

**USE OF ARTIFICIAL NEURAL NETWORKS AND COGNITIVE
MAPPING METHODOLOGY IN PREDICTING UNEMPLOYMENT
RATES AND EMPLOYMENT INDEX LEVEL**

**Ph.D. Thesis by
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**Department : Industrial Engineering
Programme: Industrial Engineering**

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ABBREVIATIONS

ILO	: International Labour Organization
GDP	: Gross Domestic Product
GET	: Global Employment Trends
LFS	: Labour Force Survey
WAP	: Working Age Population
LF	: Labour Force
TR	: Turkey
OECD	: Organisation for Economic Co-operation and Development
EU	: European Union
SIC	: Schwarz Information Criterion
MSE	: Mean Square Error
MAD	: Mean Absolute Deviation
MAPE	: Mean Absolute Percentage Error
ARIMA	: Autoregressive-Integrated Moving Average
AR	: Autoregression
VAR	: Vector Auto Regression
MA	: Moving Average
ARMA	: Auto Regressive Moving Average
US	: United States
GNP	: Gross National Product
PCA	: Principal Component Analysis

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YAPAY SİNİR AĞLARI VE BİLİŞSEL HARİTALAR YÖNTEMLERİ İLE İŞSİZLİK ORANI VE İSTİHAM ENDEKSİ SEVİYESİ ÖNGÖRÜ ÇALIŞMASI

ÖZET

Öngörü modellemesi, makro politikaların oluşturulmasında önemli bir karar destek aracı olarak görülmektedir. Bilgisayar teknolojisindeki ilerlemeler sayesinde yapay zeka sistemlerinin karar destek araçları olarak kullanımları da gün geçtikçe artmaktadır. Yapay zeka tekniklerinden yapay sinir ağları yöntemi, öngörü çalışmalarında kullanılabilecek ümit veren bir yöntem olarak araştırmacılar tarafından ilgi görmektedir. Bu çalışmada bilişsel haritalar yöntemi ile yapay sinir ağları yöntemleri kullanılarak bir öngörü modeli kurulması çalışması gerçekleştirilmiştir. Çalışmada öngörü veri seti olarak iki ayrı veri seti Türkiye’de işsizlik oranları ve imalat sektöründe istihdam endeksi verisi kullanılmıştır.

İşsizlik, ülkelerin yüzleştği en önemli problemlerden bir tanesidir. İşsizliği etkileyen faktörlerin anlaşılması ve bu faktörler kullanılarak öngörü modellerinin oluşturulması, karar vericilerin, işsizlik problemini çözümlemede kullanabilecekleri bir karar destek mekanizması oluşturulmasına yardımcı olacaktır.

Çalışmanın birinci aşamasında bilişsel haritalar yöntemi kullanılarak daha önce Türkiye ile ilgili makroekonomik çalışmaları bulunan beş akademisyenin görüşü alınıp Türkiye’de işsizliği etkileyen faktörler belirlenmiştir. Uzmanlar tarafından belirlenen onbir faktör, çalışmanın ikinci aşamasında çok katmanlı yapay sinir ağı kullanılarak oluşturulan çok değişkenli bir öngörü modeline girdi olarak kullanılmıştır. Çalışmada 1988 ve 2004 yılları arasında dört dönemlik veriler kullanılmıştır. En iyi öngörü modeli, işsizlik oranı verisi ve imalat sanayi istihdam endeksi verisi için ayrı ayrı oluşturulmuş 80 model arasından seçilmiştir. Çalışma sonunda en iyi tahmin modellerine mevsimsellikten arındırılmış veri seti ile ulaşıldığı görülmüştür. İşsizlik oranını ve imalat sektörü istihdam endeksi öngörüsünde göreceli olarak önemi yüksek olan değişkenler belirlenmiş ve son olarak yapay sinir ağı yöntemi ile elde edilen sonuçlar AR(2) ve VAR modelleri sonuçları ile karşılaştırılmıştır. Karşılaştırma sonuçları, yapay sinir ağı yönteminin AR(2) modeline göre daha iyi öngörü

yapabildiğini ancak VAR modeline göre öngörü performansının düşük olduğunu göstermektedir.

USE OF ARTIFICIAL NEURAL NETWORKS AND COGNITIVE MAPPING METHODOLOGY IN PREDICTING UNEMPLOYMENT RATES AND EMPLOYMENT INDEX LEVEL

SUMMARY

Forecasting is accepted as an important tool in the development and application of macro policies. By the developments in the computer specifications, artificial intelligence techniques have gained more attention as decision support tools. Among the artificial intelligence techniques, artificial neural networks are seen as promising techniques especially in forecasting applications. In this study, cognitive mapping methodology and artificial neural networks methodology are integrated in order to define a prediction model that can be used to understand the important factors that affect unemployment and employment in Turkey and to forecast unemployment rate and employment index in manufacturing industry in Turkey.

Unemployment is one of the most serious problems that nations face. Understanding the factors that affect unemployment and developing forecasting models by the use of these factors helps the decision makers as a decision support mechanism in defining policies to overcome unemployment problem.

In the first stage of the study cognitive mapping methodology is used in the identification of the factors that affect unemployment in Turkey by taking the views of five different experts who have made research on macroeconomic problems of Turkey. The eleven variables identified by the experts are used in the second phase of the study as the input data set in developing a multi-variate forecasting model by using multi-layer feedforward neural networks. The research period covers 1988 and 2004 quarterly data. The best neural network models are selected among 80 different types of models tested for each unemployment rate data and employment index data. The results showed that the best models for each analysis are obtained using the deseasonalized data set. Relative importance of independent variables with respect to deseasonalized unemployment rate and deseasonalized employment index data are

evaluated and finally the best models obtained using neural networks methodology are compared with an AR(2) and VAR model. The comparison results indicate that ANN models perform better compared to AR(2) models however, their performance is lower than the performance of VAR models.

1. INTRODUCTION

Unemployment is one of the most serious problems that nations face. Understanding the factors that affect unemployment and developing forecasting models by the use of these factors helps the decision makers as a decision support mechanism in defining policies to overcome unemployment problem.

The aim of this study is to develop a prediction framework with the use of artificial intelligence methods. The data set used in the study is the unemployment rate and employment index in manufacturing industry data in Turkey.

In the second section of this thesis, the global unemployment trends are summarized briefly and the labour market in Turkey is analyzed in detail. The analysis of the labour market in Turkey covers the labour force participation rates, employment information, and unemployment dynamics in Turkey. The latest SIS Labour Force Survey results are used in the analysis. At the end of the section the characteristics of unemployment in Turkey is summarized.

In the third section, unemployment theories are summarized. In the fourth section cognitive mapping methodology is described. In the fifth section, neural networks methodology is described and literature survey on neural networks and neural networks in macroeconomic predictions is given.

In the sixth section, the framework for employment and unemployment prediction analysis in Turkey is given. The cognitive mapping analysis and neural network analysis are described in detail and the results of the analyses are presented in detail. Section seven concludes the study and states areas for further research.

2. EMPLOYMENT AND UNEMPLOYMENT TRENDS IN THE WORLD AND IN TURKEY

Unemployment is one of the most serious problems that nations face. The rise of unemployment reduces personal and social income; increases the inequality of the income distribution and poverty, causes production losses since labor force cannot be fully utilized, and increases transfer expenditures of the nations. In addition to economic problems unemployment causes socio-psychological problems. It deteriorates social morale and responsibility. Unemployed person loses his human capital capacities and skills by time and gets rejected from the society. With respect to these given outcomes of high levels of unemployment, understanding the reasons of unemployment and defining policies to avoid high unemployment rates becomes crucial for nations.

In this section of the study the global unemployment trends will be summarized; and detailed information about the attempts to calculate unemployment in Turkey and the main characteristics of the labor market in Turkey will be given.

2.1 Unemployment- Global Unemployment Trends

International Labour Organizations (ILO), points out that unemployment is not a risk solely for individual countries, but it is a global problem. According to ILO's report, (January, 2006), high unemployment rates in many parts of the world remain a challenge. The trend of wages and employment lagging behind the economic growth and productivity growth is a major concern. The stock of unemployed reached to 191.8 million, the highest level recorded so far as of 2005. While the number of unemployed males increased to 112.9 million, the number of unemployed females reached 78.9 million. The trends in the unemployment stock in total and for the two genders are given in Figures 2.1, 2.2 and 2.3 below.

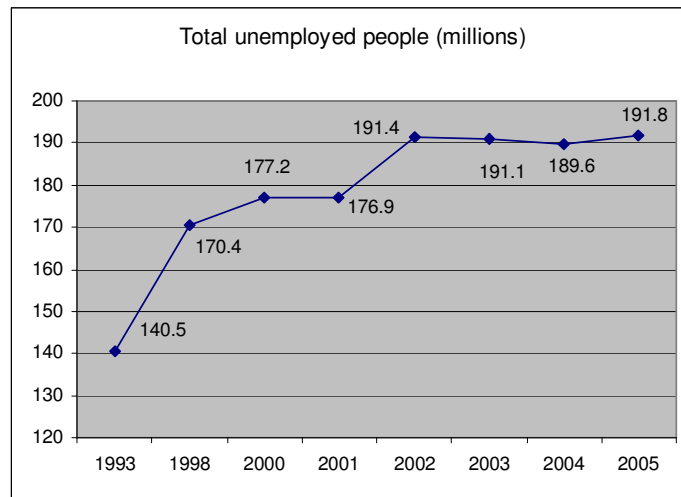


Figure 2.1: Total Unemployment Stock in the World

Similar to total unemployment, the number of unemployed young population continued to rise during the last decade. At the end of 2005, global unemployment rate remained around 6.3 % despite the economic growth in 2005 (ILO GET, 2006).

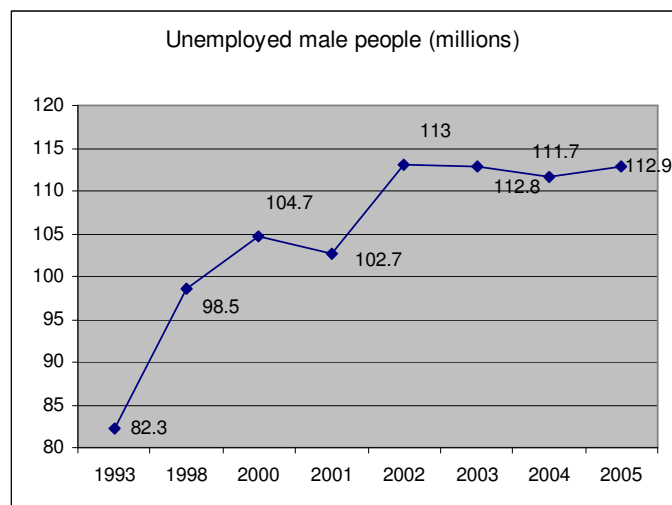


Figure 2.2: Unemployment Stock Trend for Males

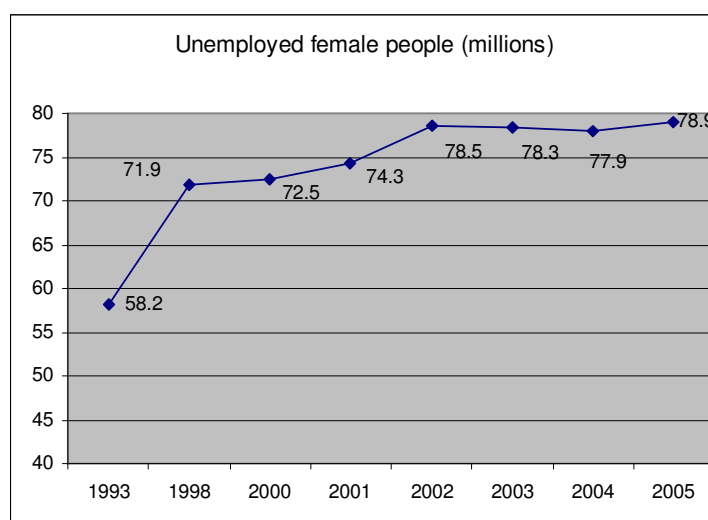


Figure 2.3: Unemployment Stock Trend for Females

Among the unemployed people, 112.7 million were men, 1,200,000 higher than the year 2004. Among women, 78.9 million were unemployed in 2005. However young people were the ones that were hardly affected with this situation. Around 88.2 million young people aged 15-24 faced a crushing unemployment rate of 14.4 % in 2003. As of 2005, almost half of the unemployed people in the world were young people (ILO GET, 2006). The global unemployment stock change in the past twelve years is given below in Table 2.1 and the unemployment trend for young people is plotted below in Figure 2.4.

Table 2.1: Unemployment in the World (millions)

Year	1993	1998	2000	2001	2002	2003	2004	2005
Total	140.5	170.4	177.2	176.9	191.4	191.1	189.6	191.8
Male	82.3	98.5	104.7	102.7	113.0	112.8	111.7	112.9
Female	58.2	71.9	72.5	74.3	78.5	78.3	77.9	78.9
Youth, total	69.5	79.3	82.0	82.9	86.5	88.2		
Youth, male	41.2	46.9	48.5	49.1	51.3	52.4		
Youth, female	28.3	32.4	33.5	33.8	35.2	35.8		

Source: ILO, Global Employment Trends 2004, ILO Global Employment Trends Model 2005 and ILO Global Employment Trends Brief, January 2006

In parallel with this pessimistic situation, the size of the informal economy increased especially in developing regions with low GDP growth rates. The growth of informal economy is a serious problem in terms of world poverty since workers in the informal economy carry a high risk of becoming working poor with earnings insufficient to raise themselves and their families above the 1 USD/day poverty line.

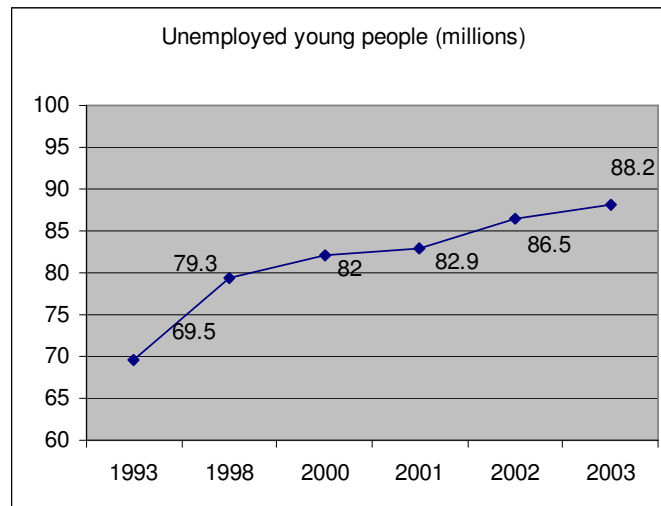


Figure 2.4: Unemployment Trend of Young People

Although the global stock of unemployed reached its highest level, this increase is not homogenous in terms of regional unemployment trends (Table 2.2). ILO report (January, 2004) indicates that especially in the second half of 2003 the industrialized regions showed a recovery from the economic slowdown. Since 1995, the average unemployment rate in the developed economies and European Union declined to 6.7 % from 7.8 %. During 1995 and 2005 the labour force grew by 0.7 % per year, while employment to population ratio increased from 55.8 % to 56.4 %. However since developed economies are diverse in their labour characteristics, there are differences among country statistics. In the sub region of major European economies, the labour force growth rate was 0.6 % annually during 1993-2003, slightly below the regional average. At the same time, the average employment-to-population ratio increased from 50.3 to 51.2 % – an additional 0.9 percentage points or 16 million more people employed. In the sub region of major non-European economies, labour force growth increased by 1.0 % annually between 1993 and 2003, due to a marked growth in population and a higher proportion of youth entering the workforce. Australia, Canada, New Zealand and the United States all showed labour force growth rates above 1.0 % per year, while Japan's labour force growth rate was significantly less. Employment-to-population ratios in the sub region increased from 60.6 % in 1993 to 60.9 % in 2003, resulting with an additional 0.3 % or 23 million more people who works.

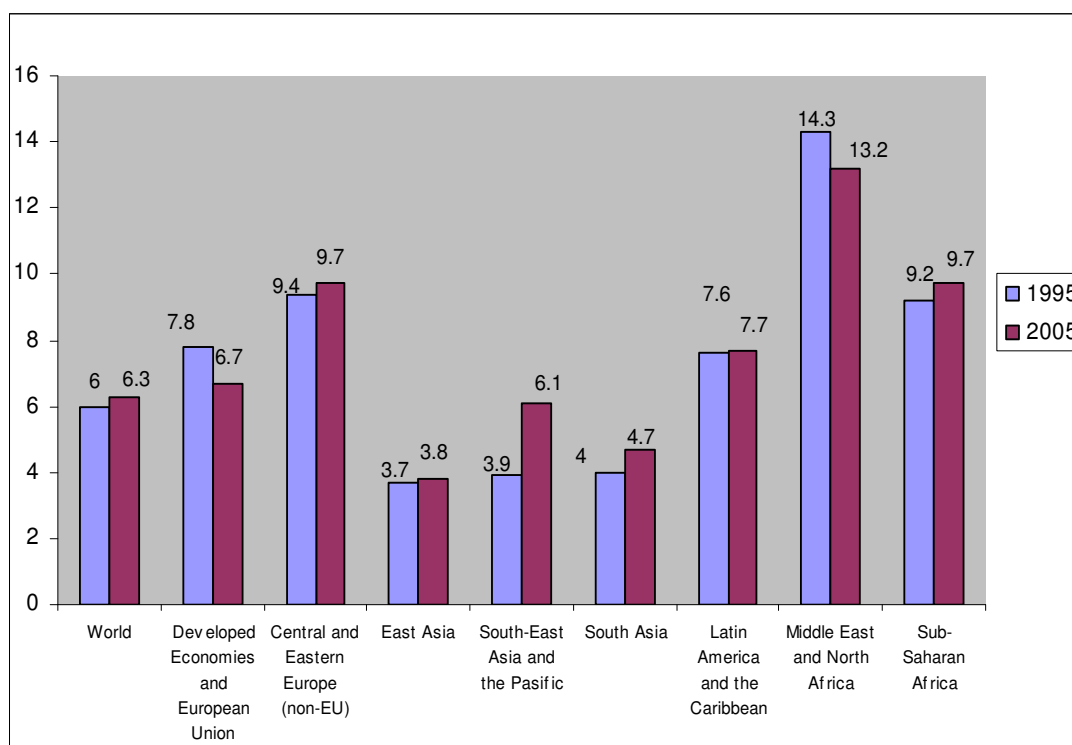


Figure 2.5: Unemployment Rates in Different Regions, Comparison of Years 1995 and 2005

Latin America and the Caribbean's unemployment rate stayed almost at the same level during the past ten years. This region was most affected by the global economic slowdown in 2001 in terms of output growth as well as employment losses and the peak in overall unemployment was reached in 2002 with 9.0 %. In 2003 there was a recovery in terms of GDP growth rates and unemployment. The regional unemployment rate dropped to 8.0 %. According to ILO (2004) this decline in unemployment rates is especially a result of the slow recovery in Argentina. In terms of gender, the unemployment rate of females has been historically high in the region. In 2003 the unemployment rate was 10.1 % for women and 6.7 % for men (Table 2.3). Youth employment is a major challenge for the region, in 2005, the unemployment rate for young people was 17.6 %, twice as high as the overall unemployment rate in the region (Table 2.4). In accordance with the structure of general unemployment in the region the unemployment rate in female youth was 21.7 %, while the male unemployment youth rate was 14.9 %. The unemployment rate comparison between year 1995 and 2005 is shown in Figure 1.5 for different regions in the world.

Table 2.2: Labour Market and Economic Indicators by Regions

	Change in unemployment rate (percentage point)	Unemployment rate (%)			GDP growth rate (%)		Employment to population ratio (%)		Annual Labour force growth rate (%)	Annual GDP growth rate (%)
	2000-2005 (I)	1995	2004	2005	2004	2005	1995	2005	1995-2005	1995 - 2005
World	0.0	6.0	6.3	6.3	4.3	4.3	62.8	61.4	1.6	3.8
Developed Economies and European Union	0.0	7.8	7.1	6.7	2.5	2.6	55.8	56.4	0.7	2.6
Central and Eastern Europe (non-EU)	-0.4	9.4	9.5	9.7	5.7	5.5	55.5	52.1	0.1	4.0
East Asia	-0.2	3.7	3.7	3.8	8.0	7.5	75.2	71.7	1.0	7.6
South-East Asia and the Pacific	1.2	3.9	6.2	6.1	5.1	5.4	67.2	65.8	2.2	3.8
South Asia	0.2	4.0	4.7	4.7	7.1	6.4	58.9	57.2	2.2	5.8
Latin America and the Caribbean	-0.5	7.6	7.4	7.7	4.0	3.8	59.2	60.9	2.5	2.8
Middle East and North Africa	-0.7	14.3	13.1	13.2	5.0	5.3	44.2	46.4	3.4	4.4
Sub-Saharan Africa	0.3	9.2	9.9	9.7	4.5	5.5	69.0	66.7	2.4	3.9

Source: ILO, Global Employment Trends, Brief, January 2006

In the East Asian region unemployment is a recent phenomenon and is still at a very low level of 3.8 % as of 2005 (Table 2.2). The increase over the past ten years was only 0.1 percentage points. However the region deals with high level of working poor that accounts for the 18 % of the total unemployed population. In terms of gender, the female unemployment rate has been historically lower than male unemployment rate with 2.7 % in 2003, while male unemployment rate was 3.7. Within the region youth employment rates are also low compared to other regions. The total youth unemployment has been twice the total unemployment with 7.0 % in 2003.

In South-East Asia, during the past ten years, unemployment rate increased to 6.1 % from 3.9 %. Even with this sharp increase the unemployment rate is comparably low in the region. However since underemployment is a serious problem in the region the relative rate of working poor remains high. Youth unemployment is also a problem in the region, with 14.7 % it is more than twice the total unemployment rate. The statistics show that young women are much more affected by unemployment than young men. In 2003 the youth unemployment rate for women was 17.6 % compared with 15.5 % for men. In the South Asia, despite the relatively high GDP growth,

unemployment rates increased to 4.7 % from 4.0 %. In 2003 the total unemployment rate in the region was 4.8 %; however the informal economy that accounts for the 90 % of the total economy region is a serious problem in the region. In terms of gender, female unemployment rates are generally higher than male unemployment rates; and youth unemployment is a serious problem. The youth unemployment rate with 10.9 % is more than twice the total unemployment rate in the region. In terms of gender, youth unemployment rate for women was 11.6 % while it was 10.6 % for men in 2004.

Table 2.3: Unemployment Rates by Region and Gender, 2001-2003 (in percentages)

	2001			2002			2003		
	Total	Female	Male	Total	Female	Male	Total	Female	Male
World	6.1	6.3	6.0	6.3	6.5	6.2	6.2	6.4	6.1
Developed Economies and European Union	6.1	6.4	5.9	6.8	7.0	6.7	6.8	7.0	6.7
Central and Eastern Europe (non-EU)	9.5	9.4	9.5	9.4	9.3	9.5	9.2	9.2	9.2
East Asia	3.3	2.7	3.8	3.1	2.6	3.6	3.3	2.7	3.7
South-East Asia	6.1	6.7	5.7	7.1	7.8	6.5	6.3	6.9	5.9
South Asia	4.7	6.0	4.1	4.8	6.1	4.2	4.8	6.2	4.3
Latin America and the Caribbean	9.0	11.3	7.6	9.0	11.2	7.6	8.0	10.1	6.7
Middle East and North Africa	12.0	16.3	10.5	11.9	16.2	10.4	12.2	16.5	10.6
Sub-Saharan Africa	10.6	9.3	11.6	10.8	9.5	11.8	10.9	9.6	11.8

Source: Global Employment Trends, ILO, 2004.

The Middle East and North Africa have also experienced high levels of unemployment, with an unemployment rate of 13.2 % - the highest incidence of unemployment in the world. The region has seen relatively low GDP growth rates during the past ten years with an average of 4.4 % annually. Although the change in unemployment rate between 2000 and 2005 has declined 0.47 percentage points; the unemployment rates within 1995 and 2005 have stayed over 13 %. Youth unemployment is again a serious problem in the region. In 2004, 21.3 % of young people in the region were unemployed. Female youth unemployment rates, 24.2 %, are higher than male unemployment rates, 20 %, as of 2004. According to ILO (2004), the highly agricultural employment, therefore informal economy, the dependency on oil prices, the high labour force growth rates which some economies are unable to absorb, the deficits in the quality of public institutions and the high incidence of poverty in some economies are all threats for real improvements in the labour markets in Middle East and North Africa region.

Table 2.4: Youth Unemployment Rates by Region and Gender (in percentages)

	1997			2002			2003			2004		
	Total	Female (F)	Male (M)	Total	F	M	Total	F	M	Total	F	M
World	12.9	12.6	13.1	14.3	14.1	14.5	13.3	13.1	13.5	13.1	12.9	13.2
Industrialized economies	14.2	14.6	13.9	13.4	12.5	14.1	14.6	13.9	15.2	14.2	13.6	14.6
Transition economies	17.9	18.3	17.6	19.3	19.2	19.4	16.8	17.1	16.5	16	17	15.1
East Asia	6.4	5.3	7.4	6.8	5.6	7.8	7.0	5.8	8.1	7.0	5.8	8.1
South-East Asia	9.9	10.6	9.4	16.4	17.6	15.5	14.9	15.9	14.1	14.7	15.8	13.9
South Asia	13.1	14.6	12.4	13.6	15.7	12.7	11.0	11.8	10.7	10.9	11.6	10.6
Latin America and the Caribbean	14.6	18.5	12.2	17.2	21.5	14.4	18.8	23.1	16.0	17.6	21.7	14.9
Middle East and North Africa	26	31.9	23.4	25.5	31.6	22.7	21.3	24.2	20.0	21.3	24.2	20.6
Sub-Saharan Africa	20.7	17.9	22.9	21.1	18.4	23.2	18.3	16.4	19.8	18.4	16	19.9

Source: Global Employment Trends, ILO, 2004 and Global Employment Trends, Brief, February 2005

Sub-Saharan Africa has neither reduced its unemployment rate nor its high level of working poverty during the past ten years. The average unemployment rate stayed around 9.7 % with 29.7 million people without work in 2005, while annual labor force growth stayed at 2.4 %; increasing the number of people for a limited number of jobs in the formal economy. According to ILO, the problems of unemployment as well as of underemployment are structural. The employed people work in low-productivity, low income activities and in agriculture. The employed poor people account for almost 45 % of the total number employed. Youth unemployment is a serious problem in this region also. In 2003 the total youth unemployment rate remained in 18.4 %, twice of the total unemployment rate in the region.

