food products, it is estimated that it would be the sector with the highest export volume in 2024. Apart from this, it is estimated that the gap between other sectors will not widen again and that the sectors would develop in parallel with their current situation. In terms of percentage, the sector that is expected to grow the most is the manufacture of fabricated metal products except machinery and equipment. In addition, the manufacture of rubber and plastics, food, non-metallic mineral, paper and leather are the potential sectors that would have higher grow performance. In addition to these, it should be noted that manufacture of basic pharmaceutical products and pharmaceutical preparations and manufacture of coke and refined petroleum products forecasts would not be reliable regarding the error rates in the models.

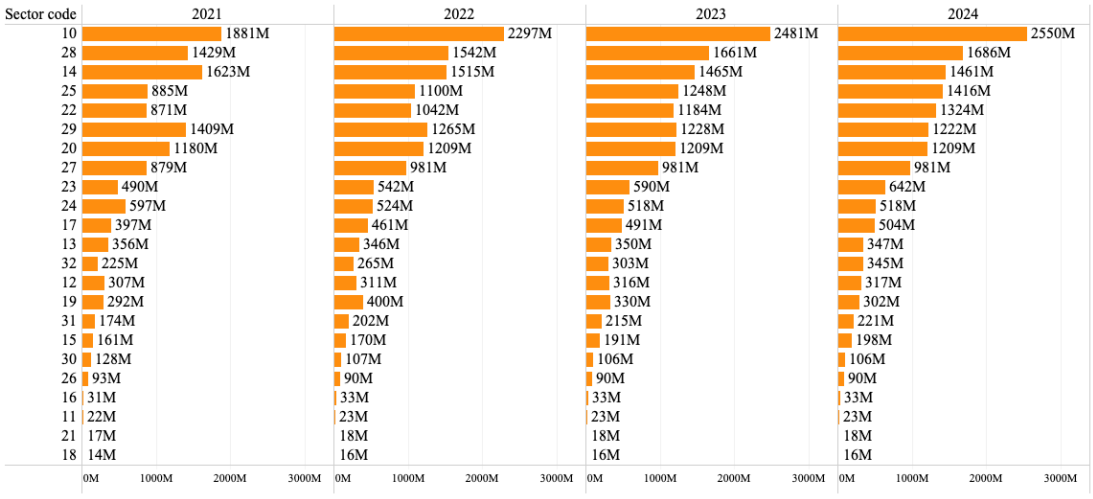


Figure 4.16 İzmir's Export Forecast by Sector (million USD, 2021-22-23-24)
Source: TurkStat

Among the manufacturing sectors of Kocaeli, the manufacture of coke and refined petroleum products has a significant export value compared to other sectors. The sector has an export value of approximately 2.8 billion USD in 2021. The manufacture of basic metals, which was the closest sector to the manufacture of coke and refined petroleum products sector, had an export value of ~2.5 billion USD in 2021. Considering the trend, it is predicted that the manufacturing of the basic metals

would be the highest exported sector in Kocaeli in 2024. While the manufacture of coke and refined petroleum products maintain their importance, the manufacture of rubber and plastics products, chemicals and chemical products, fabricated metal products except machinery and equipment are the manufacturing sectors in Kocaeli in which export value of over one billion USD are expected in 2024. In addition to these, it should be noted that manufacture of tobacco and printing and reproduction of recorded media forecasts would not be correct regarding the error rates in the models. Thus, these sectors are also not included in the competitiveness analyses. Furthermore, the manufacture of beverages and manufacture of other transport equipment have also higher MAPE values so the forecast result would not be accurate, which should also be considered.

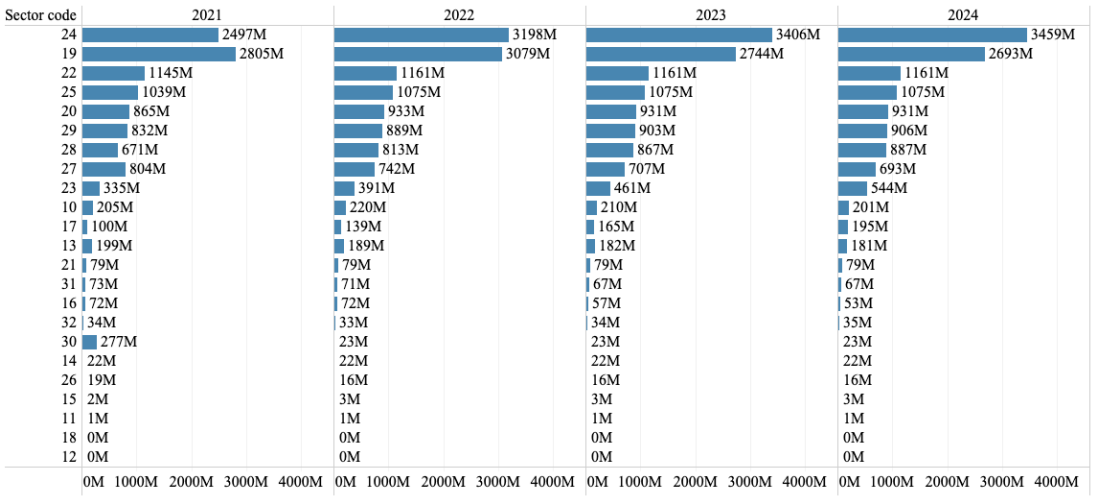


Figure 4.17 Kocaeli's Export Forecast by Sector (million USD, 2021-22-23-24)
Source: TurkStat

Manufacturing sector projections for İstanbul, İzmir, and Kocaeli are also presented in the appendix in detail.

4.5. Results of RCA Analysis

After the exports of the manufacturing sectors in 2022-23-24 were estimated for İstanbul, İzmir, and Kocaeli, the current situation and future of the export competitiveness by sector were examined with the RCA (revealed comparative advantage) analysis.

The export competitiveness of manufacturing sectors in İstanbul was analyzed for the years 2013-17-21-22-23-24. Accordingly, while 12 manufacturing sectors in 2013, 7 in 2017, and 12 in 2021 were competitive in terms of exports, it is estimated that 9 manufacturing sectors will be competitive in 2024.

The 12 competitive manufacturing sectors in 2021, from the most competitive to the least competitive, are as follows;

- Manufacture of computer electronic and optical products,
- Manufacture of wearing apparel,
- Other manufacturing,
- Manufacture of basic pharmaceutical products and pharmaceutical preparations,
- Manufacture of leather and related products,
- Manufacture of electrical equipment,
- Manufacture of basic metals,
- Manufacture of chemicals and chemical products,
- Manufacture of paper and paper products,
- Printing and reproduction of recorded media,
- Manufacture of motor vehicles trailers and semi-trailers,
- Manufacture of coke and refined petroleum products.

On the one hand, in line with current trends, it is predicted that the manufacture of leather and related products, basic metals, and motor vehicles trailers and semi-trailers sectors would lose their competitiveness in 2024. On the other hand, the competitiveness levels of manufacture of electrical equipment, manufacture of chemicals and chemical products, printing and reproduction of recorded media, manufacture of coke and refined petroleum products are expected to increase. According to these results, the 3 manufacturing sectors that would be the most competitive in terms of exports in İstanbul in 2024 are manufacture of computer electronic and optical products, wearing apparel, and basic pharmaceutical products and pharmaceutical preparations.

In the figure below, the export competitiveness of İstanbul's manufacturing sectors is presented by sector and year.

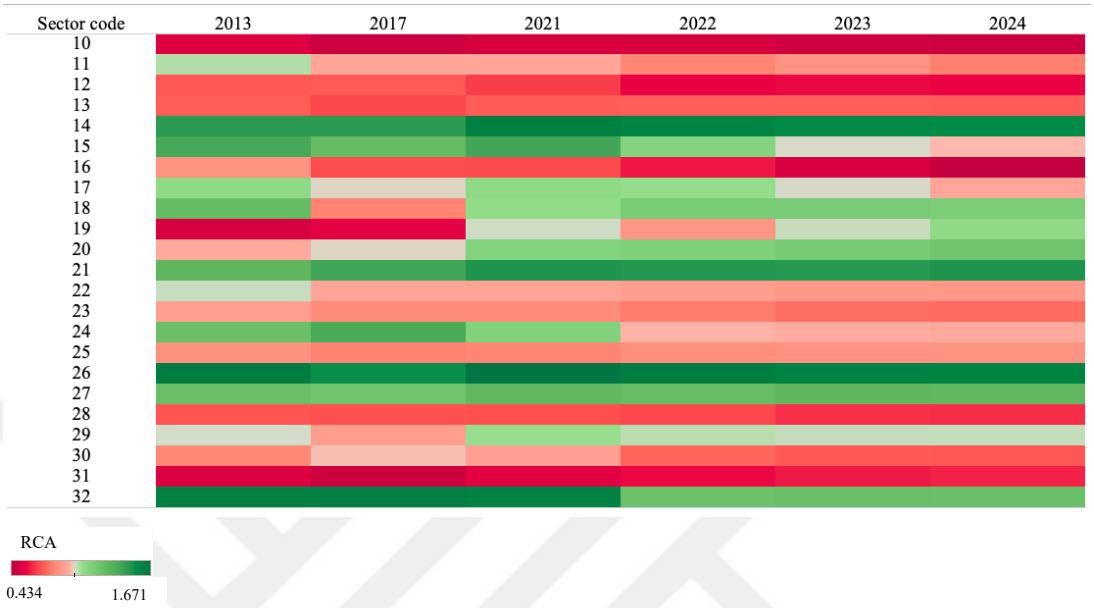


Figure 4.18 İstanbul RCA Index by Sector
Source: TurkStat

The competitiveness of the manufacturing sectors in İzmir has changed over the years. Accordingly, 10 manufacturing sectors in 2013, 11 in 2017, and 11 in 2021 have export competitiveness and it is estimated that 8 manufacturing sectors would be competitive in 2024.

