THE PERFORMANCE EVALUATION OF TURKEY'S EXPORT TO IRELAND USING DATA ENVELOPMENT ANALYSIS

(VERİ ZARFLAMA ANALİZİ İLE TÜRKİYE'NİN İRLANDA'YA İHRACATININ PERFORMANS DEĞERLENDİRMESİ)

by

Ayşe Ülgen ÖZGÜL, B.S.

Thesis

Submitted in Partial Fulfillment

of the Requirements

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Ayşe Ülgen Özgül

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List of Symbols

A^*_{WSM}	weighted sum of the best alternative
a_{ij}	actual value of the i^{th} alternative for j^{th} criterion,
w_j	importance weight of criterion j.
$R(A_K/A_L)$	weight powered multiplication of the comparison ratios of alternative A_K to alternative A_L,
u(x)	the utility function,
CI	Consistency Index
E_j	efficiency value of DMU j
u_r	weight assigned to output r
v_i	weight assigned to input i
y_{rj}	amount of output r produced by DMU j;
x_{ij}	amount of input i consumed by DMU j.
E_{j_0}	efficiency value of the evaluated decision making unit, DMU j_0,
R_{rj}	the ratio of output r to input for DMU j.
d_j	deviation of the efficiency value E_j, from the ideal efficiency value of 1)
s_i^-	input slack variables for input i,
s_r^+	output slack variables for output s,
θ_0	efficiency value of the selected DMU.

Δx_{i0}	improvement values for input i,
Δy_{r0}	improvement values for output s.
w_{rl}^{1}	weighted value of being rated in the lth place with respect to output r
w_{il}^{2}	weighted value of being rated in the lth place with respect to input i
$\boldsymbol{\gamma}_{\mathbf{rj}}$	vector indicating the rating assigned to DMU j with respect to output r
$\boldsymbol{\delta}_{\mathbf{ij}}$	vector indicating the rating assigned to DMU j with respect to input i
L	the size of the likert scale
ε	positive constant
EXO	set of exact outputs
ORDO	set of ordinal outputs
EXI	set of exact input.
E_{kj}	the cross efficiency value of DMU j with respect to DMU k,
u_{rk}	optimal weight assigned to output r for DMU k and
v_{ik}	optimal weight assigned to input i for DMU k,
M_{j}	Maverick index of DMU j.

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Abstract

This thesis aims to evaluate the performance of Turkey's export to Ireland in 2008 by focusing on the manufacturing sectors of the top 100 products exported. A robust evaluation of the export performance requires the consideration of several quantitative criteria as well as qualitative criteria, and therefore, as the solution methodology, we employ an imprecise data envelopment analysis (IDEA) model, which is a mathematical programming model applied to the multi-criteria decision making (MCDM) problems, that can successfully deal with imprecise input and output criteria. In this thesis, through the use of various DEA and IDEA models with different discriminating powers, including Minimax efficiency model, Cross efficiency, and Aggressive cross efficiency models, the manufacturing sectors considered (namely, Manufactured Food Products and Beverages, Textile Industry, Wearing Apparel, Manufacture of Paper and Paper Products, Plastic and Rubber Products, Manufacture of Non Metallic, Basic Metals Industry, Machinery and Equipment, Electric Machinery and Apparatus, Manufacture of Motor, Vehicles, Trailers, and Manufacture of Furniture) are ranked according to their export performance, and managerial insights are provided regarding which sectors should receive more attention in order to increase the overall export performance of Turkey. The types of data collected for this purpose are objective (exact) and subjective (ordinal). The objective data are supplied from different sources such as TURKSTAT (Turkish Statistical Institute), CSO (Central Statistics Office of Ireland), DTM (Undersecretariat of the Prime Ministry for Foreign Trade) and TCMB (Central Bank of Republic of Turkey). The subjective data are obtained by the help of a survey filled out by an expert. After ranking the target sectors, a sensitivity analysis is applied to the worst performing sector to figure out the factors which are needed to be modified to improve the efficiency of that sector. Moreover, a product based analysis of the best performing sectors is carried out to control whether there is any chance of further improvement for those sectors.

Résumé

Cette thèse vise à évaluer la performance de l'export de la Turquie à l'Irlande en 2008 en se concentrant sur les secteurs manufacturiers des 100 premiers produits exportés. Une évaluation solide de la performance à l'exportation a besoin de considérer de plusieurs critères quantitatifs ainsi que des critères qualitatifs. A cause de ça, comme notre méthode de solution, nous avons choisi l'analyse d'enveloppement de données imprécises (IDEA) modèle, qui est un modèle de programmation mathématique appliqué aux problèmes de prise de décision multi critère (MCDM), qui peut être utilisé de traiter des critères imprécis avec succès. Dans cette thèse, les secteurs manufacturiers (à savoir, les produits manufacturés des aliments et boissons, l'industrie textile, de l'habillement , fabrication du papier et du carton, en plastique et en caoutchouc, fabrication de produits non métalliques, l'industrie des métaux de base, matériel et outillage, de machines et appareils électriques, fabrication d'automobiles, de véhicules, remorques et fabrication de meubles) sont gradés selon leur performance a l'exportation par l'utilisation de divers modèles de DEA et IDEA qui ont de différentes pouvoirs de discrimination comme le minimax modèle, l'efficacité croisée, le modèle d'efficacité croisée agressive. A la suite des ces évaluations, les secteurs qui devraient recevoir plus attention pour améliorer la performance de l'export globale de la Turquie, sont déterminés et des perspectives de gestion liées a ces secteurs sont données.

Les types de données collectées à ce but sont objectifs (exactes) et subjectifs (ordinales). Les données objectives sont fournies par de différentes sources telles que TURKSTAT (Institut turc de statistique), CSO (Office de Statistique Centrale d'Irlande), DTM (sous-secrétariat du Premier Ministre pour le Commerce Extérieur) et TCMB (Banque centrale de la République de Turquie). Les données subjectives sont obtenues à l'aide d'une enquête remplie par un expert. Après avoir déterminé les secteurs qui ne sont pas efficaces, une analyse de sensibilité est appliquée au secteur le plus faible pour déterminer les facteurs qui doivent pour être modifiés pour améliorer

l'efficacité de ce secteur. En outre, les secteurs les plus efficaces sont analysés plus profondément au niveau de produits pour contrôler s'il n'y a aucune chance d'amélioration supplémentaire pour ces secteurs.

Özet

Bu tez çalışmasında Türkiye'nin İrlanda'ya olan 2008 yılı ihracatının performansı üretim sektöründe ilk 100 ihraç ürünü temel alınarak değerlendirilmiştir. İhracat performansının sağlıklı bir şekilde değerlendirilebilmesi çeşitli niteliksel ve niceliksel kriterlerin göz önünde bulundurulmasını gerektirmektedir. Bundan dolayı, çok kriterli karar verme (MCDM) problemlerinin çözümünde sıkça uygulanan ve sadece niceliksel kriterler kabul eden bir model olan veri zarflama analizi (DEA) modelinin yanısıra hem niceliksel hem de niteliksel kriterler ile başarılı bir şekilde çalışmaya müsade eden bir DEA modeli olan belirsiz DEA (IDEA) modeli de kullanılmıştır. Tez çalışması boyunca DEA veya IDEA'yı takiben Minimax, Çapraz Verimlilik ve Agresif Çapraz Verimlilik gibi daha yüksek ayrım gücü olan yöntemler uygulanarak ele alınan üretim sektörleri ihracat performanslarına göre sıralanmış ve Türkiye'nin toplamdaki ihracat performasını arttırmak adına hangi sektörlere eğilinmesi gerektiği konusunda yönetimsel anlamda görüşler sunulmuştur. Ele alınan sektörler işlenmiş yiyecek ürünleri ve içecekler, tekstil endüstrisi, giyim sektörü, işlenmiş kağıt ve kağıt ürünleri, plastik ve lastik ürünleri, metalik olmayan üretim, temel metal endüstrisi, makine ve ekipman, elektrikli makine ve aparatlar, motor üretimi, taşıtlar, treylerler ve mobilya üretimi şeklindedir. Sıralandırmanın gerçekleştirilebilmesi icin sektörlere dair nesnel ve öznel veriler toplanmıştır. Nesnel veriler TUİK (Turk İstatistik Kurumu), CSO (İrlanda Merkez İstatistik Ofisi), DTM (Dış Ticaret Müsteşarlığı) ve TCMB (Türkiye Cumhuriyeti Merkez Bankası) gibi farklı kurumlardan sağlanmıştır. Öznel veriler ise çalışma sırasında oluşturulan bir anketin konu üzerinde uzman bir kişi tarafından doldurulmasıyla elde edilmiştir. Hedef sektörler sıralandıktan sonra en kötü performansa sahip sektöre bir duyarlılık analizi uygulanarak hangi faktörlerin değişiminin söz konusu sektörün ihracat verimliliğini arttıracağı belirlenmiştir. Ayrıca en yüksek performansa sahip olduğu belirlenen sektörlerin verimliliklerini daha fazla iyileştirmek için hangi ürünlere ağırlık verilmesi gerektiği belirlenmiştir.

1. Introduction

As the current global market trend points out the role of exporting in a nation's economy, the interests in export performance and the actions needed in order to improve the export efficiency are getting more and more important each day.

The studies concentrated on Turkish Economy show that the export performance is a very important topic for Turkey and according to the strategic plans made for the upcoming years, its importance will continue to grow in the future. According to TURKSTAT (Turkish Statistical Institute), the value of Total Export of Turkey in 2008 is 132 billion dollars, which reflects 23.1% growth compared to 2007. When the export origin investigated, it is worth noting that 94.8% of Turkish exports are made by the manufacturing industry, which motivated us to focus specifically on the export performance evaluation of the manufacturing sectors in this study.

Ireland, despite being a small country with the estimated population of 4,422,100, was listed among the top 50 countries that Turkey made export for the first 9 months of 2008 [1]. When the top 100 products exported from Turkey to Ireland is analyzed, we see that while the total import of Ireland for these products from different countries decreased by 20% overall in 2008 because of the global crisis, the value of the import made from Turkey had a lower decrease and stays above the average by 17%. In the light of this healthy commercial relationship between Turkey and Ireland, we decided to provide a qualitative and quantitative analysis that evaluates the export performance of Turkey with Ireland.

Since this analysis requires multiple performance evaluation criteria that can be quantitative as well as qualitative, we employ not only a data envelopment analysis (DEA) model, which is a mathematical programming model applied to the multi-criteria decision making (MCDM) problems, but also an imprecise DEA (IDEA) model, which is a DEA model that can successfully deal with imprecise input and output criteria.

There exist some studies in the literature regarding a firm's export performance evaluation by using an MCDM methodology. However, to our knowledge, there is no study that evaluates the performance of Turkey's export at country level using real data and employing a MCDM method. Hence, we believe that this study which evaluates the performance of Turkey's export to Ireland (a target market) using DEA technique, applied to real data gathered from reliable sources, is an important contribution to literature.

For a general understanding of Ireland's economy and Turkey's export to Ireland, a brief summary is given below, together with helpful details such as some annual figures from 2000 to 2008 on the overall import and export of Ireland, Turkey's role in that context, and the reason for choosing top 100 manufacturing products exported by Turkey to Ireland.

The focus of Irish economy, which was mostly based on agriculture before joining the European Union, has been shifted to value-added products since 1990, such as technology products. As a part of this new economic growth strategy, medicine, e-commerce, information technology, software development, construction, and organic chemicals have been the most popular areas in the context of manufacturing, where the research and development and consultancy have been the most popular ones in the service sector. Despite having low natural resources, by the help of successful import and financial policies they applied, Ireland established a manufacturing industry which supplies most of its raw materials by importing. Based on the successful economic strategy, Ireland has been a country with foreign trade surplus for last two decades, as also shown in Table 1.1 for years between 2001 and 2008.

Table 1.1 Irish Foreign Trade (Million Euro)

	2001	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
EXPORT	92,690	93,675	82,076	84,409	86,732	86,772	88,581	86,218
IMPORT	57,384	55,628	47,865	51,105	57,465	60,857	62,356	56,964
VOLUME	150,07	149,30	129,94	135,51	144,19	147,629	150,937	143,182
EQUILIBRIUM	35,306	38,047	33,211	33,304	29,267	25,915	26,215	29,254

The commercial goods which are not produced in Ireland mostly consist of kitchen appliances, automotive products and spare parts, textile products, window frames, doors, furniture, jewelery, isolation material, construction products including heating systems and ceramic products, and chemical products including cosmetics and cleaning material, are exported from other countries. When the product list examined it's seen that due to the announced 2007-2009 Turkish Export Strategy, it perfectly matches with Turkey's short term export target products. According to the strategic plan announced, it has been stated that Turkey's main aim is to develop its export especially in value added products where Research and Development and innovations play important roles such as technology and automotive industry products. In this manner, Ireland seems to fit this purpose as a market especially for the automotive sector products.

It is examined that the economic relations between Turkey and Ireland had a yearly increasing trend before the global crisis in 2008. This trend, which is in the favor of Turkey's export, can also be observed in a report produced by the Turkish Embassy in Dublin[2], which is based on the data from CSO as also presented below at Table 1.2.

Table 1.2 Foreign Trade between Turkey and Ireland (2000-2008) (Million Euro)

	2000	2001	2002	2003	2004	2005	2006	2007	2008
TURKEY'S IMPORT	387	310	328	304	301	322	369	412	402
TURKEY'S EXPORT	125	145	227	262	322	409	515	531	402

In Table.1.3, Turkey is also ranked as the top 20th exporting country to Ireland in 2008.

In this study, the top 100 manufacturing products exported from Turkey to Ireland in 2008 are considered. These products constitute 83.95 % (by 337.6 million euro) of the total 2008 Turkish export to Ireland (402.1 million euro). Since it is a quite high percentage, we believe that the results of evaluations can give a general point of view regarding the overall export performance of Turkish Exports to Ireland and the improvements needed.

Table 1.3 Top 20 Countries Exporting to Ireland (2008)

RANK	COUNTRY	MILLION EURO
1	UK	17,899
2	USA	6,674
3	Germany	4,619
4	China	3,852
5	Netherlands	2,870
6	France	2,373
7	Italy	1,341
8	Belgium	1,293
9	Northern Ireland	1,254
10	Norway	1,236
11	Japan	1,137
12	Denmark	1,032
13	Spain	932.4
14	Singapore	726
15	Taiwan	533.5
16	Switzerland	520
17	South Korea	504
18	Sweden	484
19	Poland	458
20	**Turkey**	**402.1**

When the top 100 products that Ireland import from Turkey is analyzed, it is seen that although it shows some differences at the product base, terms of total export values, the main competitors of Turkey (337 million euro) are England (by 1022 million euro), Germany (by 839 million euro), France (by 282 million euro), Spain (by 251 million euro), China (by 245.6 million euro) and Japan (by 179 million euro).

The remainder of this thesis is organized as follows: Chapter 2 provides a brief literature survey regarding the determination of export performance criteria in sub-chapter 2.1, export performance evaluation papers using multi criteria decision making methods in sub-chapter 2.2 and finally data envelopment analysis (DEA) models in sub-chapter 2.3. In Chapter 3, the problem of the export performance evaluation of Turkey to Ireland is presented with the selected criteria and the real data used. Chapter 4 describes the DEA methodology employed. In Chapter 5, the results of our study are given, and managerial insights are provided. Concluding remarks are presented in Chapter 6.

2. Literature Survey

2.1 Survey on the Export Performance Criteria

As the current global market trend points out the role of exporting in a nation's economy, export performance evaluation and its determinants (criteria) are becoming more and more important each day especially at the international marketing-business areas. For many years the researchers from economics or marketing disciplines have tried to identify the best criteria to take into consideration for various sectors. However, according to Sousa, a fully consensus hasn't been settled yet [3].

Determination of Export performance criteria is a very wide and complex subject that has been under discussion for a very long time. According to Katsikeas et al. [4] the first attempt to identify the factors of the firm's export performance is the work of Tookey in 1964 [5]. After that time on many studies has been made to examine the interrelationship between the export performance criteria and their outcomes (measures).

When the literature is examined, it is seen that, generally the studies take place on the firm base and the ones that take place on the country base doesn't supply common criteria proposals. Their export performance factors and measures differ from country to country [6-10].

The study of Manjappa and Bisaliah, shows that the export performance for India is analyzed by using the factors such as export prices, real appreciation of Indian rupee, higher domestic / international demand, FDI, competitiveness, volume of world trade and measure as share in exports [6].

Thirkell and Dau proposed some different determinants and measures for NewZeland at their study. The measures proposed are Level of export, exporting growth intensity, perceptions towards export whereas the factors proposed are environment, competencies

(Technology, Market/Export Knowladge, Quality), Marketing Orientation (Planning for Customer Satisfaction, Management Control, Communication Cross Functional, Management Perceptions towards Risk and Profit), Strategy(Product Mix, Promotion, Pricing,Staffing) and Firm Characteristics(Firm size, Management Perceptions towards competition, delivery and service, distribution) [7].

For Brazil, Gertner et al. performs an analysis for non financial export performance measurements by using perceived export performance measures and the criteria which reflect firm characteristics, export market characteristics and export experience [9].

Redding and Venables made their export performance determinant analyzes for South Asia Region by the help of econometric analysis methods. They mainly focused on the criteria “external demand” and “supply capacity” and the factors affect them. They are mentioning in their article that increase in external demand is highly geographical. By the help of the econometric functions(gravity equation) that they formed, they are analysing export performances of countries and stating that export performance of countries are dependant to its product number of competing varieties, their price competitiveness, internal geography, country size, endowment, business environment (such as institutional quality) and external geography on supply capacity criteria and total expenditure at the target country, on internal transport costs of the target country , and on the number of competing varieties and their prices on market capacity [10].

Baldauf et al., is mentioning about the factors that influence export performance by taking into account the small economies [8]. They share the same point of view with Zou and Stan [11] and tell that export performance factors of firms can be grouped in two groups: external factors and internal factors. Industry, domestic and foreign market characteristics are accepted as external factors whereas managerial and firm characteristics and export market strategies are considered as internal factors. This article also points out that there are some inconsistencies related with some of the factors, for example some articles says that there is positive relationship between firm size and export performance, some says negative [12] and some other says that there isn’t any association in between. They also mention that traditionally researchers relied on single measures (such as: export sales, export sales growth, export profits, and export intensity) of export performance, but using multiple measures is becoming more accepted and in their study they also employed multi measures and multi criteria which are consistent of objective and subjective data. This study employs three measures (export efficiency, export intensity and export sales) to evaluate the performance through the utilization of external and internal factors.

Since it is a very broad subject, most of the times common criteria and measure determination for export performance can be made by literature surveys. The rest of the studies can either focus on just a sector or one or a few export performance criteria with the help of data gathered from firms.

Firm and sector based criteria and measure determinations are examined by the help of Freeman [13], Samiee and Walters [14], Koh [15], Guan et al. [16,17], Leonidas et al. [18], Katsikeas et al. [19], Coskun [20] and Wang et al.'s [21] articles.

Samiee and Walters [14] and Koh [15] take education as a determinant of export performance on their firm based studies.

Economists, who deal with competitiveness, analyze this criterion by taking into account organizational management, manufacturing, marketing, industry environment and technological factors. However, Freeman [13] claims that it is the technological innovation capability which creates competitive advantage.

According to Guan et al. [16], export performance criteria are formed from 3 main factor groups: Structural factors (size, age, management systems, organization and technology profiles of firms), management factors (management and entrepreneurial characteristics such as: export expectations profitability, risks, costs and experience) and incentives and obstacles in the process of internationalization. This article is mainly dealing with one of the important export performance criteria "innovation" and its related factors (Learning capability, Manufacturing Capability, Marketing Capability, R&D Capability, Organizational Capability, Resource Exploiting Capability and Strategic Capability) by using the firm size, growth rate of labour productivity, and competitive position in home market variables of Chinese firms.