In the Central and Eastern Europe, (i.e. non-EU countries), the unemployment rates have been relatively stable, increasing from 9.4 % in 1995 to 9.7 % in 2005. The labour market situation in the transition economies is expected to improve somewhat as a consequence of the foreign investment they have attracted. Strong domestic demand, trade growth and overcoming the problems associated with the transition process are encouraging signs. The ILO GET report (2006), indicates that high unemployment is still a primary concern and, youth employment is a troubling issue for the region. The unemployment rate for young people was 16 % in 2004 in the region. The unemployment rates for young people in different regions of the world are shown below in Figure 2.6 for the years 1997, 2002 and 2003.

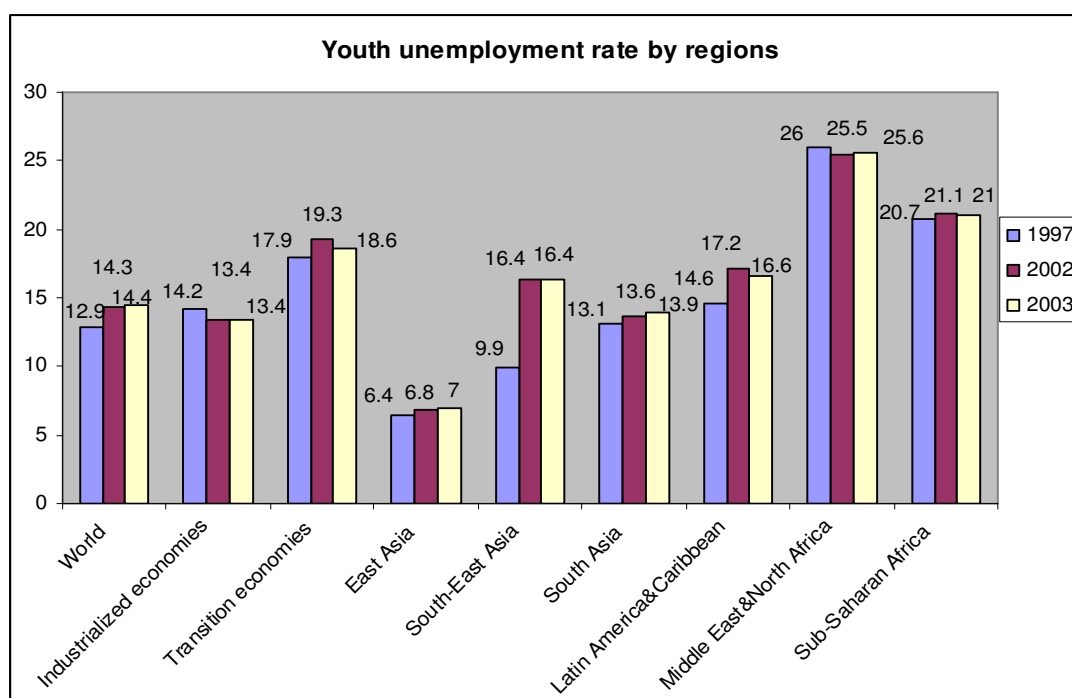


Figure 2.6: Unemployment Rates for Young People in Different Regions in Years 1997, 2002 and 2003

As implied by the previous paragraphs, there is a continuous rise in the number of unemployed in the world and in addition to unemployment; underemployment is still a risk especially in relation to world poverty. The current problems related to unemployment, and the characteristics of the global labour market structure are summarized by different ILO publications as follows:

- Most new jobs are created in the small enterprise sector; in developing countries a growing number of these jobs are in the informal part of the economy and many are of low quality. The labour market remains gender segregated although female participation rates have been rising as those of males have been falling. Unemployment rates are often higher for women and part-time work is very much a female domain. Women may spend less time on paid work than men but they spend considerably more time on unpaid work. And they continue to receive lower wages on average than men. Non-salaried male workers tend to be self-employed, non-salaried women tend to be unpaid family workers. The female unemployment rate in 2003 was slightly higher than the male rate for the world as a whole (6.4 % for female, 6.1 % for male), leaving 77.8 million women who are willing to work and actively looking for work without employment, (ILO, March 2004).

- Regional disparities in terms of unemployment are high and often increasing. In sub-Saharan Africa around 45 % of the population lives in poverty, compared to 15 % in East Asia and Latin America, and 40 % in South Asia.
- Most people work in agriculture, the informal economy, or both. Among developing countries labour market conditions vary across regions. Even today a major portion of the world's labour force still earns its living from agriculture. At the turn of the century almost 60% of the labour force in Asia and Africa worked in the agricultural sector. Three quarters of the working poor in developing countries live in rural areas. A major challenge for many developing countries is therefore to increase income, productivity, and indeed labour absorption, in both the farm and non-farm rural sectors.
- The employment generating capacity of manufacturing has declined in the advanced countries, although its indirect impact in stimulating employment elsewhere in the economy remains very strong. Its share has decreased most significantly in North America. In Asia and Africa there were marginal increases from 12.6 % and 6.5 % in 1990 to 14.1 % and 6.9 % respectively in 2000.
- In almost all over the world the share of the labour force in services has increased, although it varies across regions. The change in the share of labour force may be a consequence of the changing dynamics in the market. Technology development results with a decrease in the demand for labour in the manufacturing sector especially where high tech equipment is used. Moreover, companies tend to concentrate on their core business processes and turn over their non-core processes to their third party partners most of which act in the services sector. The share of the labour force ranges from around 80 % in North America to 60 % in Europe and Latin America and around 35 % in Africa and 25 % in Asia. The quality of jobs in the services sector varies considerably. In some parts of the developing world the growth of the services sector has been characterized by the rise of income and productivity – in others most jobs have poor quality and low payment, mostly in the informal economy, which acts as a “sponge” when the demand for labour is weak (ILO, March 2002).
- Rates of youth unemployment are alarmingly high or very high in many countries. Throughout the world, youth unemployment rates are typically two to

three times higher than the adult rates. The vast majority of the world's youth work in the informal sector. Most youth working in the informal sector lack adequate incomes, social protection, security and representation. In a vicious cycle, poorly productive enterprises, low incomes and inadequate working conditions interact to undermine enterprise competitiveness, which in turn undermines the capability to provide decent employment conditions. If current trends continue, it is likely that most of the jobs available to young people in the future will be low paid and of poor quality. Youth unemployment and underemployment impose a heavy cost upon individuals, employers, trade unions, governments and societies. Unemployment in early life may permanently impair employability. For employers, youth unemployment means that young people have less to spend on their products and services, and that personal savings are reduced for investment in business, resulting in loss of production. For trade unions, youth unemployment means loss of potential membership and weaker bargaining positions to secure improved rights, protection and working conditions for their members. For governments, youth unemployment means they have a reduced taxation base and higher social welfare costs, that investments in education and training are wasted, and that their voter support among young people is weak.

The statistics reveal that unemployment is a serious problem for the world economy and for the global poverty, and unless effective policies are taken, it will continue to be a serious threat. Especially the costs of youth unemployment summarized in the previous paragraph signify the importance of unemployment for Turkey, a still-developing country with high proportion of young population. The following sections give detail about the history of unemployment in Turkey and the current labour market characteristics.

2.2 Turkish Labour Market and Unemployment in Turkey

In this section, the unemployment rate calculation studies in Turkey; labor force characteristics, employment structure and unemployment characteristics of Turkey are described in detail.

2.2.1 Unemployment Rate Calculations

The attempts to calculate unemployment in Turkey can be grouped in two periods: The period before the 1988 Labour Force Statistics Survey and the period after 1988.

Before 1988, several institutions gathered data on the Turkish labour force. The Turkish Statistical Institute launched its first household labour force survey in 1966. However this survey was not conducted in a temporary fashion. Between 1966 and 1988 several other sources were used to gather data about Turkish labour force. These sources were population consensus results, Labour Force Statistics, State Planning Organization estimations and publications of the Labour Force Placement Office (Turkish Employment Organization) (Bulutay, 1995). However these different sources led to a series of surveys varying in methodology, definitions and areas covered.

In 1988 a new household labour force survey procedure was introduced by SIS and it was conducted twice a year (in April and October) until 2000. The household labour force survey is conducted by selecting a number of (over 20.000) sample family that can be considered as representatives for other households with respect to regions, rural-urban residence and other socio-economic variables. Surveyors visit the representative families and gather information about the family members. This information is then projected to form the labour force statistics about Turkey. This survey questionnaire was designed to conform as closely as possible to international data gathering norms, with some potentially important differences (Levent et al., 2002).

The main difference involved the length of the search period used to determine whether someone without a job is unemployed or inactive. The data convention underlying ILO and most OECD countries' survey considers a person to be unemployed if that person is not working in the reference period, currently available for work, and has been seeking work in the past four weeks (OECD, 1996). In Turkey however an investigation period of 6 months is used until 2000. This difference in the investigation period causes the unemployment rate to be relatively higher compared to the results that would be found with the same search period of the OECD countries. After a revision in 2000, the survey period was decreased the three months from six months.

Levent et al., (2002), states that the increase in the frequency of these labour force surveys may cause a modest difference between the unemployment statistics before 2000 and after 2000. The data representing unemployment before 2000 may have been exaggerated. However they assert that considering the disconcerting levels of unemployment in Turkey especially faced after 2001, this excess in the measured unemployment rate before 2000 will not cause a problem in terms of unemployment research.

In the following section the characteristics of Turkish labour market will be analyzed by the use of SIS's Labour Force Survey (LFS) results. Therefore unless otherwise stated the statistics given in the tables in this chapter are obtained from SIS Labour Force Survey database. The research period will cover 1988- 2004 since the results obtained through this period are reliable and internationally comparable.

2.2.2 Labour Force Supply

In an economy, the number of people that is either working or actively looking for a job form the labour force supply of that economy.

This definition of labour force excludes some proportion of the population. The population consists of the working age population (15 years of old and over) and the population younger than 15 years old. The working age population consists of the labour force and the population that is out of the labour force either unwillingly because of some compulsory reasons like education, military service or willingly. The labour force consists of those that are employed and not-employed. Finally the labour force participation rate is found by dividing labour force to working age population. The definitions of these terms are formulized as follows:

Population = Working age population (WAP) + Population under 15 years old.

WAP = Labour force (LF) + Population out of the labour force

LF = Employed population + Unemployed population

Labour force participation rate = (LF / WAP) *100

The labour force participation rate is an important indicator that shows the dimension of productive population. This indicator changes with respect to the changing population structure, socio-cultural structure and the economic structure. Therefore a significant gender difference is observed in this indicator (Levent et. al. 2002).

Although the population growth rate dropped to 1.8 % since 1990 in a ten-year period compared to the 2.8 % seen after World War II, Turkey still has a growing population. This increase in population causes an increase in working age population each year. Some of the working age population are still in education and therefore have not joined the labour force therefore decrease the labour force supply growth.

One of the most undesirable consequences of the growth of population is the immigration from rural areas to urban areas. The high growth rates of population in rural areas, the low income levels gained from agriculture, the desire to live in better conditions, the desire to have education and the desire to increase wealth increases the immigration rate from rural areas to urban areas.

Table 2.5: Working Age Population, Labor Force and Labor Force Participation Rates between 1988 and 2004.

Year	Working Age Population (I) (TR)	Labour Force (II) (TR)	LF Participation Rate (III) (TR)	(I) (Rural)	(II) (Rural)	(III) (Rural)	(I) (Urban)	(II) (Urban)	(III) (Urban)
1988	33746	19390	0.57	16509	11067	0.67	17237	8323	0.48
1989	34315	19930	0.58	16514	11465	0.69	17801	8465	0.48
1990	35601	20150	0.57	17013	11383	0.67	18588	8767	0.47
1991	36868	21010	0.57	16951	11798	0.70	19917	9212	0.46
1992	37985	21264	0.56	17008	11455	0.67	20977	9809	0.47
1993	38957	20313	0.52	17318	10526	0.61	21639	9787	0.45
1994	40038	21876	0.55	17486	11448	0.65	22552	10428	0.46
1995	41175	22285	0.54	17884	11762	0.66	23291	10523	0.45
1996	42243	22696	0.54	18078	11948	0.66	24165	10748	0.44
1997	43299	22755	0.53	18267	11551	0.63	25032	11204	0.45
1998	44295	23385	0.53	18206	11720	0.64	26089	11665	0.45
1999	45310	23877	0.53	18492	11824	0.64	26818	12053	0.45
2000	46211	23078	0.50	18581	10902	0.59	27630	12176	0.44
2001	47158	23491	0.50	18674	10968	0.59	28484	12523	0.44
2002	48041	23818	0.50	18850	10863	0.58	29191	12955	0.44
2003	48912	23641	0.48	18993	10550	0.56	29919	13091	0.44
2004	49906	24289	0.48	19093	10576	0.55	30813	13714	0.45
Average Growth Rate (%)									
1988-2004	2.5	1.5	-0.9	0.9	-0.2	-1.1	3.7	3.2	-0.4
1988-1996	2.8	2.0	-0.6	1.1	1.0	-0.07	4.3	3.3	-1.0
1996-2004	2.1	0.8	-1.3	0.7	-1.5	-2.1	3.1	3.1	0.14

Source: SIS, 2004

Between 1988 and 2004 the labour force participation rates showed a decreasing structure in Turkey. This structure was observed both in the urban areas and the rural areas. In 2004 the participation rate was observed to be 48 %, nine percentage points below the level observed in 1988. The SIS survey results reveal that while the participation rates in the rural areas showed a decline of 1.1 % between 1988 and 2004, the change in urban area participation rates were lower, (-0.4 %). Another important point that the results reveal is that the working age population growth in urban areas is significantly higher than the working age population in rural areas.

Between 1988 and 2004 the average growth rate of working age population was 3.7 %, whereas in the rural areas this rate was 0.9 %, (Table 2.5).

As mentioned before, the labor force participation rates show gender differences. Similar to total population statistics, the participation rates of men have declined steadily since 1988 from 81 % to 70 % as given in Table 2.6.

Table 2.6: Working Age Population, Labor Force and Labor Force Participation Rates Between 1988 and 2004 For Men.

Year	Working Age Population (I) (TR)	Labour Force (II) (TR)	LF Participation Rate (III) (TR)	(I) Urban	(II) Urban	(III) Urban	(I) (Rural)	(II) (Rural)	(III) (Rural)
1988	16661	13536	0.81	8722	6814	0.78	7939	6722	0.85
1989	16962	13663	0.81	8977	6896	0.77	7985	6767	0.85
1990	17556	13990	0.80	9365	7195	0.77	8191	6795	0.83
1991	18276	14665	0.80	9942	7652	0.77	8334	7013	0.84
1992	18839	15002	0.80	10438	8018	0.77	8401	6984	0.83
1993	19284	15045	0.78	10751	8081	0.75	8533	6964	0.82
1994	19815	15552	0.78	11227	8458	0.75	8588	7094	0.83
1995	20388	15858	0.78	11540	8548	0.74	8848	7310	0.83
1996	20924	16182	0.77	12032	8809	0.73	8892	7373	0.83
1997	21457	16464	0.77	12440	9074	0.73	9017	7390	0.82
1998	21956	16848	0.77	13016	9473	0.73	8940	7375	0.82
1999	22462	17025	0.76	13400	9670	0.72	9062	7355	0.81
2000	22916	16890	0.74	13812	9797	0.71	9104	7093	0.78
2001	23389	17040	0.73	14214	10035	0.71	9175	7005	0.76
2002	23827	17058	0.72	14573	10168	0.70	9254	6890	0.74
2003	24260	17086	0.70	14977	10323	0.69	9283	6763	0.73
2004	24755	17902	0.72	15363	10882	0.71	9393	7020	0.75
Average Growth Rate (%)									
1988-2004	2.5	1.8	-0.7	3.6	3.0	-0.6	1.0	0.3	-0.7
1988-1996	2.9	2.3	-0.6	4.1	3.3	-0.8	1.4	1.2	-0.2
1996-2004	2.1	1.3	-0.8	3.1	2.6	-0.4	0.7	-0.6	-1.2

Source: SIS, 2004

Levent et.al, (2002), state that this decline may be attributed to the relatively high growth of working age population of men compared to the growth rate of labour force. During 1988-2004 the working age population increased by 2.5 % while the growth rate of labour force was 1.8 %. The reason of the decline of participation rates may also be related to the increase in the duration of education in young population. The results also show that there is a regional difference between the participation rates. The working age population growth in urban areas has increased 3.6 % steadily between 1988 and 2004 while it has increased only 1 % in the rural areas. These statistics also show that people have a desire to live in the urban areas rather than rural areas. The labour force participation rates in terms of urban and rural areas are similar to the rates in terms of Turkey as a whole. There is a decrease in the labour force in both rural areas and urban areas however the decrease in the rural areas after 1996 is more than twice the decrease in the urban areas. This

statistics may be an indicator of the increase in the duration of education in rural areas.

The decreasing participation rates especially in the urban areas require further analysis. When the participation rates are analyzed in terms of age, the structure of this indicator can be identified clearly. As shown in Figure 2.7, the decline in the participation rates of 15-19 years old men between 1988 and 2003 is greater than any other age group. This decline is a result of the rise in the duration of education in this age group. Levent et. al, (2002) state that the decline for this age group shows that the population in this group is spending more time for education and that higher participation rates may be seen in higher education for this age group and that the average duration of being at school may reach 11 years for the 15-19 years age group of men.

The decrease in the participation rates of 20-24 age groups is also important. While the decline in participation rates between 1988 and 1996 was 1.3 %, this decline increased to 2 % on the average between 1996 and 2003. Levent et.al, (2002), state that this decline can be explained by the rise in the population that attends university in this age group. The researchers also state that the decline in the overall participation rates of men is a result of the decreasing population growth rates in Turkey, the proportion of the school age population is showing a decline and therefore the decline in participation rates will be slower and this indicator will reach its lower boundary 68 % by time.

The highest participation rate of men is seen at the 25-34 age groups in urban areas. The second high participation rates are observed in the 35-54 age groups. The statistics are not abnormal since the population in this age group, by having completed their education and their military services are ready to participate in the labour force. Levent et.al (2002), state that in the 35-54 age group, the participation rates have fallen from 90.1 % in 1988 to 82.8 % in 2003 as a result of the early pension system and that the same system is responsible for the decline in the 55+ age group.

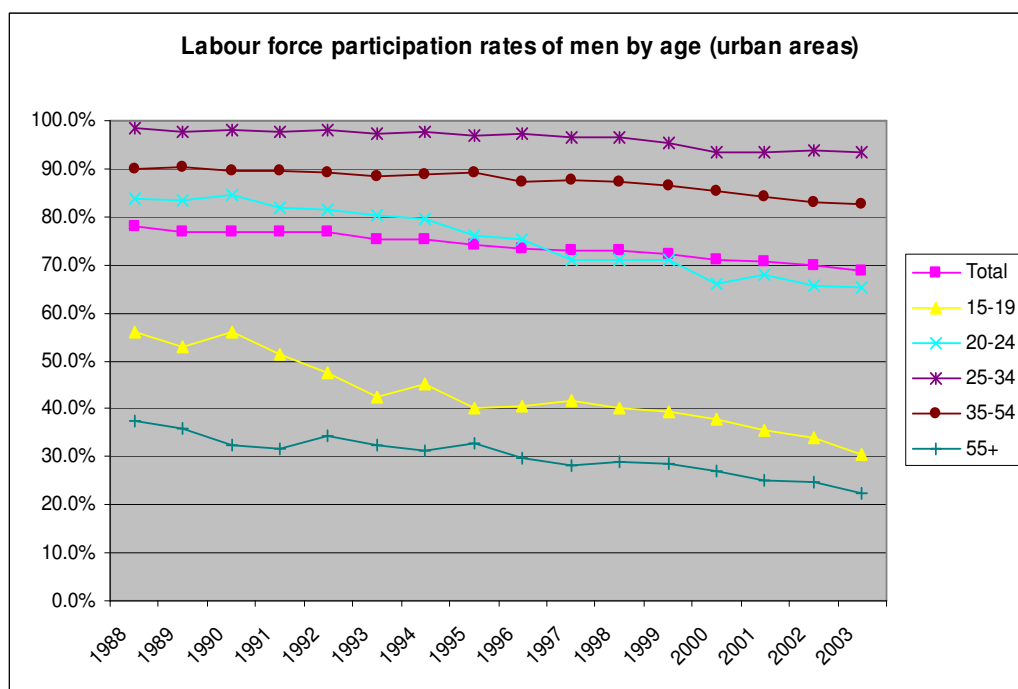


Figure 2.7: Labor Force Participation Rates with respect to Age for Men through 1988 and 2003 in Urban Areas.

The comparison of the participation rates for men and women shows that there is a significant difference between the two genders. The growth in the working age population is similar in both genders. However the total working age women population is larger than total working age men population. This indicator shows that women should be seen as an important part of the labour force; however the labour force participation rates of women reveal that Turkey is not using this important power in its economy.

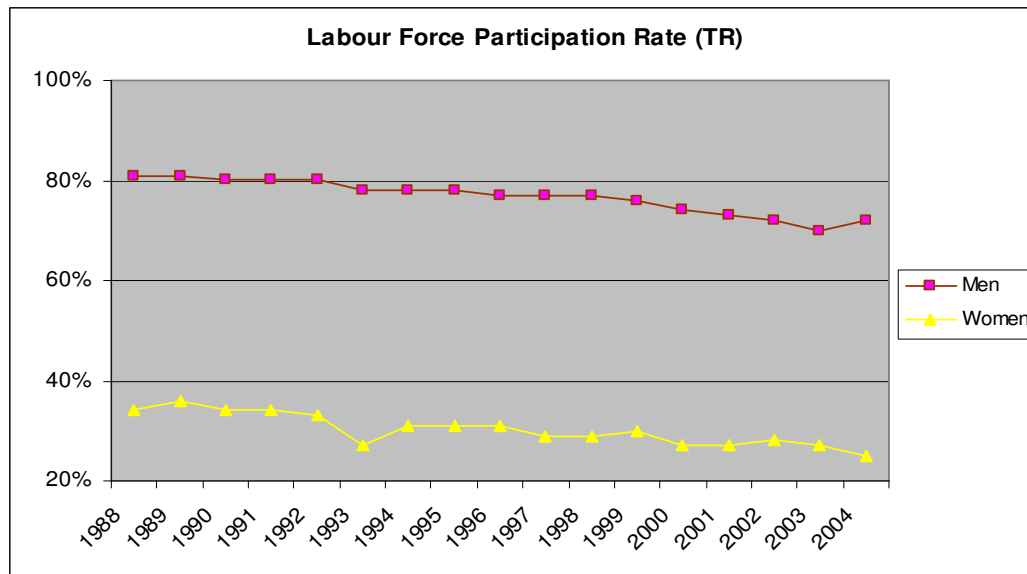


Figure 2.8: Labour Force Participation Rates of Men and Women in Turkey by Years

Women labour participation rates are far below the level of men, 27 % in Turkey, while participation rates of men are 70 % as of 2004. The labour force participation rates of men and women in Turkey are plotted in Figure 2.8. Participation rates in the rural areas are significantly higher –more than twice- than the urban area participation rates, (Table 2.7). In 1988 the labour participation rate of women in rural areas was 51 % and this number decreased to 39 % in 2003. In the urban areas the participation rate was 18 % in 1988 and this number decreased to 16 % in 1996. However after 1996 the labour force participation rate started to rise again and reached 19 % in 2002.

Baslevant and Onaran, (2003), state that, similar to labor force structure in Turkey, the decrease in the labor force participation rate may be attributed to the withdrawal of the younger population from the labour force due to the increase in years of education and that internal migration to urban areas has also played a major role in the decline.

The high participation rates of women in rural areas is an expected result since , in rural areas women is expected to work in agriculture as a non paid family worker. The decline in the participation rates of women in rural areas may be attributed to the increase in years of education as mentioned in the previous paragraph but the

technology development and the use of new technology machinery in agriculture may be another reason for the decline in participation rates.

Table 2.7: Working Age Population, Labor Force and Labor Force Participation Rates between 1988 and 2004 for Women.

Year	Working Age Population (I) (TR)	Labour Force (II) (TR)	LF Participation Rate (III) (TR)	(I) (Rural)	(II) (Rural)	(III) (Rural)	(I) Urban	(II) Urban	(III) Urban
1988	17085	5854	0.34	8515	1509	0.18	8570	4345	0.51
1989	17353	6267	0.36	8824	1569	0.18	8529	4698	0.55
1990	18045	6160	0.34	9223	1572	0.17	8822	4588	0.52
1991	18592	6345	0.34	9975	1560	0.16	8617	4785	0.56
1992	19146	6262	0.33	10539	1791	0.17	8607	4471	0.52
1993	19673	5268	0.27	10888	1706	0.16	8785	3562	0.41
1994	20223	6324	0.31	11325	1970	0.17	8898	4354	0.49
1995	20787	6427	0.31	11751	1975	0.17	9036	4452	0.49
1996	21319	6514	0.31	12133	1939	0.16	9186	4575	0.50
1997	21842	6291	0.29	12592	2130	0.17	9250	4161	0.45
1998	22339	6537	0.29	13073	2192	0.17	9266	4345	0.47
1999	22848	6852	0.30	13418	2383	0.18	9430	4469	0.47
2000	23295	6188	0.27	13818	2379	0.17	9477	3809	0.40
2001	23769	6451	0.27	14270	2488	0.17	9499	3963	0.42
2002	24214	6760	0.28	14618	2787	0.19	9596	3973	0.41
2003	24652	6555	0.27	14942	2768	0.19	9710	3787	0.39
2004	25150	6388	0.25	15450	2832	0.18	9700	3556	0.37
Average Growth Rate (%)									
1988-2004	2.4	0.8	-1.6	3.8	4.2	0.4	0.8	-0.4	-1.5
1988-1996	2.8	1.8	-1.0	4.5	3.4	-1.1	0.9	1.3	0.5
1996-2004	2.1	-0.1	-2.2	3.1	4.9	1.8	0.7	-2.4	-3.5

Source: SIS, 2004

Baslevant and Onaran state that the low labour force participation rates in urban areas, however, may be attributed to internal migration and the mismatch between the qualifications of women and the labour demand market. The low –skilled women that migrated from rural areas prefer to keep away from the labour force and choose to stay at home. Levent et.al (2002), underline that since the average educational level in women is low, the earnings of women are usually quite low. The inexistence of free kindergardens and the existence of expensive ones force women to stay at home and look after their children rather than work. Therefore educational level of women can be regarded as an important factor that increases the labour participation of women especially in the urban areas. As pointed above, the labour force participation rates have started to incline in urban areas after 1997 and reached 19 % in 2002. Levent et.al, (2002), state that this decline in the participation rates may be a result of the economic crisis in 2001. Women are forced to work and earn money to help increase family income after 2001. The increase after 1997 however may be attributed to the rise in the educational and skill level of women.