Manufacturing sectors that are competitive in terms of exports in İzmir in 2021, from the most competitive to the least competitive, are as follows;

- Manufacture of tobacco products,
- Printing and reproduction of recorded media,
- Manufacture of paper and paper products,
- Manufacture of food products,
- Manufacture of machinery and equipment n.e.c.,
- Manufacture of leather and related products,
- Manufacture of chemicals and chemical products,
- Manufacture of wearing apparel,
- Manufacture of rubber and plastics products,

- Manufacture of other non-metallic mineral products,
- Manufacture of fabricated metal products except machinery and equipment.

It is predicted that all these sectors, which were competitive in 2021 in terms of export, would not maintain their competitiveness in 2024. It is observed that the manufacture of chemicals and chemical products, wearing apparel, and other non-metallic mineral products would lose export competitiveness in İzmir. While the manufacture of tobacco products is the most competitive sector in 2021, it is predicted that it would continue to be most competitive sector in the region but by losing the competitiveness level. Besides, the following sectors stand out as both competitive and expected sectors with an export value of over 1 billion USD for 2024;

- Manufacture of food products,
- Manufacture of machinery and equipment n.e.c.,
- Manufacture of rubber and plastics products,
- Manufacture of fabricated metal products except machinery and equipment.

In addition, it should be considered the analyses results for the manufacture of basic pharmaceutical products and pharmaceutical preparations and manufacture of coke and refined petroleum products would not be accurate regarding the error rates for forecasting in the models.

In the figure 4.19, the export competitiveness of İzmir's manufacturing sectors is presented by sector and year.

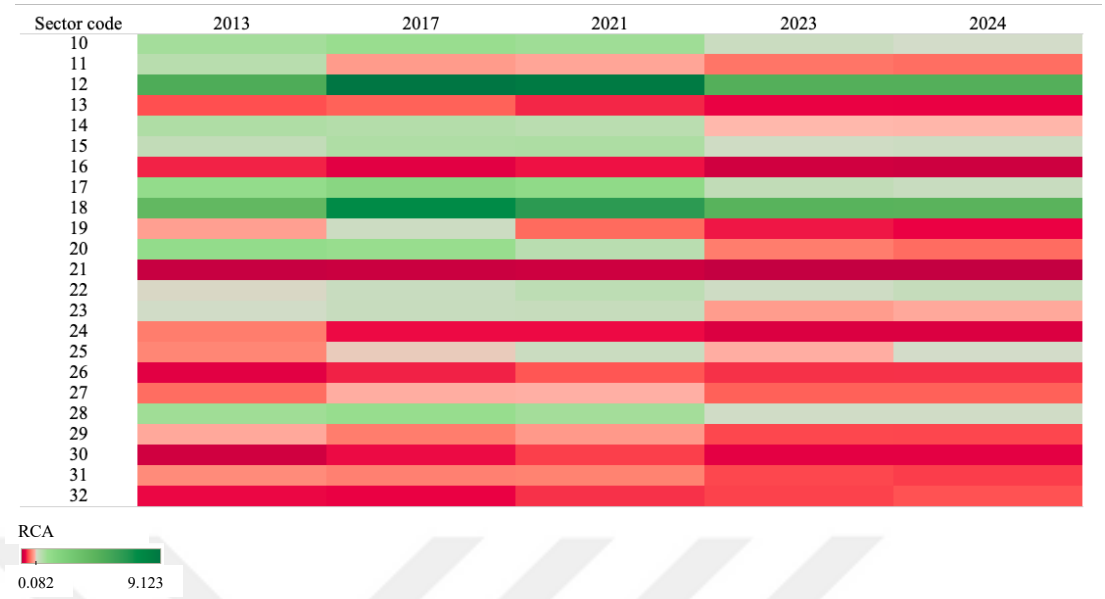


Figure 4.19 İzmir RCA Index by Sector
Source: TurkStat

In addition, when Kocaeli manufacturing sectors are evaluated in terms of export competitiveness, it is competitive in 6 sectors in 2013 and 2017, 7 sectors in 2021, and it is estimated that it would have export competitiveness in 6 sectors in 2024. In addition, the manufacture of tobacco products and printing and reproduction of recorded media are not included in the competitiveness analyses due to the inaccurate level forecast results considering the MAPE of the models. However, as mentioned before, the analyses of the manufacture of beverages and manufacture of other transport equipment sectors would not be accurate due to the higher MAPE values in the forecasting, which should be considered to interpret the results of RCA analysis.

Manufacturing sectors with export competitiveness in Kocaeli in 2021, from the most competitive to the least competitive, are as follows;

- Manufacture of coke and refined petroleum products,
- Manufacture of rubber and plastics products,
- Manufacture of fabricated metal products except machinery and equipment,
- Manufacture of basic metals,
- Manufacture of chemicals and chemical products,
- Manufacture of other transport equipment,
- Manufacture of electrical equipment.

When the competitive sectors are estimated for 2024, it is predicted that the manufacture of chemicals and chemical products, other transport equipment and electrical equipment would lose their competitiveness. However, the result for the other transport equipment would not be accurate owing to lower accuracy in forecasting. On the other hand, the manufacture of other non-metallic mineral products and the machinery and equipment are expected to be competitive. Briefly, although the number of competitive sectors in 2024 would be 6, it is foreseen that there would be changes in the sectors compared to 2021. These sectors, excluding the manufacture of other non-metallic mineral products and machinery and equipment, are also expected to be competitive in 2024 and have an export of over 1 billion USD.

In the figure below, the export competitiveness of Kocaeli's manufacturing sectors is presented by sector and year.

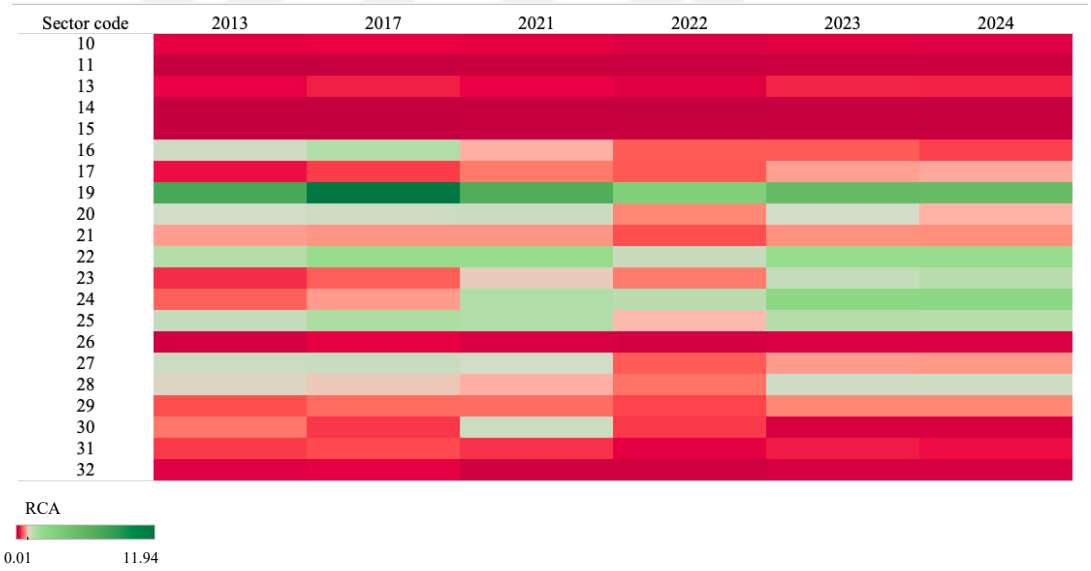


Figure 4.20 Kocaeli RCA Index by Sector
Source: TurkStat

In addition, the changes from 2021 to 2024 in the share of sectors in province and Türkiye in terms of percentage are demonstrated in the table below in order to give insight about the reasoning for gaining of losing the competitiveness.

Table 4.6 Change in the Share of the Sectors in Province and Türkiye from 2021 to 2024

Sector Code	Sector	Percentage change from 2021 to 2024			
		İstanbul	İzmir	Kocaeli	Türkiye
10	Food	3.3	2.9	0.8	7.9
11	Beverages	0	0	0	0.1
12	Tobacco	0.1	-0.1	0	0.1
13	Textiles	0.4	-0.3	0.6	0.6
14	Wearing apparel	1.7	-2	0.1	1.4
15	Leather	0	0.1	0	0.4
16	Wood	0.3	0	0.1	1
17	Paper	1.1	0.4	1.5	1.4
18	Recorded media	0	0	0	0
19	Coke and refined petroleum	3.4	-0.1	9.7	2.8
20	Chemicals	8.2	-0.6	4.2	6.3
21	Pharma	0.7	0	0.3	0.5
22	Rubber and plastics	1.8	2.2	4.7	2.2
23	Non-metallic mineral	1	0.6	3.8	1.7
24	Basic metals	-0.2	-0.9	21.4	2.7
25	Fabricated metal	3	2.7	4.5	3.3
26	Computer electronic	0.2	-0.1	0	0.2
27	Electrical equipment	5.6	0.1	1.8	4.3
28	Machinery	2	0.7	5.2	3.9

29	Motor vehicles	3.8	-2	4.2	4.3
30	Other transport	0	-0.2	-2	0.5
31	Furniture	0.9	0.2	0.2	1.4
32	Other manufacturing	-0.9	0.6	0.1	0.4

As a result of the competitiveness analyses, in the table below, competitive manufacturing sectors in İstanbul, İzmir, and Kocaeli in 2021 and 2024 are compared according to technology classification. Accordingly, competitive sectors contain technological diversity. Firstly, İstanbul has export competitiveness in a total of 12 sectors in 2021, including 2 high-technology, 4 medium-high-technology, 2 medium-low-technology, and 4 low-technology. In 2024, 9 of these 12 sectors are expected to be competitive, while one of the sectors that would lose their competitiveness is medium-low-technology and the others are low-technology. Secondly, looking at İzmir, it is an export competitor in a total of 11 sectors in 2021 of which 2 are medium-high-technology, 3 are medium-low-technology and 6 are low-technology sectors. Besides, in 2024, it is estimated that İzmir would maintain its competitiveness in 7 sectors and would lose competitiveness in 1 medium-high-technology, 1 medium-low-technology and 1 low-technology sector. Finally, Kocaeli is an export competitor in a total of 7 manufacturing sectors, including 1 high-technology, 2 medium-high-technology, and 4 medium-low-technology in 2021. Considering the current trends, it is predicted that 1 high-technology and 2 medium-high-technology would lose their competitiveness in the sector while becoming competitive in another medium-high-technology and medium-low-technology sectors in 2024.