Guan et al. [17] are examining the situation at the R&D point of view. Instead of dealing with all export performance criteria they are analysing the connection between two export performance criteria international competitiveness and technological innovation capability. The article is also stating that competitiveness of a firm is based on a complex hierarchy and in order to analyze it, a multi-factor performance measurement model should be used.

Wang et al. [21] analyzed technology innovation capability (TIC) criterion by taking into consideration its 5 main factors such as: R&D capabilities, Innovation decision capabilities, Marketing capabilities, manufacturing capabilities and Capital capabilities.

The studies made by Leonidas et al. [18], Katsikeas et al. [19] and Coskun [20] were based on export performances of firms. In their analyses, they employed economic export performance measures such as: export profitability, export volume, export sales and used firm age, shareholder structure, management understanding, environment, product segment, pricing, distribution, promotion factors.

Since determination of export performance measures and criteria is a very complicated and widely distributed research topic, many researchers need to write literature survey papers in order to make summary related with the developments and bring a structure and so consensus to the criteria proposed by many articles. Al-Khalifa and Morgan [22] is one of them. In their article by the help of literature survey that they made till 1995, they tried to understand what kind of measures has been used for "export success measurement". Article states that the most frequently used measures are percentage of total sales, export growth level, export profitability, secondly used are average export volume, firm's evaluation of new product/export venture success and the ones used for business performance are accounting measures (ROI, ROS, ROE) and market share. By taking into consideration the customer part of the export issue and eliminating some of the criteria proposed before, they formed the structure presented at Table 2.1.

Another article dealing with literature survey is Zou and Stan [11]. Through their survey of 50 articles dated between 1987 and 1997, they are presenting a criteria structure formed from internal and external factors and export performance measures. They emphasize that due to the lack of articles on export performance of product and markets, they obliged to proceed to their study on firm base export performance criteria and measures. The structured list of criteria and measures are presented by the writer as in Table 2.2 and Table 2.3 respectively.

Table 2.1 Al-Khalifa and Morgan's [22] Criteria Table

	COMPETITOR CENTERED	CUSTOMER FOCUSED
EFFECTIVENESS	Market Share Sales Growth Percentage of Total Sales Export Profitability	Customer Satisfaction Customer Retention
EFFICIENCY	ROI, ROS, ROE, etc	Profit per customer
ADAPTIVENESS	% Sales from new products Relative rate of new product information	Perceived change in product and services to meet changing customer needs

Table 2.2 Zou and Stan's [11] Measure Table

MEASUREMENT OF EXPORT PERFORMANCE
Financial Measures
Sales Measures (abs volume of sales/ export intensity) * Profit Measures Growth Measures
Non-Financial Measures
Perceived Success* Satisfaction* Goal Achievement*
Composite Scale

Katsikeas et al.,'s study [4] take place as a proceeding work to Zou and Stan [11]'s and Al-Khalifa and Morgan's [22] studies. In their study, through their literature survey of 100 articles, they are mentioning about a different factor-measure structure.

Table 2.3 Zou and Stan’s [11] Criteria Table

	DETERMINANTS OF EXPORT PERFORMANCE	
	INTERNAL	**EXTERNAL**
CONTROLLABLE	**Export Marketing Strategy** General Export Strategy* Export Planning Export Organizing Market Research Utilization Product Adaptability Product Strengths Price Adaptation Price Competitiveness Price Determination Promotion Adaptation Promotion Intensity Distribution Channel Adaptation Distribution Channel Relationships Distribution Channel Type **Management Attitudes and Perceptions** Export commitment and support* International Orientation Proactive Export Motivation Perceived Export Advantages* Perceived Export Barriers*	
UN-CONTROLLABLE	**Management Characteristics** MGMT International Experience MGMT Education/Experience **Firm's Characteristics and Competiencies** Firm's size Firm's International Competence Firm's Age Firm's Technology Firm's Characteristics Firm's Capabilities/Competencies	**Industry Characteristics** Industry's Technological Intensity Industry's Level of Instability **Foreign Market Characteristics** Export Market Attractiveness Export Market Competitiveness Export Market Barriers **Domestic Market Characteristics** Domestic Market

At the article [4] all criteria are divided into 3 groups: Background variables (managerial factors (such as personal commitment, professional experience, language proficiency), organizational factors(such as demographic aspects, operating elements, resource characteristics, goal and objectives of the exporting firm) and environmental factors(forces shaping both domestic and overseas task environment and macroenvironment which exporters operate like economic conditions and trade barriers) that indirectly effect export performance), intervening variables (marketing strategy(firms' export product, pricing, marketing and promotion related factors) and targeting(export expansion strategy, foreign market segmentation) factors that directly affect export performance) and outcome (export performance measures). Then Export Performance Measures which are defined as outcome of a firm's activities in export markets are also divided into three groups: economic measures, noneconomic measures and general measures. Economic measures are consistent of sales related (such as export sales ratio, growth, volume, transaction size...), profit related (export profitability, profit ratio, profitability growth, profit margin..) and market-share related(export market share, market share growth) items whereas non-economic measures are consistent of product related (new product s exported, contribution of exporting to product development), market related (export market number, new market exports) and miscellaneous (contribution of exporting to company reputation, years of exporting..) items. General measures are formed mostly from subjective evaluations such as: perceived export success, satisfaction with overall export performance and strategic export performance. They mention that even though they found 42 export performance measures through their survey, just 5 of them (export sales intensity, export sales growth, export profitability, export sales volume and export sales intensity growth) are very frequently used.

Sousa [3] followed Katsikeas et al. [4] by his study and proposed a new measure grouping by dividing the measures into two main groups due to their mode of assessment: Objective Measures and Subjective Measures. The measure structure that they present can be seen at below Table 2.4:

Table 2.4 Sousa’s [3] Criteria Table

PERFORMANCE MEASURES	
Objective Measures	**Subjective Measures**
Sales Related	**Sales Related**
Export Intensity*	Export Intensity
Export Intensity Growth	Export Intensity Growth
Export Sales Growth	Export Intensity Growth compared to competitors
Export Sales Volume*	Export Sales Growth
Export Sales Efficiency	Export Sales Volume
Profit Related	Export Sales Growth compared to competitors
Export Profitability	Export Sales Volume compared to competitors
Export Profit Margin	Export Sales Return on Investment
Export Profit Margin Growth	Export Sales Return on Investment comp to competitors
Market Related	**Profit Related**
Export Market Share*	Export Profitability
Export Market Share Growth	Export Profit Margin
Market Diversification	Export Profit Margin Growth
	Export Profitability compared to competitors
	Market Related
	Export Market Share
	Export Market Share Growth
	Export Market Share compared to competitors
	Export Market Share Growth compared to competitors
	Market Diversification
	Rate of New Market Entry
	Rate of New Market Entry compared to competitors
	Gaining foothold in the market
	General
	Overall Export Performance*
	Overall Export Performance compared to competitors
	Export Success*
	Meeting Expectations
	How competitors rate firm's export performance
	Strategic Export performance*
	Miscellaneous
	Contribution of exporting to the growth of the firm*
	Contribution of exporting to the quality of firm's management
	Quality of Distributor Relationships
	Quality of Distributor Relationships compared to competitors
	Customer satisfaction

Table 2.4 Continued

PERFORMANCE MEASURES	
Objective Measures	**Subjective Measures**
	Customer satisfaction compared to competitors
	Quality of customer relationships compared to competitors
	Product/Service Quality compared to competitors
	Reputation of the firm compared to competitors
	Gaining new technology/expertise
	Building awareness and image overseas
	Achievement of objectives regarding response to competitive pressures

Another source of criteria determination is econometric studies made on export performances. When economic analyses such as UNCTAD reports [23, 24] and Aysan and Hacihasanoglu [25] are investigated, it is seen that the factors used for export performance of manufacturing are divided into 3 groups. These are Supply Capacity factors (product of number of varieties, price competitiveness (ULC (unit labour cost), GDP, devaluation rate, capacity rate)), Transborder Transport Cost Factors (transportation costs between countries and other additional costs caused by export barriers) and Market Capacity (expenditure in the export country, number of varieties, their prices expressed in the price index, internal transport).

The criteria determined to be used in our study are chosen by the help of above explained literature survey and data availability of the problem. The chosen criteria and its reasons will be explained in detail at section 3.

Literature surveys reveal that a consensus related with the export performance criteria couldn't be made up until now. However they are all agreeing on Cavusgil and Zhou,'s idea [26] that in order to deal with an export performance evaluation analyzes one has to take into consideration multi criteria instead of a single one. Because of this conclusion, we take into account our export performance evaluation problem as an MCDM problem and made our analysis accordingly. By the light of this point of view, as you can see at the upcoming chapter, a further literature survey related with the utilization of MCDM methods for export performance evaluation problems is made and most commonly used MCDM methods are examined.

2.2 Survey on the Multi Criteria Decision Making Models (MCDM) and the Export Performance Evaluation using MCDM Methods

From the studies explained in the previous sub-chapter, which has mentioned about export performance evaluation criteria, it is seen that the evaluation of the export performance should be done by the utilisation of multiple criteria. That's why this sub-chapter is dedicated to MCDM methodologies and the studies that dealt with the export performance evaluation using MCDM methods. The first part of the sub-chapter gives general information regarding the MCDM models, their benefits, weaknesses and utilisation purposes whereas the second part mentions the studies made on Export Performance Evaluation by using MCDM methods. Due to the lack of studies made by MCDM methods, the papers dealt with the evaluation of export performance criteria by using MCDM methods are also included in our study.

2.2.1 Multi Criteria Decision Making Models

Multi Criteria Decision Making (MCDM) (which is also called Multi Criteria Decision Analysis (MCDA)) is a discipline of Operations Research (OR) which deals with the decision making problems. The main objective of this discipline is to help decision makers to overcome the conflicts and find a reasonable solution for the multi criteria problems. According to Saaty and Vargas [27] it involves a certain element of subjectiveness. Depending on the decision alternatives, MCDM is divided into two groups: MODM (Multi Objective Decision Making) and MADM (Multi Attribute Decision Making) [28]. MODM techniques are used when the decision space is continuous whereas MADM is used when the decision alternatives can be pre-determined. According to Linkov et al. [29], MCDA methods are based on some theoretical foundations such as optimization, goal aspiration, outranking or combination of these and according the lecture notes obtained from National Taipei University [30], by taking into account their criteria aggregation procedures, MCDA methods are classified into four groups as: Elementary Methods, Unique Synthesising Criterion Methods, Outranking Methods and Interactive Methods. In the following subsection

MCDA methods are introduced. Data Envelopment Analysis (DEA), the method we employed in our study, is also a method for solving MCDM problems. However since we'll explain it in detail in the next section, its description isn't given in this sub-section):

2.2.1.1 Elementary Methods

Elementary Methods are generally the methods used by a single decision maker who deals with a few alternatives and criteria which doesn't have any inter criteria weightings. Since the methods convert complex problems to singular basis for the selection of the alternative, they mostly can be solved without requiring any software support. That's why some other more complex methods are chosen for more challenging complex problems. In section 2.2.1.1.1-2.2.1.17, some elementary methods are described.

2.2.1.1.1 Pros and Cons Analysis

This is a qualitative comparison method in which experts identify good (pro) and bad (cons) sides of the alternatives for each criterion. After the examination of the list of the pros and cons, the alternative which has the strongest pros and weakest cons is selected Fülöp [31]. According to Linkov et al. [30] Pros and Cons analysis can be applied to decision problems with 2 to 4 alternatives that are to be examined under a few criteria (1 to 5). It is easy to apply. Some other methods which work like Pros and Cons analysis can be named as SWOT (Strengths, Weaknesses, Opportunities and Threats) Analysis and Force Field Analysis.

2.2.1.1.2 Weighted Sum Method (WSM)

This method is used for single dimensional problems with a few numbers of alternatives and criteria. According to Triantaphyllou et al. [28], the best notification of the method is given by Fishburn in 1967 with the formula below (for maximization problems):

$$A^*_{WSM} = \max_i \sum_{j=1}^{N} a_{ij} w_j \qquad \text{for } i = 1,2,3,\ldots,M \qquad (2.1)$$

where A^{*}_{WSM} is the weighted sum of the best alternative, N is the number of criteria, M is the number of alternatives, a_{ij} is the actual value of the *i*-th alternative for *j*-th criterion, w_j is the importance weight of the criterion.

Since the model is formed from the summation of the direct multiplication of the importance weights with the true output of each alternative for each criterion, actual output units of each criterion is becoming so important for this method. When all the criteria have the same units, this method can be used without any problem. However when they have different units, this method isn't be applicable with the formula presented above. This method can be applied to just single dimensional problems whose data suits additive utility assumption.

2.2.1.1.3 Weighted Product Method (WPM)

WPM can be used for multi dimensional problems as well as single ones which have a few alternatives and criteria. The formula of the method depends on the multiplication of comparison ratios between each two alternatives.

According to Triantaphyllou et al. [28], the notification of the method is given by first Bridgman in 1922 and then by Miller and Starr in 1969 with the formula below:

$$R(A_K/A_L) = \prod_{j=1}^{N} (a_{Kj}/a_{Lj})^{w_j} \tag{2.2}$$

where $R(A_K/A_L)$ is the weight powered multiplication of the comparison ratios of alternative A_K to alternative A_L, N is the number of criteria, K and L are two of the compared alternatives, a_{ij} is the actual value of the *i*-th alternative for *j*-th criterion, w_j is the importance weight of the criterion.

According to method if $R(A_K/A_L)$ is greater than 1, it means that alternative A_K is better than alternative A_L. By these pair wise comparisons, the position of each alternative can be determined with respect to another and the best among them can be chosen. Since this method employs ratios in its calculations, it automatically eliminates the units of the actual outcomes so it makes it possible to solve the multi unit decision problems.

2.2.1.1.4 Maximin and Maximax Methods

Maximin method is used in order to avoid the worst possible situation by selecting the alternative which gives maximum value among the weakest results for the pre-determined criteria. This is done by identifying the worst performing criterion for each alternative, comparing their worst results between each other and choosing the alternative which gives the highest score among them. Even though the analysis is done by taking into account multi criteria, individual alternative performance is evaluated on a single criterion basis.

Maximax method is also calculated in the same way with a difference of choosing maximum value among the maximums instead of choosing maximum value among the minimums.

In addition to these methods, minimax and minimin methods also exist and as it can be understood from their names, their calculations are made by choosing minimum among the max values and choosing the min among the min values respectively [30].

2.2.1.1.5 Conjunctive and Disjunctive Methods

Conjunctive and its complementary Disjunctive methods are goal aspiration screening methods which are used not to find the best alternative but to find the satisfactory ones. That's why generally these methods are used for the preliminary subset of alternatives selection for the other complex MCDM models. In these methods alternatives have to exceed the defined thresholds (one for conjunctive method and one for disjunctive one). For the conjunctive method, an alternative must exceed the performance threshold (which is a minimum cut off level) for all criteria where as for disjunctive method, an alternative must exceed the defined threshold at least for one of the criterion. An alternative must satisfy the requirements of both methods so called to be successful.

Since the analyses in these methods are made within each criterion, they are not unit sensitive. So these methods can be used at multi dimensional problems.

These methods are also used as the basis of the elimination by aspect strategy. In this approach the criteria are ranked due to their importance weight. Then each alternative is tested starting from the most important criteria. The ones that couldn't pass the thresholds are discarded. Then the same procedure applied for the second most important criteria to the remaining alternatives. This procedure lasts till all the criteria completed. If none of the alternatives could pass from all the criteria, then the one that eliminated last is chosen [30].

2.2.1.1.6 Lexicographic Methods

Lexicographic method aims to select the best performing alternative for the most important criterion. If there is a tie among the best performing alternatives (according to Linkov et al. [30], generally there is) then their performance for the second most important is checked. This goes on till there is left just one alternative.

The negative side of the model is; for the few alternatives, quantitative data and negligible uncertainty, since the elimination ends at the most important criterion, it can behave as a single attribute decision making model.

2.2.1.1.7 Decision Tree Analysis

Decision tree can be useful when it is used at the problems which have complex quantitative data. Since the decisions and its consequences follow some paths, it is useful for the decision maker to see the decision nodes, their effects to the results and the risks that choices are carrying. According to Linkov et al. [30], negative side of this model is the representation part. Since each additional criterion expands the tree exponentially, it is giving permission to the presentation of the just simple models.

2.2.1.2 Unique Synthesizing Criterion Methods

These methods based on the evaluation of the problem by using a main criterion created from all other multi dimensional criteria by the help of a function which is defined according to some logic and intercriteria information. The found main criterion is called “Synthesizing Criterion” and since it is formed from all the criteria of the problem it is unique [32]. Here are some frequently used “Unique Synthesizing Criterion” Methods:

2.2.1.2.1 Multi Attribute Utility Theory (MAUT)

The aim of MAUT is maximizing utility and helping the decision maker to express his/her choices in a simple way. This method converts diverse criteria (such as cost, risk, benefits) into one common dimensionless scale by the help of utility function. That's why it can be applied to multi dimensional problems. Since it depends on the decision makers preferences on direct rating, ranking or comparative judgement of alternatives with regard to individual decision criteria, the decision makers that have to participate at the application of this method have to be rational (more have to be preferred to less, preferences must be consistent and decision makers have to have perfect knowledge related with the subject) [28].

The analysis procedure for the MAUT methodology consists of 3 steps: The first step in MAUT analysis is forming an attribute tree and indicating the key elements that have to be taken into account. The Attribute tree is constructed with a hierarchy which shows the top level objectives at the top and finer attributes and criteria at the bottom. All the criteria in this analysis should be measurable. The second step is formed from the determination of the criteria weights and alternative preferences for the individual criteria by using expert opinions. Then by using the decision maker preferences for best alternative(which has utility value 1), worst alternative (which has utility value 0) and indifferent alternatives(depending on the decision makers preference, it has value between [0,1]), the utility function which has a general formula as below is solved for the parameters a, b,c:

$$u(x) = ae^{bx} + c \tag{2.3}$$

Where u(x) is the utility function, a and c are parameters which guarantee the utility is normalized between 0 and 1, and b is the risk coefficient which shows degree of risk attitude, reflecting rate at which risk attitude changes with different attribute level [33].

After the determination of the constants, the last step will be the problem solving part realized with the help of either utility graphs or multi attribute utility functions which can be applied to both quantitative and qualitative data [31]. The results of MAUT analysis gives us a complete ranking of alternatives based on the experts' choices [30, 34].

2.2.1.2.2 Multi Attribute Value Theory (MAVT)

Even though MAVT is working with the same principals as MAUT theory does, there is a slight difference in between. MAVT is constituted to supply a ranking for the problems whose outcomes of the alternatives are known with certainty whereas MAUT extends classical decision theory and adds the use of probabilities and expectations to deal with the uncertainty [35, 36].

2.2.1.2.3 Simple Multi Attribute Rating Technique (SMART)

SMART is a multi attribute ranking approach which uses simple utility relationships. Differently from the other methods, SMART method gives opportunity to decision maker to score the alternatives equally if they don't differ significantly for a particular criterion. According to Baker et al.[37] SMART analyses are robust and they give the same decision results with more complex MAUT methods with a high degree of confidence [30].

The ranking in SMART method is made by the calculation of the weighted algebraic mean of the utility values associated it. The weight calculation of the criteria is made by the method developed by Edwards [38]. According to this method, first criteria are ranked according to their importance. Then 10 point is given to the least important one and the others are evaluated with respect to this reference point. After the evaluation completed the weights are normalized by the sum of all given points. In 1994, Edwards and Barron made a new improvement to their weight calculation method by stating that calculating just the weights of criteria is meaningless unless the weights of the utility values of the alternatives are taken into account [39]. By this point of view, they created SMARTS and consider utility values of the alternatives while making their importance comparisons between criteria [31].