When the labour force participation in urban areas is analyzed with respect to age groups the findings can be summarized as follows:

There is a steady decline in the labour force participation rates of women in the 15-19 age groups as shown in Figure 2.9. Levent et.al, (2002) state that this decline is a result of the high participation rates in education and that since educational level is an important factor that increases participation rates of women in urban areas, this decline can be seen as an indicator of increase in the labour force participation of women in urban areas in the long run.

The participation rates in the 20-24 age groups have declined between 1988 and 1996. However, during 1996-2003 this number has shown an increase to 2.7 % on the average. This increase may be the result of the rise in the educational level of women.

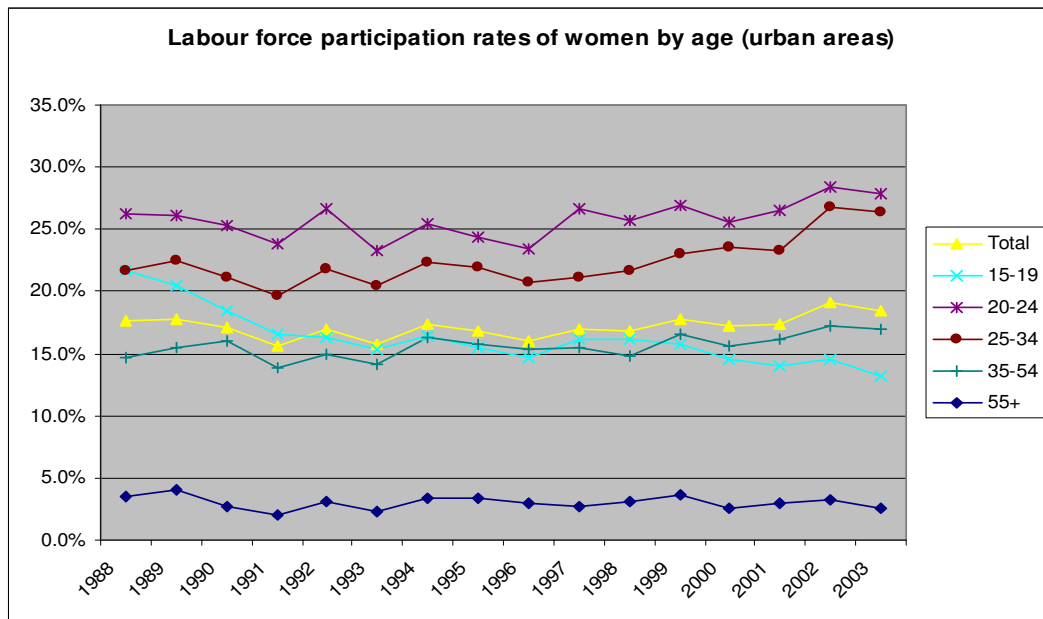


Figure 2.9: Labor Force Participation Rates with respect to Age for Women through 1988 and 2003 in Urban Areas.

Levent et.al, (2002), also mention that in the 35-54 age group, the positive effect of education and the negative effect of early pension system may be observed. In the 55+ age group, the decline is attributed to the early pension system however the researchers point out that the decline in this group is expected to end in the long run.

So far, the labor force supply side has been analyzed in terms of gender-age and area. The analysis shows that there are significant differences in the labor force participation rates in terms of gender, area and age. The decline in the participation

rates is a result of the internal immigration from rural areas to urban areas and the increase in the duration of education. The analysis also shows that in the urban areas, the participation rates in women is expected to rise in the future as a result of the education level in women; and that education is an important factor that increases labour force participation of women.

In the following section the employment structure in Turkey will be summarized.

2.2.3 Employment in Turkey

The total employment stock shows that employment in Turkey increased between 21.5 % between 1988 and 1999 and reached 22 millions in 1999, but after 1999 the employment levels showed a decrease. Employment fell 4.5 % until 2003 and reached around 21 millions (Table 2.9). When the employment data is analyzed in terms of gender it is observed that women employment increased 21 % between 1988 and 1999 and fell 6.93 % after 1999 (Table 2.10); whereas men employment increased 25.5 % between 1988 and 1999 and fell 2.91 % after 1999 (Table 2.11). The decrease after 1999 may be explained by the economic crisis faced in 2001 and the rise in the employment in informal sector. However the data shows that women are more affected by the increase in unemployment during 1999 and 2003.

Table 2.8: Sectoral Employment Proportions in Turkey during 1988 and 2003

SECTOR S	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	% Change 1998 -2003
Proportion of Agriculture	46.5	47.4	46.9	47.8	44.8	42.5	44.0	44.1	43.7	41.7	41.5	40.2	36.0	37.6	34.9	33.9	-27.0
Proportion of Mining and Quarrying	1.3	1.0	1.0	0.9	0.8	0.7	0.9	0.7	0.8	0.8	0.7	0.6	0.4	0.5	0.6	0.4	-69.4
Proportion of Manufacturing	14.4	14.5	14.2	14.2	15.2	14.6	15.1	14.7	15.3	16.2	15.9	16.1	16.9	16.6	17.5	17.3	20.6
Proportion of Electricity, Gas, Water	0.2	0.1	0.1	0.1	0.2	0.5	0.5	0.6	0.4	0.5	0.5	0.4	0.4	0.4	0.5	0.5	207.8
Proportion of Construction	5.7	5.2	4.8	5.1	5.4	6.7	6.0	6.0	6.1	6.2	6.1	6.2	6.3	5.2	4.5	4.6	-20.1
Proportion of Wholesale; Retail Trade;Restaurantsand Hotels	11.4	11.2	11.6	11.4	12.2	13.0	12.7	13.2	12.9	13.7	13.7	14.5	17.7	17.4	18.6	19.2	67.7
Proportion of Transport, Storage and Communication	4.4	4.5	4.4	4.3	4.5	5.0	4.5	4.3	4.3	4.3	4.4	4.3	4.9	4.8	4.7	4.8	10.1
Proportion of Financing, Insurance, Real estate and business services	2.4	2.4	2.2	2.2	2.4	2.3	2.4	2.3	2.4	2.5	2.5	2.6	3.3	3.2	3.3	3.5	44.8
Proportion of Community, Social and Personal Services	13.8	13.6	14.7	14.1	14.4	14.5	13.9	14.1	14.2	14.2	14.6	15.0	14.1	14.3	15.5	15.9	15.1

When the statistics are analyzed in terms of sectors, it is observed that agriculture has always been the most important source of employment for Turkey. The results of the 2003 SIS's labour force survey show that, in 2003, the agricultural sector has still the highest proportion with 33.9 % (Figure 2.10). The statistics also reveal that in time, the proportion of the agricultural sector has shown a decline in Turkey (Table 2.8). This decline is not unique for Turkey however, the proportion of agriculture in developed countries has also shown this decline and reached 3 %. Levent et.al, 2002, state that the reason for the decline in the agricultural sector employment is a result of the low income levels in the sector, the technological developments and therefore the need for less man-power and also the transition from agricultural economy to industrial economy.

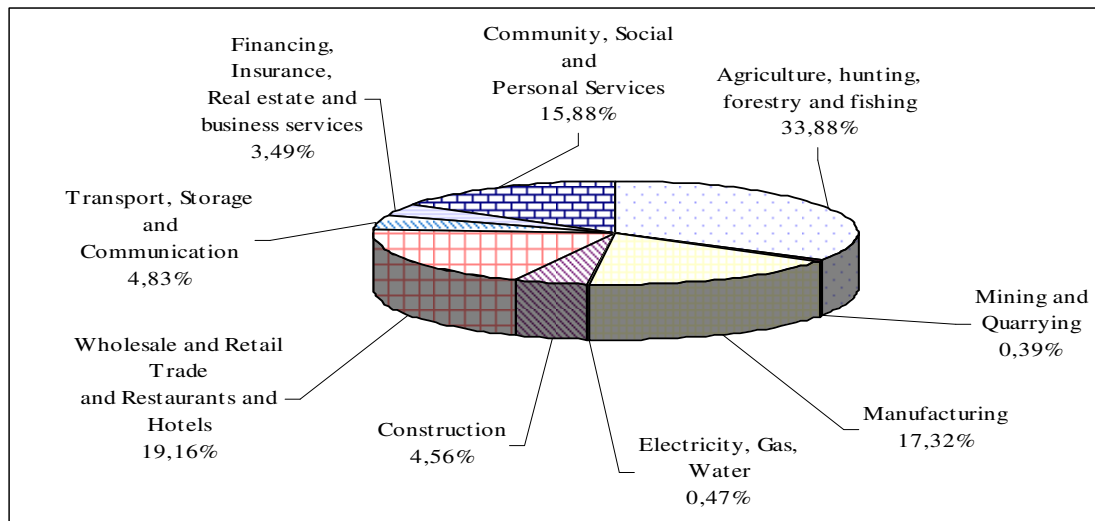


Figure 2.10: Sectoral Distribution of Turkish Employment in 2003, SIS, 2004

It is observed from the statistics that the share of manufacturing sector has increased during the analysis period (reached 17.3 % in 2003). Similar to manufacturing sector, wholesale and retail trade, restaurants and hotels sector showed a steady increase and reached 19.2 % in 2003 (Table 2.8). The same increase was observed in all sectors except construction and agriculture. Therefore the employment structure in Turkey has experienced growth in both service and manufacturing during this period. Auer and Popova, (2003) state that if compared with the EU, where around 5 % of the workforce is employed in agriculture, 20.3 % in manufacturing and around 70 % in services (73 % in Luxembourg to 57 % in Greece), Turkey has still a long way to go in order to come closer to the employment structure of a developed economy.

Table 2.9: Sectoral Employment Distribution of Women in Turkey during 1988 and 2003

SECTOR PROPORTIONS (%)	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	% Change 1998 -2003
Total female employment (000)	5233	5674	5637	5894	5777	4777	5816	5957	6126	5804	6092	6335	5800	5969	6121	5892	
Agriculture	76.78	76.61	76.62	77.25	72.1	68.93	71.42	71.66	72.14	67.87	67.79	66.44	60.48	63.33	60.02	58.5	-23.8
Mining and Quarrying	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	0.1	0.1	0.0	0.1	0.1	0.1	0.1	-61.9
Manufacturing	8.4	8.6	8.6	8.2	10.9	11.2	10.0	9.2	9.3	10.8	10.2	11.2	12.4	11.6	13.2	12.8	52.7
Electricity, Gas, Water	0.1	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0.1	0.1	0.1	0.1	0.1	77.6
Construction	0.3	0.2	0.2	0.2	0.3	0.4	0.4	0.4	0.5	0.5	0.5	0.4	0.6	0.4	0.4	0.5	71.7
Wholesale and Retail Trade and Restaurants and Hotels	2.7	2.8	2.7	2.6	3.5	4.1	4.0	4.2	3.8	5.1	4.7	5.4	6.7	6.5	7.3	8.0	193.8
Transport, Storage and Communication	0.8	0.7	0.7	0.7	0.8	1.3	0.7	0.6	0.7	0.7	0.8	0.7	1.2	1.0	1.0	1.1	30.1
Financing, Insurance, Real estate and business services	2.0	2.0	2.1	2.0	2.4	2.2	2.3	2.4	2.4	2.6	2.8	2.7	3.8	3.3	3.1	3.3	66.4
Community, Social and Personal Services	8.8	8.9	9.1	9.0	10.0	11.8	11.0	11.4	11.1	12.1	13.0	12.9	14.7	13.8	14.8	15.7	77.4

Source: SIS, 2004

When employment statistics are analyzed in terms of gender in overall Turkey, similar results are found for participation rates. It is observed that women have higher participation rates in urban areas. The same structure can be observed in the employment data. Although the share of agriculture showed a decline between 1988 and 2003 in female employment, it still accounts for the 58.5 % of total female employment (Table 2.9). The data also reveals that, women that quit agriculture have started to work especially in manufacturing (with 52 % increase since 1988), community social and personal services (with 77.5 % increase since 1988) and wholesale and Retail Trade and Restaurants and Hotels sectors with 193 % increase since 1988.

During the same period it is observed that employment share of males in agriculture declined from 33% to 24.4 % (Table 2.10). Similar decline was obvious in mining and quarrying sector (with 70% decrease since 1988), and construction sector (with 23 % decrease since 1988). During this period the share of the electricity, gas, water (21.8 %); wholesale and retail trade, restaurants and hotels (58%); financing, insurance, real estate and business services (37.6%) sectors increased in employment of men.

Levent et.al, (2002), state that there is a sexual difference in transition between to agricultural sector to non-agricultural sector. The transition is especially seen in working age, high-skilled men that can adapt themselves to non-agricultural sectors.

Table 2.10: Sectoral Employment Distribution of Men in Turkey during 1988 and 2003, SIS 2004

SECTOR	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	% Change 1998 - 2003
Total male employment (000)	12521	12548	12902	13395	13682	13723	14192	14627	15067	15399	15686	15713	15780	15555	15233	15254	
Agriculture	33.8	34.2	33.9	34.8	33.3	33.3	32.8	32.9	32.1	31.8	31.3	29.6	27.0	27.7	24.8	24.4	-27.9
Mining and Quarrying	1.8	1.4	1.5	1.3	1.1	1.0	1.3	1.0	1.1	1.0	0.9	0.8	0.5	0.6	0.8	0.5	-70.3
Manufacturing	16.9	17.1	16.6	16.8	17.0	15.8	17.1	17.0	17.7	18.3	18.1	18.1	18.5	18.6	19.2	19.1	13.1
Electricity, Gas, Water	0.2	0.2	0.2	0.2	0.3	0.7	0.7	0.7	0.5	0.7	0.7	0.6	0.5	0.6	0.6	0.6	218.1
Construction	8.0	7.4	6.8	7.2	7.6	8.9	8.3	8.3	8.4	8.4	8.3	8.5	8.4	7.0	6.1	6.1	-23.0
Wholesale and Retail Trade Restaurants and Hotels	15.1	15.0	15.5	15.2	15.9	16.2	16.3	16.8	16.6	16.9	17.3	18.2	21.7	21.5	23.2	23.5	55.8
Transport, Storage and Communication	5.9	6.3	6.0	5.8	6.1	6.4	6.0	5.8	5.7	5.6	5.9	5.8	6.3	6.2	6.2	6.3	7.0
Financing, Insurance, Real estate and business services	2.6	2.6	2.3	2.3	2.5	2.3	2.4	2.3	2.4	2.4	2.4	2.6	3.1	3.2	3.3	3.6	37.6
Community, Social and Personal Services	15.9	15.8	17.2	16.4	16.3	15.5	15.1	15.2	15.4	14.9	15.3	15.8	13.9	14.5	15.7	16.0	0.4
Proportion of non-Agriculture	66.2	65.8	66.1	65.2	66.7	66.7	67.2	67.1	67.9	68.2	68.7	70.4	73.0	72.3	75.2	75.6	14.2

When the employment statistics are analyzed in terms age groups it is observed that there is a rise in the employment in the 25-34 age groups in overall Turkey in women and men. This age group is the only group that shows a steady incline since 1998 in the age groups both in urban and rural areas. In the 20-24 age groups, it is observed that from 1988 to 1996 there is an increase in the employment rates for both genders. Men employment has increased 4 % and women employment stock has almost the same, 3.9 %, however after 1996 a decline is observed in both genders. Employment levels in 15-19 age group has decreased in both men and women. This data is in accordance with the participation rates of women and men and is a sign of increasing educational participation. (Table 2.11 and Table 2.12)

Table 2.11: Employment Stock of Men by Age in Turkey

Men Employment by Age (TR) (000)						
Year	Total	15-19	20-24	25-34	35-54	55+
1988	12520	1542	1344	3592	4516	1528
1989	12548	1479	1288	3575	4582	1624
1990	12901	1515	1337	3635	4840	1575
1991	13395	1664	1578	2189	4785	1325
1992	13682	1592	1639	4112	4951	1388
1993	13722	1487	1608	4181	5105	1342
1994	14191	1553	1726	4288	5206	1418
1995	14628	1442	1750	2382	5481	1521
1996	15067	1500	1816	4610	5610	1531
1997	15399	1523	1797	4765	5784	1529
1998	15686	1458	1760	2331	4362	1608
1999	15713	1465	1722	4931	4160	1555
2000	15780	1375	1715	5000	6148	1542
2001	15555	1228	1658	2651	6132	1520
2002	15232	1093	1503	5062	6139	1435
2003	15256	943	1458	2788	6324	1367
Average Growth Rate (%)						
1988-2003	1.3	-3.0	0.7	11.1	3.1	-0.6
1988-1996	2.3	-0.2	4.0	12.8	2.8	0.3
1996-2003	0.2	-6.3	-3.0	9.2	3.5	-1.6

Source: SIS, 2004

Table 2.12: Employment Stock of Women by Age in Turkey

Women Employment by Age (TR) (000)						
Year	Total	15-19	20-24	25-34	35-54	55+
1988	5234	1003	776	1236	1701	516
1989	5674	1056	791	1344	1834	649
1990	5637	987	807	1331	1877	635
1991	5893	1062	993	1392	1848	599
1992	5778	948	988	1402	1851	588
1993	4778	777	822	1202	1542	435
1994	5815	936	988	1421	1857	613
1995	5957	926	947	1501	1924	659
1996	6127	939	998	1484	1985	721
1997	5804	799	966	1447	1897	694
1998	6092	803	990	1551	1996	752
1999	6335	812	1039	1607	2054	822
2000	5801	686	920	1617	1917	661
2001	5969	619	955	1653	2048	694
2002	6122	603	936	1733	3169	715
2003	5891	532	844	1712	2128	676
Average Growth Rate (%)						
1988-2003	1.1	-3.6	1.1	2.4	3.0	3.0
1988-1996	2.5	-0.2	3.9	2.7	2.4	6.0
1996-2003	-0.4	-7.6	-2.2	2.1	3.7	-0.4

Source: SIS, 2004

The employment statistics in urban areas show that in the 15-19 age group of men there is a rise in the employment stock, although this rise has decreased since 1996, it is still of importance. This increase shows that there is still an increase in children employment in the urban areas. The statistics reveal that 20-24 age group is the most seriously affected group of the economic stability since 1998. The employment level of this group in 2003 is lower than even the value observed in 1996, (Table 2.13).

Table 2.13: Employment Stock of Men by Age in Urban Areas, SIS 2004

Men Employment by Age (urban areas) (000)						
Year	Total	15-19	20-24	25-34	35-54	55+
1988	6154	655	628	2038	2416	416
1989	6201	641	629	2029	2474	430
1990	6511	712	662	1133	2610	414
1991	6839	714	772	2366	2633	355
1992	7161	665	841	2499	2741	415
1993	7235	591	817	2528	2891	410
1994	7567	667	884	2613	2988	415
1995	7778	618	894	2719	3094	453
1996	8044	655	921	2844	3170	454
1997	8331	679	924	2936	3363	429
1998	8608	652	985	3046	3463	462
1999	8709	651	936	3107	3538	477
2000	9032	656	963	3237	3745	431
2001	9003	583	954	3305	3758	403
2002	8844	526	909	3297	3702	410
2003	9026	493	908	3436	3812	377
Average Growth Rate (%)						
1988-2003	2.6	-1.6	2.6	6.8	3.1	-0.4
1988-1996	3.4	0.3	5.1	10.4	3.5	1.5
1996-2003	1.7	-3.8	-0.1	2.7	2.7	-2.4

The statistics of women however show different structure. In the 20-24 age group there is a rise in the employment stock of woman in the urban areas. There is a slow

down in the rate of increase however the statistics reveal that in the overall sense, employment has risen in women (Table 2.14). This may be the result of the economic stability in Turkey. Women have started working in order to increase the family income during this term. The increase in employment stock is observed in all age groups of women and this increase also strengthens the belief that, during the term of economic stability and crisis, women join the labour force and start working.

Table 2.14: Employment Stock of Women by Age in Urban areas, SIS 2004

Women Employment by Age (urban areas) (000)						
Year	Total	15-19	20-24	25-34	35-54	55+
1988	1081	181	189	353	320	38
1989	1158	181	197	379	355	46
1990	1204	170	210	384	406	35
1991	1208	154	258	406	362	28
1992	1416	165	303	491	411	46
1993	1316	157	267	454	403	35
1994	1566	187	309	522	496	52
1995	1614	190	324	542	501	57
1996	1641	185	330	550	524	52
1997	1756	199	376	579	554	48
1998	1832	208	399	625	543	57
1999	1968	193	394	678	634	69
2000	2069	192	419	771	639	48
2001	2074	169	412	762	676	55
2002	2266	175	432	859	737	63
2003	2262	170	421	870	747	54
Average Growth Rate (%)						
1988-2003	5.2	-0.1	5.8	6.4	6.1	5.6
1988-1996	5.7	0.6	7.7	6.0	6.8	8.4
1996-2003	4.7	-1.0	3.7	6.9	5.4	2.4

The employment statistics by age in rural areas reveal that there is an important decline in the number of employed in both 15-19 age group and the 20-24 age group of men, and that 25-34 and 35-54 are the two age groups that have the highest employment stock of men in rural areas. The decrease in the number of employed men in 15-19 and 20-24 age groups have been 8.3 % and 6.6 % after 1996. This may indicate a rise in the number of youth participating in education in the rural areas.

Table 2.15: Employment Stock of Men by Age in Rural Areas

Men employment by Age (rural)						
Year	Total	15-19	20-24	25-34	35-54	55+
1988	6369	887	716	1554	2100	1112
1989	6201	838	659	1546	2108	1194
1990	6511	712	662	1133	2610	414
1991	6556	950	806	1677	2152	970
1992	6521	927	798	1613	2210	973
1993	6487	896	791	1653	2214	932
1994	6624	886	842	1675	2218	1003
1995	6850	824	856	1715	2387	1068
1996	7023	845	895	1766	2440	1077
1997	7068	844	873	1829	2421	1100
1998	7078	806	775	1859	2493	1146
1999	7004	814	786	1824	2503	1078
2000	6748	719	752	1763	2403	1111
2001	6552	645	704	1713	2374	1117
2002	6388	567	594	1765	2437	1025
2003	6230	450	550	1728	2512	990
Average Growth Rate (%)						
1988-2003	-0.1	-3.8	-1.4	1.6	1.5	5.3
1988-1996	1.3	0.2	3.1	3.3	2.4	10.9
1996-2003	-1.7	-8.3	-6.6	-0.3	0.4	-1.1

Source: SIS, 2004

The employment statistics of women in rural areas show that, similar to men employment by age, the 25-34 and 35-54 age groups account for most of the total employment stock of woman (Table 2.16). The statistics also reveal that since 1996 employment of women in rural areas show significant decline especially in younger population. The decline has been 9.5 % in the 15-19 age group; 5.7 % in the 20-24 age group; 0.6 % in the 35-54 age group and 0.6 % in the 55+ age group.

Table 2.16: Employment Stock of Women by Age in Rural Areas

Women employment by Age (rural)						
Year	Total	15-19	20-24	25-34	35-54	55+
1988	1081	181	189	353	320	380
1989	4516	875	594	965	1479	603
1990	4433	817	597	947	1471	600
1991	4685	908	735	986	1486	571
1992	4362	783	685	911	1440	542
1993	3462	620	555	748	1139	400
1994	4249	749	679	899	1361	561
1995	4343	736	623	959	1423	602
1996	4486	754	668	934	1461	669
1997	4048	600	590	868	1343	646
1998	4260	595	591	926	1453	695
1999	4367	619	645	929	1420	753
2000	3732	494	501	846	1278	613
2001	3895	450	543	891	1372	639
2002	3856	428	504	874	1395	652
2003	3629	362	423	842	1381	622
Average Growth Rate (%)						
1988-2003	20.2	20.5	12.9	11.0	24.1	5.1
1988-1996	40.3	46.9	29.2	21.8	45.7	10.1
1996-2003	-2.7	-9.5	-5.7	-1.3	-0.6	-0.6

Source: SIS, 2004

When the employment statistics are analyzed in terms of educational level, it is observed that educational level is still very low among the employed population. While men having less than high school education level covered 84.9 % of the total employed men in Turkey, high school graduates and university graduates were 9.8 % and 5.2 % respectively in 1998, today, in overall Turkey, 68.7 % of employed men is educated in less than high school level, whereas university graduates make up only 10 % of employed men (Table 2.17).