Table 4.7 Classification of Product Group by Technology Intensity (ISIC Rev.4 Classification) Regarding RCA Results by Province

Sector	**Technology classification**	**İstanbul**		**İzmir**		**Kocaeli**	
		2021	**2024**	**2021**	**2024**	**2021**	**2024**
Food	Low-technology	X	X	✓	✓	X	X
Beverages	Low-technology	X	X	X	X	X	X
Tobacco	Low-technology	X	X	✓	✓	X	X

Textiles	Low-technology	X	X	X	X	X	X
Wearing apparel	Low-technology	✓	✓	✓	X	X	X
Leather	Low-technology	✓	X	✓	✓	X	X
Wood	Low-technology	X	X	X	X	X	X
Paper	Low-technology	✓	X	✓	✓	X	X
Recorded media	Low-technology	✓	✓	✓	✓	X	X
Coke and refined petroleum	Medium-low-technology	✓	✓	X	X	✓	✓
Chemicals	Medium-high-technology	✓	✓	✓	X	✓	X
Pharma	High-technology	✓	✓	X	X	X	X
Rubber and plastics	Medium-low-technology	X	X	✓	✓	✓	✓
Non-metallic mineral	Medium-low-technology	X	X	✓	X	X	✓
Basic metals	Medium-low-technology	✓	X	X	X	✓	✓
Fabricated metal	Medium-low-technology	X	X	✓	✓	✓	✓
Computer electronic	High-technology	✓	✓	X	X	X	X
Electrical equipment	Medium-high-technology	✓	✓	X	X	✓	X
Machinery	Medium-high-technology	X	X	✓	✓	X	✓
Motor vehicles	Medium-high-technology	✓	✓	X	X	X	X

Other transport	Medium-high-technology	X	X	X	X	✓	X
Furniture	Low-technology	X	X	X	X	X	X
Other manufacturing	Low-technology	✓	✓	X	X	X	X
✓		competitive					
X		not competitive					

It has been observed that the manufacturing sectors, which have export competitiveness in İstanbul, İzmir, and Kocaeli, have changed over the years and there may be changes regarding the current situation and future forecasts comparison. In İstanbul, İzmir and Kocaeli, which represent/would represent a significant part of Türkiye's exports until 2024, it is expected to gain competitiveness in different sectors depending on the technology level, while it is predicted that competitiveness may be lost in some sectors. It is foreseen that pharma and computer electronic sectors, which are high technology sectors, would maintain their competitiveness in İstanbul. In addition, the chemicals sector, which is a medium high technology sector and competitive in İstanbul, İzmir and Kocaeli, is expected to be competitive in İstanbul and would lose competitiveness in İzmir and Kocaeli in 2024. On the other hand, competitiveness expectations in medium-high-technology and medium-low-technology sectors differ by province. For instance, in the basic metals sector, it is predicted that İstanbul would lose its current export competitiveness, while Kocaeli is expected to maintain its competitiveness. Moreover, when it is examined in the manufacturing sectors that are not and would not be expected to be export competitive in İstanbul, İzmir and Kocaeli, it is seen that these are low-technology sectors such as textiles, wood, and furniture. This situation once again reveals the importance of competitiveness in these three provinces, especially considering the level of technology. Owing to this, in order to increase the efficiency of strategies and policies, it would be important to conduct the analyses both on a provincial and on a sector/sub-sector basis during the decision-making phase and incentives are designed accordingly for the effect to be created.

CHAPTER 5

CONCLUSION

Foreign trade has always been important for countries. Especially in terms of economic development, various strategies, and policies are being developed. Increasing a country's export potential and also its competitiveness requires both following the trends in the world and being superior in various areas such as cost and technology level compared to other competing countries. Recent developments, especially the COVID-19 pandemic, have once again demonstrated the importance of international trade. However, with the COVID-19 pandemic, various developments have occurred in the supply chains and continue to be experienced, which could affect competitive sectors and markets. In addition to these, competitiveness at the provincial/regional level is of great importance for the overall export competitiveness of countries. Therefore, within the scope of this study, the export competitiveness of the manufacturing sectors of İstanbul, İzmir, and Kocaeli, which have a significant share in Türkiye's exports, were investigated. The main motivation of this study is to provide a perspective to policymakers and strategy designers and to present an approach to identify the sectors that need to be highlighted in the provinces.

In order to assess the competitiveness by province, the manufacturing sectors that are competitive in terms of exports in İstanbul, İzmir, and Kocaeli were determined and export predictions of the sectors for 2024 have been conducted on the basis of provinces and sectors by using the autoregressive integrated moving average (arima), boosting and neural network models with machine learning. By comparing the results of each model for the actual and forecasted values in 2022 with mean absolute percentage error (MAPE), arima is selected for the detail competitiveness analysis. Moreover, the training period was also compared as 2013-2018 and 2013-2021 considering the COVID-19 impact. With regard to this, the period of 2013-2021 was selected considering the MAPE of the sectors. In addition, by estimating Türkiye's exports manufacturing sectors exports in 2024, the manufacturing sectors that would be competitive in the future in these provinces were estimated. Revealed comparative advantage (RCA) index is used to determine the competitive manufacturing sectors in İstanbul, İzmir, and Kocaeli.

According to the results of these analyses, it has been seen that the competitive sectors would change in İstanbul, İzmir, and Kocaeli in 2024. This change means that some sectors lose their competitiveness, some sectors become competitive, and also change in the level of competitiveness for competitive sectors. When the sectors are assessed according to technology classification, it has also been observed that this change may differ by province in terms of the technology level. According to these results, while Istanbul is competitive in 12 manufacturing sectors in 2021, it is expected to be competitive in 9 manufacturing sectors in 2024. In addition, İzmir is export competitive in 11 manufacturing sectors in 2021 whereas it is predicted that it would be in 8 manufacturing sectors by 2024. Besides, Kocaeli is export competitive in 7 manufacturing sectors and it would be 6 by losing competitiveness in 3 sectors and becoming competitive in 2 sectors in 2024.

For this reason, the need to strategically determine the sectors that would be prioritized in the provinces has arisen. The analyses conducted in this study can be the initial step to develop strategies and policies in terms of creating attractiveness, competitiveness, and sustainable effects in the prominent sectors in the provinces. Therefore, it is recommended to re-evaluate the incentives provided at the provincial and sector level in line with these results. It is also recommended that the study should be carried out for all provinces within the scope of Türkiye's export competitiveness, by making estimations and socioeconomic impact analyses at the sub-sector/product level and taking into account the analysis results of strategies, policies, and incentives to increase the competitiveness of the country and ensure sustainable development.

Especially for the competitiveness of the country, the studies to be carried out on a provincial basis and the incentives to be provided are important for the development of the sectors and also for the development of the region. Determining the competitive sectors by province and realizing the predictions for the future would provide value added in the determination of strategies and designing policies. With regard to these, hopefully, this pilot study will contribute to Türkiye's competitiveness and development by providing innovative perspectives.