2.2.1.2.4 The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS method is developed by Hwang and Yoon [40] with the aim of choosing the alternative which has the geometrically the closest distance to the ideal solution and the farthest distance from the negative ideal one. This method is developed as an alternative to the method ELECTRE which will be explained at the next sub-section.

Since TOPSIS assumes having monotonically increasing or decreasing attribute utilities, it is easy to locate the ideal and negative-ideal solutions. By the help of used Euclidean distance approach, relative distances of the alternatives to the ideal solution so the ranking of the alternatives can be recognized.

The method is applied by following the below steps: First step is normalizing the performance measures for each criteria by dividing the performance measure of each alternative to the square root of the summation of squares of performance measures of each alternatives. Second step is finding weighted normalized decision matrix by multiplying normalized performance measures with the according weights attained by decision maker. Third step is the determination of the Ideal and the non-ideal solutions from weighted normalized decision matrix for each criterion. Fourth step is formed from the calculation of the Euclidean distances (both for ideal and negative-ideal) for each alternative. The calculation is made by taking the square root of the sum of the square differences between the weighted normalized value of the alternative and the ideal solution (negative-ideal) value of each criterion. Fifth step is the calculation of the relative closeness to the ideal solution. It is calculated for each alternative by dividing negative-ideal solution to the sum of ideal and negative ideal solution. Sixth step is forming the preference ranking by sorting the alternatives with respect to their relative closeness from higher to lower [28].

2.2.1.2.5 Analytic Hierarchy Process (AHP)

AHP is a multiple criteria decision making method. It is proposed by Saaty, while directing the research projects in the US Arms Control and Disarmament Agency. It was developed as a reaction to the finding that there is a miserable lack of common, easily understood and easy to implement methodology to enable the taking of complex decisions [27]. And since then it has been used in a very wide range of decision analysis problems.

For the application of AHP, a problem has to be stated in a hierarchy. The problem has to have first a goal or ‘a main goal and the sub-goals’, then the criteria and if it is needed the sub criteria and finally the independent alternatives. The method needs to form a weight for each horizontal hierarchy member by making a pair wise comparison. (this means each goal, criteria, sub-criteria, alternative have to be compared within themselves in pair wise in order to have a meaningful weight of priority) In the discrete cases these comparisons will form dominance matrices where as in the continuous cases it will lead to kernels of Fredholm Operators [41].

While making a comparison a fundamental scale which can define all the necessary differences or priorities between the elements must be used. In many cases, in the book of Saaty [27], a 1-9 scale is used but it can be eventually enlarged or narrowed if it is needed.

Since there is a pair-wise comparison between homogeneous elements, the judgments between the pairs are reciprocal. For example: if A is better than B(5), then B has to be worse than A(1/5). The judgment about those comparisons can be made either in two ways. The judgments either can be relative or absolute. In relative measurement, the two elements are compared with respect to one of their common point where as in absolute measurement the elements are compared wrt a standard and then a ratio among them are formed. According to its structure a problem may contain both of the evaluation systems. For example the criteria can be weighted wrt relative evaluation whereas the alternatives can be weighted wrt absolute measurement.

For the discrete AHP, after structuring the problem hierarchy, a square dominance matrix is formed from decision makers' preferences for each pair wise comparison for each hierarchy level starting from the upper levels. Since the system is formed from homogeneous- linear equations, in order to obtain a meaningful solution related with the elements, the eigenvectors and eigenvalues of the matrix must be found. If the dominance matrix is totally consistent, it has to have rank 1 (which means all the other eigen values except 1 item has to be 0) and its eigenvalue has to be equal to its trace (trace is diagonal total of the dominance matrix and in our case it is the order of the dominance matrix). However, sometimes the dominance matrices couldn't be totally consistent. In that case AHP can tolerate the inconsistency up to certain range and the magnitude of the inconsistency at the matrix in AHP is calculated as such:

When there is inconsistency at the dominance matrix, it gives more than one eigenvalue. We would use the higher eigenvalue in order to calculate the Consistency Index (CI).

$CI = (\lambda_{max} - n)/(n - 1)$ where n is the order of the matrix. (2.4)

Then we'll divide this number to a random index stated at the Table 2.5 in order to find the Consistency Ratio (CR):

$CR = CI/RI$ (2.5)

In order to continue the process Saaty suggests CR to be less than 0.1. Otherwise the comparisons related with the dominance matrix has to be checked (it is suggested to be done by the program expert choice) and corrected.

Table 2.5-Average Random Consistency Index (RI)

N	1	2	3	4	5	6	7	8	9	10
Random Consistency Index	0	0	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

If the consistency ratio is ok, then the other levels' priority weights will be found by the help of different dominance matrices and the eigenvectors obtained from them.

After calculating all weights that are needed, the process of merging weights of alternatives takes place. There are two ways for doing this synthesis: One is the Distributive Mode, the other is the Ideal Mode.

In the Distributive Mode the weight of each alternative is carried to goal level by multiplying its weight with the weight of its criteria and its goal. At the final stage all the carried weights belong to that alternative are summed and the alternatives are sorted wrt their total weights and the best is chosen.

However in the Ideal Mode, the weight of each alternative is divided to the biggest weight among them (talking about the ones under the same criteria) and their synthesis carried to the upper level by multiplying its weight with the weight of its criteria and its goal. At the final stage all the carried weights belong to that alternative are summed and the alternatives are sorted wrt their total weights and the best is chosen.

According to Bhushan et al. [41] 'the distributive synthesis mode should be used when the decision maker is concerned with the extent to which each alternative dominates all other alternatives under the criterion. Ideal synthesis mode should be used when the decision maker is concerned with how well each alternative performs relative to a fixed benchmark.' The book also suggests that ' If the decision maker indicates that the preference for a top ranked alternative under a given criterion would improve if the performance of any lower ranked alternative was adjusted downward, then one should use the distributive synthesis method.'

2.2.1.3 Outranking Methods

Outranking methods are constructed on the principal that one alternative may be dominant to another whereas unique synthesizing criterion methods suppose that a single alternative can be the best among the others. According to Linkov et al., B. Roy defines the concept of the method in 1970s as such: The alternatives' performances must be compared in pairs for each criterion. In this method in order to call the alternative "a" is better than the alternative "b"(which is called "a" outranks "b"), "a" has to have a better performance than "b" for that specific criterion and be at least as well as "b" for the rest of the criteria. If "a" couldn't be as well as "b" for the rest of the criteria, it is called as "dominated" and wouldn't be a preference for the problem. The outranking approaches also have preference and indifference thresholds introduced to each criterion. The preference threshold is used for defining alternatives strongly preferred to the others whereas indifference threshold is used to eliminate the exaggeration of the small difference which wouldn't cause any distinction between the two alternatives. In addition to these two thresholds, some more thresholds (represented by mathematical interpolation functions) might be defined in order to represent weak (or fuzzy) preferences. The combination of all these thresholds is called "preference function".

The advantages of outranking methods with respect to Unique Synthesizing Criterion Methods can be listed as; it is easier to handle non-quantitative data with outranking methods, they allow for intransitivities in criteria weightings and outranking method gives flexibility to decision makers to change their mind during the analysis.

2.2.1.3.1 Elimination Et Choix Traduisant la Realite (ELECTRE- Elimination and Choice Translating Reality)

ELECTRE method is first introduced in 1966 by the study of Benayoun et al. It is used for the problems which need choosing, ranking or sorting by using the pairwise comparison among alternatives for each of the criteria [28]. Two different sets of parameters that are employed for its criteria are importance coefficients (weights) and veto thresholds. The veto thresholds which are compared with the concordance and discordance indices, play a major role at the determination of the outranking alternatives. For paired two alternatives (alternative “a” and alternative “b”), concordance index is the sum of all the weights for the criteria where the performance of alternative “a” is at least as high as alternative “b”. The discordance index is the ratio of the “difference in the performance level of alternatives ”a” and “b”” to the “maximum difference of the performance level of any alternative for the criterion”. If alternative “a“ is called to be outranking alternative “b”, its concordance index must exceeds concordance threshold where its disconcordance index deceeds disconcordance threshold. In order to be selected by this method, an alternative must outrank at least one another but mustn’t be outranked by any other. The number of the selected alternatives obtained by the analysis can be increased o decreased by changing the thresholds used [31].

2.2.1.3.2 Preference Ranking Organisation Method of Enrichment Evaluations (PROMETHEE)

PROMETHEE is developed by Brans in 1982 and extended by Brans and Vincke in 1985 and Brans and Mareschal in 1994 [42]. It is an outranking method, typical of the European (or French) MCA school. It is a multi dimensional-multi criteria analysis method which can use performance values of each alternative without needing normalization. The only assumption related with the performance values are higher values mean better performances. Besides performance values, PROMETHEE method also employs criteria weight in its analysis as it is done at the other methods. However determination of the weights isn't included in the model, they are obtained by other appropriate models.

In order to make pair wise alternative comparison, preference functions (P)(associated to each criterion) which take value between 0 and 1, are used in PROMETHEE analysis. The preference functions are formed from four phrases and their associated values: Strict Preference (P=1), Strong Preference(P≈1), Weak Preference(P≈0) and Indifference between two actions (P=0) [31]. After the preferences are defined for each criterion, the outranking and outranked alternative relations are determined and the positive outranking flow-negative outranking flow values, which will be used at ranking of the alternatives, are calculated for each alternative. The positive outranking flow (pof) is calculated for each alternative by taking the weighted mean of the preference values obtained from the comparisons that it outranks all the others. The negative outranking flow (nof) is calculated for each alternative by calculating the weighted mean of the preference values obtained from the comparisons that it is outranked by all the others. According to the basic model, if pof of an alternative is higher, whereas nof of the same alternative is lower than the other one's, then the alternative subject to the conversation is strictly preferred to the other. If their flow values are equal, they are called indifferent. If it is none of the both, then they are called incomparable alternatives.

2.2.1.4 Interactive Methods

The main difference between the interactive decision making models and the other MCDM models is generated from the decision makers' contribution type and its timing. In the interactive models, decision maker gives a limited amount of preference information at the beginning and answer all kinds of preference and trade off questions later as it is needed whereas at the other models, he/she gives all the priori information before the analysis starts. The type of the information that they receive from decision maker is also different from each other. In interactive models, decision maker gives his/her preferences just related with just the feasible alternatives whereas since the information is gathered at the very beginning, he/she gives preferences including infeasible alternatives for the other models. According to Spronk, [43] since the decision maker is involving the problem solving steps of the interactive models, found result has more chance of implementation with respect to the other models' results.

2.2.1.4.1 Goal Programming

Goal programming is a multi-objective optimization programme developed by Charnes, Cooper and Ferguson in 1952. Initial further developments related with the model were done by Ignizio in 1976, Romeo [44] in 1991 and Ignizio and Cavalier in 1994. [43]

This method can be accepted as an extension of linear programming to handle multiple, normally conflicting objective measures in a simple and easy way. Targets are formed for each of the measures and their unwanted deviations are tried to be minimized by the help of an achievement function.

If there is a clear priority between the goals given for the measures, then the deviation of the higher priority has to be minimized before the others. This is known as lexicographic goal programming and it is solved with an algorithm found by Ignizio in 1976.

If a direct comparison of the objectives is decided to be made, then weights are defined for each goal by the usage of a technique and weighted or non pre-emptive goal programming model is used for the solution. Weights for the models are determined either by using techniques such as AHP or an interactive method.

If the aim is to find a balance between the competing objectives, then instead of sum of deviations the max unwanted deviation has to be minimized by using Chebyshev goal programming (it is found by Flavell in 1976).

Its weakest side is ability to produce solutions that may not be Pareto efficient. However some techniques [45] are found lately for the detection of this situation and transfer of the solution to the pareto efficiency in an appropriate manner.

2.2.2 Export Performance Evaluation using MCDM

For many years Export Performance Evaluation had been an important study topic for researchers, especially the economists. However our literature survey study showed us that it is still an untouched area in terms of usage of multi criteria decision making tools. When we were making our investigations to find a paper which uses MCDM for country wise export performance evaluation studies, we couldn't find any. However there are a very few firm based export or international competitiveness (in our case this term is accepted as capability of making export) study which deals with just a sector of a country.

One of these papers is the paper written by Sirikrai et al. [45]. In their paper they use AHP method for determining the priority of the criteria that effect international competitiveness of automotive industry of Thailand. In their analysis after selecting their competitiveness indicators (manufacturing excellence, value-added of product, market expansion, financial return and intangible values such as trust and the relation between suppliers and customers) and drivers, they have taken experts' evaluation as it is told at the previous sub-sub-chapter and applied AHP procedure to determine the areas to focus in order to improve the industrial competitiveness of the sector. They are also mentioning that this procedure can be applied to other sectors in Thailand.

Kuosmanen et al. [46]'s also dealing with one of the divers (price) of the competitiveness criteria which is one of the major criterion of the export performance. In their analysis using the DEA method (this linear programming method will be explained in detail at the upcoming chapters) they are trying to find the efficient price for the market equilibrium by restricting weight flexibility. In their analysis they take into account all firms and their related measures.

When it is examined, it is seen that the usage of MCDM methods take place mostly at the export performance criteria analysis area. These studies generally made either for a geographic region, for a certain sector or for a certain type- group of criteria.
"Demand for good (market attractiveness)" is a criterion used at the export performance evaluations of firms. However this criterion is examined for countries in the study of

Tripodo et al. [47] by the help of an MCDM method, AHP. In their study they are using two groups of variables: Economic (Growth rate of Gross Domestic Product (GDP), GDP per person, Inflation rate, Current account over GDP, Risk of direct investment) and political (Turmoil, Strategic relevance). The data related with the variables are collected from the experts in Scale-5. The results for the determination of the weights show that GDP growth is the most important criteria among the economic ones, then comes inflation rate and GDP per person. Among the political ones because of the current world environment "turmoil" might, in some cases, be more important than "strategic relevance". The article also mentions that in order to be an attractive market a country should be in expansion phase and it has to have low risk.

The papers which are using MCDM methods generally cumulated at the technology sector analysis. In the recent years some studies has started to be done by using MCDM models and operations research tools.

By the help of AHP method, Chen et al. [48] analysis critical operations factors of information sector (in Taiwan) which affects export (sales to international market). In order to have a preliminary criteria list, they made a literature survey on software industry and had experts' opinions related with the issue and come up with the critical criteria which are cumulated under 6 indicators such as: product competition (product based criteria related with quality, image, price), market segment, service implement model, revenue efficiency, strategic alliance, distribution channel. The AHP analysis results show that the most important indicator is product competition, whereas the least important is distribution channel in Taiwan.

Guan et al. [17] uses DEA model for studying the relationship between technology innovation capability (TIC) and competitiveness (which is also one of the criteria in export performance evaluation) through the data that they collected from 182 firm located in China. In their study they employed TIC factors (Learning, R&D, Manufacturing, Marketing, Organizing, Resource) as inputs and competitiveness factors (Market share, Sales growth, Export rate, Profit growth, Productivity, New product rate) as outputs and they deal with the quantitative relationship at enterprise level. They gathered data from experts by using surveys which use likert scales 1-7 and 1-6 and use

them in both classic CCR-DEA model and BCC-DEA models. While the results of the CCR-DEA show that 16% of the enterprises are efficient (efficiency=1), about 80% of the enterprises have scores between 0.55 and 0.95, and only 3.4% have scores below 0.5. The results of BCC-DEA show that about 34% of the enterprises are efficient, and the other enterprises' efficiency scores are distributed between 0.55 and 0.95. Analysis on slack variables of competitiveness shows that the results related with new product sales rate is good, sales growth rate is poor and the other five outputs (market share, export rate, profit growth rate, productivity growth rate and new product rate) is fair.
Wang et al. [21] analyzed same issue by applying a novel fuzzy hierarchical analytical approach by utilizing subjective judgments of experts. The TIC hierarchy structure that they analyzed has 5 main aspects such as: R&D capabilities, Innovation decision capabilities, Marketing capabilities, Manufacturing capabilities and Capital capabilities. They used triangular fuzzy numbers to represent linguistic variables for innovative capability and rate the importance of evaluation criteria and crisp numbers for the rest. The fuzzy averaging technique and defuzzying method are effective in the final weighting of each criterion by various experts.

2.3 Survey on the Data Envelopment Analysis (DEA)

DEA is a linear programming based methodology formally developed by Charnes, Coopers and Rhodes (CCR) in 1978 building on the ideas of Farrell [49]. The DEA model is a multi-factor productivity analysis model for measuring the relative efficiencies of a homogeneous set of decision making units (DMUs) by using the common multiple inputs and outputs. Different from MCDA methods, this multiple criteria technique is not generally used to make a selection among the set of alternatives but it is used to evaluate decision making units [50]. Whereas MCDA models can rank the alternatives by using the subjective guidance of decision makers, the CCR-DEA model (original DEA model) usually can not supply a full ranking among the DMUs. The CCR-DEA model deals with classifying DMUs into two groups, efficient and inefficient, by using multiple criteria with objective weightings and without requiring any apriori information from decision makers [17, 51].

DEA methodology is used at many performance evaluation studies in many different sectors. Some examples of these applications are Byrnes and Freeman [52] and Schaffnit et al. [53]. Byrnes and Freeman use DEA method to evaluate the performance of contractors of a Mental Health Care Institution (The Franklin County Alcohol, Drug Addiction, and Mental Health (ADAMH) Services Board that take place at Columbus, Ohio) for the fund allocation supplied by government. Schaffnit et al. present an application where DEA is used to evaluate the personnel performance of a large Canadian bank for its branches located in Ontario.

In DEA Methodology, the efficiency score in the presence of multiple input and output factors is defined as: Efficiency = (Weighted sum of exact outputs/Weighted sum of exact inputs)) [54]. The proposed measure of the efficiency of any DMU is obtained as the maximum of a ratio weighted outputs to weighted inputs subject to the condition that the similar ratios for every DMU be less than or equal to unity [55]. Since each DMU is trying to maximize its own efficiency score in CCR DEA model, because of having weight flexibility and due to the structure of the method which makes us to solve the problem for each DMU separately, sometimes the optimal weight outcomes can be out of logic [54]. When one DMU can be efficient and give very good results under a certain weight combination, it can be inefficient and give very poor results for another one. Since an efficient DMU is expected to be efficient or at least close to be efficient for all weight combinations, these DMUs are called “false positive” and it is accepted as a problem of the method. In order to solve full ranking and overcome false positiveness problem of the method many approaches have been developed in the DEA methodology to increase its discrimination capability.

Several approaches have been proposed to overcome this problem: one approach is to combine DEA method with MCDM methods TOPSIS, AHP or MAUT to provide ranking between these efficient units [51,56,57]. Hua et al, try to evaluate College Education Quality, by first examining the efficiency of each DMU using the method DEA and then applying TOPSIS to have an overall evaluation of Colleges. Stern et al, are proposing an DEA/AHP model for fully ranking organizational units. In their model, first they are running DEA for each pair of DMUs and obtaining two efficiency results for each DMU (one from their own iteration and the other DMU’s iteration).

Then for finding their relative importance they are summing the efficiency results of each DMU and dividing them to each other. By repeating this calculation to all pairs they are obtaining a pairwise evaluation matrix which they will use at their AHP analysis. At the final stage, they are applying AHP and obtaining a full ranking of organizational units. Belton and Vicker, propose an approach, which is implemented as visual interactive decision support system. According to the article the model is formed from combination of DEA and MAUT and it gives effective solution for the small numbers of DMUs.

Other approaches of increasing discrimination power of the model is changing it by adding new weight restriction constraints or by using other objective functions which have better discriminating power among DMUs (such as the minimax efficiency objective (i.e. the minimization of the maximum deviation from the ideal efficiency score 1)).