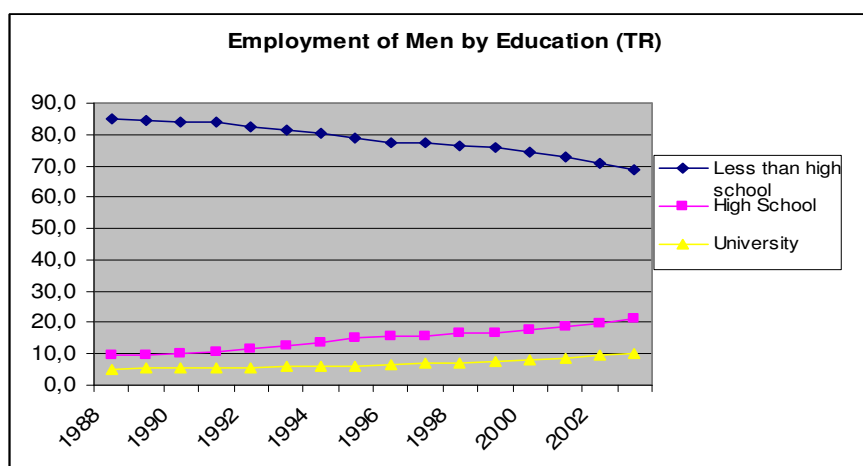


Figure 2.11: Employment of men by Educational Status in Turkey, SIS, 2004

Table 2.17: Educational Status of Employed Men in Turkey

Men Employment by Education (TR)				
Year	Total Employment	Less than high school	High School	University
1988	100	84.9	9.8	5.2
1989	100	84.7	9.8	5.5
1990	100	84.1	10.3	5.6
1991	100	84.0	10.6	5.4
1992	100	82.6	11.9	5.5
1993	100	81.3	12.7	6.0
1994	100	80.4	13.5	6.1
1995	100	78.7	15.0	6.3
1996	100	77.5	15.7	6.7
1997	100	77.3	15.7	7.0
1998	100	76.3	16.7	7.0
1999	100	75.6	16.8	7.7
2000	100	74.2	17.8	8.0
2001	100	73.0	18.6	8.4
2002	100	70.6	20.0	9.4
2003	100	68.7	21.0	10.3

Source: SIS, 2004

The educational level of employed women on average is even worse than men. In 1988, 88.8 % of the employed women were educated in less than high school level. High school graduates were 7.1 % and university graduates were 4.1%. In 2003, the ratio of employed women educated in less than high school level has decreased to

74 %, (Table 2.20). The ratio of high school and university graduates reached 13 % and 12.9 % respectively. These statistics reveal that the number of educated women as well as the level of educated women that are employed is increasing. The change in the educational level of employed men and women is shown in Figure 2.11 and Figure 2.12.

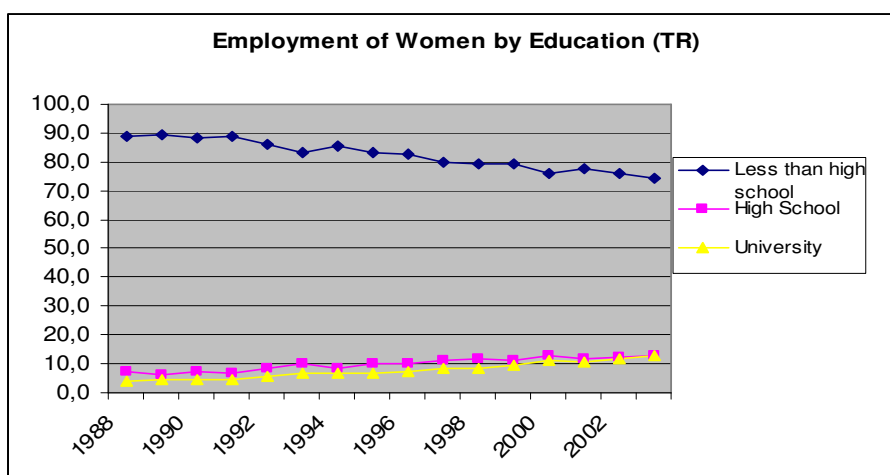


Figure 2.12: Employment of women by Educational Status in Turkey

When the employed population on urban and rural areas is analyzed in terms of educational level, it is observed that educational levels are higher than the overall educational levels for both genders. In the urban areas, the ratio of employed men with less than high school educational level has decreased from 78.5 % to 58.9 % in 2003. During the same period the high school graduates` ratio increased from 13.5 % to 26.5 % and the ratio of university graduates reached 14.4 % (Table 2.19).

Table 2.18: Educational Status of Employed Women in Turkey

Women Employment by Education (TR)				
Year	Total Unemployment	Less than high school	High School	University
1988	100	88.8	7.1	4.1
1989	100	89.5	6.1	4.4
1990	100	88.2	7.2	4.6
1991	100	88.7	6.5	4.7
1992	100	86.1	8.3	5.6
1993	100	83.4	10.1	6.5
1994	100	85.3	8.3	6.4
1995	100	83.4	9.9	6.7
1996	100	82.7	10.3	7.1
1997	100	80.0	11.4	8.6
1998	100	79.4	11.9	8.7
1999	100	79.4	11.3	9.3
2000	100	76.0	13.1	10.9
2001	100	77.4	11.8	10.8
2002	100	76.2	12.3	11.5
2003	100	74.1	13.0	12.9

Source: SIS, 2004

Compared to the overall employment by educational status in Turkey, the educational level of employed women in urban areas is better. Furthermore, the educational level of employed women is better than the educational level of men in urban areas. The ratio of the women that have less than high school level education has decreased from 59.7 % in 1998 to 42.7 % in 2003. During the same period the ratio of high school graduates increased to 27.1 % from 25.4 % and the ratio of university graduates increased to 29.4 % from 14.9 % (Table 2.20.). These statistics indicate that in urban areas high skilled women participate in the labour force and get employed.

Levent et.al, (2002), state that this high educational level of women in the urban employment is an expected result since the participation rate of women in urban areas is related to their educational status. The more they are educated the more they participate in the labour force.

Table 2.19: Employment of Men by Educational Status in Urban Areas

Men Employment by Educational Status in Urban Areas				
Year	Total Unemployment	Less than high school	High School	University
1988	100	78.5	13.5	8.0
1989	100	78.0	13.8	8.2
1990	100	77.4	14.1	8.5
1991	100	76.4	15.3	8.2
1992	100	75.1	16.3	8.6
1993	100	73.1	17.7	9.2
1994	100	71.6	18.6	9.8
1995	100	69.7	20.0	10.2
1996	100	68.6	20.8	10.7
1997	100	68.4	20.5	11.1
1998	100	67.5	21.6	10.9
1999	100	66.4	22.0	11.6
2000	100	63.9	23.5	11.8
2001	100	63.4	24.0	12.3
2002	100	61.1	25.4	13.5
2003	100	58.9	26.1	14.4

Source: SIS, 2004

When the educational history of employed women is plotted on a time scale (Figure 2.13) it is observed that, the ratio of employed university graduates has gradually reached the ratio of high school graduates over time. This result is expected since the educational demand of women is higher than men in urban areas. Between 1990 and 2000, the average duration of being at school has increased to 10.1 years from 8.4 years in women and to 8.4 from 7.0 years in men.

Table 2.20: Employment of Women by Educational Status in Urban Areas

Women Employment by Educational Status In Urban Areas				
Year	Total Unemployment	Less than high school	High School	University
1988	100	59.7	25.4	14.9
1989	100	60.2	23.0	16.8
1990	100	57.0	25.1	17.8
1991	100	54.8	25.9	19.4
1992	100	53.0	27.6	19.4
1993	100	51.1	29.0	19.9
1994	100	54.8	24.0	21.1
1995	100	48.3	29.2	22.6
1996	100	46.2	29.6	24.1
1997	100	44.3	29.6	26.1
1998	100	42.3	31.5	26.2
1999	100	43.3	29.3	27.4
2000	100	41.7	30.3	27.5
2001	100	44.3	27.5	28.0
2002	100	44.9	26.9	27.7
2003	100	42.7	27.1	29.4

Source: SIS, 2004

When the educational status of employed men is analyzed in rural areas, it is observed that the ratio of high school graduates and university graduates is on the rise. The ratio of high school graduates has reached 13.6 % in and the ratio of university graduates has reached 4.3 % (Table 2.21). Similar to women employment characteristics in rural areas, the employees having elementary school education account for the most of men employment in rural areas.

Table 2.21: Employment of Men by Educational Status in Rural Areas

Employment of Men in Rural Areas				
Year	Total Unemployment	Less than high school	High School	University
1988	100	91.1	6.3	2.6
1989	100	91.2	5.9	2.9
1990	100	91.0	6.3	2.7
1991	100	91.9	5.7	2.4
1992	100	90.8	7.0	2.1
1993	100	90.5	7.1	2.4
1994	100	90.5	7.6	1.9
1995	100	88.8	9.4	1.8
1996	100	87.8	10.0	2.2
1997	100	87.8	10.0	2.2
1998	100	87.0	10.7	2.4
1999	100	87.1	10.5	2.8
2000	100	88.1	10.1	2.9
2001	100	86.2	11.2	3.0
2002	100	84.0	12.6	3.8
2003	100	82.9	13.6	4.3

Source: SIS, 2004

The educational level of women in rural areas is far worse than that of men employment. In 2003 the 93.6 % of total employed women have elementary level education 2.6 % are graduates and 4.3 % are high school graduates (Table 2.22). These statistics are expected since, in the rural areas, the most important sector of

employment is agriculture and women are expected to work in agriculture as non paid family workers. According to Levent et.al, 2002 women account for the 70 % of total workers in agriculture and only 0.1 % are paid workers.

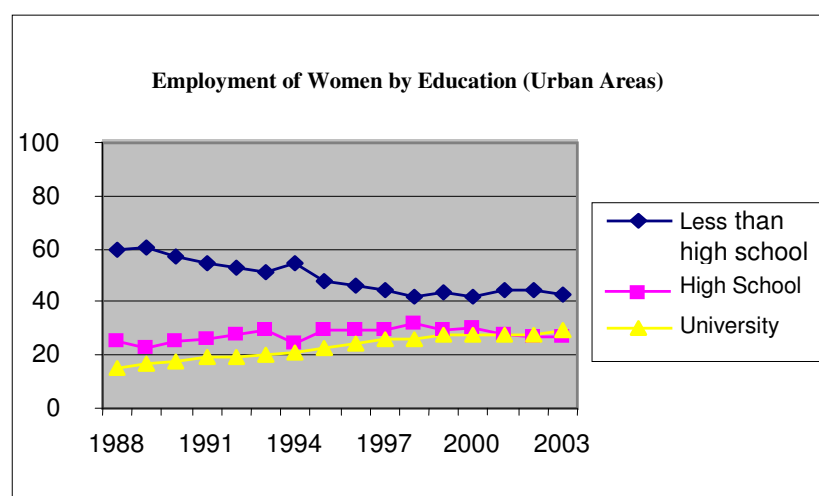


Figure 2.13: Employment of women by Educational Status in urban areas

Table 2.22: Employment of Women by Educational Status in Rural Areas

Year	Total Unemployment	Less than high school	High School	University
1988	100	96.4	2.3	1.3
1989	100	97.0	1.8	1.2
1990	100	96.6	2.4	1.0
1991	100	97.5	1.5	1.0
1992	100	96.9	2.0	1.1
1993	100	95.8	2.9	1.4
1994	100	96.6	2.4	1.0
1995	100	96.4	2.7	0.9
1996	100	96.0	3.2	0.8
1997	100	95.6	3.5	0.9
1998	100	95.4	3.5	1.1
1999	100	95.6	3.2	1.1
2000	100	95.0	3.6	1.7
2001	100	95.1	3.5	1.6
2002	100	94.6	3.8	2.0
2003	100	93.6	4.3	2.6

Source: SIS, 2004

The important characteristics of Turkish employment analyzed so far can be summarized as follows:

- Agriculture is still the most important sector in employment. It accounts for the 34 % of the total employment. However, as a result of transition from agriculture to industry and as a result of internal immigration the service sector and the manufacturing sectors ratio are on the rise.

- Women are less employed compared to men in urban areas and are especially employed in agricultural sector in rural areas. In the urban areas the educational status of women is quite high, 29 % of total women employees are university graduates, however in the rural areas they are low skilled un-paid family workers.
- Young population, the age groups of 20-24 and 25-34 are highly affected by economic stability and their employment levels have decreased especially after 1996.

In the following section the characteristics of Turkish unemployment will be analyzed in terms of gender, age, educational status and area.

2.2.4 Unemployment Characteristics of Turkey

The unemployment statistics reveal that Turkey has observed a period of significant decrease in unemployment levels during 1988 and 1996. Gursel and Ulusoy, (1999), stated that this decrease is a result of the increase in the number of new jobs created. However they pointed out that this decrease might not be stable. Turkey might face high unemployment rates as a result of the further transition of employment in agriculture to industry, the slowdown in economic growth and the ending of the early pension system.

The evaluations of Gursel and Ulusoy, (1999), came true in time and unemployment rates have shown an increase in both urban areas and rural areas after 1996. Unemployment rates increased by 7 % in overall Turkey, 6 % in urban areas and 9 % in rural areas and reached 10.3 % in overall Turkey (Table 2.23). These levels are quite high compared to the average unemployment rate of 7.9 % in major European countries (Table 2.2). However even 10.3 % is misleading. Turkey has 33.8 % agricultural employment and unemployment rates are quite low in rural areas compared to Turkey. Even 1 hour of daily work of the family members in agriculture is considered a being employed and thus lowers the overall unemployment rates in rural areas. Therefore, in Turkey the unemployment rates in the urban areas are of more importance. As mentioned in the previous paragraphs, there is a continuing internal migration from rural areas to urban areas, the participation rates in urban areas are on the rise, most of the highly- skilled population live in the urban areas and agricultural employment is in negligible levels in urban areas. Therefore the

unemployment statistics of the urban areas should be taken into account while evaluating the unemployment rates in Turkey.

Levent et. al. (2002), state that the increase in unemployment rates is not surprising. The participation rates of woman have significantly raised in 1996 with a smaller rise in men participation rates. During the second period of 1990s, growth has showed an unstable behaviour and this situation has seriously decreased employment in manufacturing sector and therefore the unemployment rates in urban areas have reached 11.4 % in 1999. With the effect of the economic crisis faced in 1999 and 2001, this level has increased and unemployment levels have reached 13.8 % in 2002.

Table 2.23 : Unemployment Rates in Turkey, by Area

	Unemployment rate (TR)	Unemployment rate (Urban) %	Unemployment rate (Rural)
1988	8.4	13.1	5.0
1989	8.6	13.1	5.3
1990	8.0	12.0	4.9
1991	8.2	12.6	4.7
1992	8.5	12.6	5.0
1993	8.9	12.6	5.5
1994	8.5	12.4	5.0
1995	7.6	10.8	4.8
1996	6.6	9.9	3.7
1997	6.8	10.0	3.8
1998	6.9	10.5	3.3
1999	7.7	11.4	3.8
2000	6.5	8.8	3.9
2001	8.4	11.6	4.7
2002	10.3	14.2	5.7
2003	10.5	13.8	6.5
2004	10.3	13.6	5.9
Average Growth Rate (%)			
1988-2003	2.1	1.1	2.5
1988-1996	-2.8	-3.3	-3.1
1996-2003	7.8	6.2	9.0

Source: SIS, 2004

When the unemployment rates are analyzed with respect to age in order to understand the characteristics of unemployment, it is observed that in the urban areas the highly affected group is young population similar to the structure in global unemployment (Table 2.24 and Table 2.25).

Table 2.24: Unemployment Rates of Men by Age in Urban Areas, SIS 2004

Men Employment by Age (Urban)						
Year	Total	15-19	20-24	25-34	35-54	55+
1988	9.7	21.8	21.3	5.7	5.1	11.7
1989	10.1	20.8	18.7	6.1	6.8	13.1
1990	9.5	20.1	19.6	5.0	5.3	9.8
1991	10.6	19.4	23.3	8.0	6.1	7.8
1992	10.7	20.0	21.5	8.8	6.4	7.6
1993	10.5	21.4	24.1	8.5	5.2	6.8
1994	10.5	21.4	21.8	8.0	6.4	6.3
1995	9.0	19.1	19.3	6.9	5.2	8.1
1996	8.7	17.4	20.1	7.1	4.8	4.2
1997	8.2	17.3	17.6	6.9	4.7	4.7
1998	9.1	18.4	20.6	7.4	5.4	4.9
1999	9.9	18.0	21.7	8.8	6.2	5.4
2000	7.8	13.9	17.1	7.0	4.9	5.7
2001	10.3	18.3	21.2	9.0	7.2	5.8
2002	13.0	22.6	24.6	11.6	9.8	8.9
2003	12.6	20.9	24.8	11.4	9.1	10.0
Average Growth Rate (%)						
1988-2003	2.6	0.5	1.9	6.5	6.2	1.7
1988-1996	-1.1	-2.6	-0.1	4.8	1.3	-9.1
1996-2003	6.9	4.1	4.2	8.5	11.9	14.1

By 2003, unemployment rate in 15-19 age group of men has reached 20.9 %, in the 20-24 age group 24.8 %; in women, in the 15-19 age group 28.6 % and in the 20-24 age group 29.1 %. The high levels in youth employment is threatening since as mentioned in the previous sections unemployment in early life may permanently impair employability. The statistics also reveal that in the 35-54 and 55+ age groups, the rise in unemployment levels have risen significantly during 1996 and 2003. The rise in average annual increase in men unemployment rates in the 35-54 and 55+ are 11.9 % and 14.1 %, the same increase has been 10.7 % in 35-54 age group and 9.6 % in the 55+ age group.

The rise in older age groups may be explained by the high indemnity levels. The statistics also show that unemployment rates in women during 1988 and 1996 have decreased significantly however this trend has not continued after 1996, the year in which participation rates of women started to increase.

Table 2.25: Unemployment Rates of Women by Age in Urban Areas, SIS 2004

Women unemployment by Age (Urban)						
Year	Total	15-19	20-24	25-34	35-54	55+
1988	28.3	40.8	42.0	22.8	14.9	9.5
1989	26.2	38.4	38.6	22.0	14.7	11.5
1990	23.5	37.7	35.0	20.0	11.9	2.8
1991	22.6	35.8	31.9	20.5	9.7	3.4
1992	21.0	34.5	31.8	17.2	9.7	4.2
1993	22.9	36.2	33.9	20.6	9.8	5.4
1994	20.5	31.3	31.2	19.4	9.5	3.7
1995	18.3	28.0	28.9	16.5	8.4	3.4
1996	15.3	25.4	25.3	13.8	5.6	3.7
1997	17.5	29.9	27.4	15.5	6.4	4.0
1998	16.4	27.3	24.6	13.6	8.4	5.0
1999	17.4	32.3	26.1	15.7	8.1	4.2
2000	13.0	24.4	21.5	10.5	6.2	2.0
2001	16.6	32.9	25.5	14.2	8.3	3.5
2002	18.7	33.2	28.1	17.2	10.1	6.0
2003	18.2	28.6	29.1	16.9	10.1	3.6
Average Growth Rate (%)						
1988-2003	-2.0	-1.3	-1.9	-0.4	-0.7	3.8
1988-1996	-7.1	-5.6	-6.0	-5.4	-10.7	-1.3
1996-2003	3.8	3.5	2.7	5.3	10.7	9.6

As previously mentioned, the unemployment rates in urban areas are quite low compared to unemployment rates in urban areas. Therefore rather than analyzing the percentage change in unemployment rates, the general structure in terms of age will be summarized briefly. The unemployment is lowest in old age group population in both men and women in rural areas. In the population with ages of 25 and over, unemployment rates are low, these rates are lowest in the age group 35+ (Table 2.26 and Table 2.27). The reason for the relatively high unemployment levels of youth may be explained by the fact that, younger population have higher educational levels compared to older population and therefore do not get involved in the agricultural sector, and can not find a suitable work that matches their skills.

Table 2.26: Unemployment Rates of Men by Age in Rural Areas (SIS, 2004)

Men unemployment by Age (Rural)						
Year	Total	15-19	20-24	25-34	35-54	55+
1988	5.3	14.0	12.6	3.5	2.0	1.0
1989	10.1	14.5	14.1	6.1	2.7	1.3
1990	5.9	12.8	14.1	6.8	2.4	0.8
1991	6.5	13.5	14.2	6.0	2.8	1.0
1992	6.6	13.1	17.3	6.1	1.9	0.8
1993	6.8	12.3	17.1	6.6	3.0	0.5
1994	6.6	12.3	14.4	6.8	3.1	0.9
1995	6.3	14.6	14.7	6.3	2.1	0.4
1996	4.7	9.3	11.8	4.7	1.9	0.7
1997	4.4	8.8	12.2	3.8	1.8	0.4
1998	4.0	7.2	11.2	4.1	1.8	0.7
1999	4.8	8.4	12.5	5.3	2.2	0.6
2000	4.9	8.2	13.9	4.6	2.8	0.6
2001	6.5	11.6	15.2	7.0	4.2	1.1
2002	7.3	11.7	18.7	7.6	5.3	1.1
2003	7.9	16.4	20.1	9.3	4.6	1.0

Table 2.27: Unemployment Rates of Women by Age in Rural Areas (SIS, 2004)

Women unemployment by Age (urban)						
Year	Total	15-19	20-24	25-34	35-54	55+
1988	4.5	7.7	8.7	4.6	1.6	0.6
1989	3.9	7.3	7.2	4.5	1.3	0.5
1990	3.4	6.5	6.7	3.2	1.3	0.7
1991	2.1	3.6	4.1	2.2	0.7	0.2
1992	2.4	3.7	6.0	2.1	1.0	0.0
1993	2.8	6.6	5.6	2.2	0.6	0.0
1994	2.4	5.1	4.6	2.5	0.7	0.0
1995	2.4	5.2	5.6	2.2	0.6	0.0
1996	2.0	4.2	5.0	1.7	0.5	0.0
1997	2.7	6.3	6.8	2.6	0.4	0.2
1998	2.0	5.1	3.7	2.4	0.4	0.1
1999	2.3	4.8	5.6	2.5	0.7	0.0
2000	2.0	2.9	4.6	2.5	1.2	0.2
2001	1.7	3.8	4.1	2.0	0.7	0.2
2002	2.9	5.1	7.0	3.5	1.6	0.1
2003	4.2	9.1	9.2	5.4	2.0	0.6

Since the highly educated people are employed in the urban areas, the highly affected educational levels should be analyzed with more detail. The statistics reveal that although the unemployment rate in elementary school level educated population and high school graduates are highest, it is observed that university graduates are also highly affected by the unemployment trend in the urban areas. Since 1996 the unemployment rate in university graduates has increased 10.6 % on the average. Similar structure can be observed in women. Although elementary school and high school graduates have the highest unemployment rate (these statistics are not surprising since higher skilled women are employed in urban areas. While men can work in less skill-dependent jobs like construction, women can not get employed in these sectors, therefore their sectors of employment are smaller in size compared to men), the unemployment rate increase in university graduates has been 9.2 % since 1996. The unemployment rates of men and women by education in urban areas are given below in Table 2.28 and Table 2.29 respectively.

Table 2.28: Unemployment Rates of Men by Education in Urban Areas

Men unemployment by Education (TR)				
Year	Total Unemployment	Less than high school	High School	University
1988	9.7	9.3	13.7	6.5
1989	10.1	10.0	12.5	5.9
1990	9.5	9.6	11.4	5.5
1991	10.6	10.9	11.9	6.0
1992	10.7	10.4	13.6	7.1
1993	10.5	10.4	12.4	6.9
1994	10.5	10.8	11.8	5.5
1995	9.0	9.1	10.6	5.1
1996	8.7	8.4	11.5	5.2
1997	8.2	7.9	10.6	5.4
1998	9.1	8.7	11.4	7.2
1999	9.9	10.3	11.7	7.6
2000	7.8	8.0	8.2	5.8
2001	10.3	10.5	11.2	6.9
2002	13.0	13.9	12.5	9.5
2003	12.6	13.9	11.1	9.3
Average Growth Rate (%)				
1988-2003	2.6	2.2	-0.3	3.9
1988-1996	-1.1	-0.9	-1.9	-2.1
1996-2003	6.8	5.7	1.4	10.6

The current unemployment situation shows that, unemployment is a threatening subject especially in urban areas and especially for the young population of Turkey. The young people are better educated compared to old population, however they are unable to use their skills in the current economic situation.

Table 2.29: Unemployment Rates of Women by Education in Urban Areas

Women unemployment by Education (Urban)				
Year	Total Unemployment	Less than high school	High School	University
1988	28.4	29.0	32.4	17.0
1989	26.2	28.0	30.5	11.0
1990	23.3	24.0	28.7	11.2
1991	22.5	23.4	27.9	10.3
1992	21.0	22.0	24.7	11.6
1993	22.9	22.9	28.2	13.5
1994	20.4	19.2	29.5	10.5
1995	18.3	18.9	23.9	8.3
1996	15.4	13.8	22.4	8.8
1997	17.5	16.0	25.3	9.5
1998	16.5	15.2	22.1	10.8
1999	17.4	17.1	21.2	10.6
2000	13.0	12.8	16.2	9.4
2001	16.6	17.4	21.5	10.1
2002	18.8	18.0	24.4	14.6
2003	18.4	17.0	22.1	15.1
Average Growth Rate (%)				
1988-2003	-2.0	-2.0	-1.5	0.9
1988-1996	-7.1	-8.4	-4.1	-6.3
1996-2003	3.8	5.3	1.4	9.2

Bulutay (1995), states that the principal characteristics of Turkish labour market is the main reason behind the unemployment problem in Turkey. There is high population growth (1.5 % as of 2003), with a large number of population stock. A large proportion of the population lives in the rural areas and works in agriculture

with low productivity. As a result, there is a serious employment problem with the unpaid family workers. Migration to cities is another major problem (currently % 60 of whole population live in cities) since the job creating capacity in cities and industry is limited. Therefore there is a serious unemployment problem in the cities. Labour is heterogeneous and there are large wage differentials. The economy and the labour market are somewhat insensitive to trade cycles. Although GNP increases, this does not affect unemployment rates. There is high level of unregistered unemployment as a result of high levels of labour costs.

Moreover, as a result of globalization, firms tend to produce goods and services with minimum costs. This results with the higher average working hours and higher productivity of workers with high levels of unregistered employment and informal economy. Technological improvements force the firms to look for more educated, skilled workers and therefore cause a mismatch problem in the labour market.

Bulutay, (1995), also states that investment, capital accumulation is an important factor in the analysis of employment, unemployment and wages in Turkey. Contrary to the Western economic literature that states that unemployment is a result of rigidity of the labour market, high levels of wages, high and long term unemployment benefits, the problem in Turkey is about lack of work to do and therefore insufficient investment. Gursel and Ulusoy, (1999), state that unemployment is a result of lack of sustainable growth in Turkey.