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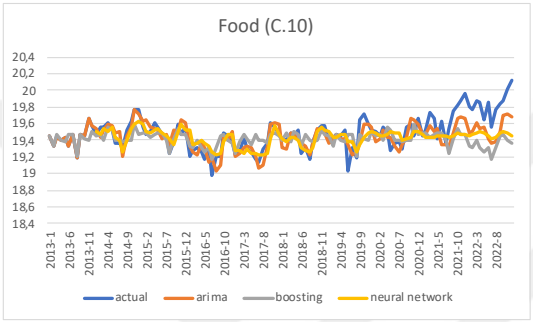
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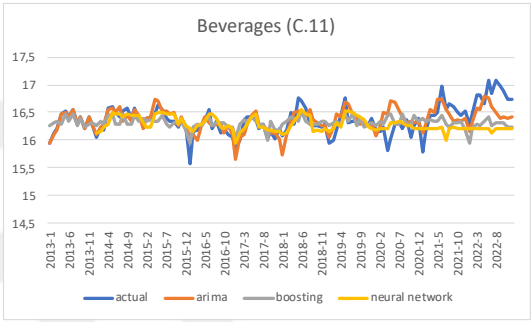
APPENDICES

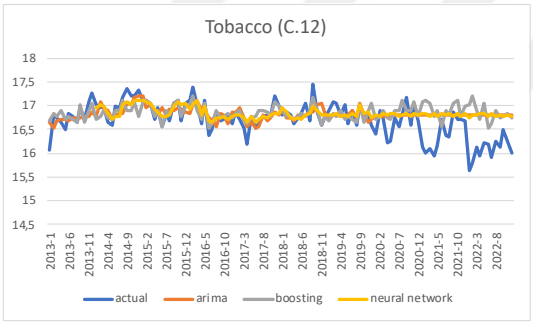
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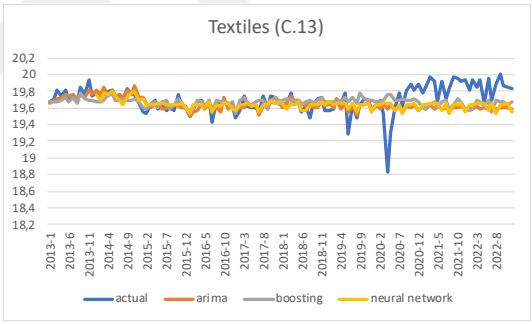
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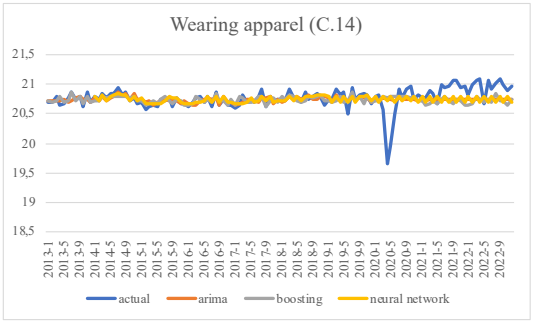
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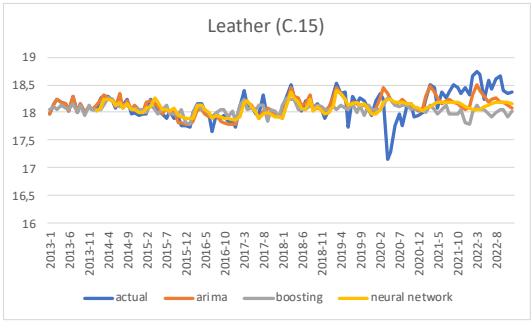