The weights, which maximize the efficiency of DMUs, are calculated by the method itself. However, if we have any further information on to weights, DEA also gives permission to use additional weight restrictions which we call Assurance Region (AR). These constraints also restrict the flexibility of the weight computations and give more reasonable efficiency results so an increasing discrimination between the DMUs. Weight restrictions aren't obliged to be applied alone, they also can accompany to the other discrimination approaches such as Cross Efficiency. One example of this study is given at Wu et al. [58]. They analyze performance of countries at Olympic game by using the DEA game cross efficiency approach with weight restrictions. By the model that they propose they are trying to find the point that a DMU reaches its best position among the others under defined weight restrictions. Since the position of the DMU is dependant to the other DMUs, the model also employs iterative approaches leading to Nash's equilibrium.

When there isn't any priori information given related with the factors, the minimax, minisum objective functions and cross efficiency analysis. Cross efficiency analysis is developed by Sexton et al.[59]. In this analysis, the performance of each DMU is evaluated with respect to the optimal input and output weights of other DMUs, and the efficiency scores obtained this way are presented in a matrix named "Cross Efficiency Matrix" (CEM). The cross efficiency values of DMUs are found by taking average of these efficiency values. Since the averages coat the fluctuations, it is difficult to distinguish the good and bad performers for the problem set and so determine the optimal weights through the results when there are more than one optimal weight combination. In order to overcome this problem, Doyle and Green developed a technique in 1994 by introducing an aggressive formulation [60]. This technique tries to find the optimal weights that maximize the efficiency of the DMU under consideration while minimizing the average efficiency of other DMUs. Moreover, this technique provides a full ranking of the DMUs by indicating the false positive ones as well. One application of this model take place at Sarkis and Talluri [61]. In their study they focus on the operational performance evaluation of the 44 US airports across five years. They perform their analysis by using cross efficiency model and identify the appropriate benchmarks for the poorly performing airports. Further development related cross efficiency models are made at the article of Liang et al. [62]. They say that when the result of cross efficiency isn't unique, when there is more than one optima, usefulness of cross efficiency model is decreasing. In order to solve this problem their proposal is to introduce a secondary goal in order to eliminate decrease the number of optimum DMUs to one.

Minisum and minimax methods are applied to DEA multi objective formulation by Li and Reeves [63]. They tried to minimize the max deviation of DMUs in their minimax formulation, whereas minimize the sum of all DMU deviations in their minisum formulation in order to increase the discrimination capability. According to Bal et al. [64], due to the complexity of multiple objective problems and the scarcity of software for the solutions, usage area of the model proposed by Li and Reeves is limited. By the inspiration that they take from the multi criteria DEA model proposed by Li and Reeves, Bal et al. propose another approach to increase discrimination capability of DEA by using goal Programming tools in DEA model. The aim of the article is to convert a multi objective model to a single-composite objective model and minimize the total deviation of DMUs under homogeneity of weight distribution by using by a weighted goal programming DEA analysis. Some of other common set of weights integrated DEA studies in order to determine the most efficient DMU are Amin and Toloo [65], Liu and Peng [66].

Standard CCR-DEA was just dealing with the problems which employ exact input and output data for all DMUs. However it is not always the case, sometimes the data obtained can be imprecise (ordinal, interval or fuzzy). As long as imprecise data is used at the DEA model, the model becomes non-linear. Because, as well as the importance weights, the imprecise data also have to be defined as variables, and their multiplication forms non-linearity and non-convexity [67, 68]. In order to solve this problem, so deal with imprecise data, a new approach named IDEA is developed by Cook et al. [69, 70]), which transforms non-linear equation to a linear one. By the model they propose they manage to analyze both ordinal and exact data. Three years later Cooper et al. [71] propose another model to analyze ordinal, interval and exact data. Then Despotis and Smirlis [72] proposed a new model by making alternative transformation to interval data, ordinal and exact data. In 2006, Cook and Zhu [73] brought a general framework to the DEA model by including the weight-importance restrictions to the ordinal data.

Another way of dealing with imprecise data is converting them to exact data. Zhu, [67] first transform imprecise data to exact one, then apply classic DEA to solve it.

The methods used to increase the discrimination capability of classic DEA can also be applied to IDEA. Cooper et al. [71] called the IDEA model which they apply weight restrictions: AR-IDEA (Assurance Region-IDEA). One another method used to increase the discrimination power of the IDEA is to apply ε as minimum limit for the weights and for the difference between the consecutive ranks. Max value of this parameter is calculated by Cook et al. [70] and used for max discrimination. Later on Karsak [74] has applied a two step technique to discriminate the DMUs. At first step he applied Cook et al.'s model and obtained the efficient DMUs. Then at the second step, he applied cross efficiency technique by using the optimum weights obtained from Cook et al. [70]. Sarkis and Talluri [75] formed a pairwise comparison matrix in order to be used at Cook et al.'s model.

There are also some other techniques developed for specific types of problems. Ahiska and Karsak [76] propose a model for the single input, multi output models. By this model, they are suggesting to use efficiency measures that aren't specific to a particular DMU but common to all. To do that first the problem is rewritten in terms of deviation between the ideal efficiency (=1) and efficiency obtained. Then in order to obtain a solution wrt common weights, minimization of max deviation will be used as objective function [68]. Kao and Liu [77], employ stochastic DEA for their performance analysis of Taiwan commercial banks. They use the input/output data in stochastic distribution form and obtain a stochastic efficiency result for each DMU. They mention that the data that they could supply was formed from wide intervals. If their real data can give them opportunity to work with smaller intervals, they may also obtain the same result by using interval DEA instead of stochastic one.

3. Problem Description

In this study the problem of the performance evaluation of Turkey's export to Ireland in year 2008 is analysed in light of top 100 exported manufacturing products by using DEA techniques. The purpose of the analysis is to determine the efficient and inefficient sectors in light of the different data sets used, and try to: 1) point out the criteria that are needed to be adjusted for improving the worst sector so as to enhance the overall export performance, 2) to make product wise analysis for the best sectors.

In order to start dealing with the problem, the first act was to supply the list of top 100 manufacturing products from Central Statistics Office Ireland (CSO). Then these products are grouped into their sectors. Since the sector definitions of Ministry of Foreign Trade (DTM) and TURKSTAT do not match with each other, the grouping is made with the help of an expert by using TURKSTAT sector definitions. The list of the products and their corresponding sectors are given in Appendix A in Table A.1.

The results of grouping showed that the top 100 products consist of 11 sectors, which are reported in Table3.1 These sectors will be considered as decision making units in our DEA and IDEA analysis in the following chapters.

After the determination of the export performance criteria by the help of a literature survey presented in sub-chapter 2.1, we had to eliminate most of the criteria under the constraint of the real data availability, which is a common problem for most MCDM problems. The remaining 11 criteria, whose explanation will be given in detail below, formed our criteria list.

In order to start our analysis, first the selected criteria are classified into two groups as: inputs and outputs. Then, these inputs and outputs are once more classified according to the type of data collected such as objective (exact) and subjective (ordinal).

The objective data are supplied from different sources such as TURKSTAT, CSO, DTM (Undersecretariat of the Prime Ministry for Foreign Trade) and TCMB (Central Bank of

Republic Turkey) whereas the subjective data are obtained by the help of a survey we formed and are filled out by an expert.

Table 3.1 List of the Sectors considered

Sectors	**Manufacturing Sectors**
Sector1	Manufactured Food Products and Beverages
Sector2	Textile Industry
Sector3	Wearing Apparel
Sector4	Manufacture of Paper and Paper Products
Sector5	Plastic and Rubber Products
Sector6	Manufacture of Non Metallic
Sector7	Basic Metals Industry
Sector8	Machinery and Equipment
Sector9	Electric Machinery and Apparatus
Sector10	Manufacture of Motor, Vehicles, Trailers
Sector11	Manufacture of Furniture

As it is mentioned in Sousa [3] and used in many studies such as Cook and Zhu [75] and Manoharan et al. [78], Likert scale -5 is one of the most common scale used for collecting L-point scale data. Hence, the ordinal data that we gathered through our survey is also supplied in the form of Likert scale-5. In Likert Scale score of 5 represents “the best” and score of 1 “the worst” and in our survey two different wording groups are used: one of them is; 5-Extremely important, 4-Very Important, 3-Important, 2-Low in Importance, 1-Not Important, and the other is; 1-Fair, 2-Satisfactory, 3-Good, 4-Very Good, 5-Excellent. The outcomes of the scale evaluation must also be interpreted in ordinal sense instead of cardinal sense. This means that numeration of the scale signifies a preference instead of coefficient of how better it is with respect to the other one and the results of data supplied is threaded as such in our analysis.

The input and output criteria employed in our study and their corresponding values are presented below:

Objective Outputs (Exact Outputs)

***Export Share:** This criterion is calculated as the ratio of export of decision making unit to Ireland in 2008/ total sectoral export of Turkey in 2008 for the decision making units we consider. This criterion is formed by inspiring from export intensity criterion which is calculated by the ratio of export to total production of the firm.[3]. This criterion is calculated by the data supplied from TURKSTAT and its results are presented below at Table 3.2.

Table 3.2 Sectoral Export Share Data

SECTORS	Export Share	Normalization
Manufactured Food Products and Beverages	0.029	0.488
Textile Industry	0.026	0.437
Wearing Apparel	0.008	0.134
Manufacture of Paper and Paper Products	0.049	0.819
Plastic and Rubber Products	0.032	0.526
Manufacture of Non Metallic	0.007	0.116
Basic Metals Industry	0.013	0.213
Machinery and Equipment	0.016	0.267
Electric Machinery and Apparatus	0.021	0.354
Manufacture of Motor, Vehicles, Trailers	0.008	0.127
Manufacture of Furniture	0.060	1.000

* **Export Value:** Exports in terms of monetary value. This criterion is supplied from CSO and presented below at Table3.3.

* **Import Share:** This criterion is calculated as export value of a decision making unit of Turkey to Ireland in 2008/total import of Ireland for that specific decision making unit in 2008. This criterion is formed by inspiring from market share criterion which is calculated by the ratio of import to total market [22]. This criterion is calculated by the data supplied from CSO and its results are presented below at Table 3.4.

Table 3.3 Sectoral Export Value Data

SECTORS	Export VALUE-EURO	Normalization
Manufactured Food Products and Beverages	5935	0.061
Textile Industry	5309	0.054
Wearing Apparel	78974	0.808
Manufacture of Paper and Paper Products	7819	0.080
Plastic and Rubber Products	8387	0.086
Manufacture of Non Metallic	14693	0.150
Basic Metals Industry	38653	0.396
Machinery and Equipment	18195	0.186
Electric Machinery and Apparatus	58581	0.600
Manufacture of Motor, Vehicles, Trailers	97694	1.000
Manufacture of Furniture	3363	0.034

Table 3.4 Sectoral Import Share Data

SECTORS	Import Share	Normalized
Manufactured Food Products and Beverages	0.782	1.000
Textile Industry	0.184	0.235
Wearing Apparel	0.106	0.135
Manufacture of Paper and Paper Products	0.064	0.081
Plastic and Rubber Products	0.068	0.088
Manufacture of Non Metallic	0.135	0.173
Basic Metals Industry	0.088	0.113
Machinery and Equipment	0.098	0.125
Electric Machinery and Apparatus	0.180	0.231
Manufacture of Motor, Vehicles, Trailers	0.045	0.058
Manufacture of Furniture	0.240	0.307

Subjective Outputs (Ordinal Outputs)

* **Overall Export Performance:** This criterion is used for measuring expert's subjective evaluation related with the overall export performance of the sectors analyzed by the help of survey [3].

* **Strategic Export Performance:** This criterion is used for measuring expert's subjective evaluation compliance of the exports realized with Turkey's foreign trade policy for year 2008 by the help of survey [3].

* **Contribution of the export to the growth of the Turkey:** This criterion is used for measuring expert's subjective evaluation related with contribution of exporting that specific sector to the growth of the country by the help of survey [3]

***Goal Achievement:** This criterion is used for measuring compliance of exports with the pre-determined export targets to Ireland for year 2008 by the help of survey [11]

***Contribution of the export to the Turkey's reputation:** This criterion is used for measuring expert's subjective evaluation related with contribution of exporting that specific sector to the reputation of the country by the help of survey [4].

Likert Scale Survey Results for the 5 Subjective output are given in Table 3.5.

Objective Inputs (Exact Inputs)

***ULC** ("The cost of labour required to produce one unit of output in a particular industry, sector or total economy"): This criterion is accepted to be one of the major indicators of the international competitiveness and it is calculated as: Wage per hour worked (euro/hour)(Table B.4)/labour productivity (Table B.3) [25]. Since Labour Productivity is no longer calculated by Central Bank of Republic Turkey since 2006, we calculated this parameter at Appendix B by using the instructions given at their webpage. (Labour Productivity (Table B.3): Indices of Partial Productivity of Production Workers per Capita and per Hours Worked at Production in Manufacturing Industry= Quarterly Industrial Production Index(Table B.1) / index of hours worked at production in manufacturing industry (Table B.2))

Table 3.5 Sectoral Survey Results in Likert Scale-5

	Likert Scale Survey Results				
SECTORS	**Overall Export Performance**	**Strategic Export Performance**	**Goal Achievement**	**Contribution to Turkey's Reputation**	**Contribution to Turkey's Growth**
Manufactured Food Products and Beverages	3	3	3	2	2
Textile Industry	4	4	3	3	3
Wearing Apparel	4	4	4	4	4
Manufacture of Paper and Paper Products	4	4	4	3	3
Plastic and Rubber Products	4	4	4	4	4
Manufacture of Non Metallic	3	3	3	3	3
Basic Metals Industry	4	4	4	4	4
Machinery and Equipment	4	4	4	5	5
Electric Machinery and Apparatus	4	4	4	5	5
Manufacture of Motor, Vehicles, Trailers	4	4	4	5	5
Manufacture of Furniture	3	4	4	4	4

This data is calculated by using the data supplied from TURKSTAT and TCMB. However since some data is given in quarterly form whereas the others in monthly form, in order to overcome the incompatibility problem, quarterly data is converted to monthly forms by assuming that they stay same within the quarters. A second data adjustment is made related with the last quarter of Index of Wages per Production Hour Worked in Manufacturing Industry. Since last quarter data of 2008 for Index of Wages per Production Hour Worked in Manufacturing Industry hadn't been announced during our analysis, it is calculated by taking the average of previous 3 quarters. The average ULC data which we'll use in our analysis, are calculated by the data given at Appendix B can be found at Table 3.6.

* **Hours Spent:** This data is supplied from our survey in terms of precise data. It measures the time spent for helping the exporters. Our expert mentions that since they also deal with other responsibilities, in average total amount of hours spent dealing with exporters and export problems is around 30 hours. When these hours are distributed to the sectors, the total amount spent for our 11 sector becomes 19 hours. The hours spent per week for 11 sectors analyzed are presented at Table 3.7:

Table 3.6 Sectoral Hours Spent Data

SECTOR NAME	HOURS SPENT PER WEEK	Normalized Data
Manufactured Food Products and Beverages	1.79	0.80
Textile Industry	1.34	0.60
Wearing Apparel	1.79	0.80
Manufacture of Paper and Paper Products	0.90	0.40
Plastic and Rubber Products	1.79	0.80
Manufacture of Non Metallic	1.79	0.80
Basic Metals Industry	1.34	0.60
Machinery and Equipment	2.24	1.00
Electric Machinery and Apparatus	1.79	0.80
Manufacture of Motor, Vehicles, Trailers	2.24	1.00
Manufacture of Furniture	1.79	0.80

* **Import Growth of Ireland(%):** This criterion is calculated in terms of % change of the import of Ireland between 2007-2008 for the decision making units exported by using the CSO data. The data are presented at Table 3.8.

As it is seen from the data presentations, after supplying all the data required, in order to eliminate the different scale effect, the data is normalized using maximum value normalization.

Table 3.7 Sectoral UCL Data

UCL	Manufac-ture of food products and beverages	Manufac-ture of textiles	Manufac. of wearing apparel dressing and dyeing of fur	Manufac-ture of paper and paper products	Manufac-ture of rubber and plastics products	Manufac-ture of other non-metallic mineral products	Manufac-ture of basic metals	Manufac-ture of machinery and equipment	Manufac-ture of electrical machinery	Manufac. of motor vehicles, trailers and semi-trailers	Manufacture of furniture; manufac-turing
Jan-08	24.350	18.279	17.606	15.465	18.871	19.102	17.291	21.140	16.725	13.160	18.793
Feb-08	26.402	18.673	17.945	16.198	19.388	19.041	18.214	19.513	17.256	12.883	17.718
Mar-08	23.593	17.956	18.317	14.605	17.165	15.429	16.105	17.577	16.104	11.473	12.904
Apr-08	26.764	18.010	20.158	15.848	16.525	15.745	17.047	18.521	18.365	11.319	16.895
May-08	23.395	18.010	19.465	15.002	16.089	14.613	16.371	17.379	17.842	11.750	17.208
Jun-08	24.200	18.360	19.337	15.246	17.829	15.357	16.937	18.403	17.445	12.760	17.406
Jul-08	25.605	18.395	19.208	17.247	18.357	15.337	17.232	18.483	19.787	13.674	18.193
Aug-08	25.489	19.252	19.630	16.893	19.407	16.498	18.892	21.592	23.146	25.987	19.256
Sep-08	23.677	18.454	21.018	17.204	20.059	17.996	20.286	20.810	21.518	15.882	19.120
Oct-08	17.792	16.743	21.113	17.088	18.739	16.057	22.869	20.375	18.340	15.016	16.323
Nov-08	16.684	16.690	18.515	16.751	19.287	16.297	22.707	18.150	19.311	18.747	16.741
Dec-08	22.014	22.895	20.049	21.230	26.141	22.923	25.407	22.204	20.392	26.358	17.277
Average	**23.330**	**18.477**	**19.363**	**16.565**	**18.988**	**17.033**	**19.113**	**19.512**	**18.852**	**15.751**	**17.319**
Normalized Value	**1**	**0.792**	**0.830**	**0.710**	**0.814**	**0.730**	**0.819**	**0.836**	**0.808**	**0.675**	**0.7424**

Following the normalization, two different data sets are formed for the analysis. One (which we call exact data set) is composed of only quantitative inputs (ULC, Hours Spent, Import Growth of Ireland) and outputs (share, import share, export value) the other (which we call exact and ordinal data set) is composed of all the above listed inputs and outputs including subjective data in order to see the effect of considering the subjective criteria to the efficiency of the analyzed sectors.

Table 3.8 Sectoral Import Growth of Ireland Data

	Subtotal-EURO-2007	Subtotal-EURO-2008	Growth	Normalized Value
Manufactured Food Products and Beverages	4204	7592	1.806	1.000
Textile Industry	34107	28865	0.846	0.469
Wearing Apparel	759493	747600	0.984	0.545
Manufacture of Paper and Paper Products	101545	123100	1.212	0.671
Plastic and Rubber Products	126522	122479	0.968	0.536
Manufacture of Non Metallic	132292	108486	0.820	0.454
Basic Metals Industry	384212	439044	1.143	0.633
Machinery and Equipment	238993	185901	0.778	0.431
Electric Machinery and Apparatus	343106	324721	0.946	0.524
Manufacture of Motor, Vehicles, Trailers	3233684	2164039	0.669	0.371
Manufacture of Furniture	14644	13991	0.955	0.529

The analysis is performed using several DEA, IDEA, Minimax models, Cross Efficiency and Aggressive Cross Efficiency analysis by using the data and the criteria presented above. The details of the analysis and its results are explained in the Chapter 5 in detail.

4. Proposed Methodology

As in many multi criteria decision making problems, choice of the methodology that will be employed in the analysis depends on many factors such as: the main purpose of the study, the criteria that will be taken into account, type of the data that is available.