3. LITERATURE REVIEW ON THEORIES AND TYPES OF UNEMPLOYMENT

In this section of the study, the basic types of unemployment, and the basic unemployment theories are summarized. Since this study aims to develop a methodology to predict actual unemployment in Turkey and to identify the relative importance of macroeconomic factors on unemployment in Turkey, the detailed analysis of the theories and of types of unemployment is beyond the scope of this study and will be described just briefly.

3.1 Types of Unemployment

According to its characteristics, unemployment can be grouped into different types. These types are namely, structural unemployment, frictional unemployment, natural unemployment and cyclical unemployment.

3.1.1 Structural Unemployment

The long term and chronic unemployment that exists when the economy is not in a recession is called structural unemployment (Abel and Bernanke, 1998). Structural unemployment occurs because of skill mismatch. Unskilled or low skilled workers are often unable to find desirable, long term jobs. The jobs available for unskilled or low skilled workers are generally short termed, offering low wages and whenever these jobs end, workers enter the stock of unemployed. Structural unemployment can be regarded also as a result of the fast changes in technology and industries. Since the requirements of the industries can not be matched by the skills of the unemployed workers in the labour force, these workers remain being unemployed.

3.1.2 Frictional Unemployment

Frictional unemployment occurs as workers search for suitable jobs and firms look for suitable workers. This type of unemployment is relatively a short termed

unemployment which is a result of the movement of people between jobs in and out of the labour force.

3.1.3 Natural Rate of Unemployment

Due to the combination of frictional and structural unemployment, the unemployment rate of an economy is never zero, even when the economy is at full employment level (The equilibrium level of employment, achieved after the complete adjustment of wages and prices where labour demand is equal to labour supply). The rate of unemployment that occurs when output and employment are at the full employment level is called the natural rate of unemployment which reflects the unemployment due to frictional and structural causes (Abel and Bernanke, 1998). There is no single measure for natural rate of unemployment, many economists believe that natural rate was in the 4-5 % during 1950s and increased gradually to about 6 % in the 1980s. Since it is not possible to understand whether economy is at full employment it is not possible to directly observe natural rate of unemployment therefore it is generally estimated.

3.1.4 Cyclical Unemployment

The difference between the actual unemployment rate and the natural rate of unemployment is called cyclical unemployment. It occurs because of the lack of jobs to get involved.

3.2 Theories of Unemployment

3.2.1 Classical Theory

According to Classical or Neoclassical theory people pursue their own economic self interests and prices adjust quickly to achieve equilibrium in all markets. Employment and output are determined in the labour market by the demand for labour and the supply of labour. There is no involuntary unemployment and any involuntary unemployment would disappear as real wages declined (Carlin and Soskice, 1990). The real wage rate is the price of labour, equilibrating the demand for labour to supply of labour. When wage is above the equilibrium rate, the supply of labour will exceed the demand for labour. Competition among the suppliers of labour will bring the wage rate to the equilibrium level (Bulutay, 1995.)

3.2.2 Keynesian Theory

Keynesian theory was a response to the classical theory as it was unable to analyze the high level of unemployment in the depression in 1930s. According to Keynesian model, wages and prices did not adjust rapidly to achieve equilibrium. Slow wage and price adjustment meant that markets could be out of equilibrium, and with a fixed money wage, employment and output are determined by aggregate demand in the product market, this feature of the model stated that there can be involuntary unemployment (Carlin and Soskice, 1990). Unemployment is a result of the lack of effective demand for goods and services and that the demand for labour may be increased by increasing the demand for goods and services. According to Keynes, by the increase in the expenditures of governments, the aggregate demand for goods and services and therefore for labor may be increased. The newly hired workers also create further demand for the output and would raise employment further. Moreover, by causing the interest rates to fall, governments may increase investment which increases employment.

An important component of Keynesian economics, the Philips curve was developed by A.W. Philips. The curve shows a quantitative relationship between inflation and unemployment. According to the Philips curve, there is a trade off between unemployment and inflation. Unemployment tends to be low during high levels of inflation and high during low rates of inflation. In the 1960s, the Philips curve was observed in U.S. economy, however the following decades showed that the relationship between unemployment and inflation failed to hold in U.S. In 1970s the U.S. economy showed high rated of unemployment as well as high rates of inflation simultaneously (stagflation) (Abel and Bernanke, 1998).

3.2.3 Monetarist Theories

Friedman and Phelps questioned the logic of Philips curve and stated that there exists a negative relationship between unanticipated inflation (the difference between the actual and expected inflation rates) and unemployment (Abel and Bernanke, 1998). When expectations are not fulfilled, and the inflation is unanticipated, it could increase unemployment. In this case, the Philips curve with the known shape could exist. In the other case, when expectations are fulfilled, when inflation is anticipated, it will have no effect on employment. In this case, the Philips curve would move

upward to cause higher inflation. Friedman stated that, there is no stable trade-off between inflation and unemployment and that there is a natural rate of unemployment. Unemployment can be kept below that level only by accelerating inflation or above it only by accelerating deflation. Therefore Friedman introduced the concept of natural rate of employment (Bulutay, 1995). Friedman's argument was that households base their labour supply decision on the expected real wage, for which they have to rely on outdated price information. If the estimate of the current real wage is based on last periods rate of inflation, then rising inflation creates a misperception on the part of workers and leads to the supply of more labour than the supply of labour if the ex post real wage had been known. With the adaptive expectations, unemployment below the natural rate requires that this illusion be recreated each year and hence implies rising inflation (Carlin and Soskice, 1990).

3.2.4 New Classical Theories

The new classical economists replaced the adaptive expectations used in Friedman's model with rational expectations. Under the rational expectations, there are no systematic errors in making price forecasts. The new classical model states that there is no role for the government in securing the operation of the economy at the natural rate, since, apart from random disturbances; the economy is continuously at equilibrium at the unique natural rate. Furthermore, any systematic attempt by the government to reduce unemployment below the natural rate will be totally unsuccessful. According to the new classical model, agents know that there is a single real equilibrium in the economy. In response to an announced expansion of demand by the government, they will simply adjust prices and wages upward immediately, leaving the economy at the natural rate of unemployment with a higher price level (Carlin and Soskice, 1990).

3.2.5 NAIRU Theory

Many Keynesians have preferred to use NAIRU (Non-accelerating inflation rate of unemployment) rather than the natural rate to describe the rate of unemployment with stable inflation. The dramatic rise in unemployment rates, particularly in Europe, during the 1980s, suggested that natural unemployment rate or NAIRU must have risen and estimates by econometricians confirmed this view (Snowdon et.al., 1994). The rise in European unemployment is attributed to the changes in the rigidity

of the labour market, like the more powerful trade unions, higher unemployment compensation, minimum wage laws, excessive regulations, and higher taxation.

In this section the unemployment theories as well as the types of unemployment are summarized briefly. The different unemployment types and the theories of unemployment help us to develop an understanding of the basic sources of unemployment. According to the different views of different schools and theoreticians, different factors are identified that affect unemployment in nations. In order to aggregate the different views on the list of factors that affect unemployment in Turkey, it is decided to apply cognitive mapping methodology. In the following section, Section 4, the cognitive mapping methodology which is used in this study to extract expert knowledge on the identification of the variables related to unemployment in Turkey, as well as the affects of these variables on unemployment in Turkey, is described in detail.

4. COGNITIVE MAPPING

In this part of the study, cognitive mapping methodology will be described in detail. Cognitive mapping method will be used in choosing the relevant variables in the modeling of unemployment rate in Turkey in the following sections.

While working with messy, complex systems there is a need to understand the behavior of these systems. Each statement in the system needs to be defined and the relations among these statements are needed to be known. Cognitive maps are directed graphs used in understanding and capturing the cause-effect relationships in these complex causal systems and facilitate understand the interconnections within the elements of the systems. Cognitive mapping technique is a popular technique in investigating individuals' cognitive representations in strategic decision making. (Hodgkinson et.al, 2004). Eden and Ackerman, (1998) define cognitive mapping as a technique designed to capture the thinking of an individual about a particular issue or problem in a diagrammatic format. The map also reveals how the elements of the issues relate to each other and how changes in the character of one element may have effects on another. Similar to Eden and Ackerman's (1998) definition, Tegarden and Sheetz (2003) define cognitive mapping as a technique that captures the individuals' view of a particular issue in a graphical representation. Özesmi and Özesmi (2004) define cognitive map as a qualitative model of how a given system operates and state that they are especially applicable and useful tools for modeling complex relationships among variables.

One of the typical frameworks of cognitive mapping is Axelrod's theory of 'structure of decision'. Wang, (1996) states that Axelrod's cognitive map is a representation of the relationships which are perceived to exist among the elements of a given environment. Axelrod's approach to cognitive mapping is based on the diagrammatic representation and analysis of the causal relations hidden in documents and speeches to help the decision making process in political problems. Eden, (2004), states that the basis for the approach to cognitive mapping used by Axelrod and colleagues in the field of political science was that "when a cognitive map is pictured in graph

form it is then relatively easy to see how each of the concepts and causal relationships related to each other and to see the overall structure of the whole set of portrayed assertions”.

Eden and Ackerman`s approach to cognitive mapping is based on personal construct theory (Kelly, 1955) which proposes an understanding of how humans make sense of their world by seeking to manage and control it (Eden, 2004). Humans try to develop different plans to manage and control their lives with respect to different possible situations they face in their lives by relying on their past experiences and their instinct. In this respect, personal construct theory sees man as a scientist constantly trying to make sense of the world in order to act within and upon that world.

In Eden and Ackerman`s approach, cognitive mapping based on personal construct theory is used as a decision aid tool in organizational strategy making. It is assumed that like the humans do in their personal lives, decision makers, stakeholders related to a business situation are able to interpret an event, identify the causes and predict consequences and that they can generate actions to handle the event in their business domain. Eden and Ackerman developed SODA (Strategic Options Diagnostic Analysis) methodology to elicit beliefs, values and expertise of decision makers and stakeholders relevant to the issue by making computer aided guided interviews and to construct a visual representation of their beliefs about causes and consequences of particular events (Eden and Ackerman, 1998). SODA was firstly developed as a methodology to resolve complex strategic problems in organizations, however as time passed it was used for problem solving and management teams used the process and its outcomes as an influence on their strategy. The methodology was later developed into a process oriented management science strategy making and delivery methodology called JOURNEY making (Eden and Ackerman, 2004).

A cognitive map is made up of two basic elements: concepts and causal beliefs. The concepts are the variables in the map and causal beliefs are treated as the relationships between the variables (Axelrod, 1976). The concepts in the map are represented as nodes or points and the causal beliefs are represented as directed arrows. There are basically three types of cognitive maps:

Simple cognitive maps	$A \rightarrow^+ B$	$C \rightarrow^- D$	$E \rightarrow^0 F$
Weighted cognitive maps	$A \rightarrow^{+0.2} B$	$C \rightarrow^{-0.6} D$	$E \rightarrow^0 F$
Fuzzy cognitive maps	$A \rightarrow^{+low} B$	$C \rightarrow^{-medium} D$	$E \rightarrow^0 F$

Depending on the representation of the causal relation between the concepts, the cognitive maps may take the type of either a basic cognitive map, a weighted cognitive map or a fuzzy cognitive map. In simple cognitive maps the relations between the concepts may take three values. “+”, “-“, and “0”. “+” signifies a positive causal relation between the concepts (in other words, other things being equal, an increase in concept A will results in an increase in concept B); “-“ signifies a negative causal relation between the concepts and “0” signifies that there is no causal relation between the concepts. In weighted cognitive maps the relation between the concepts are shown in a weighted form and in fuzzy cognitive maps the relation between the concepts the weights are shown in a fuzzy form taking the values like “positively low, positively very low, negatively medium etc.”.

Cognitive maps are especially applicable and useful tools for modeling complex variables among variables. To model complex issues, addition of different experts/ decision makers` cognitive maps may yield better results (Eden et.al., 2003). The use of different experts in the modeling process makes it possible to compare and discuss the similarities and differences defined by different experts. Once the cognitive maps are derived, they act as an important aid in decision making. There are mainly four basic types of decision problems that the cognitive maps may be helpful (Axelrod, 1976):

- The Decision-Making Problem: Given a cognitive map with one or more policy variables and a utility variable, it is possible to define the policies that have positive effect on the utility variable and those that have negative effect on the utility variable. In this problem, the policies that have positive effect on the utility variable should be chosen and others should be rejected.
- The Forecasting Problem: This problem is related to understanding the consequences of a change in the value in certain given variables. This problem may be regarded as a generalization of the decision making problem.

- The Explanation Problem: Given a cognitive map and given some observed changes in some of the points, it is possible to find where these changes come from. This problem is a reverse for of the forecasting problem.
- The Strategic Problem: Given a cognitive map, it is possible to find the consequence of changing the sign of a variable. For example, it is possible to find which changes in the causal link would change an undesirable policy into a desirable policy.

4.1 Derivation of Cognitive Maps

The derivation of cognitive maps is an important step in cognitive mapping. Axelrod (1976) states that the derivation method used for building cognitive maps should satisfy four basic requirements:

- The methods should be unobtrusive.
- The derivation should not require advance specifications of the concepts a particular decision maker may use in his cognitive map.
- The derived cognitive map should include all the options, goals, ultimate utility and relevant intervening concepts of a decision maker.
- The method for deriving the cognitive map should be valid, that is, the map should be an accurate representation of the assertions and the relationships among them used by the decision maker and reliable, that is, the method should yield the same results when used by different researchers under the same conditions.

There are three types of derivation methods in literature that satisfy these requirements: Questionnaires, the coding from a document, and through interviews.

The derivation of a cognitive map from a document requires coding of a given text, speech or declaration, sentence by sentence or even phrase by phrase. The first stage of the coding process generates two lists, a list of concept variable in the text and a list of the causal assertions. In the second stage the assertions made by a given person are put together to construct that person's cognitive map (Axelrod, 1976). In deriving a cognitive map from a document by coding, the analyst/coder looks for the cause concept, linkage and effect concept relationships. In other words the coder looks for the sentences, phrases, or paragraphs that assert a causal relationship. For

example in the sentence “Nuclear escalation harms world peace” it is asserted that the cause concept “nuclear escalation” has a negative linkage to “world peace”, the effect concept. Although in this example the relationship is explicitly stated, in many cases the relations in the statements are implicit. In order not to distort the meaning, and put coder bias into the analysis, the coder must be careful in maintaining the original language especially in the statements where the relations are implicit, and should also be careful about not imputing his own assumptions and beliefs in the map (Wrightson, 1976).

Cognitive maps may also be derived by using questionnaires. In the questionnaire method experts are chosen who are knowledgeable, well-read, or concerned about the problem, but who do not necessarily represent a specific technical discipline.

The procedure starts with the identification of related variables. In this step experts are asked to list as many variables as they can think of, that might be relevant to (constrain, influence, cause, effect, be affected by, and so on) the problem at hand. If necessary, the variables are classified into groups, subgroups with respect to the suggestions of the experts.

If the number of variables is large, there may be a need to limit these variables. Roberts (1976), state that the variables may be limited by either clustering or by using a rating methodology. Once the variables are rated by the experts, the next stage is to choose the relevant variables. However, there are no firm rules in choosing the relevant variables. Roberts (1976), suggests firstly clustering and then choosing among the variables in the different clusters. From each cluster he suggests choosing the variables that have a median overall importance rating of five or greater in a seven-point scale. The next phase in the process is to determine the arrows and signs. The variables chosen in the previous phase are presented to the experts in an ordered pair like (x, y) where x and y represent different relevant variables. The expert is asked to decide whether a change in x has a significant effect on y and if it has, whether the effect is negative or positive. After these judgments or arrows and signs are gathered these judgments are aggregated to form the cognitive map. In case of a disagreement of the experts on the relationship of a pair of variables, the relationship defined by 60 % of the experts is taken into consideration.

A third method for deriving a cognitive map is the use of an open ended probing interview. The method can be seen as a hybrid model of the two given methodologies

above. Open ended probing has the advantage of allowing the researcher to interact actively with the source of his data and the method can be used to generate comparable cognitive maps (Axelrod, 1976).

4.2 The Mathematics of Cognitive Maps

To build a map from a set of assertions it is necessary to combine all the assertions that have the same cause variable and same effect variable into one relationship, by taking the intersection of their values. For example, if a person says “A can’t hurt B” and also says that “A helps B” the relationship is entered into the cognitive map as “A helps B”. As another example, the intersection of + and – is the empty set that is represented by the ambivalent value, $\emptyset$. Thus if a person says “C helps D” and also says “C hurts D” this should be taken as a neutral relation.

Once the relationships between all the variables are determined, the cognitive map can be drawn. Relationships that are in sequence form paths, and paths transmit indirect effects. For example, suppose there is a positive arrow (causal relationship) from A to B and another positive arrow from B to C, then there is a path from A to C from B and this path carries indirect positive effect. The operation of combining direct effects of relationships that are in sequence into indirect effects is called multiplication. The rules of multiplication in calculating the indirect effects are as follows:

1. Positive times anything is that thing.
2. Zero times anything is zero.
3. Ambivalent times anything (except zero) is ambivalent.
4. Negative times negative is positive.
5. Multiplication distributes over union.

For example, $(-)(\emptyset) = (-)(- \cup 0) = ((-)(-)) \cup ((-)(0)) = (+) \cup (0) = \emptyset$

6. Multiplication is symmetric.

For example, $(\emptyset)(-) = (-)(\emptyset)$

When two or more paths start with the same point and end with the same point, their effects can be added into a total effect of the first point on the second. This operation is called addition and the rules of addition operation are as follows:

1. Zero plus anything is that thing.

2. Ambivalent plus anything is ambivalent.
3. Positive or negative plus itself is itself.
4. Positive plus negative is universal.
5. Addition distributes over union.
6. Addition is symmetric. (Axelrod,1976)

4.3 Analysis of Cognitive Maps

Cognitive maps are complex systems because they are made up of a large number of variables that have many interconnections and feedback loops. The analysis of complex cognitive maps is difficult however; the matrix algebra tools of graph theory provide a simple way to analyze their structure. (Özesmi and Özesmi, 2004). The cognitive map may be transformed into a matrix format and the relationships may be represented in this matrix called the “valency matrix”. The valency matrix A is a square matrix of n X n where n is the total number of concepts in the corresponding cognitive map. A is a signed matrix composing of the values (v_{ij}) representing the strength of the relations between the variables in the map. $v_{ij} = 1$ if a positive relationship from i to j is present in the cognitive map, -1 if a negative relationship from i to j is present and 0 if the variables are unrelated. The diagonal elements in the map are considered to be 0.

The valency matrix has a number of useful properties: The sum of the absolute values of the elements of a row i gives the outdegree (od) of concept i, that is, the number of concepts perceived to be affected directly by concept i. Similarly, the coloumn sum of the absolute values of the elements of coloumn i gives the indegree (id) of concept i, the number of concepts perceived to affect concept i directly. The sum of the indegree and outdegree for concept i gives the total degree (td) of concept i, a useful operational measure of the concept’s cognitive centrality in the decision maker’s belief structure (Nozicka et.al., 1976).

Mathematically, these relationships may be expressed as:

$$id(i) = \sum_{j=1}^n v_{ij} \quad (4.1)$$

$$od(i) = \sum_{j=1}^n v_{ji} \quad (4.2)$$

$$td(i) = id(i) + od(i) \quad (4.3)$$

Özesmi and Özesmi, (2004) state that outdegree, indegree and total degree are important indicators in a cognitive map. The contribution of a variable in a cognitive map can be understood by calculating its centrality; the total number of receiver variables (variables having a positive indegree and zero outdegree) in a map can be considered an index of complexity and a large number of transmitter variables (variables having positive outdegree and zero indegree) indicates flatness of a cognitive map where causal arguments are not well elaborated. Additionally, transmitter variables can be seen as a forcing function in the map, which can not be controlled by any other variables and in contrast, a receiver variable can be seen as a variable having no affect on other variables in the system.

Another useful property of the valency matrix is that it permits the computation of the reachability matrix R . The reachability matrix raised to the second power is a square matrix also of size $n \times n$, each of whose elements r_{ij} is 1 if concept j is reachable from concept i , and 0 otherwise. While, the valency matrix A indicates only direct relationships between concepts, that is, concept linkage paths of length 1, the reachability matrix reflects the existence of indirect and deductive relationships as well.

The cognitive mapping methodology described in this section is used to identify the relevant variables in forecasting unemployment as well as employment in Turkey. In the next section, Section 5, artificial neural networks methodology is described in detail. Unemployment is a complex subject in which possible nonlinear interrelationships lie within the factors that affect unemployment. To overcome this complexity and the possible problems of applying a linear model to predict unemployment rates and employment index levels, neural networks methodology which is successfully used in regression and prediction analyses of complex nonlinear models in which the relationships between the input variables and the output variables are hidden, is applied. The variables identified by cognitive mapping methodology are used as the inputs to the neural networks analysis.

5. ARTIFICIAL NEURAL NETWORKS

Artificial intelligence can be simply defined as the capability of a computer to perform functions usually completed with human intelligence such as reasoning, learning and self-improvement. The general area of AI is broad, including the study of pattern recognition, robotics, process control methods, machine learning, expert systems, cognitive learning, artificial neural networks (ANNs), and genetic algorithms, (DeLurgio S.A., 1998).

Artificial intelligence technology has the basic objective of trying to gain an understanding of the inside mechanisms of a real life system and to predict and explain its behaviour. One of the emerging areas in artificial intelligence and machine learning is the Artificial Neural Network technique. Neural networks have been widely used in science, engineering, medical and business applications, economics, statistics and econometrics, (Qi, 2001; Smith and Gupta, 2001; Gately, 1996; Tckaz, 2001).

The main reasons for the growing interest in using Artificial Neural Networks (ANNs) are, their ability to approximate existing hidden relationships without imposing a priori assumptions on the behaviour of the system elements under consideration; their ability to learn, to deal with chaotic, fuzzy, or ill defined, category based data, and adapt successfully to nonlinear systems.

This chapter of the study reviews the basics of ANNs technique, the procedure in the implementation of ANNs, the use of ANNs in economic analysis and time series forecasting and the motivation of the study.

5.1 The Basic Structure of Artificial Neural Networks

The basic idea behind a neural network lies on the tremendous data processing capability of the human brain. Human brains are composed of large number of cells called neurons. These neurons are interconnected and signals are transmitted from one cell to another through connections. When the combined value of incoming

signals reaches a threshold, a signal is sent to other nerve cells. This structure of signal processing between the nerve cells can be described mathematically by neural networks. Haykin, (1999), describes the relation between the working of nerve cells and the mathematical neural network models in detail.

A node (representing a neuron in the human brain) is the basic element in a neural network. The nodes that provide external information to the network are called input nodes. These nodes have no entering arcs. The output nodes produce outputs of the network. Nodes which are neither input nor output are intermediate nodes in other words, hidden nodes.

A simple node in a neural network is given in Figure 5.1.

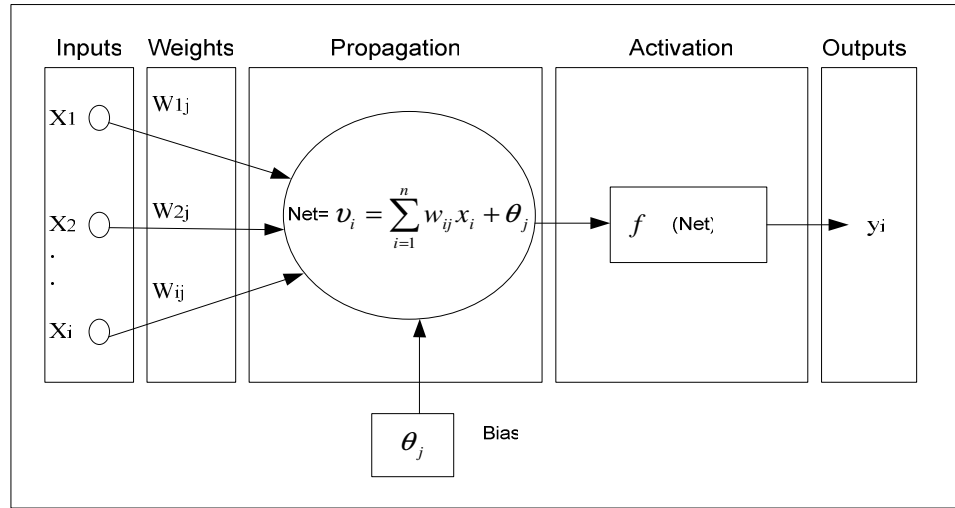


Figure 5.1: A Basic Node in a Neural Network (Elmas, 2003)

The computational process of each node is as follows. A node, as a processing unit receives inputs from a number of other nodes or from an external signal. A weighted sum of these inputs including the bias makes up the argument (generally called the net input) that is transferred to the activation function (from the propagation stage shown in Figure 5.1). The activation of a node is computed from the activation of nodes directly connected to it and the corresponding weights for those connections. The resulting value of the activation function is the output node. While the propagation process, is in most cases, a simple addition, it can be a maximum, minimum, majority, cumulative weighted sum or product. The activation function is a function, when applied to the net input of a neuron, determines the output of that neuron. Its domain must generally be real numbers as there is no theoretical limit to

what the net input can be. Nevertheless, the values it can output are usually limited. The most common limits are 0 -1, while some range from -1 to 1. While in the early studies of neural networks including the perceptron, simple threshold function is used as the activation function, it is generally accepted that a differentiable function is more appropriate as an activation function. The majority of current models use a sigmoid (S-shaped) activation function. A sigmoid function may be loosely defined as a continuous, real valued function whose domain is real numbers, whose derivative is always positive, and whose range is bounded. The most commonly employed sigmoid function is the logistic function, (Masters, 1993).

The operational characteristics of a neuron are primarily controlled by the weights, w_i . Although the activation function $f(\cdot)$ is also important, the neuron's operation is generally little affected by the exact nature of the activation function. However, training speed may be strongly impacted by the activation function, (Masters, 1993).

5.2 Network Architectures

Neural Networks are classified according to the differences between the structures of nodes and their connections (Elmas, 2003). A network is classified either as a feedforward network if it does not contain directed cycles, or recurrent if it does contain such cycles.

Most applications use a three layer network consisting of one input, one hidden and one output layer. Hidden nodes with their activation function are needed to introduce nonlinearity into the network.