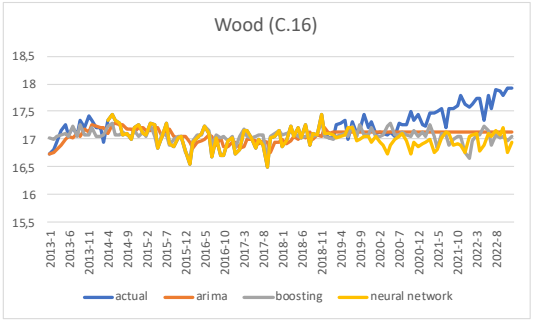


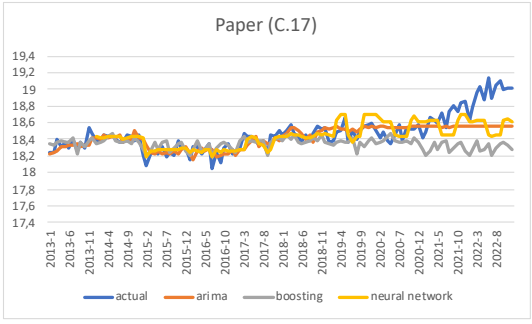


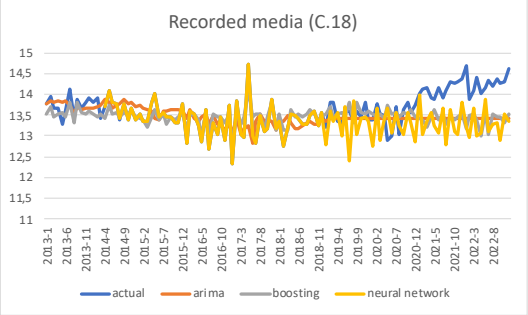


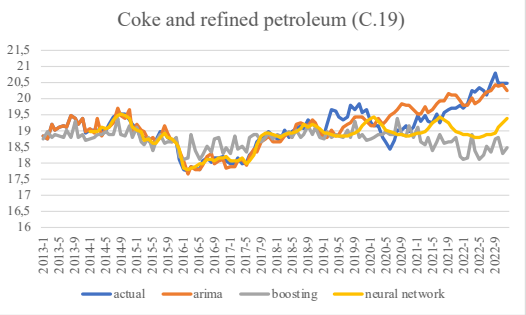


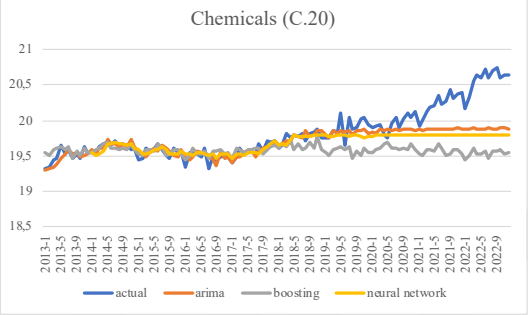


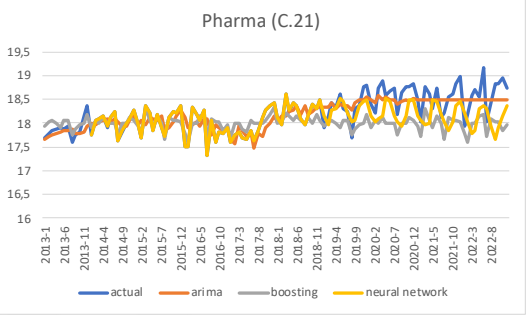


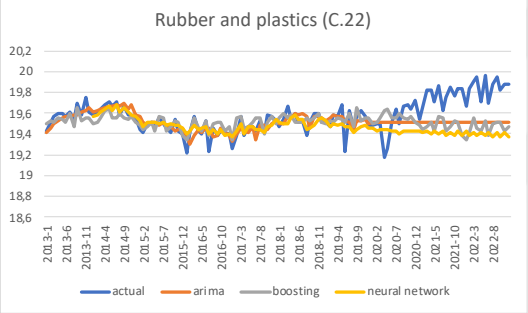


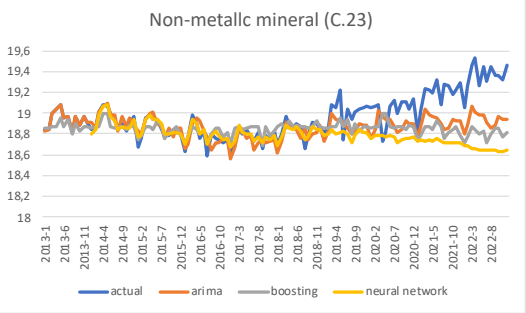

Recorded media (C.18)
actual
arima
boosting
neural network

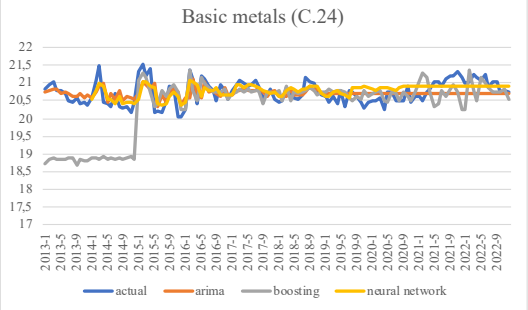

Coke and refined petroleum (C.19)
actual
arima
boosting
neural network

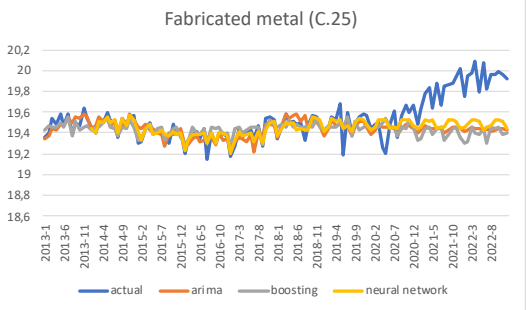

Chemicals (C.20)
actual
arima
boosting
neural network

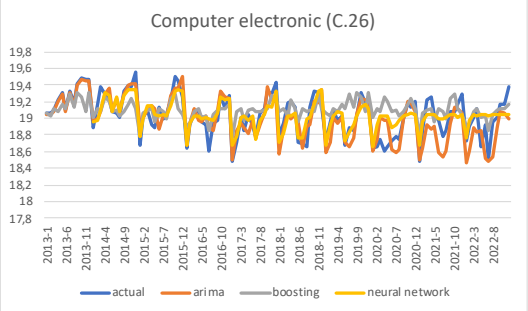

Pharma (C.21)
actual
arima
boosting
neural network

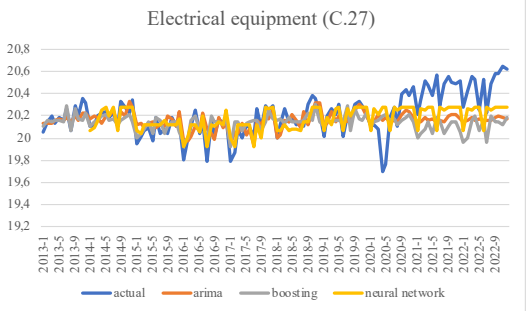

Rubber and plastics (C.22)
actual
arima
boosting
neural network


Non-metallc mineral (C.23)
actual
arima
boosting
neural network


Basic metals (C.24)
actual
arima
boosting
neural network


Fabricated metal (C.25)
actual
arima
boosting
neural network


Computer electronic (C.26)
actual
arima
boosting
neural network


Electrical equipment (C.27)
actual
arima
boosting
neural network

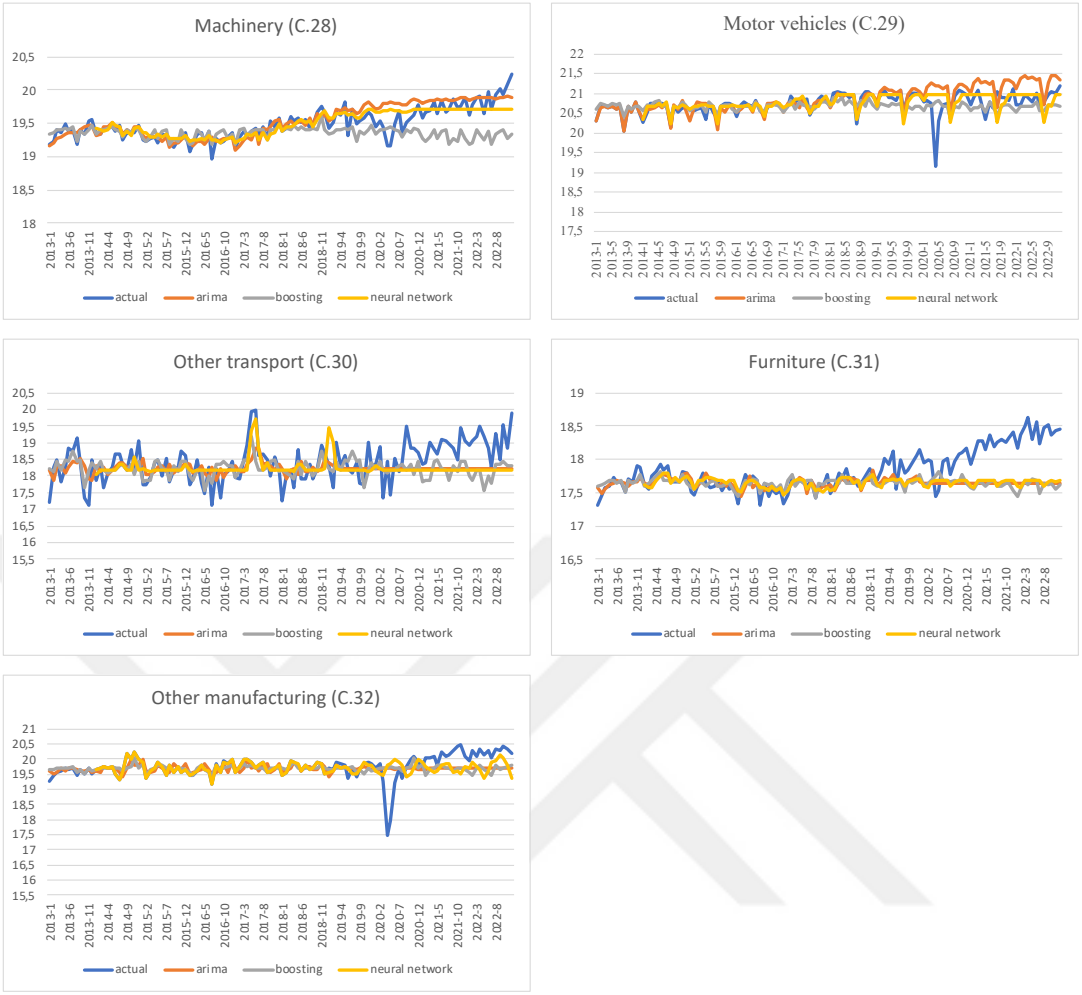
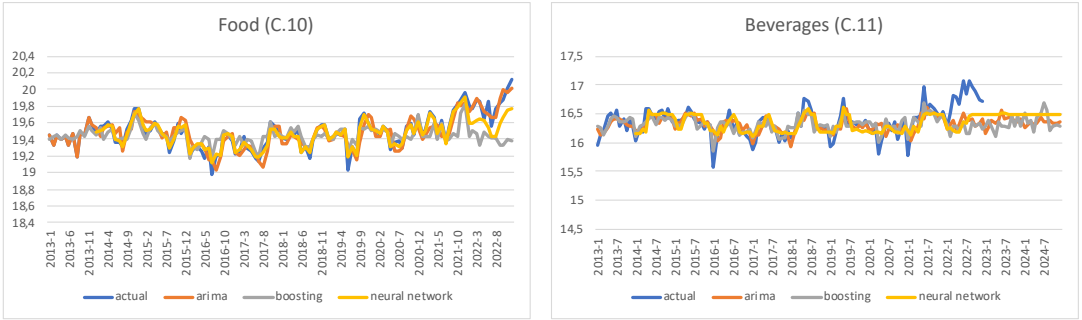
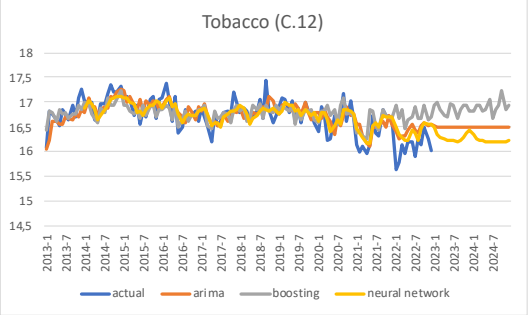


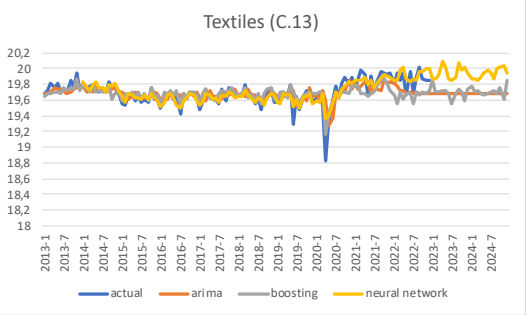
Figure A.1 Comparison of Forecast Methods for İstanbul for the Period of 2013-2018
Note: Training period is 2013-2018 and test period is 2019-2022 that is compared with actual data.
Source: TurkStat

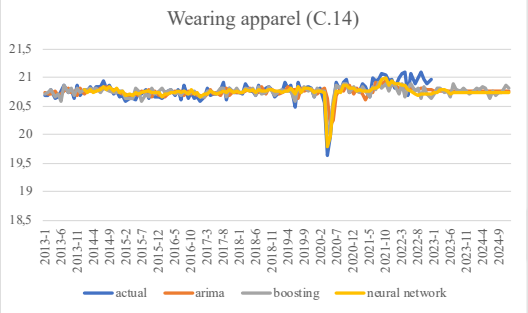
A.2. Training Period: 2013-2021

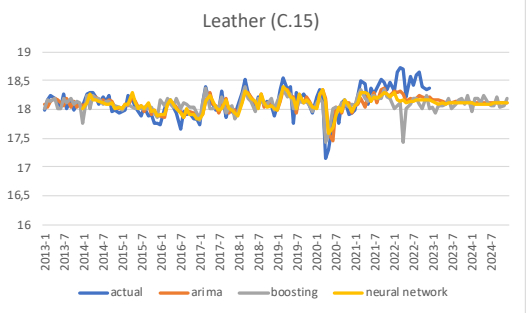
The results of the training period of 2013-2021 considering arima, boosting, and neural network for İstanbul by using monthly and logarithmic data are illustrated below.