Since our MCDM problem is on evaluation of the performance of exports made from Turkey to Ireland in year 2008 by using actual export values for top 100 manufacturing products, we needed to use a technique, which could be employed for MCDM problems and helps us to deal with the evaluation of the outcomes (efficiency determination of DMUs). Our aim in our analysis is to determine the efficient and inefficient sectors (DMU) in light of the different data sets used and try to point out what to do as well as the criteria that needed to be improved for improving the worst DMU and so the overall export performance. That's why we chose to apply DEA methodology which gives us opportunity to have both ranking and sensitivity analysis for the data sets we used in our problem.

In order to do our analyses under the constraint of data availability, several different types of DEA models have been used and efficiency rankings are obtained by using different type of data combinations. In order to explain the methods employed in our analysis, first the general information related with data types will be given, then after mentioning about the data that we employed in our problem, the related DEA methods used will be explained and the models adjusted to our data type will be presented in the sub-chapters in detail.

Data are classified as ordinal and cardinal data. Ordinal data consist of imprecise data, whereas cardinal data consist of exact and imprecise data. The imprecise data under ordinal data group is formed from "Ranking" and "L-point scale" data while the imprecise data under cardinal data group is formed from "Interval" and Fuzzy" data.

When data is precisely known (such as cost, price, income, quantity sold, etc.), it is called exact data, otherwise it is named as imprecise data. Imprecise Cardinal data is used to represent two types of data: “interval data” when the exact value isn’t known but the lower and upper boundaries of data can be predicted, and “fuzzy data” when the membership function of the data isn’t binary and there is vagueness at the estimation of the quantitative data involved. Imprecise Ordinal Data (all ordinal data are classified as imprecise data) is used to represent ordinal relationships either interms of importance rankings (Ranking Data) or categorization of DMUs in some scale (L-Point Scale Data) (in our case it will be Likert-Scale-5) in order to show the preference of an alternative to another.

DEA is a linear programming based methodology formally developed by Charnes, Coopers and Rhodes (CCR) in 1978 building on the ideas of Farrell [49]. The DEA model is a multi-factor productivity analysis model for measuring the relative efficiencies of a homogeneous set of decision making units (DMUs) by using the common multiple inputs and outputs. Since it tries to find relative efficiency of the DMUs by using normalized data and without needing any priori defined weights and production functions, it is classified as a non-parametric method. Because the method defines its importance weights by itself without needing any priori weight information, it is considered more objective wrt other MCDM models. There are some specific terms used at this methodology to define some general terms used at MCDM models. The alternatives are called DMUs, the criterion that should be minimized is called input whereas the criterion that should be maximized is called output, the weight that shows the importance of criterion is called importance weight.

In our study we used exact data and ordinal data gathered through a survey which is filled out by an expert in 5-point scale. That’s why eventhough DEA has quite a number of different techniques, which gives us opportunity to deal with many types of data, the techniques employed in our study will consist of just exact and ordinal and exact data used form of models.

As it is explained in Chapter 3 and at the beginning of this chapter, our criteria selection and data employed serve us to use the below DEA models:

4.1 CCR-DEA Model

CCR-DEA is the original DEA model developed by Charnes et al. [55] for efficiency calculations in the existence of exact data. The model aims to find input/output weights that maximize the efficiency value of the evaluated DMU under the constraint that all DMUs' efficiency value will be less than or equal to the ideal efficiency value, which is 1.

In DEA, the efficiency measure of a DMU is defined as the sum of its weighted outputs over the sum of its weighted inputs, as follows:

$$E_j = \frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}}, \ \forall j \tag{4.1}$$

where E_j is the efficiency value of DMU j; u_r and v_i are the weights assigned to output r and input i, respectively; y_{rj} is the amount of output r produced by DMU j; x_{ij} is the amount of input i consumed by DMU j.

It assumes that all input and output data are positive and the ideal efficiency value equals to 1, therefore, all the efficiency values determined by CCR DEA model are between 0 and 1. The decision making units that receive the score of 1 are called "efficient" and they are said to lie on the efficient frontier while the decision making units that receive a score less than 1, are called "inefficient" and they lie under the efficient frontier.

By using the efficiency calculation given above, the CCR-DEA model is formulated as:

$$\max E_{j_0} = \frac{\sum_r u_r y_{rj_0}}{\sum_i v_i x_{ij_0}}$$

st

$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \le 1, \quad \forall j \tag{4.2}$$

$$u_r \ge \varepsilon, \ \ \forall r$$

$$v_i \ge \varepsilon, \quad \forall i$$

where E_{j_0} is the efficiency value of the evaluated decision making unit, DMU j_0, ε is a very small positive number used to assure the positivity of multipliers u_r and v_i in order to avoid neglecting any of inputs or outputs under consideration.

As it is seen above, due to the fractions employed, the preliminary form of the model is non-linear. In order to solve this non-linearity problem, it is converted into a linear model (which we employ in our analysis) as follows:

$$\max E_{j_0} = \sum_r u_r y_{rj_0}$$

st

$$\sum_i v_i x_{ij_0} = 1$$

$$\sum_r u_r y_{rj} - \sum_i v_i x_{ij} \le 0, \ \forall j \tag{4.3}$$

$$u_r \ge \varepsilon, \ \ \forall r$$

$$v_i \ge \varepsilon, \quad \forall i$$

The CCR-DEA model aims to find the relative efficiency values of DMUs by either minimizing the deviation from efficiency or maximizing the efficiency of particular DMU by the help of an objective specific to one particular DMU. Therefore, to be able to determine the efficiency value for n DMUs, we need to formulate n models.

As exact value of input and output data is known, for our single input CCR-DEA analysis, we used the below form of the model given by Ahiska [68] which is obtained by replacement of y_{rj} / x_j with R_{rj}:

$$\max E_0 = \sum_{r=1}^{m} u_r R_{rj_0}$$

st

$$\sum_{r=1}^{m} u_r R_{rj} \leq 1, \forall j \tag{4.4}$$

$$u_r \geq \varepsilon, \forall r$$

where x_j is the amount of input consumed by DMU j, R_{rj} indicates the ratio of output r to input for DMU j.

This single input model can also be written interms of d_j (the deviation of the efficiency value E_j, from the ideal efficiency value of 1) where $d_j = 1 - E_j$. The model interms of deviation becomes:

$$\min d_{j_0}$$

st

$$\sum_{r=1}^{m} u_r R_{rj} + d_j = 1, \forall j \tag{4.5}$$

$$u_r \geq \varepsilon, \quad \forall r$$

$$d_j \geq 0, \quad \forall j$$

Besides giving opportunity to find the efficiency for the DMUs, the most valuable contribution of the method DEA is to give opportunity to make sensitivity analysis for the inefficient alternatives by the help of its dual program. By this analysis the DMUs that could be used as benchmark can be determined and the inputs that needed to be improved in order to make the DMU efficient can be recognized and a good managerial point of view could be supplied for the further development actions.

Duality of the CCR-DEA model is given by Cooper et al. [79] and Cook and Seiford [80] as follows:

Min $\theta_0 - \varepsilon(\sum_r s_r^+ + \sum_i s_i^-)$

st

$$\sum_j \lambda_j x_{ij} + s_i^- = \theta_0 x_{i0}, \tag{4.6}$$

$$\sum_j \lambda_j y_{rj} + s_r^+ = y_{r0} \,,$$

$$\lambda_j, s_i^-, s_r^+ \geq 0 \,, \qquad \forall i, j, r$$

where s_i^- is used for input slack variables for *i* inputs, s_r^+ is used for output slack variables for s outputs, λ_j is used for efficiency constraint coefficient of *j* alternatives and θ_0 is efficiency value of the selected DMU.

In order to be efficient, a DMU ought to have 0 slack variables and efficiency value of 1. If it does not satisfy these conditions, it is accepted as inefficient and its improvement input and output values and reference DMUs (benchmarks) can be calculated by the given formulas below:

For the benchmark;

$$E_0 = \{ j \mid \lambda_j^* > 0 \} \tag{4.7}$$

The above formula states that benchmark of any inefficient DMU is found by looking at the λ_j values found from its dual calculation. Any alternative whose λ_j is greater than 0 can be a reference for the tested inefficient DMU.

For input and output improvement values;

$$\Delta x_{i0} = x_{i0} - (\theta^* x_{i0} \text{-} s_i^{-*}) \ , \ \forall i \tag{4.8}$$

$$\Delta y_{r0} = s_r^{+*} \ , \ \forall r$$

where Δx_{i0} is the improvement values for inputs, Δy_{r0} is the improvement values for outputs.

As a result of dual analysis of the DMU, slack variables which are greater than 0, indicate that the efficiency improvement of the before mentioned DMU is dependant to the related input and/or output variables. Therefore any improvement at the efficiency of that DMU can be made either by decreasing the input level or increasing the output level depending on the type of the slack variable found at the amounts computed with the formula above. So the final input and output levels for converting the inefficient DMU into an efficient one is computed by the equations below:

$$\widehat{x_{i0}} = x_{i0} - \Delta x_{i0} \qquad , \ \forall i \tag{4.9}$$

$$\widehat{y_{r0}} = y_{r0} + \Delta y_{r0} \qquad , \ \forall r$$

where $\widehat{x_{i0}}$ is the required input level for the efficiency of the test DMU, $\widehat{y_{r0}}$ is the required output level for the efficiency of the test DMU.

Since the CCR-DEA model classifies decision making units into two groups; efficient DMUs (the ones which has efficiency value 1) and inefficient DMUs (the ones which has efficiency value smaller than 1), and since all efficient DMU takes efficiency value 1, it is not possible to rank them with the CCR-DEA model. Therefore it might not be appropriate to use CCR-DEA for the cases when the decision maker needs to rank all DMUs or select the best DMU.

Furthermore, even though the model is appreciated for supplying objective solutions for the determination of the efficient DMUs, its flexibility to choose the weights that maximize the test DMU's efficiency value is questioned. Because, giving permission to weight flexibility may result in identifying a DMU to be efficient by giving an extremely high weight to criteria which it has shown an extremely good performance and an extremely small weight to those which it has shown an extremely bad one. Such an extreme weighting is unrealistic and causes DEA model to have a poor discriminating power among DMUs.

In order to solve these problems, many methods have been proposed to increase the discriminating power of this original model. We'll explain in the upcoming sub-chapters the methods that we employed at our analysis in the form that we used for our data set.

4.2 Cook et al. Ordinal DEA Model

Since the original model (CCR-DEA) is used just for the evaluation of exact data, in the cases where inputs/outputs aren't exact in nature and can only be represented by qualitative data, some different models should be developed in order to accommodate such qualitative data. Due to our data set which contains ordinal data in addition to exact one, we employed the IDEA model introduced by Cook et al [70].

Cook et al. has introduced an ordinal DEA model which permits the inclusion of ordinal inputs/outputs within the standard CCR DEA model [70]. The model they propose can analyze the input/output data in the form of L-point scale or simply ordinal ranking of the DMUs.

In L-point scale data form, each DMU will receive one of the scores of 1, 2, …, L where score of L represents "the best" and score of 1 "the worst" for an ordinal output while the reverse is true for an ordinal input. In our case since we used Likert scale-5 for our ordinal output data, score 5 represented "best" and score 1 represented "worst". Similarly, if DMUs are ranked according to an ordinal input/output, each DMU will receive one of the scores of 1, 2,…,n, where n indicates the number of DMUs. In that case too, DMU having score of n may be considered as "the best" if the criterion under consideration is an output and "the worst" if it is an input. However since we wouldn't use any ordinal ranking type data, we wouldn't take into consideration that part of the model in our analysis.

Since ordinal data are imprecise and their exact values aren't known, they are defined as unknown decision variables like the importance weight variables. As the multiplication of two unknown variables converts the model into a non-linear one, Cook et al., propose following transformation to supply back the linearity of the model:

L-dimensional unit vectors, $\boldsymbol{\gamma}_\mathbf{r}(\mathbf{j}) = [\gamma_{r1}(j),\ldots,\gamma_{rl}(j),\ldots,\gamma_{rL}(j)]$ and $\boldsymbol{\delta}_\mathbf{i}(\mathbf{j}) = [\delta_{i1}(j),\ldots,\delta_{il}(j),\ldots,\delta_{iL}(j)]$ are defined respectively:

$$\gamma_{rl}(j) = \begin{cases} 1 & \text{if alternative } j \text{ is rated in the } l\text{th place on the } r\text{th ordinal output} \\ 0 & \text{otherwise} \end{cases}$$

and

$$\delta_{il}(j) = \begin{cases} 1 & \text{if alternative } j \text{ is rated in the } l\text{th place on the } i\text{th ordinal input} \\ 0 & \text{otherwise} \end{cases}$$

In other terms, the vectors $\boldsymbol{\gamma}_\mathbf{r}(j)$ and $\boldsymbol{\delta}_\mathbf{i}(j)$ indicate the rating (place) assigned to DMU j with respect to ordinal output r and ordinal input i, respectively.

Cook et al. define also worth vectors $\mathbf{w}_\mathbf{r}^\mathbf{1} = [w_{r1}^1, w_{r2}^1, \ldots, w_{rL}^1]$ and $\mathbf{w}_\mathbf{i}^\mathbf{2} = [w_{i1}^2, w_{i2}^2, \ldots, w_{iL}^2]$, where w_{rl}^1 and w_{il}^2 represents the worth(weighted normalized value) of being rated in the lth place according to the rth output, and ith input, respectively, for $\forall r,i,l$. By this transformation, ordinal unit vector becomes scalar, whereas the weighted normalized value is left as the unknown decision variable. So it becomes once more a linear model which could process exact+ordinal data by the formula given below:

$$\max h_0 = \sum_{r \in EXO} u_r y_{rj_o} + \sum_{r \in ORDO} \mathbf{w}_\mathbf{r}^\mathbf{1} \boldsymbol{\gamma}_{\mathbf{rj_o}}$$

st

$$\sum_{i \in EXI} v_i x_{ij_o} + \sum_{i \in ORDI} \mathbf{w}_i^2 \boldsymbol{\delta}_{\mathbf{ij_o}} = 1 \tag{4.10}$$

$$\sum_{r\in EXO} u_r y_{rj} + \sum_{r\in ORDO} \mathbf{w}_\mathbf{r}^\mathbf{1} \boldsymbol{\gamma}_\mathbf{rj} - \sum_{i\in EXI} v_i x_{ij} - \sum_{i\in ORDI} \mathbf{w}_i^2 \boldsymbol{\delta}_\mathbf{ij} \le 0$$

$u_r \ge \varepsilon$ for $r \in EXO$

$v_i \ge \varepsilon$ for $r \in EXI$

$$\mathbf{w}_\mathbf{r}^\mathbf{1}, \mathbf{w}_\mathbf{i}^\mathbf{2} \in \Psi = \begin{Bmatrix} w_{rl+1}^1 - w_{rl}^1 \ge \varepsilon, w_{r1}^1 \ge \varepsilon, & for\ l = 1,2,\ldots,L-1;\ r \in ORDO \\ w_{il+1}^2 - w_{il}^2 \ge \varepsilon, w_{i1}^2 \ge \varepsilon & for\ l = 1,2,\ldots,L-1;\ i \in ORDI \end{Bmatrix}$$

where u_r and v_i are the importance weight variables assigned to output r and input i, respectively; $\mathbf{w}_\mathbf{r}^\mathbf{1}$ and $\mathbf{w}_\mathbf{i}^\mathbf{2}$ are the worth vectors including variables w_{rl}^1 and w_{il}^2, which indicate the worth (weighted values) of being rated in the lth place with respect to output r and input i, respectively; $\boldsymbol{\gamma}_\mathbf{rj}$ and $\boldsymbol{\delta}_\mathbf{ij}$ are the vectors indicating the rating assigned to DMU j with respect to output r and input i, respectively; L is the size of the likert scale; x_{ij} is the amount of input i consumed by DMU j; and ε is a positive constant. Finally, EXO, ORDO is the set of exact and ordinal outputs, respectively. Similarly, EXI is the set of exact input.

As it can be seen from the model, the correct ordinal relationship is set on the components of the worth vectors by the prioritization of the worth vectors according to the type of data used.

Since we just used the exact input and exact&ordinal output in our analysis, the IDEA model that we used in our problem is formulated as below:

$$\max h_0 = \sum_{r\in EXO} u_r y_{rj_o} + \sum_{r\in ORDO} \mathbf{w}_\mathbf{r}^\mathbf{1} \boldsymbol{\gamma}_{\mathbf{rj_o}}$$

st

$$\sum_{i\in EXI} v_i x_{ij_o} = 1$$

$$\sum_{r \in EXO} u_r y_{rj} + \sum_{r \in ORDO} \mathbf{w_r^1} \boldsymbol{\gamma}_{\mathbf{rj}} - \sum_{i \in EXI} v_i x_{ij} \leq 0 \qquad (4.11)$$

$$u_r \geq \varepsilon \text{ for } r \in EXO$$

$$v_i \geq \varepsilon \text{ for } r \in EXI$$

$$\mathbf{w_r^1} \in \Psi = \left\{ w_{rl+1}^1 - w_{rl}^1 \geq \varepsilon, w_{r1}^1 \geq \varepsilon, \quad for\ l = 1,2,\ldots,L-1; r \in ORDO \right\}$$

For sure Cook et al.'s [70] study isn't the only one that deals with ordinal data. Cooper et al. [74] also have a IDEA model that they proposed for the efficiency determination of DMU. However according to Ahiska [68] in the existence of ordinal input/output data expressed on L-point scale, because of the number of decision variables and constraints to be solved, if number of DMU is greater that the number of Likert scale, the efficiency of Cook et al. model is better than that of Cooper et al. model. Furthermore since it is possible to model ordinal relationships in a general format with Cook et al. but it is needed to be programmed manually for each DMU by Cooper et al.'s model, the use of Cook et al.'s model is easier. Since we employed in our analysis L-point scale data and since our number of DMU(11) is greater than our number of Likert scale (5), we choose to apply Cook et al.'s IDEA model in our analysis.

4.3 Determination of Optimum Epsilon Value for Maximum Discrimination

Since the discrimination power of the original CCR-DEA and IDEA model is low, to overcome the poor discriminating power of the DEA models, several approaches have been proposed in the literature. One of these methods is using epsilon value (ε) to limit the flexibility of the weights [70].

It is observed that when IDEA and the standard DEA models applied to a data set under different ε values, different efficiency values are obtained sensitive to the choice of ε. The larger ε is preferred to a smaller value, because increasing ε serves the model to take into account all the criteria employed and by limiting the weights it decreases the number of efficient units. As a result of studies made to identify the max possible ε

that can be used for the max ε discrimination, below given formulas are produced by Cook et al. [70]. In order to determine the max epsilon efficiency for the data set, the models has to be solved for each DMU and the minimum value of the max ε must be used for the efficiency calculations:

$$\varepsilon_{\max} = \min_{j=1,2,\ldots,n} \{\hat{\varepsilon}_j\} \tag{4.12}$$

$$\max \hat{\varepsilon}_j = \varepsilon , \; \forall j$$

Subject to the constraints of the any DEA model whose max epsilon value is willing to be calculated.

4.4 Minimax Efficiency Model

One another method to overcome the poor discriminating power of the DEA models, is modifying the formulation of the model whose discrimination is willing to be increased by changing its objective function. There are several forms of modified objective functions supplied by defining another efficiency measure with more discriminating power such as cross efficiency measure or minimization of maximum deviation from the ideal efficiency score of 1, namely, minimax efficiency measure. In this sub-chapter we'll be mentioning about the type of minimax DEA models that we employed in our study.