5.2.1 Single-Layer Feedforward Networks

Nodes in a neural network are arranged by layers (Zhang et al., 1998). In the simplest form of a layer, there exists an input layer of source nodes that projects onto an output layer of neurons (computation nodes). The information flows from the input layer to the output layer in one direction. This network is called a single layer feedforward network where the single layer represents the output layer of the network (Haykin, 1999). The single layer feedforward network corresponds to the linear regression model when the output layer uses a linear activation function.

5.2.2 Multi-Layer Feedforward Networks

A multi-layer feedforward neural network consists of a set of neurons that are logically arranged into two or more layers (Masters, 1993). In addition to the input and output layers there exists one or more hidden layers, whose computation nodes are called hidden neurons or hidden units.

Hidden units with their activation function are used to capture the nonlinear structures in the system observed (Zhang et al., 2001). The ability of hidden nodes to extract nonlinear structures is particularly valuable when the system under consideration is complex, where the size of the input layer is large and the underlying relationship between the input and output units are undeterminable.

The process in the multilayer feedforward networks starts with the sending of the signals from the input layer to the second layer- the first hidden layer, the signals are processed in the second layer and the outputs of the second hidden layer are used as the inputs of the incoming layer. The set of signals of the neurons in the output layer constitutes the overall response of the network. Figure 5.2, shows a multi layer feedforward network having two hidden layers.

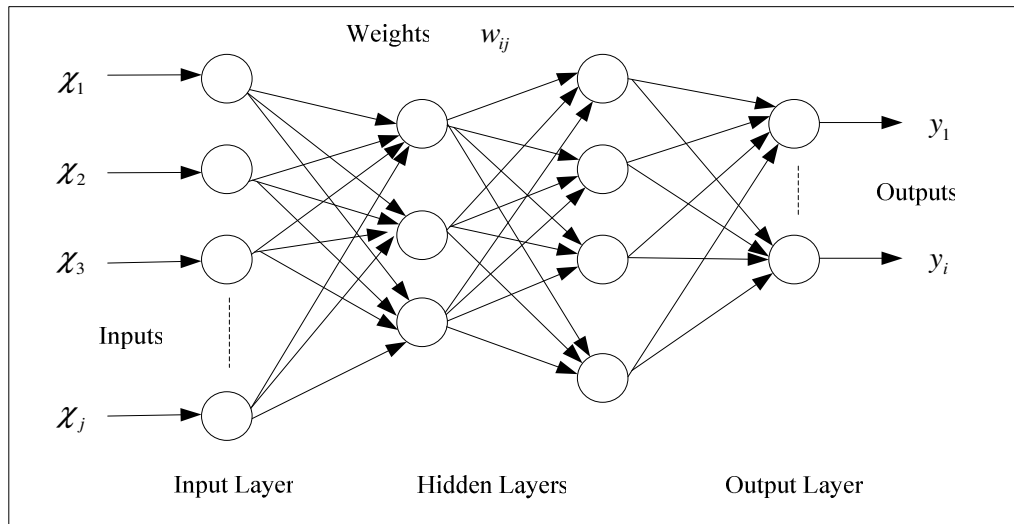


Figure 5.2: Multi-Layer Feedforward Neural Network (Haykin, 1999).

Multi-layer feedforward neural networks, especially the one hidden layer feedforward network type is the mostly used model form in literature (Masters, 1993). The popularity of the one hidden layer feedforward networks come from the fact that they are universal approximators (Zhang et al., 2003).

5.2.3 Recurrent Neural Networks

A recurrent neural network is different from the feedforward neural networks by having at least one feedback loop. The feedback loop helps to implement a delay in the system.

5.3 Learning in Neural Networks

All knowledge in an artificial neural Networks (ANN) is encoded in its interconnection weights among the neurons determined by the learning process. A weight represents the strength of association among connected features, concepts, propositions or events during a training period. A neural network learns by adaptation in the training phase in which the interconnection weights are changed appropriately. Therefore, learning can be simply defined as the modification in weights so that they perform according to the required performance criteria (Haykin, 1999).

There are basically three learning types by which a neural network can be trained. In “supervised learning”, it is assumed that a teacher or supervisor exists and this supervisor presents a set of input patterns to the network with their desired outputs in order to train the network (Masters, 1993).

The second principal learning method is “unsupervised learning”. In unsupervised learning inputs are provided, however, the outputs corresponding to those inputs are not given to the network. The assumption in this type of learning is that each input arises from one of several classes, and the networks output is an identification of the class to which its input belong. Unsupervised learning method is applicable especially to classification problems.

The third type of learning is the hybrid learning which is a combination of the supervised learning and unsupervised learning, labeled as the reinforcement learning.

In this study, supervised learning methodology will be described in detail since it will be used in the analysis of the factors affecting unemployment problem in Turkey. Further information about unsupervised learning and reinforcement learning may be found in Haykin, 1999 and Schalkoff, 1997.

Learning in neural networks is accomplished by the use of learning algorithms. The learning algorithms aim to reduce the differences between network output and the target output by minimizing a cost function, in most of the cases, an error function. The most popular type of supervised learning algorithm is the backpropagation algorithm and the learning process performed with the algorithm is called the backpropagation learning.

Backpropagation learning consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass an activity pattern (input vector), selected from the training set is applied to the network, and its effect propagates through the network layer by layer. Finally a set of outputs is produced as the actual response of the network. During the forward pass, the weights of the network are all fixed. During the backward pass, the weights are all adjusted in accordance with an error minimization rule. The actual response of the network is subtracted from a desired- target response to produce an error signal. This error signal is then propagated through the network against the direction of the weights. The interconnection weights are adjusted to make the actual response of the network move closer to the desired response in a statistical sense (Haykin, 1999). Simply, in backpropagation algorithm, the weights are continually modified until the total error across all the training patterns is reduced below some predefined tolerance level. Proof of that the effect of these weights updates gradually minimizes the mean square error across all input patterns relies on the fact that backpropagation learning algorithm performs gradient descent of the error function (Smith and Gupta, 2001).

In the following paragraphs the backpropagation learning process is described using mathematical representations.

The backpropagation algorithm starts with the first pass. The weights of the network are initialized and the input patterns in the training set are sent through the network in the first pass.

The net values of the hidden nodes are calculated as follows:

$$v_j^\mu = f\left(\sum_k w_{jk}^1 * x_k^\mu\right) \quad (5.1.)$$

The output signal from the i th output node is calculated by using Equation 5.1. as the input signal from the j th hidden node to the i th output node. Equation 5.2. gives the mathematical formulation of the output signal from the i th output node.

$$y_i^\mu = f(\sum_j w_{ij}^2 * v_j^\mu) = f(\sum_j w_{ij}^2 * f(\sum_k w_{jk}^1 * x_k^\mu)) \quad (5.2.)$$

In the formulations given above; “ f ” represents the activation function, “ y_i ” represents the i th output, “ x_k ” represents the k th input, “ v_j ” represents the hidden layer nodes, “ w_{jk}^1 ” represents the weights between the input layer and the hidden layer, “ w_{ij}^2 ” represents the weights between the hidden layer and the output layer, “ μ ” is used for the input pattern where the training set is made up of p number of input patterns.

The formulation given in Equation 5.2. does not include the bias term however. When the bias term is included in the formulation, the output signal is found as follows:

$$y_i^\mu = f(w_{oi}^2 + \sum_j w_{ij}^2 * v_j^\mu) = f(w_{oi}^2 + \sum_j w_{ij}^2 * f(w_{ok}^1 + \sum_k w_{jk}^1 * x_k^\mu)) \quad (5.3)$$

The first pass of the backpropagation algorithm is completed with the calculation of the output signals, the actual response of the network. In the second pass, the actual response of the network is compared with the target values of the input pattern. The weights of the network are adapted according to an error minimization rule, that aims to minimize the difference between the target values and the actual network response. Sum of squared errors is the most popular performance measure in backpropagation learning as given in Equation 5.4.

$$E = \frac{1}{2} \sum_{\mu} (o_i^\mu - y_i^\mu)^2 \quad (5.4)$$

When equation 4.2 is used in equation 5.4. the following error formula is found:

$$E = \frac{1}{2} \sum_{\mu} (o_i^\mu - f(\sum_j w_{ij}^2 * f(\sum_k w_{jk}^1 * x_k^\mu)))^2 \quad (5.5)$$

The error found from the output layer is back propagated to the network and the weights are recalculated depending on their individual contribution to the error term. In order to update the weights, gradient descent algorithm is used. Equation 5.5 reveals that the error function is a function of the unknown weights w_{jk}^1 and w_{ij}^2 . Therefore, the partial derivative of the error function with respect to a weight

represents the rate of change of the error function with respect to that weight (it is the slope of the error function). Moving the weights in a direction down this slope results in a decrease in the error function. Therefore, the error function's partial derivative is calculated with respect to the weights and then the weights changed until the error function no longer decreases (Warner and Misra, 1996). The mathematical representation of the change in the weight is given as follows:

$$\Delta w_{ij}^2 = -\eta \frac{\partial E}{\partial w_{ij}^2} \quad (5.6)$$

The term η is known as the learning rate parameter of the back-propagation algorithm. The use of the minus sign accounts for gradient descent in weight space – seeking a direction for weight change that minimizes the error- (Haykin, 1999).

When equation 4.5 is expanded using the chain rule, equation 5.7 is found.

$$-\eta \frac{\partial E}{\partial w_{ij}^2} = -\eta \sum_{\mu} (o_i^{\mu} - y_i^{\mu}) * f'(\sum_j w_{ij}^2 * v_j^{\mu}) * v_j^{\mu} \quad (5.7)$$

The change in weight can then be defined as follows:

$$\Delta w_{ij}^2 = -\eta \sum_{\mu} \delta_i^{\mu} * v_j^{\mu} \quad (5.8)$$

where

$$\delta_i^{\mu} = (o_i^{\mu} - y_i^{\mu}) * f'(\sum_j w_{ij}^2 * v_j^{\mu}) \quad (5.9)$$

and the next weight is found as:

$$w_{ij}^2(t+1) = w_{ij}^2(t) + \Delta w_{ij}^2 \quad (5.10)$$

The weights between the hidden layer and the input layer are updated in a similar manner:

$$\Delta w_{jk}^1 = -\eta \frac{\partial E}{\partial w_{jk}^1} = -\eta \sum_{\mu} \frac{\partial E}{\partial v_j^{\mu}} * \frac{\partial v_j^{\mu}}{\partial w_{jk}^1} \quad (5.11)$$

Expanding the chain rule,

$$\Delta w_{jk}^1 = \eta \sum_{\mu} (o_i^{\mu} - y_i^{\mu}) * f'(\sum_j w_{ij}^2 * v_j^{\mu}) * w_{ij}^2 * f'(\sum_j w_{jk}^1 * x_k^{\mu}) * x_k^{\mu} \quad (5.12)$$

$$\Delta w_{jk}^1 = \eta \sum_{\mu} \delta_i^{\mu} * w_{ij}^2 * f'(\sum_j w_{jk}^1 * x_k^{\mu}) * x_k^{\mu} \quad (5.13)$$

$$\Delta w_{jk}^1 = \eta \sum_{\mu} \delta_j^{\mu} * x_k^{\mu} \quad (5.14)$$

where,

$$\delta_j^{\mu} = f'(\sum_j w_{jk}^1 * x_k^{\mu}) * \sum_{\mu} w_{ij}^2 * \delta_i^{\mu} \quad (5.15)$$

and the next weight is found as:

$$w_{jk}^1(t+1) = w_{jk}^1(t) + \Delta w_{jk}^1 \quad (5.16)$$

For the gradient descent algorithm a step size which is called the learning rate η must be specified. Learning rate determines the magnitude of changes in the weights. While higher learning rates are better for less complex data, low learning rate with high momentum should be used for more complex data series. Steepest descent algorithm is very sensitive to learning rate. Smaller learning rates tend to slow the learning process while larger rates may cause oscillation in the weight space. Furthermore, steepest descent suffers the problems of slow convergence, inefficiency and lack of robustness- getting stuck into a local minima rather than the global minimum of the error function. One way to improve the original gradient descent algorithm is to include an additional momentum parameter to allow for larger learning rates resulting faster convergence while minimizing tendency to oscillation.

When the momentum term is included in the weight change equations, the following two equations are found:

$$\Delta w_{jk}^1(n) = \eta \sum_{\mu} \delta_j^{\mu} * x_k^{\mu} + \alpha \Delta w_{jk}^1(n-1) \quad (5.17)$$

$$\Delta w_{ij}^2(n) = -\eta \sum_{\mu} \delta_i^{\mu} * v_j^{\mu} + \alpha \Delta w_{ij}^2(n-1) \quad (5.18)$$

The idea of adding momentum is to make the next weight change in more or less the same direction as the previous one and hence reduce oscillation effect of larger learning rates (Zhang et. al, 1998). Learning rate and momentum rate both take values between 0 and 1. There is no specific value used for learning rate and momentum term in literature however, it is suggested to start with a relatively high

learning rate like 0.5 and lower the learning rate as the performance measure minimizes while increasing the momentum rate.

5.4 Design of Artificial Neural Networks

Building a neural network requires the determination of several parameters and variables that define the network and that affect the learning performance of the network.

One critical decision is the determination of the appropriate architecture, the number of layers, the number of nodes in each layer and the number of arcs which interconnect the nodes.

Other network design decisions include the selection of the activation functions of the hidden and output nodes, the training algorithm, data transformation and normalization methods, training and test sets and performance measures (Zhang et al.,1998)

5.4.1 The Determination of the Number of Hidden Nodes and Hidden Layers

The hidden layer and nodes are an important part of the neural networks since they allow the networks to detect the pattern hidden in the data and to perform nonlinear mapping between the input and the output variables; without hidden nodes simple perceptrons with linear output nodes are equivalent to linear statistical forecasting methods.

Literature shows that a network does not need more than two hidden layers to solve most problems including forecasting (Zhang et.al., 1998). In addition Masters, (1993), state that those problems that require two hidden layers are only rarely encountered in real life situations. In practice two hidden layers may be required when the network must learn a function having discontinuities. Gately, (1996), states that about 85 % of all problems are trained in a backpropagation one hidden layer network. The popularity of the use of backpropagation based one layer hidden neural network comes from the proof that by using a backpropagation algorithm and sigmoid activation function, a neural network with one hidden layer is sufficient to approximate any continuous function . Dahl and Hylleberg, (2005), and Zhang (2003), state that single hidden layer feedforward neural network model possesses

the universal approximation property and can approximate any nonlinear function to a degree of accuracy with a suitable number of hidden nodes.

The determination of the number of hidden nodes in a hidden layer is also an important step in neural networks building. In general neural networks with few hidden nodes are preferable since they usually have better generalization ability and less overfitting problem. -In the overfitting problem the network fits the training data very well learning everything including the insignificant relations in the network and the noises but generalizes or forecasts very poorly in out of samples- ; however networks with too few hidden nodes may not have enough power to learn and model data (Masters,1993).

There is no theoretical basis for selecting the number of hidden nodes. The most common way in determining the number of hidden nodes is by experiments of by trial and error.

To avoid overfitting problem several rules of thumb have been proposed to restrict the number of hidden nodes. In the case of one hidden layer Networks, the number of hidden nodes may be computed as “ $2n+1$ ”; “ $2n$ ”; “ n ”; “ $n/2$ ” where n is the number of input nodes (Zhang et.al., 1998). However, none of these heuristic choices Works well for all problems. Masters, (1993), state that another rough guideline for choosing the number of hidden nodes in many problems is the geometric pyramid rule. This rule states that for many practical Networks, the number of neurons follows a pyramid shape, with the number decreasing from the input node towards the output node. In a three layer neural network case, the number of hidden nodes may be computed as $\sqrt{m*n}$ where m corresponds to the output nodes and n corresponds to the input nodes. When the pyramid rule is applied to a four layer problem, the number of hidden nodes in the first hidden layer equals to mr^2 ; the number of the second hidden layer nodes, where $r = \sqrt[3]{n/m}$. Masters, (1993) also states that this heuristic may not be optimal for every problem, the best approach to determine the number of hidden nodes is to start with a small number of nodes like two neurons, choose an appropriate performance measure for the network and train and test the network while increasing the number of hidden nodes until an acceptable performance level is reached.

It has been pointed by Tang and Fishwick (1993), that the number of hidden nodes has an effect on the forecast performance of the network however it is not significant. The study performed by Gately (1996), is in accordance with Tang and Fishwick. Gately (1996) has investigated the effect of different number of neurons in the hidden layer on the minimum average error, in a one hidden layer feedforward network. The results as given if Table 5.1 reveal that the error varies by only five per cent and even the network with only one hidden neuron is within the five per cent of the best network.

Table 5.1: Effect of Number of Hidden Neurons on Accuracy, (Gately, 1996, pg. 73)

Number of Neurons in Hidden Layer	Minimum Average Error
1	0.00446
2	0.00441
3	0.00425
4	0.00433
5	0.00440
7	0.00435
10	0.00430
15	0.00431
20	0.00426
30	0.00425
40	0.00426

5.4.2 The Activation Function

The activation function determines the relationship between the inputs and the outputs of a node and a network. In general it introduces nonlinearity into the network. In theory, any differentiable function may be used as an activation function, however, in practice only a small number of functions are used. These include the sigmoid function, the hyperbolic tangent function, the sine or cosine function and the linear function. Among them the sigmoid function is the most popular function. However, there is no restriction and no consensus on the determination of the use of the activation function. Zhang et.al, (1998), state that logistic activation function seems well suited for the output nodes for many classification problems where the target values are often binary. For forecasting problems which involves continuous target values, it is reasonable to use a linear activation function for the output nodes, however feedforward neural networks with linear output nodes have the limitation that they cannot model a time series containing trend.

5.4.3 The Training Sample and Test Sample

In ANN analysis, a set of the input patterns are set aside for testing training the network and the rest of the patterns are used for testing and validating the network performance. The important point in selecting the training sample is that the input patterns selected as the training set should be representative of the population and the underlying structure (Roiger and Geats, 2003). Inappropriate selection can cause a misspecified network and thus low performance.

There is no consensus in literature on the determination of the training sample and test sample sizes. Most researchers select the training and testing and validation sets on the rule of 90 % vs. 10 %, or, 80 % vs 20 %, or 70 % vs. 30 %, (Zhang et.al., 1998). Gately, (1996), suggests that 20% of sample should be used for out of sample forecasting evaluation as the test set. Although as the sample size gets larger the accuracy of the results get better (Masters, 1993), in reality, the sample size is constrained by the data in hand. Zhang et.al, (1998), state that with a large enough sample ANNs can model any complex structure in data and can benefit from large samples than linear statistical models can. ANNs do not necessarily require a larger sample than is required by linear models in order to perform well. Zhang et al., (1998), state that ANN forecasting models perform quite well even when the sample size is less than 50, while the linear models typically require more.

5.4.4 The Sequential and Batch Modes of Training

For a given training set, backpropagation learning may proceed in one of two ways; in sequential mode or in batch mode.

In the sequential mode which is also known as online pattern or stochastic mode, the weight updating is performed after the presentation of each training pattern to the network. Every single pattern in the epoch is presented to the network one by one and weight updating operation is performed for each of the input patterns presented.

In batch mode of training weight updating is performed after the presentation of all the training examples that make up the epoch. Haykin, (1999), states that it is less likely for the backpropagation algorithm to get stuck in a local minimum with sequential mode of training.

5.4.5 The Stopping Criteria

Backpropagation learning process should be stopped when reached a predefined criterion. The training is stopped either when the training performance reaches a target performance or when a specific epoch is reached. Haykin, (1999), states that the backpropagation algorithm is considered to have converged when the absolute rate of change in the average squared error per epoch is sufficiently small, lying in the range of 0.1 to 1 % per epoch.

Another theoretically supported convergence criterion is testing the generalization performance of the network after each learning iteration. The learning process is stopped when the generalization performance is adequate. To test the generalization performance of the network, the data is divided into a training set and a test set. The training set is further divided into a validation subset and an estimation subset. The network is trained using the estimation set, and the generalization ability of the network is checked using the validation set. If the performance of the network on the validation set is significantly worse than on the estimation set, it is concluded that either overfitting has occurred or that an important information present in the validation set was not present in the estimation set.

5.4.6 The Data Transformation

Nonlinear activation functions like the sigmoid function restricts the output from a node to (0,1) or (-1,1). Data transformation is therefore performed before the training process begins. When nonlinear activations are used at the output nodes, the desired output values must be transformed to the range of actual outputs of the network.

Zhang et al., (1998), state that even if a linear output function is used, it may be advantageous to standardize the outputs as well as the inputs to avoid computational problems and facilitate network learning.

5.4.7 The Performance Measures

Various performance measures exist in literature that is used to evaluate the accuracy of the neural networks. The most frequently used measures in prediction problems are given in Table 5.2. The performance measures may be used individually as well as in pairs to evaluate the performance of the network. Mean square error (MSE) is the most frequently used performance measure in literature.

Table 5.2: Common Performance Measures for Prediction Problems (Gately, 1996)

Mean Squared Error (MSE)	$\frac{\sum (e_t)^2}{N}$
Mean Absolute Deviation (MAD)	$\frac{\sum e_t }{N}$
Sum of Squared Error (SSE)	$\sum (e_t)^2$
Root Mean Squared Error (RMSE)	$\sqrt{\frac{\sum (e_t)^2}{N}}$
Mean Absolute Percentage Error (MAPE)	$\frac{1}{N} \sum \left \frac{e_t}{y_t} \right * 100$

The “ e_t ” in Table 5.2, corresponds to the individual forecast error; “ y_t ” is the actual value and “N” is the number of error terms.

5.5 The Specification of Variable Importance in Artificial Neural Networks

Artificial neural networks are effective methods that are widely used to predict the output variables, using the predetermined input variables especially when the underlying structure between the input and output variables are not known clearly. However, in artificial neural network studies, the understanding of the mechanisms that occur within the network are often ignored. That is why artificial neural networks are labeled as “black boxes”. Various studies have been made to explore this problem and several methods have been proposed to identify the influence of each input variable and its contribution to the output.

In a recent study, Olden et.al., (2004), summarize and compare the frequently used methods to quantify the variable importance in artificial neural networks. The researchers compare the methodologies by using simulated data from a dataset exhibiting defined and consequently known numeric relationships (known correlations) and rank the methodologies according to their ability to correctly estimate the true ranked importance of each individual variable in the neural network. The most widely used methodologies in quantifying the variable importance are Garson’s algorithm (Garson, 1991), Connection Weight Approach (Olden and Jackson, 2002), partial derivatives (Dimopoulos et.al., 1995), input perturbation (Gevrey et al., 2003), forward stepwise addition and backward stepwise elimination, and improved stepwise selection method I and improved stepwise selection method II. The results show that although Garson’s Algorithm is the most

widely used methodology, Connection Weight Approach shows the best performance and the best precision for estimating the correct ranked importance of input variables. The following best performing methods are partial derivatives, improved stepwise selection method 1 and improved stepwise selection 2 methodologies. Garson's algorithm performs worst according to the study.

Gately, (1996), uses a simpler methodology to assess the importance of input variables on the output variables. The weights connected to each input is added, and input with a large total of weights are accepted to be significant than an input with only a small total of weights.

In this study the Connection Weight Approach, the improved stepwise selection 1 method and improved selection 2 methods, the methods showing the highest performance when applied to a dataset simulated from a dataset with prior known correlation structure are applied. The average per cent change in MSE for each input variable is calculated and this average is taken as a reference quantifying the importance of each input variable.

In the Connection Weights Approach, the importance of input variable x is calculated as the total of the sum of products of the weights connected to input i to each hidden layer and each hidden layer to the output unit j . The inputs are then ranked according to their total weights. The equation used in the weights connection approach is as follows:

$$\text{Importance}_{ij} = \sum_{k=1}^n (W_{ki} * U_{jk}))$$

W_{ki} is the weight between the k th hidden unit and i th input unit. U_{jk} corresponds to the weight between k th hidden unit and the j th output unit.

In the improved stepwise selection method 1, each input and its weights are sequentially removed from the neural network. The resulting change in the mean square error of the network for each variable removal illustrates the relative importance of the input variable. (Gevrey et.al, 2003).

In the improved stepwise selection method 2, the change in the mean square error of the neural network is assessed by sequentially setting input variables at its mean value. In each of the improved stepwise selection methods, the input variable causing

the highest per cent change in the networks mean square error is regarded as the most important variable.

In Figure 5.3, an example is given to illustrate the difference between the widely used Garson's algorithm and the Connection Weight Approach (Olden et al, 2004).