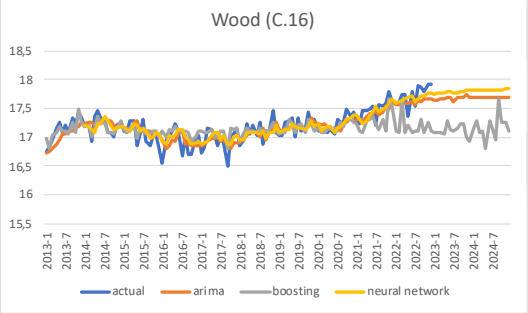


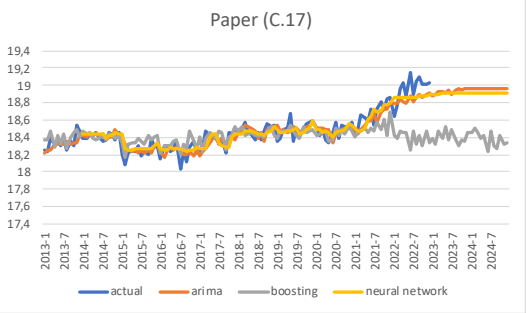

Tobacco (C.12)
actual
arima
boosting
neural network

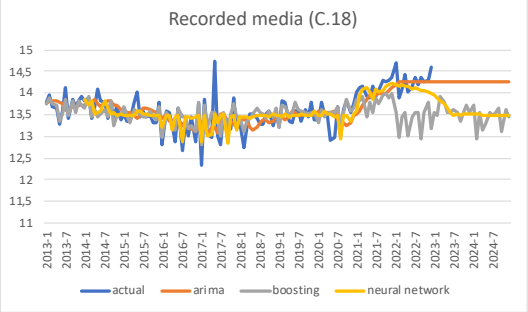

Textiles (C.13)
actual
arima
boosting
neural network

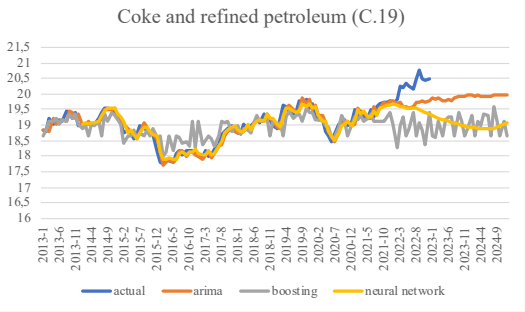

Wearing apparel (C.14)
actual
arima
boosting
neural network

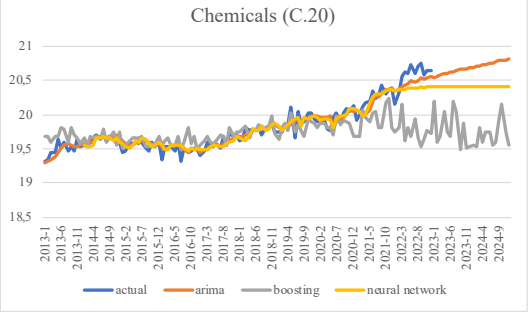

Leather (C.15)
actual
arima
boosting
neural network

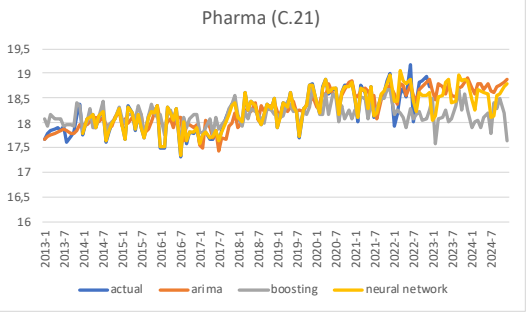

Wood (C.16)
actual
arima
boosting
neural network

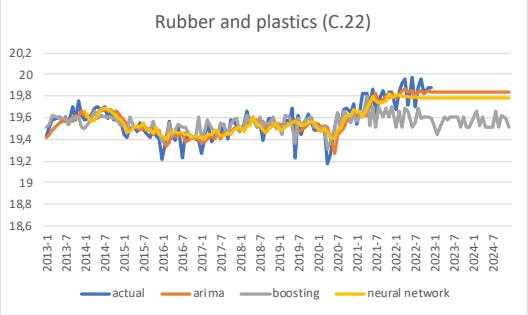

Paper (C.17)
actual
arima
boosting
neural network

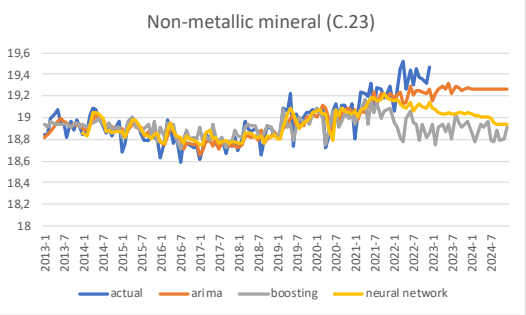

Recorded media (C.18)
actual
arima
boosting
neural network

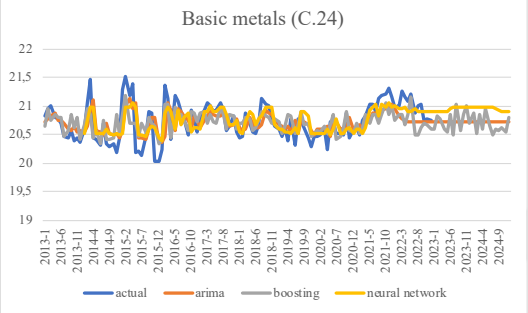

Coke and refined petroleum (C.19)
actual
arima
boosting
neural network

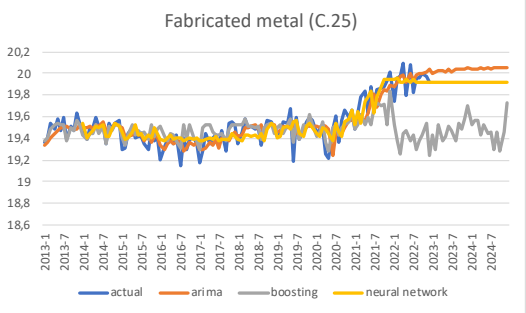

Chemicals (C.20)
actual
arima
boosting
neural network

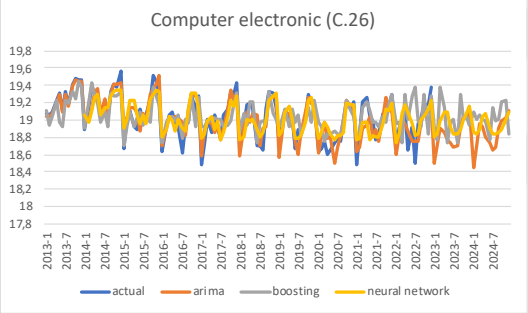

Pharma (C.21)
actual
arima
boosting
neural network

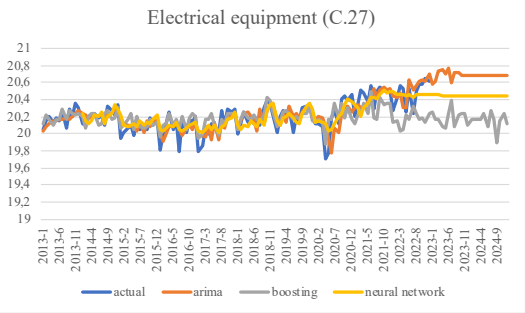

Rubber and plastics (C.22)
actual
arima
boosting
neural network

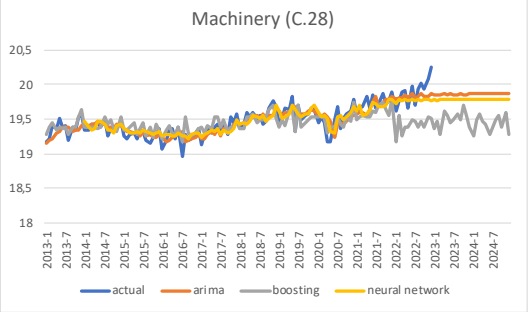

Non-metallic mineral (C.23)
actual
arima
boosting
neural network

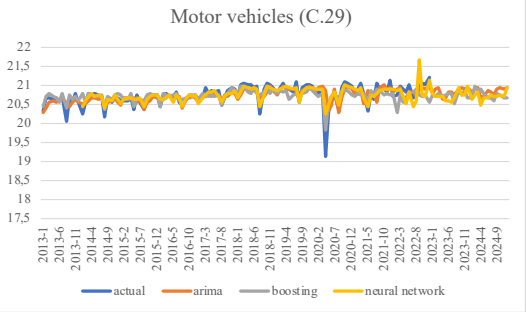

Basic metals (C.24)
actual
arima
boosting
neural network

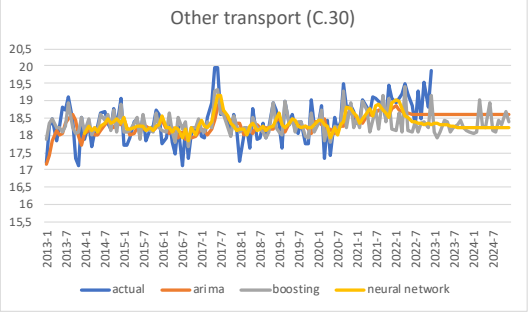

Fabricated metal (C.25)
actual
arima
boosting
neural network

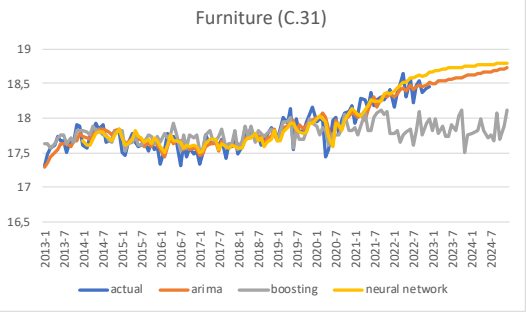

Computer electronic (C.26)
actual
arima
boosting
neural network


Electrical equipment (C.27)
actual
arima
boosting
neural network


Machinery (C.28)
actual
arima
boosting
neural network


Motor vehicles (C.29)
actual
arima
boosting
neural network


Other transport (C.30)
actual
arima
boosting
neural network


Furniture (C.31)
actual
arima
boosting
neural network

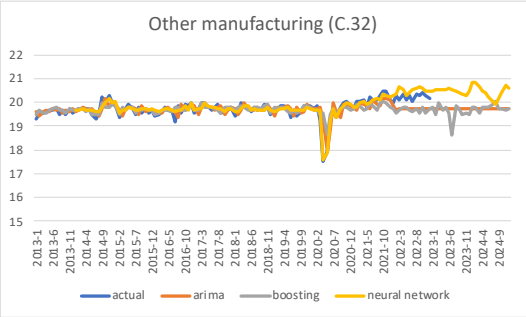


Figure A.2 Comparison of Forecast Methods for İstanbul for the Period of 2013-2021
Note: Training period is 2013-2021 and test period is 2022 that is compared with actual data.
Source: TurkStat