Minimax efficiency measure aims to determine optimal weights that minimize the maximum deviation from efficiency. As it considers all DMUs' deviation from efficiency at the same time, the flexibility of a particular DMU to choose the weights in its favor is restricted. Thus, it is more difficult for a DMU to achieve minimax efficiency than to achieve classical efficiency [63]. In conclusion, minimax efficiency measure discriminates better among DMUs. Since our calculations for both exact and exact and ordinal data sets show us that even though we can eliminate some of the DMUs by simple efficiency calculation models, in order to eliminate more DMU to obtain a ranking and find the most efficient sector, we need to apply models with more discriminating power, such as the minimax efficiency model. The version of the model adapted to our data set is presented below:

$\min M$

st

$$M \geq d_j \qquad \text{for } \forall j$$

$$\sum_{i \in EXI} v_i x_{ij_o} = 1$$

$$\sum_{r \in EXO} u_r y_{rj} + \sum_{r \in ORDO} \mathbf{w_r^1 \gamma_{rj}} - \sum_{i \in EXI} v_i x_{ij} + d_j = 0 \tag{4.13}$$

$$u_r \geq \varepsilon \text{ for } r \in EXO$$

$$v_i \geq \varepsilon \text{ for } i \in EXI$$

$$\mathbf{w_r^1} \in \Psi = \left\{ w_{rl+1}^1 - w_{rl}^1 \geq \varepsilon, w_{r1}^1 \geq \varepsilon, \quad for\ l = 1,2,\ldots,L-1; r \in ORDO \right\}$$

$$d_j \geq 0 \qquad for\,\forall j$$

where M represents the maximum deviation from efficiency and $M \geq d_j$ are the constraints which are added into the model to assure that $M = \max_j d_j$.

Since this model is formulated for the efficiency calculation of a particular DMU, in order to determine the efficiencies of all DMUs, it has to be solved for each DMU separately.

For our single input exact data minimax analysis we used the model presented by Ahiska [68] which allows to determine the efficiencies of all DMUs by solving just one formulation which is given below:

$$\min M$$

st

$$M \geq d_j, \ \forall j$$

$$\sum_{r=1}^{m} u_r R_{rj} + d_j = 1, \forall j \tag{4.14}$$

$$u_r \geq \varepsilon, \ \forall r$$

$$d_j \geq 0, \ \forall j$$

when the formulation (4.13) or (4.14) is solved, the efficiency value of each DMU can be calculated by $1 - d_j$.

4.5 Cross Efficiency Analysis

One another method to overcome the poor discriminating power of the DEA models, is cross efficiency model. The model is developed by Sexton et al. [59] and since then many improvements and applications have been made. The model depends on the efficiency value of DMU calculated with the optimal weights that maximizes the efficiency of other DMUs and it gives information about how well it performs with the other DMUs' optimal weights. Its formula is given as:

$$E_{kj} = \frac{\sum_r u_{rk} y_{rj}}{\sum_i v_{ik} x_{ij}} \quad , \forall i, j, r \tag{4.15}$$

where E_{kj} is the cross efficiency value of DMU j with respect to DMU k, u_{rk} is the optimal weight assigned to output r for DMU k and v_{ik} is the optimal assigned to input i for DMU k. E_{kj} values are also called "peer appraisal" values for $j \neq k$ and "self appraisal" or "simple efficiency" values for $j = k$. Simple efficiency value of each DMU is directly calculated by either CCR-DEA or IDEA models.

After calculation of the cross efficiencies, a matrix called "cross efficiency matrix" (CEM) is formed as shown in Table 4.1 The diagonal of this matrix is formed from the simple efficiency values of the DMUs.

Table 4.1 Cross Efficiency Matrix

DMU	*1*	*2*	...	*J*	...	*N*
1	E_{11}	E_{12}	...	E_{1j}	...	E_{1n}
2	E_{21}	E_{22}	...	E_{2j}	...	E_{2n}
...	...	...	...	...	...	...
K	E_{k1}	E_{k2}	...	E_{kj}	...	E_{kn}
...	...	...	...	...	...	...
N	E_{n1}	E_{n2}	...	E_{nj}	...	E_{nn}
Mean cross efficiency	e_1	e_2	...	e_j	...	e_n

Mean cross efficiency value of a DMU j is calculated by taking column mean of the CEM with or without simple efficiency values. Since an overall good performer DMU gives high cross efficiency results whereas the false positive gives several low cross efficiency values, the mean cross efficiency value can be used to distinguish good performers from the false positive ones. The equation of mean cross efficiency e_j without self appraisal is calculated as below:

$$e_j = \frac{\sum_{j \neq k} E_{kj}}{n-1} \quad , \ \forall j \tag{4.16}$$

4.6 Aggressive Cross Efficiency Model

Aggressive cross efficiency model is developed by Doyle and Green [60] to overcome "multiple optimal weight" problem in cross efficiency model and so supply a true discrimination between DMUs.

The multiple optimal weight problems occur when the optimal weights aren't unique. In those situations the decision maker wouldn't know which optimal weight set should be used in cross efficiency calculations. Since the usage of the different optimal weights will directly affect the cross efficiency values, cross efficiency matrices formed by different decision makers will be different from each other and so the rankings of the DMUs. To solve this problem Doyle and Green established a two step procedure. First step is to obtain the simple efficiency values ($E_{kk}, k = 1, 2, \ldots, n$) using the CCR-DEA or Cook et al.'s models. Second step is to use the aggressive cross efficiency model for each DMU k in order to obtain the optimal weights that will be used in the calculation of cross efficiency values (E_{kj}).

The aim of the aggressive cross efficiency procedure is increasing discrimination power of the cross efficiency model by finding an optimum point that minimizes the sum of the efficiencies of the all DMUs other than the test DMU for the optimal weights of the test DMU. By trying to find the optimal weight which makes all the other DMUs as bad as they can, the method is decreasing its multiple optimal weights to one and also increasing its discrimination capability.

The aggressive cross efficiency formulation that deals with both exact and ordinal data is formulated below:

$$\min \quad \sum_{r \in EXO} u_{rk} \sum_{j \neq k} y_{rj} + \sum_{r \in ORDO} \mathbf{w}^{\mathbf{1}}_{\mathbf{r}k} \sum_{j \neq k} \boldsymbol{\gamma}_{\mathbf{rj}}$$

st

$$\sum_{i} v_{ik} \sum_{j \neq k} x_{ij} = 1$$

$$\sum_{r \in EXO} u_{rk} y_{rk} + \sum_{r \in ORDO} \mathbf{w}^{\mathbf{1}}_{\mathbf{r}k} \boldsymbol{\gamma}_{\mathbf{r}k} - E_{kk} \sum_{i \in EXI} v_{ik} x_{ik} = 0$$

$$\sum_{r \in EXO} u_{rk} y_{rj} + \sum_{r \in ORDO} \mathbf{w}^{\mathbf{1}}_{\mathbf{r}k} \boldsymbol{\gamma}_{\mathbf{rj}} - \sum_{i \in EXI} v_{ik} x_{ij} \leq 0, \ \forall j \neq k \tag{4.17}$$

$u_{rk} \geq \varepsilon$, $\forall r$ for $r \in EXO$

$v_{ik} \geq \varepsilon$, $\forall i$ for $i \in EXI$

$$\mathbf{w}_{\mathbf{r}k}^{\mathbf{1}} \in \Psi = \left\{ w_{rl+1}^{1} - w_{rl}^{1} \geq \varepsilon, w_{r1}^{1} \geq \varepsilon, \quad for\ l = 1,2,\ldots,L-1; r \in ORDO \right\}$$

where E_{kj} is the cross efficiency value of DMU *j* with respect to DMU *k*, u_{rk} is the optimal weight assigned to output *r* for DMU *k* and v_{ik} is the optimal assigned to input *i* for DMU *k,* $\mathbf{w}_{\mathbf{r}k}^{\mathbf{1}}$ is the worth vector including variables w_{rl}^{1}, which indicate the worth (weighted values) of being rated in the lth place assigned to output r for DMU k.

For n units of DMU, aggressive cross efficiency method requires 2n formulas to be solved (n formula for the determination of simple efficiencies by either CCR-DEA or IDEA and n formula for the aggressive cross efficiency). After solving aforementioned formulas and finding all E_{kj} values, mean cross efficiency values are found for each DMU. Then in order to check their false positiveness Maverick Index is calculated as it is explained below.

Since the mean cross efficiency value is obtained by taking average, it can't distinguish the good overall performers from the poor performers (false positives). To detect these poor performers and measure the degree of their false positiveness in an effective manner, Doyle and Green suggest Maverick index to be calculated. The index is formulated as follows:

$$M_j = \frac{E_{jj} - e_j}{e_j} \times 100, \forall j \qquad (4.18)$$

where M_j is the Maverick index of DMU j. Since the index shows the deviation of the simple efficiency from the average cross efficiency values, it ought to be small to be preferred. Higher Maverick index indicate higher degree of false positiveness for the DMU under consideration.

5. Results

As it is mentioned in the previous chapters, our analysis consists of two steps. First, the sectors are analyzed with two different sets of data (exact only data and exact and ordinal data), through the use of several DEA and IDEA models, minimax efficiency model, cross efficiency and aggressive cross efficiency techniques. The aim of the first step is to see the effect of subjective criteria consideration on the efficiency of sectors and to determine the worst and best performing sectors for further analysis. The second step consists of applying the duality analysis to the sector determined as the worst to find out the criteria that should be improved and making single input exact data analysis for the best sectors in order to see if they can be improved further.

The approach in the first step is the following: First, all the sectors are analyzed for $\varepsilon = 0$ by using the exact data set. To do so, our starting point is the application of the original model CCR-DEA for the simple efficiency calculations. After those calculations, to improve the discrimination power and determine the best performing sectors, other DEA models such as minimax efficiency model, cross efficiency analysis, aggressive cross efficiency model are used and, Maverick index is calculated in order to eliminate the false positive sectors. Then, all the sectors are analyzed by using both exact and ordinal data set, again for $\varepsilon=0$. For this purpose, Cook et al.'s IDEA model is employed and as well as the same models mentioned above, such as minimax efficiency model and cross efficiency analysis for further discrimination. After the computation of the maximum ε values for exact as well as exact and ordinal data sets, the analyses described above are repeated for the new ε values and the results are compared.

After performing all the analyses above, the second step begin with determining the worst performing and best performing sectors with respect to both exact and exact and ordinal data. We perform sensitivity analysis by using the CCR-DEA dual formulation (formula 4.6) for the worst sector and apply product-wise single input and multiple outputs exact data analysis to the best DMUs.

5.1 Results for Exact Data, ε=0

While there are many variations of the DEA methodology, our starting point is to use the original model CCR-DEA (formula 4.3) for the simple efficiency calculations in the existence of exact data.

Table 5.1 Cross Efficiency Matrix (CEM)-Exact Data-ε=0

FOR EXACT DATA with ε =0	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6	Sector 7	Sector 8	Sector 9	Sector 10	Sector 11
Sector1	1.000	0.545	0.172	1.000	0.347	0.190	0.263	0.189	0.360	0.089	0.764
Sector2	1.000	0.709	0.932	0.874	0.512	0.402	0.654	0.433	1.000	1.000	1.000
Sector3	1.000	0.371	1.000	0.325	0.175	0.324	0.710	0.255	0.864	0.908	0.324
Sector4	0.313	0.374	1.000	1.000	0.361	0.231	0.750	0.278	0.868	0.974	0.537
Sector5	0.37	0.579	0.819	1.000	0.581	0.260	0.572	0.403	0.866	1.000	1.000
Sector6	1.000	0.702	0.704	0.450	0.437	0.488	0.419	0.533	0.880	1.000	1.000
Sector7	1.000	0.557	1.000	1.000	0.383	0.333	0.783	0.321	0.947	0.913	0.695
Sector8	1.000	0.702	0.704	0.450	0.437	0.488	0.419	0.533	0.880	1.000	1.000
Sector9	1.000	0.709	0.944	1.000	0.523	0.384	0.694	0.415	1.000	0.968	1.000
Sector10	0.023	0.043	0.550	0.044	0.059	0.123	0.232	0.16	0.424	1.000	0.024
Sector11	1.000	0.702	0.704	0.450	0.437	0.488	0.419	0.533	0.880	1.000	1.000
Mean Cross Efficiency	0.771	0.528	0.753	0.660	0.367	0.322	0.513	0.352	0.797	0.885	0.734

The simple efficiency results of CCR-DEA are presented in the diagonal of the CEM in Table 5.1, showing that there are 6 efficient sectors according to the CCR-DEA model, which are Sector 1 (Manufactured food products and beverages), Sector 3 (Wearing apparel), Sector 4 (Manufacture of paper and paper products), Sector 9 (Electric machinery and apparatus), Sector 10 (Manufacture of motor, vehicles, trailers) and Sector 11 (Manufacture of furniture).

Since our computations show that there are multiple efficient DMUs, further analysis is needed to discriminate among those efficient sectors. For this purpose, minimax efficiency model is used next (formulation 4.13). With the minimax efficiency analysis, the number of efficient sectors decreases from 6 to 2. The two efficient sectors are Sector 10 (Manufacture of motor, vehicles, trailers) and Sector 11 (Manufacture of furniture). Efficiency results of this study are presented in the 3rd column of Table 5.3. Then, by the help of CEM (Table 5.1), the mean cross efficiencies of all sectors are calculated by the formulation 4.16 and the scores are presented in the 4th column of the Table 5.3.

Table 5.2 Aggressive Cross Efficiency Matrix-Exact Data-ε=0

Sectors	1	2	3	4	5	6	7	8	9	10	11
1	1.000	0.314	0.135	0.163	0.088	0.173	0.150	0.100	0.231	0.046	0.307
2	1.000	0.709	0.924	0.852	0.510	0.405	0.644	0.435	0.996	1.000	1.000
3	0.074	0.089	1.000	0.192	0.106	0.187	0.645	0.186	0.742	1.000	0.043
4	0.298	0.356	0.082	1.000	0.321	0.071	0.173	0.131	0.216	0.062	0.610
5	0.369	0.578	0.817	0.995	0.581	0.260	0.569	0.403	0.865	1.000	1.000
6	1.000	0.699	0.704	0.444	0.433	0.488	0.418	0.530	0.878	1.000	0.992
7	0.998	0.557	1.000	1.000	0.383	0.333	0.783	0.321	0.947	0.913	0.695
8	0.999	0.702	0.703	0.450	0.437	0.488	0.419	0.533	0.880	1.000	1.000
9	1.000	0.637	1.000	0.889	0.447	0.377	0.722	0.383	1.000	1.000	0.844
10	0.023	0.043	0.550	0.044	0.059	0.123	0.232	0.160	0.424	1.000	0.024
11	0.362	0.410	0.120	0.856	0.480	0.118	0.193	0.237	0.325	0.140	1.000
e_j	0.612	0.439	0.604	0.589	0.326	0.254	0.417	0.289	0.650	0.716	0.652
M_j	63.32	61.69	65.70	69.92	78.00	92.50	88.00	84.51	53.75	39.65	53.49

Afterwards, by using the simple efficiency values obtained from CCR-DEA analysis in the aggressive cross efficiency formulation (4.17), the CEM of the aggressive cross efficiency is constructed, as given in Table 5.2 and through this matrix its mean aggressive cross efficiency values (formula 4.16) and the Maverick indices (formula 4.18), which indicate the degree of false positiveness, are calculated and presented in the 5th and 6th columns of Table 5.3, respectively. As a result of all these analyses, a full ranking of Sectors is obtained.

As it can be seen from Table 5.3, for the exact data for ε=0, Sector 1,3 and 4 are false positive because of the high Maverick Index values. Sector 10 (Manufacture of Motor, Vehicles, Trailers) is the best DMU having the highest efficiency values and the lowest Maverick Index, whereas Sector 6 (Manufacture of Non Metallic) is the worst one with the lowest efficiency values and highest Maverick Index.

Table 5.3 Analysis Results for Exact Data-ε=0

	CCR-DEA	Minimax	Cross Efficiency	Aggressive Cross Efficiency	Maverick Index
Sector1	1.000	0.920	0.771	0.610	63.32
Sector2	0.710	0.580	0.528	0.440	61.69
Sector3	1.000	0.800	0.753	0.600	65.70
Sector4	1.000	0.630	0.659	0.590	69.92
Sector5	0.580	0.490	0.367	0.330	78.00
Sector6	0.490	0.430	0.322	0.250	92.50
Sector7	0.780	0.510	0.513	0.420	88.00
Sector8	0.530	0.470	0.352	0.290	84.51
Sector9	1.000	0.950	0.797	0.650	53.75
Sector10	1.000	1.000	0.885	0.720	39.65
Sector11	1.000	1.000	0.734	0.650	53.49

5.2 Results for Exact and Ordinal Data, ε=0

To deal with exact and ordinal data, our analysis starts with Cook et al. Ordinal DEA model and continues with other previously used efficiency models which have higher discriminating power than single efficiency such as minimax, cross efficiency, and aggressive cross efficiency. All results are presented in Table 5.4.

Table 5.4-Analysis Results for Exact and Ordinal Data-ε=0

	Cook et al. Model	Minimax	Cross Efficiency	Aggressive Cross Efficiency	Maverick Index
Sector1	1.000	0.930	0.531	0.110	778.0
Sector2	1.000	1.000	0.669	0.260	288.2
Sector3	1.000	0.910	0.585	0.380	163.8
Sector4	1.000	1.000	0.831	0.380	163.0
Sector5	1.000	0.900	0.555	0.370	168.7
Sector6	1.000	0.890	0.193	0.060	1473
Sector7	1.000	0.920	0.645	0.400	147.9
Sector8	1.000	0.910	0.589	0.560	77.12
Sector9	1.000	1.000	0.785	0.670	49.25
Sector10	1.000	1.000	0.687	0.660	50.92
Sector11	1.000	1.000	0.612	0.430	133.6

The analysis results show that by the use of subjective data, all the sectors become efficient according to Cook et al. model (formulation 4.10). Applying minimax efficiency model decreases the number of efficient sectors to 5 sectors (Textile industry, Manufacture of paper and paper products, Electric machinery and apparatus, Manufacture of motor, vehicles, trailers, Manufacture of furniture). The results of aggressive cross efficiency model and Maverick index show that all the sectors, other than Sector 9 (Electric machinery and apparatus) and 10 (Manufacture of motor, vehicles, trailers) are false positive. The best sector is determined as Sector 9 (Electric machinery and apparatus) with the highest efficiencies and lowest Maverick index whereas the worst is Sector 6 (Manufacture of non metallic).

When exact data set results are compared with exact and ordinal data set results, we see that the subjective judgements related with the DMUs can change the efficiency of DMUs and so the decisions. This indicates that even though some sectors could not reach the efficiency in terms of numerical performance, when the side effects and the strategic plans are taken into account, they can be considered as efficient.

That's why while Manufacture of motor, vehicles, trailers is the best sector for exact data, Electric machinery and apparatus becomes the best sector for exact and ordinal data. Moreover, comparison of the CCR-DEA results with Cook et al.'s results also shows that the discriminating power of an exact and ordinal data model is lower than an exact data model for our problem.

5.3 Results for Exact Data, ε=0.357

Since the models can neglect some of the inputs or outputs in order to maximize the efficiencies of sectors when ε=0, to obtain more meaningful and discriminative solutions where the models take into account all the inputs and outputs, the maximum ε values for exact and the exact and ordinal data sets will be calculated and the aforementioned analyses will be repeated for the new ε values.

For the exact data set, by the formulations 4.12, 4.03 and 4.13, the max ε values of CCR-DEA and minimax models are found as 0.357. Since the aggressive cross efficiency model gives infeasible solutions for this ε value, this model is removed from this analysis.

Table 5.5 Analysis Results for the Exact Data-ε=0.357

	CCR-DEA	**Minimax**	**Cross Efficiency**
Sector1	1.000	1.000	0.854
Sector2	0.660	0.656	0.580
Sector3	0.915	0.827	0.834
Sector4	1.000	0.679	0.769
Sector5	0.544	0.480	0.453
Sector6	0.419	0.419	0.350
Sector7	0.674	0.546	0.570
Sector8	0.441	0.441	0.386
Sector9	0.974	0.927	0.888
Sector10	1.000	1.000	0.963
Sector11	1.000	1.000	0.898

As it is seen in Table 5.5, the results show that the employment of higher ε values decreases the number of efficient sectors from 6 to 4 for CCR-DEA model. However it doesn't affect the best sector (Manufacture of motor, vehicles, trailers) and the worst sector (Manufacture of non metallic) choices.