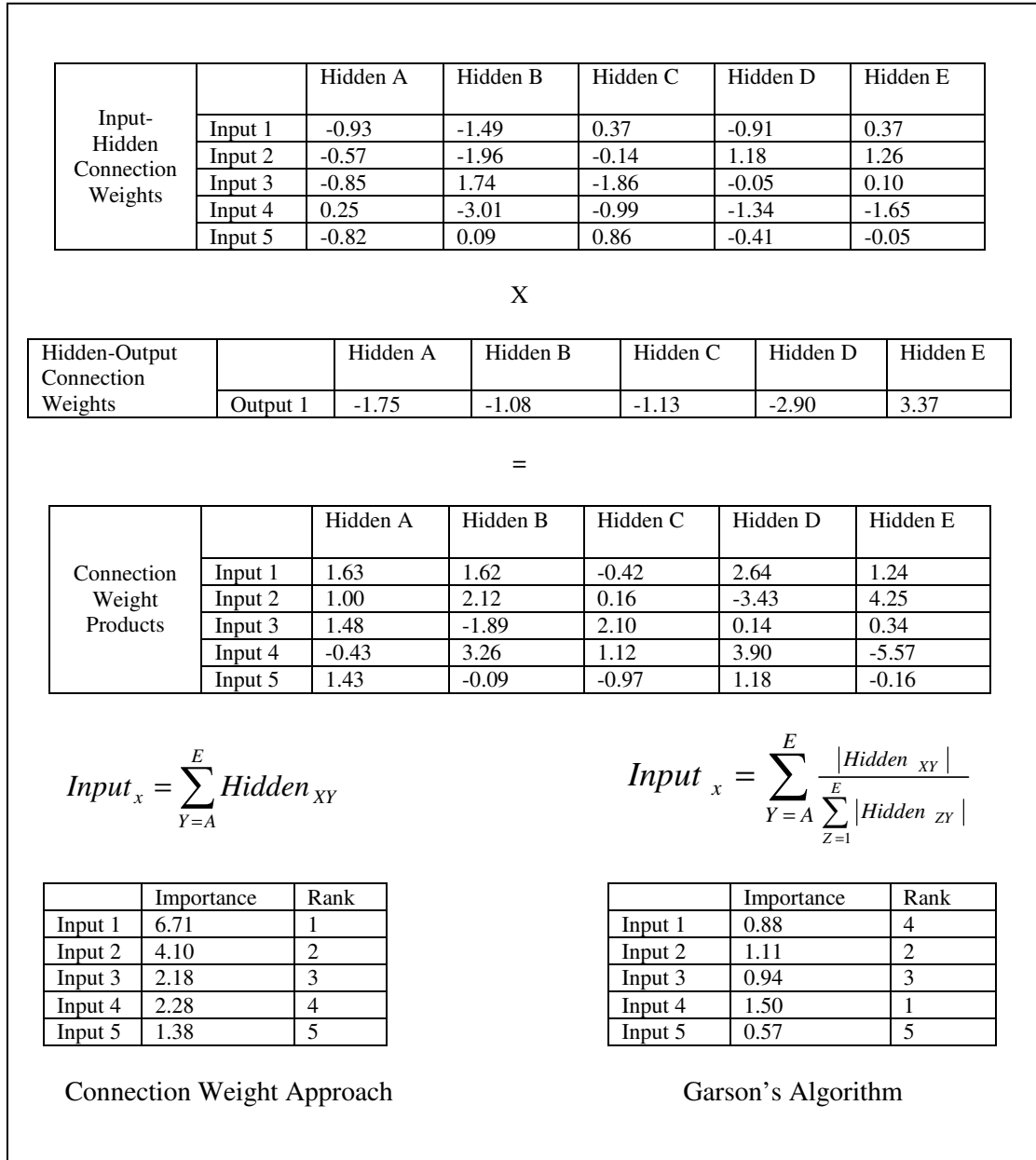


Figure 5.3: Difference between Garson's Algorithm and the Connection Weight Approach, (Olden et al., 2004).

5.6 Neural Networks for Macro Economic Analysis and Prediction

Moody, (1995), states that since a convincing and accurate scientific model of business dynamics does not exist due to the complexity of the economic system and since doing controlled experiments on the economy is not possible, macroeconomic analysis and forecasting becomes a challenging task.

Current approaches used in macroeconomic analysis and forecasting involve econometric models and time series models. Econometric models are based on predefined structures with respect to the variable under analysis. The model structures are chosen and parameters are estimated from the data. They provide understanding about the workings of the economy, however are not useful in prediction analyses.

Time series models generally rely on various assumptions about the data used in the analysis, like stationarity of the data linearity that conflicts with the dynamic behavior of the economic systems. Macroeconomic series are nonstationary series due to the evolution of the world's economies over time. Underlying dynamics of an economy as well as the noise distributions for economic series change with time. Majority of the time series analyses studies in literature use linear models however, recent studies state that nonlinearities can improve macroeconomic forecasting models.

To identify an appropriate multivariate time series model for an economic system, several tests should be applied including the test for joint stationarity, individual stationarity, normality and independence.

The use of ANNs that are proved to be universal function approximators help to approximate the underlying functional relationships between the input variables and output variables without the need of specifying a priori functional form or imposing prescribed assumptions about the behavior of the data. The superiority of ANNs is their ability of learning nonlinear relationships inherent in the data.

Warner and Misra, (1996), state that any generalized linear regression model can be mapped onto an equivalent single layer network. The activation function is selected as the inverse of the link function in the regression model. They also state that the functional form imposed on the data in regression models may lead to error in prediction especially in the multivariate models. In regression analysis neural

networks are advantageous since they do not assume any functional relationship and let the data learn the relationship. Therefore neural networks are extremely useful when the relationship between the dependent and the independent variables is unknown. On the other hand, the power of the regression models is their validation power. When the linear relationship may be justified between the input and output variables, regression models may be used and the individual coefficients can be tested for statistical significance.

Artificial neural networks have been applied to several time series analysis problems in macroeconomy. In most of these studies ANNs have been compared with the traditional time series models like linear regression, autoregression (AR) models and their variations and vector autoregression models (VARs). The results reveal that in some of the analyses ANNs perform better than others and in others ANNs are perform poorly compared to other models.

Qi and Zhang (2001), summarize the criterion that may be used in selecting an appropriate neural network model. They state that neural networks is equivalent to a nonlinear autoregressive (AR) model for time series forecasting problems when the inputs are taken as the past observations of the data series and the output is the future value. The researchers state that in order to select the best neural network forecasting model, several criterion should be applied. The first approach is the out of sample performance criterion- cross validation. Networks of different number of inputs different number of middle units may be trained by using the training set. These networks are compared using the validation set and the best model is used in the test set. Another method is to use in sample criteria used in the traditional time series forecasting literature; such as Akaike's information criterion (AIC) and Bayesian information Criterion (BIC) and their variations, which penalize the models that often tend to overfit. The model having the least AIC and/or BIC criterion may be used as the final model to be used in prediction. The researchers suggest that these criterions may be useful in building a systematic approach in the model building of neural networks.

Qi (2001), has examined the relevance of financial and economic indicators in predicting U.S. recessions by using neural networks. Qi states that business cycles are asymmetric and modeling them with linear constant parameter models is inadequate, and that the models used in modeling the business cycle need to be

extended from univariate to multivariate settings since the business cycle is about co-movements in a broad range of macroeconomic variables. The researcher suggests the use of neural networks as the nonlinear nonparametric models that can flexibly and accurately approximate almost any functional form, especially when there exists very little a priori knowledge about the appropriate functional representation of the relationship under investigation. He also states that economic studies that utilize neural networks are very few and neural networks have attracted attention from statisticians and econometricians in recent years. Qi has used 27 indicators to predict U.S. economic recessions in a single hidden layer network having three hidden nodes. Neural network model is estimated 10 times based on 10 sets of initial weights in order to avoid local minima and MSE performance criteria is used to evaluate the model performance. The results reveal that interest rate spread between the 10 year treasury bond and the 3-month treasury bill is the single best predictor of the U.S. economic recessions in 2 to 6 quarters in the future.

Moshiri, S. and Brown, L., (2004), have applied neural networks to estimate and forecast post-war aggregate unemployment rates in the USA, Canada, UK, France and Japan. The researchers compare the out of sample results obtained in the analysis with the results obtained by linear AR and nonlinear generalized autoregressive and exponential autoregressive time series models. The analysis shows that neural network models are able to forecast the unemployment series as well as, and in some cases better than, the other univariate econometrics time series models.

Swanson and White, (1997), have used neural networks and adaptive and non adaptive univariate and multivariate models to predict nine seasonally adjusted macroeconomic variables, unrevised quarterly U.S. data on unemployment, interest rates, industrial production, nominal GDP, corporate profits, real GNP, personal consumption expenditures, the change in business inventories and the net exports of goods and services.

The researchers have used a stepwise (nonlinear) least squares regression process using the Schwarz information criterion (SIC) as the in sample complexity penalized model selection criterion in order to determine the included regressors and the appropriate number of hidden units. They have started with a no single layer neural network and added the regressors one at a time to determine the linear coefficients. In the second step they have added a single hidden unit and connected the regressors

one by one to the hidden unit until the SIC can no longer be improved. Then a second hidden unit is added and the process is repeated until five hidden units have been tried or the SIC for q hidden units exceeds that for $q-1$ hidden units. The procedure is re-applied each time the data window moves forward one period. The model having the best performance according to the SIC criterion is selected to be used in forecasting. The researchers have used different performance criterion to evaluate the out of sample performance criterion like SIC, MSE, MAD, MAPE and Theil's U. They conclude that adaptive multivariate linear and nonlinear models outperform univariate and nonadaptive multivariate models and they suggest that SIC is not superior to the other out of sample forecast performance measures.

Tkacz, (2001), has used neural networks to forecast Canadian GDP growth in short term (one quarter) and long term (four quarter) by using multivariable. Tkacz (2001), points out that neural networks are useful in contexts where the apriori beliefs about the functional forms are unknown, because neural networks are data driven and can learn from and adapt to underlying relationships and that they are universal approximators. Moreover he states that there is growing evidence that macroeconomic data follow nonlinear processes and neural networks are powerful since they are nonlinear models, and that there are still relatively few applications of neural networks in macroeconomics.

Tcakz, (2001), has used five variables with a single layer neural network with hidden layers varying from one to four, a logistic function and backpropagation algorithm. The results reveal that, financial and economic variables do not provide short term forecasts of output growth and naïve forecasting methods like autoregression (AR), exponential smoothing models outperform neural networks and multilinear models in one quarter forecasts however, at four quarter forecast horizon, financial and monetary variables have leading indicator properties with linear and nonlinear models (ANNs) exceeding the performance of univariate models. The best NN model outperforms the best linear model with MSE and MAD errors being 31 % and 22 % lower than those of the linear multivariate regression model. Tcakz concludes that the gains in forecasting accuracy in neural networks are likely to originate from the ability of NNs to capture nonlinear relationships in the longer term forecasts.

Dahl and Hylleberg, (2005), state that although the results of Swanson and White's (1997) and Stock and Watson's (1998) studies are in favour of linear models when

compared to nonlinear models, these results may be due to the choice of model selection criterion and limited class of flexible models used. The researchers state that nonlinear models should be taken into consideration while predicting economic time series.

Zhang, (2003), states that ARIMA models are quite flexible because they can represent different types of time series like pure autoregressive AR, pure moving average (MA) and combined AR and MA (ARMA) series, but their major limitation is the preassumed linear form of the model. On the other hand neural networks are flexible models that are capable of dealing with nonlinear components of the series. Zhang states that analyzing the linear components of the series with ARIMA method in the first stage and then analyzing the nonlinear components with ANN methodology may improve forecasting accuracy. He has applied hybrid methodology to three data sets Wolf's sunspot data, Canadian lynx data and British pound/US dollar exchange rate data. The results reveal that better MSE and MAD are obtained with the hybrid model.

Stock and Watson, (1998-1999), have compared linear and nonlinear univariate models namely, autoregressions, exponential smoothing, ANNs and smooth transition autoregressions for forecasting macroeconomic time series. Their results are in favour of autoregression models with unit root tests.

Qi and Wu, (2003), have applied neural networks to predict exchange rates for four currencies in 1, 6 and 12 month forecast horizons. The researchers have used a monetary model of exchange rates to determine the predictor variables; those are namely, money supply by M1, real income by industrial production and interest rates. Their results reveal that in overall multivariate ANN models produce higher forecast errors than the random walk and linear regression models. Several examples on the research on application of artificial neural networks to macroeconomic prediction are given below in Table 5.3.

In this section, artificial neural networks methodology, the structure of artificial neural networks, their advantages on prediction problems and applications of artificial neural networks methodology to macroeconomic problems are described in detail. In the following section, the framework developed for employment index and unemployment rate prediction for Turkey is described in detail.

Table 5.3: Research Examples on Application of Artificial Neural Networks to Macroeconomic Prediction

Study	Predicted Variable(s)	Predictors	Method(s)	Performance Criteria	Results
Qi (2001)	U.S. recessions	27 indicators grouped as interest rates and spreads, monetary aggregates, stock prices, individual macro indicators, indexes of leading indicators	Adaptive Neural networks,	MSFE (Mean Squared Forecast Error)	N.A.
Tkacz (2001)	Canadian GDP growth	Short term and long term interest rates and spreads, price level inflation expectations, real short term rate, monetary aggregates, GDP	Neural networks, simple random walk model, AR(m), exponential smoothing, multivariate linear models	MSE, MAE, % Δ MSE, % Δ MAE	In short term forecasts of output growth univariate naïve forecasting methods outperform neural networks and multilinear models, at four quarter forecast horizon, linear and nonlinear multivariate models (ANNs) exceed the performance of univariate models. The best NN model outperforms the best linear model with MSE and MAD errors being % 31 and %22 lower than those of the linear multivariate regression model.
Swanson and White (1997)	unrevised quarterly U.S. data on unemployment, interest rates, industrial production, nominal GDP, corporate profits, real GNP, personal consumption expenditures, the change in business inventories and the net exports of goods and services	Selected variables from the predicted variables	Adaptive Neural networks, adaptive non adaptive univariate models, adaptive and nonadaptive multivariate models,	MSE, MAD, MAPE, Theil's U, SIC, contingency tables	Adaptive multivariate linear models outperform univariate and nonadaptive multivariate linear and nonlinear (ANN) models
Qi and Wu (2003)	Exchange rates	Money supply by M1, real income by industrial production, interest rates	Levenberg- Marquardt Algorithm	RMSE	Linear regression and random walk models outperform ANNs.
Moshiri, S. and Brown, L. (2004)	Unemployment rates	Univariate	Backpropagation, Generalized Regression Neural Networks	SSE, AIC, Adjusted R ²	Neural network models are able to forecast the unemployment series as well as, and in some cases better than, the other univariate econometrics time series models

6. A FRAMEWORK FOR EMPLOYMENT- UNEMPLOYMENT PREDICTION: THE CASE OF TURKEY

In this section of the study, a framework is developed and applied in order to predict employment and unemployment rates in Turkey and to identify the relative importance of economic variables on employment and unemployment. The framework suggested is a combination of cognitive mapping methodology and neural networks. In the first phase of the study cognitive mapping methodology is applied to reveal the expert knowledge on the determinants of unemployment and employment in Turkey. In the second phase of the study, the factors that are identified by the experts are used as the inputs to a multilayer feed-forward neural network where the output of the network is the unemployment rate data Turkey in the first analysis and the employment index data in manufacturing industry in Turkey in the second analysis.

The reason of making two separate analyses of employment and unemployment rates is a result of the lack of data in Turkey. Employment is a complement of unemployment and it is assumed that the factors that affect unemployment also affect employment. The lack of sufficient data about unemployment is the result of the changes in the calculation of unemployment. As previously stated in Section 2.1, different sources have made surveys to calculate unemployment before 1988. In 1988 a new household labour force survey procedure has been introduced by SIS and it has been conducted twice a year (in April and October) until 2000. After a revision in 2000, the survey period was decreased to three months from six months. The two data series are combined in the study and to make quarterly data, interpolation is applied to the unemployment rate data set. Through the same period however, it is possible to find accurate quarterly data on employment index data in manufacturing industry in Turkey. Therefore in the study employment index data set is also analyzed as a complement to unemployment rate analysis. The framework for the proposed methodology is given below in Figure 6.1. In the following subsections, the cognitive mapping analysis and neural network analysis will be described.

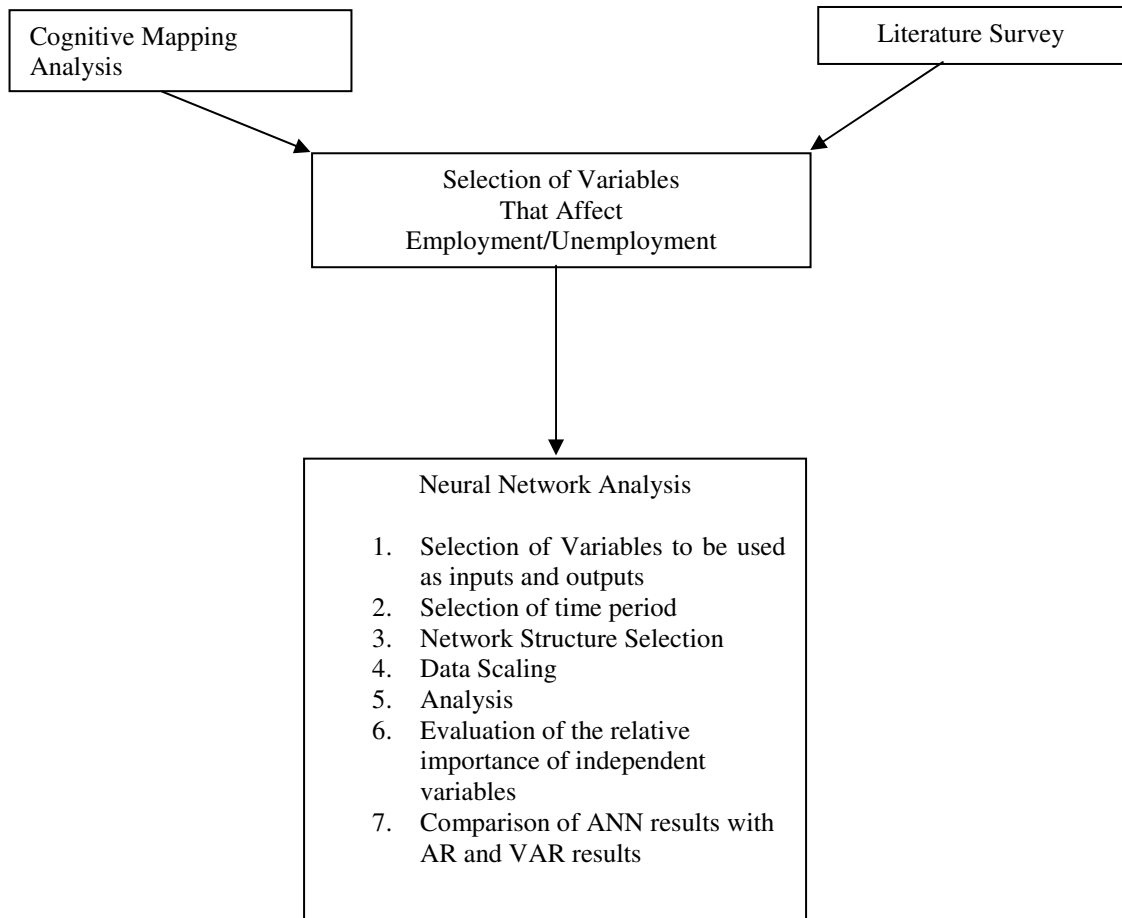


Figure 6.1: Framework for Unemployment/Employment Prediction

In the following section the cognitive mapping methodology used in the selection of variables related to unemployment is described in detail.

6.1 Unemployment Analysis with Cognitive Maps

In order to identify the basic factors that are directly related with unemployment in Turkey, it is decided to reveal different perspectives. For this purpose, initially five researchers, one professor of economics from Bilgi University, two professors from İstanbul Technical University, an associate professor of economics from İstanbul Technical University and associate professor of economics from Galatasaray University who have made research on macroeconomic problems of Turkey are requested to list all the factors they believe to be the basic causes of unemployment in Turkey. As a result, 34 variables were specified. Those are participation rate into labour force, population growth rate, literacy rate, urbanization rate, exports, imports, real wages, country competitiveness, unregistered unemployment, technological

improvements, capital cost, GDP, per capita income, the agricultural, service and manufacturing sectors' ratio in GDP, income distribution, public sector investments, purchasing power, private sector investments, capacity utilization rate, labour productivity, inflation, uncertainty, domestic demand, union power, skill mismatch, tax burden, minimum wage, unemployment in the previous period, current period unemployment rate, black economy, unemployment payments level, and duration of unemployment payments.

In the second step of the analysis, the aggregated list of variables is given to experts and they are asked to rank these variables according to their importance in terms of their impact on unemployment. As a result, two variables namely, duration of unemployment payments in Turkey and unemployment payment levels were excluded from the variables list since unemployment payments are new in Turkey and they are, thus negligibly low in amount. The experts also decided to exclude, purchasing power from the study since they stated that the purchasing power is especially a result of unemployment rather than a cause, and that it may be represented by domestic demand variable in the model, also black economy was excluded from the study since it may be represented with unregistered employment. The variables are then grouped into demographic –labour supply-, macro, macro-demand side-, labour market labels, in terms of their character so to facilitate the cognitive mapping process as shown in Table 6.1.

The experts are then asked to evaluate the relations between each pair of variables in a -1,0,1 scale where 0 indicates that a causal relationship does not exist between the two variables, -1 indicates a negative relationship and 1 indicates a positive relationship. The relationship matrices developed by the experts are given in Appendices 1 to 5. After the judgments of the experts are gathered, they are aggregated to form the cognitive map. As defined in Axelrod, (1976), 60 % judgments of the experts are taken into consideration while aggregating the cognitive maps. The aggregated relation matrix is given in Appendix B. The cognitive map is then analyzed in Decision Explorer (2002).

Table 6.1: Variables Related to Unemployment Problem in Turkey

Variable Group	Variable No	Variable Name
Demographic (Labour Supply)	1	Participation rate in Employment
	2	Population growth rate
	3	Literacy Rate
Macro	4	Urbanization Rate
	5	Export Level
	6	Import Level
	7	Real Wages
	8	Country Competitiveness (real effective exchange rates)
	9	Unregistered Employment
Macro-Demand Side	10	Technological Improvements
	11	Capital Cost
	12	GDP growth
	13	Per capita Income
	14	Agricultural Sector/GDP
	15	Service Industries /GDP
	16	Manufacturing Sector/GDP
	17	Income Distribution
	18	Public Investments
	19	Private sector Investments
	20	Capacity Utilization rates
	21	Labour Productivity
	22	Inflation
	23	Uncertainty
	24	Domestic Demand
	25	Union Power
Labour Market	26	Skill Mismatch
	27	Tax Burden
	28	Minimum wage
	29	Unemployment rate in the previous period
	30	Current period unemployment rate

The results of the centrality analysis used to identify the key variables, indicate that most of the variables are important for the system. The domain analysis is found to be more discriminating between the variables. The domain analysis reveals that there are two domain variables having the largest number of in-out links. These variables are “GDP growth’ and “Income per capita” with 50 links. “Real wages” and “Private investments/GDP” are the next two domain variables, each having 43 links. When the results of the domain analysis and centrality analysis are combined, GDP growth and income per capita with 50 links, real wages and private sector investments/GDP with 43 links and technological improvements with 41 links are found to be the most important five factors that affect unemployment in Turkey. The results of the centrality analysis and domain analysis are given in Figure 6.2 and Figure 6.3 respectively.

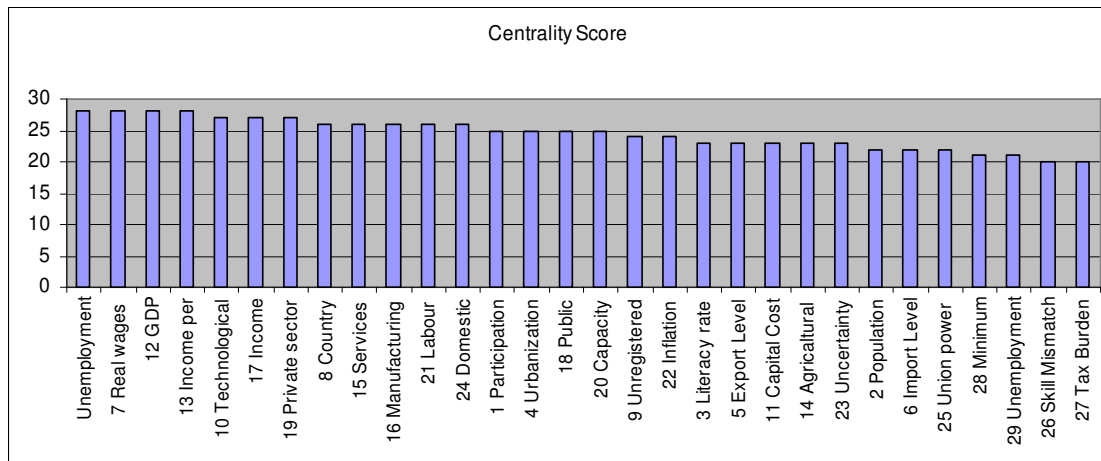


Figure 6.2: Centrality Scores of Variables

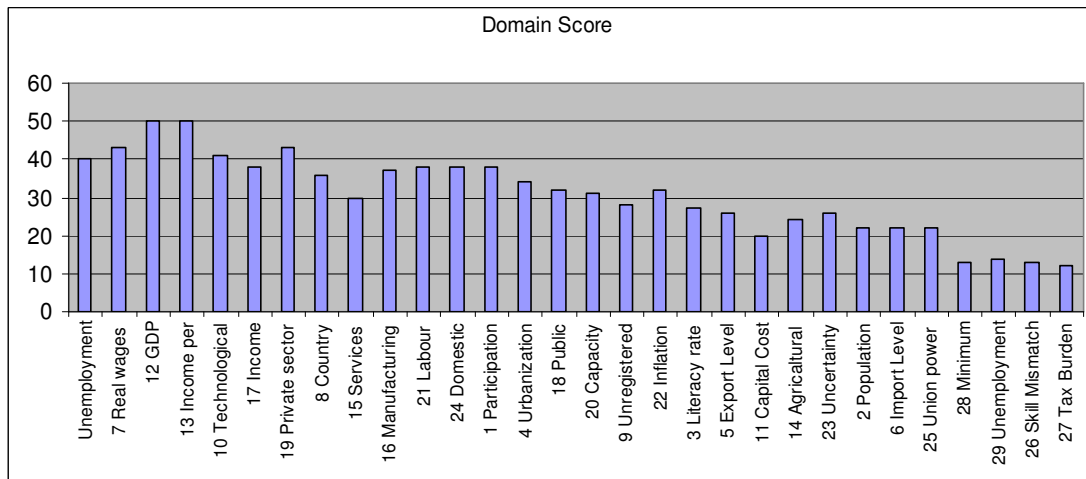


Figure 6.3: Domain Scores of Variables

Moreover, the loop analysis of the cognitive map reveals that the system is quite complicated and there are cycles affecting each of the variables in the system. Eden, (1992), states that the cycles in a system are indicators of possible dynamic nature of the system.