B. Export by Province and Sector

İstanbul

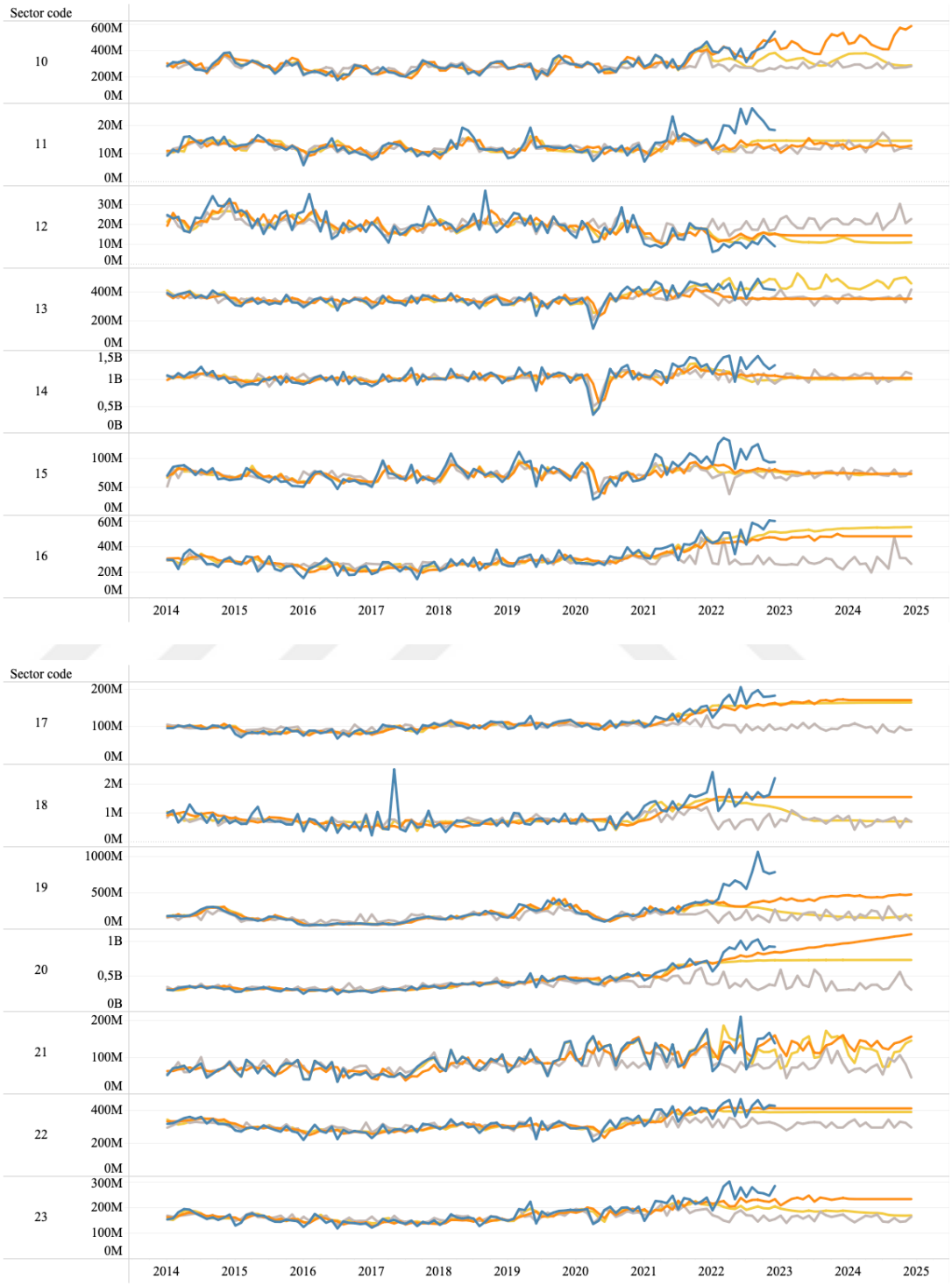




Figure B.1 Forecast Results for İstanbul by Sector and Model
Note: Training period is 2013-2021 and test period is 2022 that is compared with actual data.
Source: TurkStat

İzmir


Sector code
10
400M
200M
0M
11
2M
1M
0M
12
40M
20M
0M
13
40M
20M
0M
14
150M
100M
50M
15
15M
10M
5M
0M
16
20M
10M
0M
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025
Sector code
17
40M
20M
0M
18
1,5M
1M
0,5M
0M
19
80M
60M
40M
20M
20
150M
100M
50M
21
10M
5M
0M
22
100M
50M
0M
23
60M
40M
20M
0M
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025

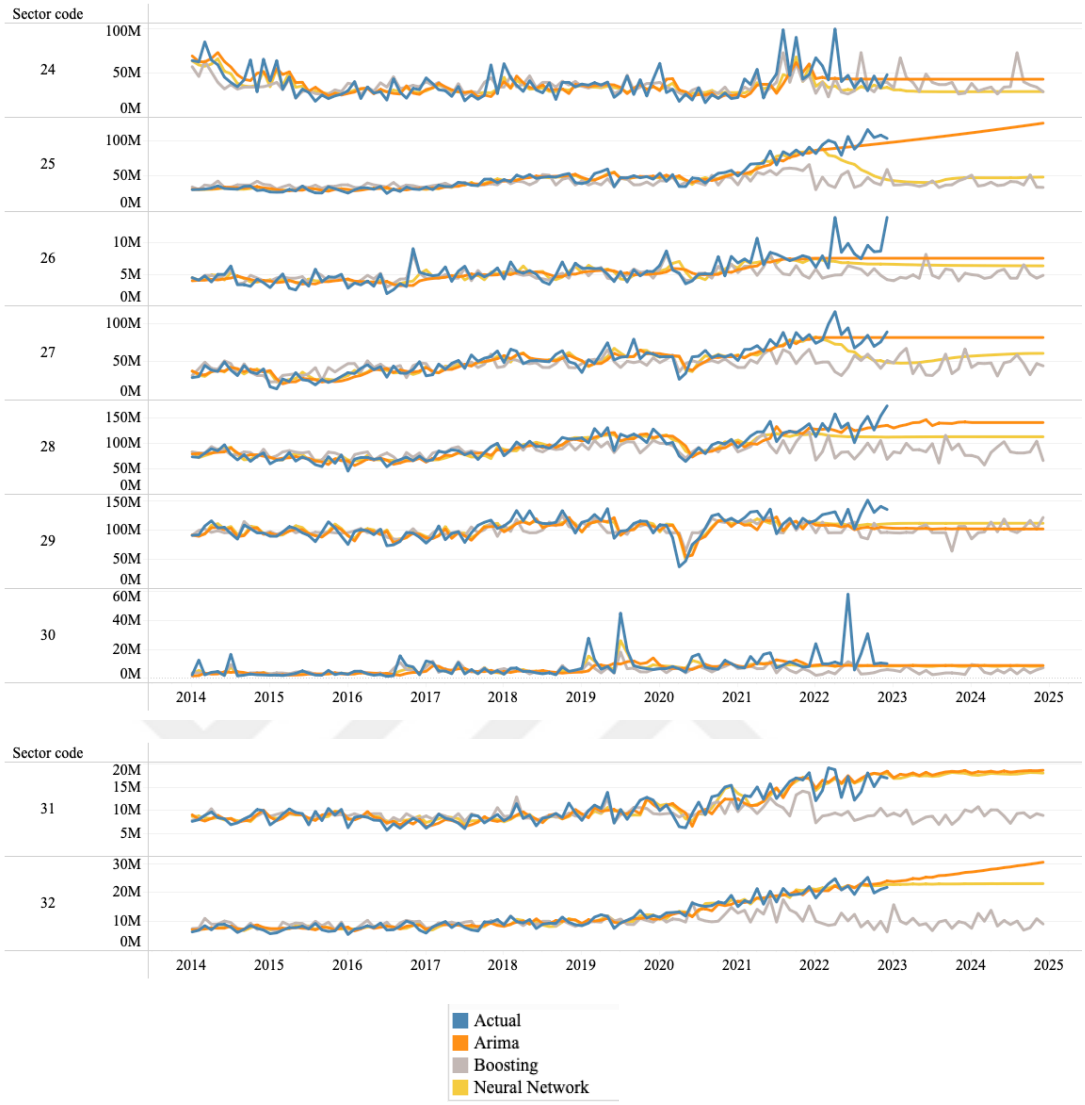
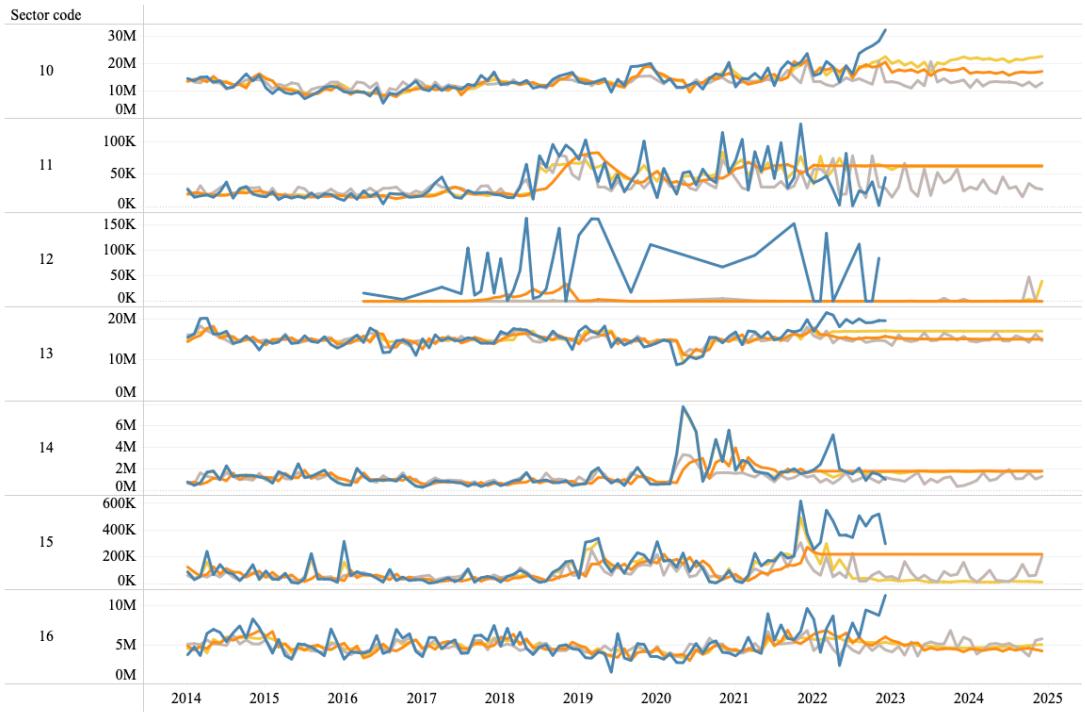