5.4 Results for Exact and Ordinal Data, ε=0.034

For the exact and ordinal data set, by the formula 4.12, 4.10 and 4.13 the max ε values of Cook et al. and minimax models are found as 0.034. Since the aggressive cross efficiency model gives infeasible solutions for the ε value of this data set, this model is removed from this analysis set.

As it is seen in Table 5.6, the results show that the use of a higher ε value decreases the number of efficient sectors from 11 to 6 for the Cook et al. model. It also shows that even though the best sector is not affected by the ε value, the worst sector (Manufactured food products and beverages) becomes Sector 1. However it should also be noted the efficiency scores of Sector 6 (Manufacture of non metallic) are still very close to those of Sector 1.

Table 5.6 Analysis Results for Exact and Ordinal Data-ε=0.034

	Cook et al. Model	**Minimax**	**Cross Efficiency**
Sector1	0.673	0.673	0.529
Sector2	1.000	0.908	0.805
Sector3	0.983	0.873	0.769
Sector4	1.000	0.945	0.903
Sector5	0.948	0.856	0.742
Sector6	0.801	0.793	0.568
Sector7	1.000	0.913	0.820
Sector8	0.962	0.910	0.774
Sector9	1.000	1.000	0.904
Sector10	1.000	1.000	0.871
Sector11	1.000	0.993	0.789

In summary, when all four sets of analyses results are examined, the best manufacturing sectors are determined as Manufacture of motor, vehicles, trailers (Sector 10) for exact only data and Electric machinery and apparatus (Sector 9) for exact and ordinal data. A common worst sector is determined as Manufacture of non metallic (Sector 6) for both of the data sets.

By taking into account the export strategic plans of both countries, it can be seen that these results are logical and are consistent with those strategic plans and the recent conjuncture emerged after the global crisis. It is important to note that the intention to export value added products has higher priority than the others, as stated previously in the latest export strategic plans announced by Turkey, and the two sectors above, which are determined as the best sectors, are also in the same category. Accordingly, it was also stated that Manufacture of motor, vehicles, trailers and Electric machinery and apparatus were two sectors that Ireland was interested in importing, due to the production complexity. Furthermore, Manufacture of non metallic sector, which is determined as the worst performing sector in this work, is directly linked to the construction sector which is the most affected sector in Ireland during the global crisis in 2008.

5.5 Sensitivity Analysis Results for the Worst Performing Sector

Based on the results above, we can proceed to the second step of our analysis. Since the worst performing sector is determined (Manufacture of non metallic (Sector 6)), the second step of our evaluations start with a sensitivity analysis. In our sensitivity analysis, the CCR-DEA dual model (formulation 4.6) with $\varepsilon=0$ is applied to the exact only data set. The results of analysis show that Manufacture of non metallic sector chooses Sector 1(Manufactured food products and beverages), sector 10 (Manufacture of motor, vehicles, trailers) and sector 11 (Manufacture of furniture) as benchmark sectors for itself and it is sensitive to ULC (unit labour cost) and Hours Spent, slack variables found for these inputs being 0.088 and 0.107, respectively. Since these two inputs are overvalued, they have to be decreased for making this sector efficient. By the formula 4.8 the amount of the inputs that should be decreased to reach the efficiency for this sector is calculated as; 0.461 for ULC and 0.51 for Hours spent. These improvement amounts correspond to 63.25% and 64.57% decrease in ULC and Hours Spent inputs respectively. ULC and Hours spent must be decreased to 0.268 and 0.283, respectively in order to provide the efficiency. In a managerial point of view, either the working hours or the wages should be decreased by %63, or the number of employees has to decrease as well as the hours spent by the government to support the export of this sector.

5.6 Product-wise Performance Analysis for the Best Performing Sectors

After concluding our analysis regarding the worst performing sector, two best performing sectors are analyzed to see if any further improvement is possible for them. In order to analyze the two best performing sectors, under the constraint of product wise data availability, one exact input (Import Growth of Ireland) and two exact outputs are employed. The data collected for each product is normalized used maximum mauve for normalization and the data obtained is presented at Table 5.7 and 5.8.

By using these data and applying single input CCR-DEA model, Minimax efficiency model and Cross Efficiency analysis (formulations 4.5, 4.14 and 4.16), the results presented in Table 5.9 and Table 5.10 are obtained.

Table 5.7 Data for the Products Included in Sector 10

Sector10 Products	Product Name	Input-Import Growth of Ireland	Output-Export Value	Output-Import Share
AProduct1	New pneumatic tyres, of rubber, of a kind used for motor cars, incl. station wagons and racing cars	0.945	0.019	0.021
AProduct2	Pneumatic tyres, new, of rubber, of a kind used for buses or lorries, with a load index of > 121	0.727	0.018	0.056
AProduct3	Motor cars and other motor vehicles principally designed for the transport of persons, incl. station wagons and racing cars, with spark-ignition internal combustion reciprocating piston engine, of a c	0.568	0.047	0.017
AProduct4	Motor cars and other motor vehicles principally designed for the transport of persons (other than those of heading No 8702), incl. station wagons and racing cars, with spark-ignition internal combusti	0.387	0.479	0.110
AProduct5	Motor cars and other motor vehicles, principally designed for the transport of persons, incl. station wagons, with compression-ignition internal combustion piston engine 'diesel or semi-diesel engine'	0.783	0.027	0.005
AProduct6	Motor vehicles for the transport of goods, with compression-ignition internal combustion piston engine 'diesel or semi-diesel engine' of a gross vehicle weight <= 5 t, of a cylinder capacity <= 2.500	1.000	1.000	0.333
AProduct7	Road wheels and parts and accessories thereof, for the industrial assembly of: pedestrian-controlled tractors, motor cars and vehicles principally designed for the transport of persons, vehicles for t	0.751	0.011	1.000

Table 5.8 Data for the Products Included in Sector 9

Sector9 Products	Product Name	Input-Import Growth of Ireland	Output-Export Value	Output-Import Share
EProduct1	Transformers having a power handling capacity > 500 kVA (excl. liquid dielectric transformers)	1.000	0.583	0.727
EProduct2	Electric cookers incorporating at least an oven and a hob, for domestic use	0.377	0.370	0.151
EProduct3	Electric ovens, for domestic use (excl. space-heating stoves, electric cookers incorporating at least an oven and a hob, microwave ovens and electric ovens for building in)	0.549	0.122	0.236
EProduct4	Radio-broadcast receivers, for mains operation only, not combined with sound recording or reproducing apparatus and not combined with a clock (excl. those of a kind used in motor vehicles)	0.345	0.483	0.622
EProduct5	Television projection equipment, colour, designed to incorporate a video display or screen	0.281	0.516	1.000
EProduct6	Reception apparatus for television, colour, incorporating a video recorder or reproducer	0.899	0.738	0.681
EProduct7	Reception apparatus for television, colour, with integral tube, with a screen width/height ratio < 1,5, with a diagonal measurement of the screen of <= 42 cm (excl. incorporating video recording or re	0.165	0.109	0.337
EProduct8	Reception apparatus for television, colour, with a screen width/height ratio < 1,5 (excl. with integral tube or incorporating video recording or reproducing apparatus and monitors, and television proj	0.301	0.340	0.291
EProduct9	Reception apparatus for television, colour, with a screen width/height ratio >= 1,5 (excl. with integral tube or incorporating video recording or reproducing apparatus and monitors, and television pro	0.334	0.187	0.040
EProduct10	Relays for a voltage > 60 V but <= 1.000 V	0.486	1.000	0.611
EProduct11	Winding wire for electrical purposes, of copper, insulated (excl. lacquered or enamelled)	0.379	0.217	0.065

Table 5.8 Continued

Sector9 Products	Product Name	Input-Import Growth of Ireland	Output-Export Value	Output-Import Share
EProduct12	Coaxial cable and other coaxial electric conductors, insulated	0.463	0.933	0.273
EProduct13	Electric conductors, for a voltage <= 1.000 V, insulated, fitted with connectors, n.e.s. (other than of a kind used for telecommunications)	0.359	0.178	0.044
EProduct14	Electric wire and cables, for a voltage <= 1.000 V, insulated, not fitted with connectors, with individual conductor wires of a diameter > 0,51 mm, n.e.s.	0.225	0.214	0.195
EProduct15	Conductors, electric, for a voltage <= 80 V, insulated, not fitted with connectors, n.e.s. (excl. winding wire, coaxial conductors, wiring sets for vehicles, aircraft or ships, and wire and cables wit	0.384	0.144	0.303
EProduct16	Electric conductors for a voltage > 80 V but < 1.000 V, insulated, not fitted with connectors, n.e.s. (excl. winding wire, coaxial conductors, wiring sets for vehicles, aircraft or ships, and wire and	0.559	0.078	0.027
EProduct17	Electric conductors for a voltage > 1.000 V, insulated, with copper conductors, n.e.s.	0.218	0.205	0.138
EProduct18	Optical fibre cables made up of individually sheathed fibres, whether or not containing electric conductors or fitted with connectors	0.842	0.548	0.109

Table 5.9 Sector10-Product wise Analysis-Exact Data-Single Input-ε=0

	CCR-DEA	Minimax	Cross Efficiency
AProduct1	0.03	0.026	0.023
AProduct2	0.073	0.061	0.053
AProduct3	0.074	0.072	0.063
AProduct4	1	1	0.869
AProduct5	0.027	0.026	0.023
AProduct6	0.886	0.868	0.754
AProduct7	1	0.762	0.671

When the product wise data are analyzed for Sector 10 (Manufacture of motor, vehicles, trailers), we see that although there is a considerable amount of contraction in the imports of many products, some products performs relatively better. By the analysis presented above, it is noticed that our export performance for those relatively better products such as AProduct5 (Diesel motor vehicles), AProduct3 (Motors >2500 cm^3), AProduct1 (Tyres for cars) and AProduct2 (Tyres for Busses) are not good enough. In order to have improvement in the export performance of those products, some supportive actions might be needed such as Advertisement and Market activities, depending on their costs.

Table 5.10 Sector9-Product wise Analysis-Exact Data-Single Input-ε=0

	CCR-DEA	**Minimax**	**Cross Efficiency**
EProduct1	0.299	0.283	0.269
EProduct2	0.477	0.477	0.388
EProduct3	0.121	0.108	0.115
EProduct4	0.721	0.680	0.651
EProduct5	1.000	0.894	0.950
EProduct6	0.410	0.399	0.358
EProduct7	0.573	0.322	0.391
EProduct8	0.560	0.548	0.486
EProduct9	0.271	0.271	0.212
EProduct10	1.000	1.000	0.848
EProduct11	0.278	0.278	0.221
EProduct12	0.978	0.978	0.777
EProduct13	0.240	0.240	0.189
EProduct14	0.475	0.462	0.415
EProduct15	0.221	0.182	0.198
EProduct16	0.068	0.068	0.054
EProduct17	0.460	0.457	0.392
EProduct18	0.316	0.316	0.246

When the product wise data is analyzed for Sector 9 (Electric machinery and apparatus), we see that the export performance of the value-added products in this sector such as TV projection appliances (EProduct5), some cables (EProduct12) and radio receivers (Eproduct4), seems alright. However, product wise, perhaps firm-based studies are needed to be done further, especially for conductors and cooker products in order to improve the export performance.

6. CONCLUSION

In this thesis, export performance of Turkey to Ireland is evaluated through the use of DEA methods, such as the CCR-DEA, Cook et al.'s model, minimax efficiency model, cross efficiency, aggressive cross efficiency, in the presence of exact only and exact and ordinal data sets. The data sets are obtained by considering top 100 Turkish manufacturing products exported to Ireland in 2008. It is shown that the inclusion of the ordinal data has a considerable effect on the results since the side factors, such as strategic plans and human subjectivity, are also taken into account in addition to the numerical performance figures, while evaluating the efficiency of the target sectors. In the presence of ordinal data, it is observed that the efficiencies of sectors with very different numerical performance levels are getting closer and the most efficient sector is not necessarily the one with the best numerical performance. After determining the efficiency ranking of the target sectors, a sensitivity analysis is applied to the worst performing sector, and the factors that can be modified to improve the sector performance are specified. It is important to note that the same analysis can also be applied to the other inefficient sectors, similarly. Moreover, product-wise analyses of two best performing sectors are carried out to determine if there is any chance of further improvement.

After applying the aforementioned DEA methods, the best manufacturing sectors are determined as Manufacture of motor, vehicles, trailers for exact data and Electric machinery and apparatus for exact and ordinal data. A common worst performing sector is determined as Manufacture of non metallic for both of the data sets. It can be seen that these results are logical and are consistent with the two countries' strategic plans and the recent conjuncture emerged after the global crisis. It is important to note that the intention to export value added products has higher priority than the others, as stated previously in the latest export strategic plans announced by Turkey, and the two sectors above, which are determined as the best sectors in this thesis, are also in the same category. Accordingly, it was also stated that Manufacture of motor, vehicles, trailers and Electric machinery and apparatus were two sectors that Ireland was interested in importing, due to the production complexity. Furthermore, Manufacture of Non Metallic sector, which is determined as the worst performing sector in this work, is directly linked to the construction sector which is the sector in Ireland that is most affected by the global crisis in 2008.

A sensitivity analysis is applied to the Manufacture of Non Metallic sector, in order to determine the actions needed to improve the efficiency of this sector. The results of the analysis reveal that the ULC and Hours Spent inputs have to be decreased by 63.25% and 64.57%, respectively. In a managerial point of view, either the working hours or the wages have to be decreased by %63, or the number of employees has to decrease as well as the hours spent by the government to support the export of this sector.

The analysis on the products of Manufacture of Motor, Vehicles, Trailers sector shows that there are some improvement opportunities for the products whose import growth performance is relatively better and the analysis on the products of Electric Machinery and Apparatus reveals that product wise detailed further analysis can be made for exports of the conductors and cookers.

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Appendix A

Table A.1 List of the Top 100 Manufacturing Products and their Sector Grouping

PRODUCT DESCRIPTION	SECTOR
Sultanas	15-Manufactured Food Products and Beverages
Jams, fruit jellies, marmalades, fruit purée and pastes, obtained by cooking, whether or not containing added sugar or other sweetening matter (excl. with a sugar content of > 13% by weight, homogenis	15-Manufactured Food Products and Beverages
Kaolin	26-Manufacture of Non-metallic
Dead-burned 'sintered' magnesia, whether or not containing small quantities of other oxides added before sintering	26-Manufacture of Non-metallic
Non-cellular polyethylene film of a thickness of >= 20 micrometres but <= 40 micrometres, for the production of photoresist film used in the manufacture of semiconductors or printed circuits	25-Rubber and Plastics Product
Sacks and bags, incl. cones, of polymers of ethylene	25-Rubber and Plastics Product
Sacks and bags, incl. cones, of plastics (excl. those of poly'vinyl chloride' and polymers of ethylene)	25-Rubber and Plastics Product
Builders' ware for the manufacture of flooring, walls, partition walls, ceilings, roofing, etc. guttering and accessories, banisters, fences and the like, fitted shelving for shops, factories, warehouses	25-Rubber and Plastics Product
New pneumatic tyres, of rubber, of a kind used for motor cars, incl. station wagons and racing cars	34-Manufacture of Motor, Vehicles, Trailers
Pneumatic tyres, new, of rubber, of a kind used for buses or lorries, with a load index of > 121	34-Manufacture of Motor, Vehicles, Trailers
Folding cartons, boxes and cases, of non-corrugated paper or paperboard	21-Manf. of Paper and Paper Products
Cartons, boxes and cases, of corrugated paper or paperboard	21-Manf. of Paper and Paper Products

Table A.1 Continued

PRODUCT DESCRIPTION	SECTOR
Women's or girls' trousers, bib and brace overalls, breeches and shorts of cotton, knitted or crocheted (excl. panties and swimwear)	18-Wearing Apparel
Men's or boys' shirts of cotton, knitted or crocheted (excl. nightshirts, T-shirts, singlets and other vests)	18-Wearing Apparel
Women's or girls' blouses, shirts and shirt-blouses of cotton, knitted or crocheted (excl. T-shirts and vests)	18-Wearing Apparel
Women's or girls' blouses, shirts and shirt-blouses of man-made fibres, knitted or crocheted (excl. T-shirts and vests)	18-Wearing Apparel
Women's or girls' briefs and panties of cotton, knitted or crocheted	18-Wearing Apparel
Women's or girls' briefs and panties of man-made fibres, knitted or crocheted	18-Wearing Apparel
T-shirts, singlets and other vests of cotton, knitted or crocheted	18-Wearing Apparel
T-shirts, singlets and other vests of textile materials, knitted or crocheted (excl. of wool, fine animal hair, cotton or man-made fibres)	18-Wearing Apparel
Men's or boys' jerseys, pullovers, cardigans, waistcoats and similar articles, of cotton, knitted or crocheted (excl. lightweight fine knit roll, polo or turtleneck jumpers and pullovers and wadded wa	18-Wearing Apparel
Women's or girls' jerseys, pullovers, cardigans, waistcoats and similar articles, of cotton, knitted or crocheted (excl. lightweight fine knit roll, polo or turtleneck jumpers and pullovers and wadded	18-Wearing Apparel
Women's or girls' jerseys, pullovers, cardigans, waistcoats and similar articles, of man-made fibres, knitted or crocheted (excl. lightweight fine knit roll, polo or turtleneck jumpers and pullovers a	18-Wearing Apparel
Full-length or knee-length stockings, socks and other hosiery, incl. footwear without applied soles, of cotton, knitted or crocheted (excl. graduated compression hosiery, pantyhose and tights, women's	18-Wearing Apparel
Full-length stockings, socks and other hosiery, incl. footwear without applied soles, of synthetic fibres, knitted or crocheted (excl. graduated compression hosiery, women's pantyhose and tights, full	18-Wearing Apparel

Table A.1 Continued

RODUCT DESCRIPTION	SECTOR
Women's or girls' overcoats, raincoats, car coats, capes, cloaks and similar articles, of cotton, of a weight per garment of <= 1 kg (excl. knitted or crocheted)	18-Wearing Apparel
Men's or boys' trousers and breeches of cotton denim (excl. knitted or crocheted, industrial and occupational, bib and brace overalls and underpants)	18-Wearing Apparel
Men's or boys' trousers and breeches of cotton (excl. denim, cut corduroy, knitted or crocheted, industrial and occupational, bib and brace overalls and underpants)	18-Wearing Apparel
Women's or girls' ensembles of synthetic fibres, industrial and occupational (excl. knitted or crocheted)	18-Wearing Apparel
Women's or girls' jackets and blazers of synthetic fibres (excl. knitted or crocheted, industrial and occupational, wind-jackets and similar articles)	18-Wearing Apparel
Women's or girls' dresses of cotton (excl. knitted or crocheted and petticoats)	18-Wearing Apparel
Women's or girls' skirts and divided skirts of cotton (excl. knitted or crocheted and petticoats)	18-Wearing Apparel
Women's or girls' cotton denim trousers and breeches (excl. industrial and occupational, bib and brace overalls and panties)	18-Wearing Apparel
Women's or girls' trousers and breeches, of cotton (not of cut corduroy, of denim or knitted or crocheted and excl. industrial and occupational clothing, bib and brace overalls, briefs and tracksuit b	18-Wearing Apparel
Women's or girls' trousers and breeches, of synthetic fibres (not of cut corduroy, of denim or knitted or crocheted and excl. industrial and occupational clothing, bib and brace overalls, briefs and t	18-Wearing Apparel
Men's or boys' shirts of cotton (excl. knitted or crocheted, nightshirts, singlets and other vests)	18-Wearing Apparel
Women's or girls' blouses, shirts and shirt-blouses of cotton (excl. knitted or crocheted and vests)	18-Wearing Apparel
Toilet linen and kitchen linen, of terry towelling or similar terry fabrics of cotton (excl. floorcloths, polishing cloths, dishcloths and dusters)	17-Textile Industry
Toilet linen and kitchen linen of cotton (excl. of terry fabrics, floorcloths, polishing cloths, dishcloths and dusters)	17-Textile Industry