Figure B.2 Forecast Results for İzmir by Sector and Model
Note: Training period is 2013-2021 and test period is 2022 that is compared with actual data.
Source: TurkStat

Kocaeli


Sector code
10
30M
20M
10M
0M
11
100K
50K
0K
12
150K
100K
50K
0K
13
20M
10M
0M
14
6M
4M
2M
0M
15
600K
400K
200K
0K
16
10M
5M
0M
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025

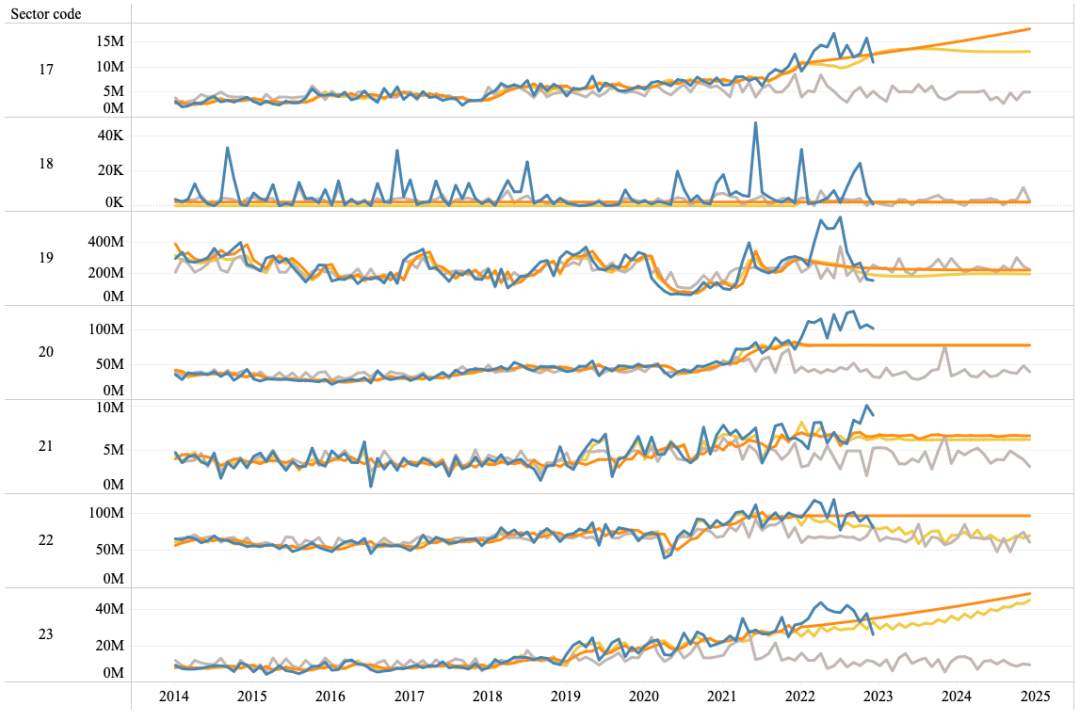

Sector code
17
15M
10M
5M
0M
18
40K
20K
0K
19
400M
200M
0M
20
100M
50M
0M
21
10M
5M
0M
22
100M
50M
0M
23
40M
20M
0M
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025



Figure B.3 Forecast Results for Kocaeli by Sector and Model
Note: Training period is 2013-2021 and test period is 2022 that is compared with actual data.
Source: TurkStat

C. Error Rates

The accuracy of the model was tested by considering the performance metric which is mean absolute percentage error (MAPE) by sector and province.

As mentioned before in the section "4.3. Forecast Model", there are thresholds for the interpretation of MAPE results. Accordingly, if the MAPE value is smaller than 10, it is interpreted as high accuracy forecasting. If it is between 10-20, it means that it is a good forecasting while if it is between 20-50, it is a reasonable forecasting. However, if it is bigger than 50, it is interpretated as inaccurate forecasting. In addition to these, the MAPE results that are shown below are the results of each arima model by sector for monthly data considering 2022.

Table C.1 The Error Rates of Türkiye Forecast

Türkiye		
Sector code	**Sector**	**MAPE**
10	Food	6
11	Beverages	20
12	Tobacco	14
13	Textiles	14
14	Wearing apparel	16
15	Leather	12
16	Wood	11
17	Paper	11
18	Recorded media	13
19	Coke and refined petroleum	31
20	Chemicals	11
21	Pharma	25
22	Rubber and plastics	7
23	Non-metallic mineral	9
24	Basic metals	15
25	Fabricated metal	6
26	Computer electronic	16

27	Electrical equipment	7
28	Machinery	9
29	Motor vehicles	9
30	Other transport	26
31	Furniture	9
32	Other manufacturing	28

Table C.2 The Error Rates of İstanbul Forecast

İstanbul		
Sector code	**Sector**	**MAPE**
10	Food	7
11	Beverages	34
12	Tobacco	46
13	Textiles	14
14	Wearing apparel	16
15	Leather	23
16	Wood	15
17	Paper	13
18	Recorded media	18
19	Coke and refined petroleum	44
20	Chemicals	14
21	Pharma	25
22	Rubber and plastics	7
23	Non-metallic mineral	14
24	Basic metals	20
25	Fabricated metal	7
26	Computer electronic	13
27	Electrical equipment	10
28	Machinery	13
29	Motor vehicles	14

30	Other transport	38
31	Furniture	9
32	Other manufacturing	39

Table C.3 The Error Rates of İzmir Forecast

İzmir		
Sector code	**Sector**	**MAPE**
10	Food	6
11	Beverages	27
12	Tobacco	16
13	Textiles	21
14	Wearing apparel	10
15	Leather	12
16	Wood	20
17	Paper	9
18	Recorded media	45
19	Coke and refined petroleum	58
20	Chemicals	20
21	Pharma	78
22	Rubber and plastics	15
23	Non-metallic mineral	17
24	Basic metals	21
25	Fabricated metal	10
26	Computer electronic	20
27	Electrical equipment	12
28	Machinery	12
29	Motor vehicles	17
30	Other transport	34
31	Furniture	14
32	Other manufacturing	8

Table C.4 The Error Rates of Kocaeli Forecast

Kocaeli		
Sector code	**Sector**	**MAPE**
10	Food	18
11	Beverages	812
12	Tobacco	Inf
13	Textiles	19
14	Wearing apparel	33
15	Leather	42
16	Wood	42
17	Paper	14
18	Recorded media	Inf
19	Coke and refined petroleum	32
20	Chemicals	27
21	Pharma	17
22	Rubber and plastics	10
23	Non-metallic mineral	17
24	Basic metals	50
25	Fabricated metal	10
26	Computer electronic	25
27	Electrical equipment	20
28	Machinery	8
29	Motor vehicles	12
30	Other transport	116
31	Furniture	16
32	Other manufacturing	32

D. Classification of Product Group by Technology Intensity (ISIC Rev.4 classification)

Table D.1 Classification of Product Group by Technology Intensity (ISIC Rev.4 classification)

ISIC Rev. 4	Definition	Technology Classification
C.10	Manufacture of food products	Low-technology
C.11	Manufacture of beverages	Low-technology
C.12	Manufacture of tobacco products	Low-technology
C.13	Manufacture of textiles	Low-technology
C.14	Manufacture of wearing apparel	Low-technology
C.15	Manufacture of leather and related products	Low-technology
C.16	Manufacture of wood and of prod. of wood and cork except furniture; manuf. of articles of straw and plaiting materials	Low-technology
C.17	Manufacture of paper and paper products	Low-technology
C.18	Printing and reproduction of recorded media (excl. C.18.2)	Low-technology
C.18.2	Reproduction of recorded media	Medium-low-technology
C.19	Manufacture of coke and refined petroleum products	Medium-low-technology
C.20	Manufacture of chemicals and chemical products	Medium-high-technology
C.21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	High-technology
C.22	Manufacture of rubber and plastics products	Medium-low-technology

C.23	Manufacture of other non-metallic mineral products	Medium-low-technology
C.24	Manufacture of basic metals	Medium-low-technology
C.25	Manufacture of fabricated metal products except machinery and equipment (excl. C.25.2)	Medium-low-technology
C.25.2	Manufacture of weapons and ammunition	Medium-high-technology
C.26	Manufacture of computer electronic and optical products	High-technology
C.27	Manufacture of electrical equipment	Medium-high-technology
C.28	Manufacture of machinery and equipment n.e.c.	Medium-high-technology
C.29	Manufacture of motor vehicles trailers and semi-trailers	Medium-high-technology
C.30	Manufacture of other transport equipment (excl. C.30.1 and C.30.3)	Medium-high-technology
C.30.1	Building of ships and boats	Medium-low-technology
C.30.3	Manufacture of air and spacecraft and related machinery	High-technology
C.31	Manufacture of furniture	Low-technology
C.32	Other manufacturing (excl. C.32.5)	Low-technology
C.32.5	Manufacture of medical and dental instruments and supplies	Medium-high-technology