Table A.1 Continued

PRODUCT DESCRIPTION	SECTOR
Flexible intermediate bulk containers, for the packing of goods, of man-made textile materials (excl. of polyethylene or polypropylene strip or the like)	17-Textile Industry
Sacks and bags, for the packing of goods, of polyethylene or polypropylene strip or the like, of fabric weighing <= 120 g/m² (excl. knitted or crocheted and flexible intermediate bulk containers)	17-Textile Industry
Marble, travertine and alabaster articles thereof, simply cut or sawn, with a flat or even surface (excl. with a completely or partly planed, sand-dressed, coarsely or finely ground or polished surfac	26-Manufacture of Non-metallic
Marble, travertine and alabaster, in any form, polished, decorated or otherwise worked, carvings of marble, travertine or alabaster (excl. alabaster polished, decorated or otherwise worked, but not ca	26-Manufacture of Non-metallic
Articles of stone or other mineral substances, n.e.s. (excl. containing magnesite, dolomite or chromite, articles of graphite or other carbon, and articles of refractory mineral substances, chemically	26-Manufacture of Non-metallic
Ceramic mosaic tiles, cubes and similar articles, glazed, whether or not square or rectangular, the largest surface area of which is capable of being enclosed in a square of side of < 7 cm, whether or	26-Manufacture of Non-metallic
Ceramic sinks, washbasins, washbasin pedestals, baths, bidets, water closet pans, flushing cisterns, urinals and similar sanitary fixtures of porcelain or china (excl. soap dishes, sponge holders, too	26-Manufacture of Non-metallic
Ceramic sinks, washbasins, washbasin pedestals, baths, bidets, water closet pans, flushing cisterns, urinals and similar sanitary fixtures (excl. of porcelain or china, soap dishes, sponge holders, to	26-Manufacture of Non-metallic
Ceramic articles of porcelain or china, n.e.s.	26-Manufacture of Non-metallic
Drinking glasses, gathered mechanically (excl. glasses cut or otherwise decorated, or of glass ceramics, lead crystal or toughened glass and stemware)	26-Manufacture of Non-metallic

Table A.1 Continued

PRODUCT DESCRIPTION	SECTOR
Articles of jewellery and parts thereof, of precious metal other than silver, whether or not plated or clad with precious metal (excl. articles > 100 years old)	26-Manufacture of Non-metallic
Flat-rolled products of iron or non-alloy steel, of a width of <= 1.250 mm, not in coils, simply hot-rolled on four faces or in a closed box pass, not clad, plated or coated, of a thickness of >= 4 mm	27-Basic Metals Industry
Bars and rods, of iron or non-alloy steel, with indentations, ribs, groves or other deformations produced during the rolling process	27-Basic Metals Industry
U sections of iron or non-alloy steel, simply hot-rolled, hot-drawn or extruded, of a height >= 80 mm but <= 220 mm	27-Basic Metals Industry
I sections with parallel flange faces, of iron or non-alloy steel, simply hot-rolled, hot-drawn or extruded, of a height >= 80 mm but <= 220 mm	27-Basic Metals Industry
Precision tubes, welded, of circular cross-section, of iron or non-alloy steel, with a wall thickness of > 2 mm	27-Basic Metals Industry
Threaded or threadable tubes 'gas pipe', welded, of circular cross-section, of iron or non-alloy steel, plated or coated with zinc	27-Basic Metals Industry
Other tubes, pipes and hollow profiles, welded, of circular cross-section, of iron or non-alloy steel, of an external diameter of <= 168,3 mm, plated or coated with zinc (excl. line pipe of a kind use	27-Basic Metals Industry
Tubes, pipes and hollow profiles, welded, of circular cross-section, of stainless steel (excl. products cold-drawn or cold-rolled 'cold-reduced', tubes and pipes having internal and external circular	27-Basic Metals Industry
Tubes and pipes and hollow profiles, welded, of square or rectangular cross-section, of iron or steel other than stainless steel, with a wall thickness of > 2 mm	27-Basic Metals Industry
Structures and parts of structures of iron or steel, n.e.s. (excl. bridges and bridge-sections; towers; lattice masts; gates; doors, windows and their frames and thresholds; equipment for scaffolding,	27-Basic Metals Industry
Radiators for central heating, non-electrically heated, and parts thereof, of iron or steel (excl. parts, elsewhere specified or included, and central-heating boilers)	27-Basic Metals Industry

Table A.1 Continued

PRODUCT DESCRIPTION	SECTOR
Radiators for central heating, non-electrically heated, and parts thereof, of iron other than cast iron or steel (excl. parts, elsewhere specified or included, and central-heating boilers)	27-Basic Metals Industry
Stranded wire, cables, plaited bands and the like, of copper alloys (excl. electrically insulated products)	27-Basic Metals Industry
Solid profiles, of aluminium alloys, n.e.s.	27-Basic Metals Industry
Aluminium foil, not backed, rolled but not further worked, of a thickness of < 0,021 mm (excl. stamping foils of heading 3212, and foil made up as christmas tree decorating material)	27-Basic Metals Industry
Parts of turbojets or turbopropellers, n.e.s.	29-Machinery and Equipment
Parts of industrial or laboratory furnaces, non-electric, incl. incinerators, n.e.s.	29-Machinery and Equipment
Combined refrigerator-freezers, of a capacity <= 340 l, fitted with separate external doors	29-Machinery and Equipment
Household refrigerators, absorption-type	29-Machinery and Equipment
Dishwashing machines of the household type	29-Machinery and Equipment
Household or laundry-type washing machines, of a dry linen capacity <= 6 kg (excl. fully-automatic machines and washing machines with built-in centrifugal drier)	29-Machinery and Equipment
Bending, folding, straightening or flattening machines, incl. presses, not numerically controlled, for working flat metal products	29-Machinery and Equipment
Punching or notching machines, incl. presses, and combined punching and shearing machines, not numerically controlled, for working metal (excl. machines for working flat metal products)	29-Machinery and Equipment
Electric ovens, for domestic use (excl. space-heating stoves, electric cookers incorporating at least an oven and a hob, microwave ovens and electric ovens for building in)	31-Electrl. Mac. and Apparatus
Radio-broadcast receivers, for mains operation only, not combined with sound recording or reproducing apparatus and not combined with a clock (excl. those of a kind used in motor vehicles)	31-Electrl. Mac. and Apparatus
Transformers having a power handling capacity > 500 kVA (excl. liquid dielectric transformers)	31-Electrl. Mac. and Apparatus

Table A.1 Continued

PRODUCT DESCRIPTION	SECTOR
Electric cookers incorporating at least an oven and a hob, for domestic use	31-Electrl. Mac. and Apparatus
Television projection equipment, colour, designed to incorporate a video display or screen	31-Electrl. Mac. and Apparatus
Reception apparatus for television, colour, incorporating a video recorder or reproducer	31-Electrl. Mac. and Apparatus
Reception apparatus for television, colour, with integral tube, with a screen width/height ratio < 1,5, with a diagonal measurement of the screen of <= 42 cm (excl. incorporating video recording or re	31-Electrl. Mac. and Apparatus
Reception apparatus for television, colour, with a screen width/height ratio < 1,5 (excl. with integral tube or incorporating video recording or reproducing apparatus and monitors, and television proj	31-Electrl. Mac. and Apparatus
Reception apparatus for television, colour, with a screen width/height ratio >= 1,5 (excl. with integral tube or incorporating video recording or reproducing apparatus and monitors, and television pro	31-Electrl. Mac. and Apparatus
Relays for a voltage > 60 V but <= 1.000 V	31-Electrl. Mac. and Apparatus
Winding wire for electrical purposes, of copper, insulated (excl. lacquered or enamelled)	31-Electrl. Mac. and Apparatus
Coaxial cable and other coaxial electric conductors, insulated	31-Electrl. Mac. and Apparatus
Electric conductors, for a voltage <= 1.000 V, insulated, fitted with connectors, n.e.s. (other than of a kind used for telecommunications)	31-Electrl. Mac. and Apparatus
Electric wire and cables, for a voltage <= 1.000 V, insulated, not fitted with connectors, with individual conductor wires of a diameter > 0,51 mm, n.e.s.	31-Electrl. Mac. and Apparatus
Electric wire and cables, for a voltage <= 1.000 V, insulated, not fitted with connectors, with individual conductor wires of a diameter > 0,51 mm, n.e.s.	31-Electrl. Mac. and Apparatus
Conductors, electric, for a voltage <= 80 V, insulated, not fitted with connectors, n.e.s. (excl. winding wire, coaxial conductors, wiring sets for vehicles, aircraft or ships, and wire and cables wit	31-Electrl. Mac. and Apparatus

Table A.1 Continued

PRODUCT DESCRIPTION	SECTOR
Electric conductors for a voltage > 80 V but < 1.000 V, insulated, not fitted with connectors, n.e.s. (excl. winding wire, coaxial conductors, wiring sets for vehicles, aircraft or ships, and wire and	31-Electrl. Mac. and Apparatus
Electric conductors for a voltage > 1.000 V, insulated, with copper conductors, n.e.s.	31-Electrl. Mac. and Apparatus
Optical fibre cables made up of individually sheathed fibres, whether or not containing electric conductors or fitted with connectors	31-Electrl. Mac. and Apparatus
Motor cars and other motor vehicles principally designed for the transport of persons, incl. station wagons and racing cars, with spark-ignition internal combustion reciprocating piston engine, of a c	34-Manufacture of Motor, Vehicles, Trailers
Motor cars and other motor vehicles principally designed for the transport of persons (other than those of heading No 8702), incl. station wagons and racing cars, with spark-ignition internal combusti	34-Manufacture of Motor, Vehicles, Trailers
Motor cars and other motor vehicles, principally designed for the transport of persons, incl. station wagons, with compression-ignition internal combustion piston engine 'diesel or semi-diesel engine'	34-Manufacture of Motor, Vehicles, Trailers
Motor vehicles for the transport of goods, with compression-ignition internal combustion piston engine 'diesel or semi-diesel engine' of a gross vehicle weight <= 5 t, of a cylinder capacity <= 2.500	34-Manufacture of Motor, Vehicles, Trailers
Road wheels and parts and accessories thereof, for the industrial assembly of: pedestrian-controlled tractors, motor cars and vehicles principally designed for the transport of persons, vehicles for t	34-Manufacture of Motor, Vehicles, Trailers
Mattresses with spring interiors	36-Manufacture of Furniture
Mattresses, stuffed or internally filled with any material (excl. cellular rubber or plastics, with spring interior, and pneumatic or water mattresses and pillows)	36-Manufacture of Furniture
Electric ceiling or wall lighting fittings, of plastics, used with filament lamps	36-Manufacture of Furniture

Appendix B

Table B.1 Industrial Production Index

Industrial Production Index (2005=100)(TURKSTAT)(Monthly)(New Series)											
	Manufacture of food products and beverages	**Manufacture of textiles**	**Manufac.of wearing apparel dressing and dyeing of fur**	**Manufacture of paper and paper products**	**Manufacture of rubber and plastics products**	**Manufacture of other non-metallic mineral products**	**Manufacture of basic metals**	**Manufacture of machinery and equipment**	**Manufacture of electrical machinery**	**Manufac. of motor vehicles, trailers and semi-trailers**	**Manufacture of furniture; manufacturing**
01-2008	96.50	94.70	100.4	117.2	108.7	92.40	130.3	103.1	139.9	139.4	123.6
02-2008	89.00	92.70	98.50	111.9	105.8	92.70	123.7	111.7	135.6	142.4	131.1
03-2008	99.60	96.40	96.50	124.1	119.5	114.4	139.9	124.0	145.3	159.9	180.0
04-2008	97.20	94.50	87.20	124.1	121.7	122.6	137.9	124.7	136.6	171.7	142.9
05-2008	111.2	94.50	90.30	131.1	125.0	132.1	143.6	132.9	140.6	165.4	140.3
06-2008	107.5	92.70	90.90	129.0	112.8	125.7	138.8	125.5	143.8	152.3	138.7
07-2008	109.3	94.40	92.90	119.3	120.2	127.9	138.8	124.3	139.2	139.5	134.0
08-2008	109.8	90.20	90.90	121.8	113.7	118.9	126.6	106.4	119.0	73.40	126.6
09-2008	118.2	94.10	84.90	119.6	110.0	109.0	117.9	110.4	128.0	120.1	127.5
10-2008	146.0	94.90	79.10	114.3	105.6	108.5	98.10	104.4	131.2	105.5	132.2
11-2008	155.7	95.20	90.20	116.6	102.6	106.9	98.80	117.2	124.6	84.50	128.9
12-2008	118.0	69.40	83.30	92.00	75.70	76.00	88.30	95.80	118.0	60.10	124.9

Table B.2 Industrial Hours Worked

QUARTERLY INDUSTRIAL HOURS WORKED INDEX (Converted Monthly Form)

	Manufacture of food products and beverages	Manufacture of textiles	Manufac.of wearing apparel dressing and dyeing of fur	Manufacture of paper and paper products	Manufacture of rubber and plastics products	Manufacture of other non-metallic mineral products	Manufacture of basic metals	Manufacture of machinery and equipment	Manufacture of electrical machinery	Manufac. of motor vehicles, trailers and semi-trailers	Manufacture of furniture; manufacturing
01-2008	109.6	97.80	96.90	102.3	118.3	103.9	117.8	118.7	132.9	122.0	112.6
02-2008	109.6	97.80	96.90	102.3	118.3	103.9	117.8	118.7	132.9	122.0	112.6
03-2008	109.6	97.80	96.90	102.3	118.3	103.9	117.8	118.7	132.9	122.0	112.6
04-2008	117.3	94.50	94.30	105.9	118.9	114.2	118.7	119.5	131.7	122.6	111.7
05-2008	117.3	94.50	94.30	105.9	118.9	114.2	118.7	119.5	131.7	122.6	111.7
06-2008	117.3	94.50	94.30	105.9	118.9	114.2	118.7	119.5	131.7	122.6	111.7
07-2008	119.3	91.70	91.50	104.7	117.0	112.7	117.4	115.6	126.3	108.8	107.0
08-2008	119.3	91.70	91.50	104.7	117.0	112.7	117.4	115.6	126.3	108.8	107.0
09-2008	119.3	91.70	91.50	104.7	117.0	112.7	117.4	115.6	126.3	108.8	107.0
10-2008	116.2	87.20	88.80	104.7	111.8	101.9	113.5	110.8	123.5	98.20	99.50
11-2008	116.2	87.20	88.80	104.7	111.8	101.9	113.5	110.8	123.5	98.20	99.50
12-2008	116.2	87.20	88.80	104.7	111.8	101.9	113.5	110.8	123.5	98.20	99.50

Table B.3 Partial Productivity Index

PARTIAL PRODUCTIVITY INDEX=LABOR PRODUCTIVITY

	Manufacture of food products and beverages	**Manufacture of textiles**	**Manufac.of wearing apparel dressing and dyeing of fur**	**Manufacture of paper and paper products**	**Manufacture of rubber and plastics products**	**Manufacture of other non-metallic mineral products**	**Manufacture of basic metals**	**Manufacture of machinery and equipment**	**Manufacture of electrical machinery**	**Manufac. of motor vehicles, trailers and semi-trailers**	**Manufacture of furniture; manufacturing**
01-2008	88.03	96.80	103.6	114.6	91.90	88.94	110.6	86.87	105.3	114.2	109.7
02-2008	81.19	94.75	101.6	109.4	89.45	89.22	105.0	94.12	102.0	116.7	116.4
03-2008	90.86	98.53	99.57	121.3	101.0	110.1	118.8	104.5	109.3	131.0	159.8
04-2008	82.85	100.0	92.49	117.2	102.4	107.3	116.2	104.4	103.7	140.0	128.0
05-2008	94.78	100.0	95.78	123.8	105.2	115.7	121.0	111.2	106.8	134.9	125.7
06-2008	91.63	98.11	96.42	121.8	94.89	110.1	117.0	105.0	109.2	124.2	124.2
07-2008	91.59	102.9	101.6	113.9	102.7	113.5	118.3	107.5	110.2	128.2	125.3
08-2008	92.01	98.34	99.39	116.3	97.15	105.5	107.9	92.03	94.24	67.44	118.3
09-2008	99.04	102.6	92.83	114.2	93.99	96.69	100.5	95.49	101.4	110.4	119.2
10-2008	125.6	108.8	89.03	109.1	94.48	106.5	86.46	94.18	106.3	107.5	132.8
11-2008	134.0	109.1	101.5	111.3	91.80	104.9	87.08	105.7	100.9	86.07	129.5
12-2008	101.5	79.55	93.76	87.8	67.73	74.58	77.82	86.42	95.57	61.21	125.5

Table B.4 Index of Wages Per Production Hour Worked In Manufacturing

Index of Wages Per Production Hour Worked In Manufacturing Industry (1997=100)(TURKSTAT)

	Manufacture of food products and beverages	Manufacture of textiles	Manufac.of wearing apparel dressing and dyeing of fur	Manufacture of paper and paper products	Manufacture of rubber and plastics products	Manufacture of other non-metallic mineral products	Manufacture of basic metals	Manufacture of machinery and equipment	Manufacture of electrical machinery	Manufac. of motor vehicles, trailers and semi-trailers	Manufacture of furniture; manufacturing
01-2008	2143.6	1769.3	1823.8	1771.6	1734.3	1698.9	1913.1	1836.5	1760.4	1503.2	2062.0
02-2008	2143.6	1769.3	1823.8	1771.6	1734.3	1698.9	1913.1	1836.5	1760.4	1503.2	2062.0
03-2008	2143.6	1769.3	1823.8	1771.6	1734.3	1698.9	1913.1	1836.5	1760.4	1503.2	2062.0
04-2008	2217.4	1801.3	1864.4	1857.4	1691.8	1690.0	1980.7	1933.1	1904.6	1584.6	2162.3
05-2008	2217.4	1801.3	1864.4	1857.4	1691.8	1690.0	1980.7	1933.1	1904.6	1584.6	2162.3
06-2008	2217.4	1801.3	1864.4	1857.4	1691.8	1690.0	1980.7	1933.1	1904.6	1584.6	2162.3
07-2008	2345.1	1893.3	1951.0	1965.3	1885.4	1740.1	2037.8	1987.2	2181.3	1752.7	2278.7
08-2008	2345.1	1893.3	1951.0	1965.3	1885.4	1740.1	2037.8	1987.2	2181.3	1752.7	2278.7
09-2008	2345.1	1893.3	1951.0	1965.3	1885.4	1740.1	2037.8	1987.2	2181.3	1752.7	2278.7
10-2008	2235.4	1821.3	1879.7	1864.8	1770.5	1709.7	1977.2	1918.9	1948.8	1613.5	2167.7
11-2008	2235.4	1821.3	1879.7	1864.8	1770.5	1709.7	1977.2	1918.9	1948.8	1613.5	2167.7
12-2008	2235.4	1821.3	1879.7	1864.8	1770.5	1709.7	1977.2	1918.9	1948.8	1613.5	2167.7

Biographical Sketch

Ayse Ulgen Ozgul was born on 9^{th} of October, 1976 at Trabzon. In 1987, she started her secondary school education at Aksaray Anatolia High School and studied over there till she concluded her high school education in 1994.

She took her bachelor of science degree from Bogazici University Civil Engineering Department in 1998. In 2001, she started her master degree study at Industrial Engineering Department of University of Galatasaray.