The cycles in the cognitive map are indicators of the complexity as well as the dynamic nature of the problem. The complexity and dynamic nature of the problem is also an indicator of the possible nonlinear relationships in the system. To overcome this complexity and the possible problems of applying a linear model to predict unemployment rates and employment index levels, neural networks methodology which is successfully used in regression and prediction analyses of

complex nonlinear models in which the relationships between the input variables and the output variables are hidden is applied in this study. The variables identified by the experts are all taken into consideration in the neural networks analysis except minimum wage, skill mismatch and tax burden having the lowest domain scores and centrality scores. In addition to their low domain scores and centrality scores, it should be noted that it is impossible to find data for tax burden and skill mismatch for the analysis period. Unemployment rate in the previous is used in the study as a representative of the affect of previous periods of unemployment on current period unemployment. Uncertainty, literacy rate, unregistered employment, participation into labour force, population growth rate, income distribution, technological improvements, services sector/GDP, manufacturing sector/GDP, agricultural sector/GDP, union power were further eliminated according to the last evaluations of the experts as well as the lack of accurate data of these variables in the analysis period. The last visits to the experts indicated that GNP growth rates may be used in the model as a representative of both domestic demand and income per capita. Country competitiveness is represented in the model by real effective exchange rates and capital cost is represented by real deposit rates in the study. In the next section of the study, neural networks analysis is described in detail.

6.2 Neural Network Analysis

In Section 6.2, the application of neural networks methodology to unemployment rates and employment index levels in Turkey are explained in detail. The lack of data about the unemployment rates in Turkey is a burden, therefore in this study it is decided to apply the neural networks also to employment index levels in the manufacturing industry in Turkey. Due to the fact that manufacturing industry is one of the most important sectors of Turkey and it is possible to find accurate data on employment levels, in this thesis the manufacturing industry is also selected as a case study.

6.2.1 Unemployment Rate Prediction with Artificial Neural Networks

The variables identified by the experts are regarded as the basis for the variables used in the neural network analysis. However, as mentioned at the end of Section 5, the variables identified by the experts are reduced to 11 due to the impossibility of

finding data and the results of the last meetings with the experts. The unemployment rate in Turkey is considered as the dependent variable and the rest as the independent variables. The analysis covers the period 1988Q3 to 2004Q4, because the data before 1988Q3 is unreliable. The data for the variables are obtained from SIS and since the unemployment rates between 1988 and 1999 are gathered twice a year, every April and October, the unemployment rates during these years are interpolated to 4-periods. The variables selected for the analysis are given in Table 6.2 and the data set is given in Appendix A.

Table 6.2 : Variables Used in the Unemployment Rate Prediction Analysis

Dependent Variable	unemployment rate in Turkey
Independent Variables	GNP % growth
	capacity utilization rate in manufacturing industry
	real effective exchange rates
	inflation
	real deposit rates
	index level of real wages
	total exportation
	total importation
	productivity in manufacturing industry
	private investments/GDP
	public investments/GDP

The data on capacity utilization rates, index of real wages and productivity levels are found for the manufacturing sector and it is assumed that they are representatives of the actual capacity utilization rates, index of real wages and productivity levels of other sectors.

In order to find the best performing model for unemployment rate prediction, 20 different models were tested. In the models 1 to 4, 11 of all the 11 variables are used as the inputs to the network analysis. In the models 5 to 8, the unemployment rate in the previous period is added to the inputs, because the results of the cognitive mapping reveal that unemployment in the past periods affect unemployment in the current period. In the models 9 to 12, a lag analysis is initially performed on the variables and the lagged variables are used as the inputs to the network, the reason of using the lagged models is that macroeconomic variables affect each other after a time delay and lagged models take these delays of the variables into consideration while predicting the unemployment rates. In the models 13 to 16, initially a regression analysis is performed and the significant variables, are used as the inputs to the network analysis. In the models 17 to 20, initially a principal component

analysis is performed and the outcoming factors are used as the inputs to the network analysis. Regression analysis and principal component analysis are used in order to reduce the number of inputs and identify the performance of the network with a considerably lower number of inputs. In the models 1 to 20, the data about the output variable and all the input variables except GNP are taken in levels. However, since it is stated in literature, that the performance of the networks could be improved when the change in the values of the output and input variables are used (Gately, 1996), rather than using the levels, the network analysis is re-done using the per cent changes in the input and output variables. The networks using the per cent change values are analyzed in models through 21 to 40. The models using unemployment as the output and their properties are given below in Table 6.3. In model 1, the data is used in its current period levels, all the 11 inputs are used in the neural network analysis, the data is scaled to -0.9,0.9 and the output activation function is taken as a linear function; whereas in model 28, the data on the variables are used as % changes. The % change in the value of the data between the past period and the current period, all inputs and additionally % change in unemployment rate in one past period are used as the inputs in the model, the data is scaled to 0.1, 0.9 and a nonlinear function is used as the output activation function.

There is an ongoing discussion in literature on the affect of deseasonalization on the neural network prediction performance. While some studies like Franses and Draisma, (1997); Sharda and Patil, (1992), state that neural networks can detect possible changes in seasonal patterns and Nelson et. al. (1999), state that networks trained on deseasonalized data forecast significantly better than those trained on seasonally nonadjusted data. In a recent study Zhang and Qi, (2005), found that either detrending or deseasonalization can dramatically reduce forecasting errors in univariate models. Since the performance of neural networks on seasonally nonadjusted and seasonally adjusted data is still under discussion it is decided to analyze employment and unemployment data once again after deseasonalizing the both data.

Table 6.3: Models Used in the Neural Networks Analysis and their Characteristics

Model No	Data	Inputs	Scale	Output Activation Function
1	Level	All inputs	-0.9 0.9	Purelin
2	Level	All inputs	-0.9 0.9	Tansig
3	Level	All inputs	0.1 0.9	Purelin
4	Level	All inputs	0.1 0.9	Tansig
5	Level	All inputs plus unemployment (t-1)	-0.9 0.9	Purelin
6	Level	All inputs plus unemployment (t-1)	-0.9 0.9	Tansig
7	Level	All inputs plus unemployment (t-1)	0.1 0.9	Purelin
8	Level	All inputs plus unemployment (t-1)	0.1 0.9	Tansig
9	Level	Lagged inputs	-0.9 0.9	Purelin
10	Level	Lagged inputs	-0.9 0.9	Tansig
11	Level	Lagged inputs	0.1 0.9	Purelin
12	Level	Lagged inputs	0.1 0.9	Tansig
13	Level	Outputs of regression analysis	-0.9 0.9	Purelin
14	Level	Outputs of regression analysis	-0.9 0.9	Tansig
15	Level	Outputs of regression analysis	0.1 0.9	Purelin
16	Level	Outputs of regression analysis	0.1 0.9	Tansig
17	Level	Outputs of PCA analysis	-0.9 0.9	Purelin
18	Level	Outputs of PCA analysis	-0.9 0.9	Tansig
19	Level	Outputs of PCA analysis	0.1 0.9	Purelin
20	Level	Outputs of PCA analysis	0.1 0.9	Tansig
21	% change	All inputs	-0.9 0.9	Purelin
22	% change	All inputs	-0.9 0.9	Tansig
23	% change	All inputs	0.1 0.9	Purelin
24	% change	All inputs	0.1 0.9	Tansig
25	% change	All inputs plus unemployment (t-1)	-0.9 0.9	Purelin
26	% change	All inputs plus unemployment (t-1)	-0.9 0.9	Tansig
27	% change	All inputs plus unemployment (t-1)	0.1 0.9	Purelin
28	% change	All inputs plus unemployment (t-1)	0.1 0.9	Tansig
29	% change	Lagged inputs	-0.9 0.9	Purelin
30	% change	Lagged inputs	-0.9 0.9	Tansig
31	% change	Lagged inputs	0.1 0.9	Purelin
32	% change	Lagged inputs	0.1 0.9	Tansig
33	% change	Outputs of regression analysis	-0.9 0.9	Purelin
34	% change	Outputs of regression analysis	-0.9 0.9	Tansig
35	% change	Outputs of regression analysis	0.1 0.9	Purelin
36	% change	Outputs of regression analysis	0.1 0.9	Tansig
37	% change	Outputs of PCA analysis	-0.9 0.9	Purelin
38	% change	Outputs of PCA analysis	-0.9 0.9	Tansig
39	% change	Outputs of PCA analysis	0.1 0.9	Purelin
40	% change	Outputs of PCA analysis	0.1 0.9	Tansig

In the following sections, the input preparation steps of the study are described. Seasonal adjustment, lag analysis, regression analysis and principal component analysis and data scaling are defined in detail as the data preparation steps.

6.2.1.1 Seasonal Adjustment

The seasonal variations in the data are separated using the classical decomposition method, (DeLurgio, 1998). The key assumption in many different seasonal adjustment methods is that seasonality can be separated from other components in time series. The seasonal time series y_t can be decomposed into seasonal S_t and nonseasonal terms N_t using the multiplicative decomposition model as follows:

$$y_t = S_t \cdot N_t$$

The nonseasonal component can further be decomposed into trend, cycle and error term. The multiplicative decomposition method that is used for time series with increasing seasonal variations is the most frequently used method. If seasonal variation is relatively constant with trend, then additive model that decomposes the series into a sum of seasonal and other nonseasonal components can be used (Zhang and Qi, 2005).

In the seasonal adjustment process, in the first step, the seasonal indices are estimated and in the second step they are removed from the original series by dividing the series with the seasonal factors for the multiplicative model. In this study, the calculation of the seasonal indexes is accomplished through the use of centered moving averages using the ratio to moving average method which is the most widely used method for seasonal component estimation. The seasonally adjusted series is given as an SPSS output in Appendix F below for the unemployment and employment data. The seasonal indexes for unemployment data are, for quarter 1, 1.12; for quarter 2, 8.7; for quarter 3, 9.26 and for quarter 4, 1.07. The seasonal indexes for employment are, 9.7, 1.00, 1.02 and 1.00 for quarter 1 to 4 respectively. All the models are trained once more and tested using the deseasonalized series.

6.2.1.2 Lag Analysis

Since macroeconomic variables affect each other only with a time delay, it is decided to use a lag analysis in the first step for the lagged models. All the independent variables are included in the lag analysis. The analysis is performed using Eviews 4.0. The lag lengths are selected using the Schwarz information criterion. The outputs of the analysis is given in Appendix C, and the lag lengths for the independent variables for unemployment rate data and unemployment per cent change data are given in Table 6.4 and Table 6.5, respectively.

The results of the lag analysis indicate that GNP % growth back to 4 periods behind has an affect on current period unemployment rate. Similarly, total exportation back to 5 periods behind has an affect on current period unemployment rate. The lag lengths for each input variable for unemployment rate data are given in Table 6.4

coloumn 1, and the lag lengths for each input variable in deseasonalized unemployment rate data are given in Table 6.4 coloumn 2.

Table 6.4: Lag Lengths for Independent Variables for Unemployment Rate Data and Deseasonalized Unemployment Rate Data

VARIABLE	Lag lengths for unemployment rate	Lag lengths for deseasonalized unemployment rate
GNP % growth	4	4
Total exportation	5	5
Total importation	4	1
Public investments /GDP	4	5
Private investments/GDP	5	1
Capacity utilization rate in manufacturing industry	5	1
Productivity in manufacturing industry	5	1
Real exchange rates	5	1
Real wages	5	1
Real deposit rates	5	1
Inflation	5	1
Unemployment	1	1

In addition to the lag analysis of independent variables, a regression analysis is applied to define the effect of previous unemployment on current unemployment. Unemployment at the current period (t) is regressed on its past period values, using unemployment (t-1) to unemployment (t-8) as the regressors. The results reveal that change in unemployment (t-1) has the lowest value with respect to the Schwarz information criteria. This regression analysis is also applied to deseasonalized unemployment rate data and it is found that again the model using unemployment (t-1) as the independent variable has the lowest Schwarz information criteria value.

The lag lengths found in the lag analysis show the latest lags that should be taken into the analysis. In other words, when GNP % growth lag length is found to be 4 , this indicates that GNP % growth (t-1), GNP % growth (t-2), GNP % growth (t-3) and GNP % growth (t-4) should be included in the prediction analysis. However since the inclusion of all these lag lengths for each of the input variables is impossible with respect to the available data for neural network training in hand, it is decided to use only the latest lag for each input variable in this study. Therefore, in the lagged input models through models 9 to 12 in the unemployment rate prediction analysis, GNP % growth (t-4), total exportation (t-5), total importation (t-4), public investments/GDP (t-4), private investments/GDP(t-5), capacity utilization rate in manufacturing industry(t-5), productivity in manufacturing industry(t-5), real exchange rates(t-5), real wages(t-5), real deposit rates (t-5), inflation(t-5) and unemployment(t-1) are used as the inputs to the neural network.

Through the models 9 to 12 in the deseasonalized unemployment rate prediction analysis, GNP % growth (t-4), total exportation (t-5), total importation(t-1), public investments/GDP(t-5), private investments/GDP(t-1), capacity utilization rate in manufacturing industry(t-1), productivity in manufacturing industry(t-1), real exchange rates(t-1),real wages (t-1), real deposit rates (t-1), inflation(t-1) and unemployment(t-1) are used as the inputs to the neural network.

The results of the lag length analysis for unemployment data in per cent changes and deseasonalized unemployment data in per cent changes are summarized below in Table 6.6 and the outputs of the Eviews analyses are given in Appendix C.

The inputs used in the models through 29 to 32 in the unemployment per cent change data are GNP % growth (t-5), per cent change in total exportation (t-4), per cent change in total importation(t-2), per cent change in public investments/GDP(t-4), per cent change in private investments/GDP(t-2), per cent change in capacity utilization rate in manufacturing industry(t-3), per cent change in productivity in manufacturing industry(t-3), per cent change in real exchange rates(t-4), per cent change in real wages (t-2), per cent change in real deposit rates (t-2), inflation(t-2) and per cent change in unemployment(t-4) are used as the inputs to the neural network.

Through the 29 to 32 in prediction of deseasonalized per cent change unemployment rate data, GNP % growth (t-4), per cent change in total exportation (t-4), per cent change in total importation(t), per cent change in public investments/GDP(t-4), per cent change in private investments/GDP(t), the per cent change in capacity utilization rate in manufacturing industry(t), per cent change in productivity in manufacturing industry(t-3), per cent change in real exchange rates(t), per cent change in real wages(t), per cent change in real deposit rates (t), inflation(t) and the per cent change in unemployment(t-2) are used as the inputs to the neural network.

Table 6.5: Lag Lengths for Independent Variables for Unemployment Rate per cent change Data and Deseasonalized Unemployment Rate per cent change Data

VARIABLE	Lag lengths for unemployment rate in per cent changes	Lag lengths for deseasonalized unemployment rate in per cent changes
GNP % growth	5	4
% change in total exportation	4	4
% change in total importation	2	0
% change in public investments/GDP	4	4
% change in private investments/GDP	2	0
% change in capacity utilization rate in manufacturing industry	3	0
% change in productivity in manufacturing industry	3	0
% change in real exchange rates	4	0
% change in real wages	2	0
% change in real deposit rates	2	0
Inflation	2	0
% change in unemployment	4	2

6.2.1.3 Regression Analysis

In addition to the models using the current values of variables, models using the outputs of a pre-applied regression analysis are also tested in the study. These models use the outputs of the regression analysis as the inputs to the neural network study. The aim of this hybrid methodology is to decrease the number of inputs in the analysis and to identify a possible hidden nonlinear relationship between the significant variables identified through a linear regression analysis and the output in the study- unemployment rate in Turkey. The regression analysis is performed using SPSS statistics package version 12.0.

The results of the regression analysis reveal that only GNP variable is found to be significant in the regression model for a significance level of 0.01 without having a multicollinearity problem. In the models through 13 to 16, GNP is used as the only input variable.

The regression analysis is also performed for the models using the per cent changes in data. The significant variables in this regression model are found to be per cent change in exportation and per cent change in public investment/GDP again without having a multicollinearity problem. The two variables are used as the inputs in the models through 32 to 35.

Regression analysis applied to deseasonalized unemployment rates identifies two variables as significant. These variables are namely, inflation and real deposit rates.

These two variables are used as the inputs in the models through 13 to 16 in the prediction of deseasonalized unemployment rates.

The regression analysis applied to deseasonalized unemployment rates in per cent changes does not identify any variable as a significant variable for a significance level of 0.01. The results of the regression analysis for each type of unemployment data are summarized below in Table 6.6, and the SPSS outputs for each of the regression analyses are given in Appendix D.

Table 6.6: Significant Variables for Different Types of Unemployment Data

unemployment rate	unemployment rate in per cent changes	deseasonalized unemployment rate	deseasonalized unemployment rate in per cent changes
GNP	Per cent change in total exportation	inflation	-
	Per cent change in public investment /GPD	Real deposit rates	

6.2.1.4 Principal Component Analysis

Principal Component Analysis (PCA) based models are the models in which the results of a principal component analysis is used as the inputs. Principal component analysis is a widely used statistical methodology in data preprocessing in neural networks. The aim of this analysis is to decrease the dimensionality of the data set; in other words to decrease the number of input variables and to predict the output with using unredundant variables. The highly correlated input variables are classified into factors that have no significant correlation in between. PCA can often extract a very small number of components from quite high-dimensional original data and still retain the important structure. The principal component analysis is also performed by using SPSS statistics package version 12.0. The outputs of the PCA analysis is given in Appendix E.

The results of the factor analysis identify four factors when the factors with eigenvalues greater than 1 are considered. The four components are also shown in the scree plot in Appendix E. These four component factors accounts for the 78.76 % of the total variance between variables. Figure 6.4 below shows that component one is highly correlated to the variables export, import and productivity, public investments/GDP and real effective exchange rates; the second component is highly correlated to real deposit rates, inflation and capacity utilization; the third component

is highly correlated to realwages and private investment/GDP and the fourth component is highly correlated to GNP. In the models 16 to 20, these four components are used as the input to the network analysis for the unemployment rate prediction analysis and deseasonalized unemployment rate analysis.

Rotated Component Matrix(a)

	Component			
	1	2	3	4
GNP	-,084	-,020	-,005	,935
capacity	,316	,614	,370	,058
reefexrate	,638	,535	,092	-,169
inflation	-,146	-,922	,190	,039
realdeprate	,176	,945	-,135	-,029
realwage	-,026	-,054	,847	,123
export	,849	,345	-,228	-,160
import	,858	,406	-,098	-,103
productivity	,909	,277	-,088	-,052
privinvgdp	-,318	-,083	,609	-,268
publicinvgdp	-,644	,226	,062	-,277

Figure 6.4: Rotated Component Matrix for Unemployment Data in Levels

PCA analysis is also performed for the per cent change data (Figure 6.5). The results reveal that for the per cent change data, five components are identified. These five components accounts for the 79.09 % of the total variance between variables. Component 1 is mainly representative of the per cent change in productivity, per cent change in importation, per cent change in capacity, per cent change in public investments/GDP and per cent change in exportation; component 2 mainly represents per cent change in real wages and inflation. Component 3 mainly represents per cent change in private investment/GDP and GNP per cent growth. Components 4 and 5 are representatives of per cent change in exchange rates and per cent change in deposit rates respectively. In the models 36 to 40, these five components are used as the inputs to the network analysis for unemployment rate prediction in per cent changes and deseasonalized unemployment rate in per cent changes. The outputs of the PCA and the scree plot are given in Appendix E.

Rotated Component Matrix^a

	Component				
	1	2	3	4	5
GNPch	,325	-,135	-,745	-,082	,220
capacitych	,798	,195	-,194	,296	,073
exratech	,092	,024	,030	,972	,013
Inflationch	-,130	-,813	-,105	-,153	,002
deporatech	-,055	,061	,007	,018	,965
realwagech	-,080	,849	-,095	-,105	,061
exportxh	,747	-,031	,374	-,049	-,125
importch	,895	,060	,090	,154	,049
prodch	,933	,034	-,099	,047	-,070
privinvgnpch	,266	-,103	,768	-,031	,205
publicinvgnpch	,780	-,123	-,026	-,122	,010

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Figure 6.5: Rotated Component Matrix for unemployment data in per cent changes

6.2.1.5 Data Scaling

Scaling the data into an appropriate range, improves the performance of the neural network analysis (Masters, 1994). The scaling range is generally limited to a range between (-1,1). The neural networks are sensitive to the data processed. Therefore, it is decided to scale the data in two different ranges and see the effects of two different scale ranges on the network performance. The data is once scaled to (-0.9; 0.9) and in the second trial the data is scaled to (0.1; 0.9) according to the given formula:

$$\hat{x} = x_{\min} + \frac{x - x_{\min}}{x_{\max} - x_{\min}} (\hat{x}_{\max} - \hat{x}_{\min}) \quad (6.1)$$

where, $\hat{x}_{\min}$ and $\hat{x}_{\max}$ correspond to the minimum and maximum values of the scaling range respectively. $x_{\min}$ and $x_{\max}$ correspond to the minimum and maximum values of the original data series on which scaling is applied. x corresponds to the value to be scaled and $\hat{x}$ shows the scaled value of x .

6.2.1.6 Neural Network Structure and Analysis

A two layered feedforward neural network is selected as the network type to be applied because they are widely approved to be general approximators. The literature shows that there is no theoretical basis for the selection of the number of hidden nodes, and the most common way in determining the number of hidden nodes is by

trial and error. In the determination of the number of hidden units in the hidden layer, several equations suggested in literature (Zhang et.al., 1998 and Masters, 1993), are taken into consideration. The number of hidden units is found as the maximum of the various formulations given in literature.

Number of Hidden Units = $\max ("2n+1", "2n", "n", "n/2", "\sqrt{m*n})$, where m corresponds to the output nodes and n corresponds to the input nodes.

The maximum number of hidden units is found to be 23, maximum of ("23","22","11","6","4") for the models using 11 inputs; 25 for the models using 12 inputs; 11 for the models using 5 inputs; 9 for the models having four inputs and 3 for the models having one single input.

Since none of the defined equations give the optimum number of hidden units, it is decided to increase the number of the hidden units from 1 to maximum number found according to the equation given above, and to select the network having the minimum error. The error used in the analysis is the widely used MSE. In the hidden layer the activation function is selected as the tansig. Zhang et.al., (1998) state that, for forecasting problems which involves continuous target values, a linear activation function is reasonable to use for the output nodes, however feedforward neural networks with linear output nodes have the limitation that they can not model a time series with trend. Therefore it is decided to use both a linear activation function and a nonlinear activation function -tangent sigmoid- in the output node and see the difference between the performances of these two activation functions.

Approximately 20 % of the 67 samples are taken as the test set and the remaining samples are used as the training set. The networks are trained by MATLAB version 6.5 using the TRAINGDX algorithm that adapts the learning rate and momentum by itself. The MATLAB code (the Matlab m. file) used in the neural network training and analysis is given in Appendix F. In order to avoid local minima, each network is retrained 10 times by changing the initial weights of the inputs.

6.2.1.7 Results of the Neural Network Prediction Analysis for Turkey's Unemployment Rates

During the analyses for unemployment rate prediction a total of 80 models have been tested and 11360 runs have made. For each model and for each unit the runs are performed by starting 10 different initial weights in order to avoid getting stuck in local minimum. Since the data set is not large enough to use a validation set, training is stopped at epoch 1000, and the model is tested using the test set; and for each model-hidden unit combination, the minimum test errors found and their corresponding training errors are summarized. The results showed that as also previously stated in literature (Gately, 1996), the networks get overtrained as the hidden units increase. This overtraining-hidden unit relationship is observable in almost all models, an example of such behaviour is given below in Figure 6.6 for model 22 in unemployment rate prediction with seasonal values.

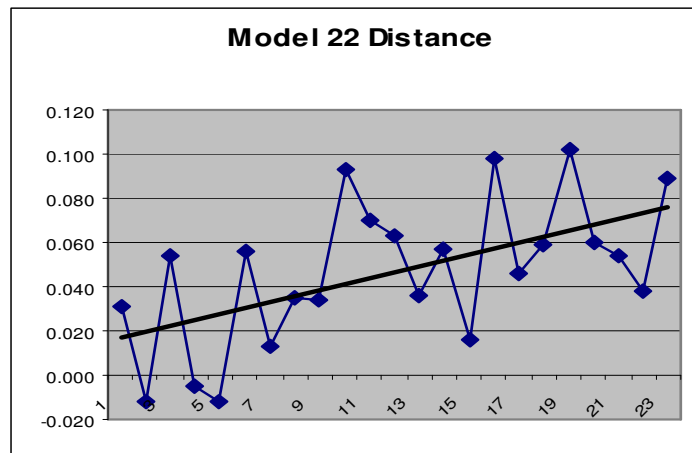


Figure 6.6: Distance between Training and Test MSEs for Different Hidden Units in Model 22 for Unemployment Rate Seasonal Data

To avoid selecting an overtrained model as the best model, it is decided to discard the results obtained with more than 20 hidden units from the analysis. Moreover, the best model for each data set is selected as the model having the minimum average value of test and training MSE. The selected models are summarized below in Table 6.7.

The training errors and test errors obtained in the analyses indicate that mean square errors obtained in the unemployment data in levels are smaller than the overall mean square error reached with the per cent change data within the best models. This result indicates that overall prediction performance is better in the data using level values of the variables rather than the per cent change values. The results also show that

models using the deseasonalized data perform better compared to the models using seasonal unemployment rate data.

Table 6.7: Best Networks Found for Different Unemployment Data Sets

DATA ANALYZED	BEST MODEL	STRUCTURE OF THE BEST MODEL	TEST ERROR (MSE)	TRAINING ERROR (MSE)
Unemployment in Levels	MODEL 11	Lag purelin 0.1-0.9 Scale	0.00426	0.0051
Unemployment % Change	MODEL 28	T-1 tansig 0.1-0.9 Scale	0.00465	0.0060
Deseasonalized Unemployment in Levels	MODEL 8	T-1 tansig 0.1-0.9 Scale	0.00147	0.0029
Deseasonalized Unemployment % Change	MODEL 32	Lag tansig 0.1-0.9 Scale	0.00284	0.0065

The results of the neural networks analysis applied to unemployment rates in Turkey indicates that the best network having the minimum test MSE is found in the model using the lagged variables as the inputs. Model 11, using the lagged variables as the inputs, with a scaling range of 0.1-0.9, a purelin output activation function and 17 hidden units has the minimum test error with a value of 0.00425. The training error for the same network is found to be 0.00514. The normalized test set and the outputs of the network analysis are given below in Table 6.8 and plotted below in Figure 6.7.

Table 6.8: Real Normalized Unemployment Rates and Forecasted Unemployment Rates

Sample	Normalized Unemployment Rate	Forecast
1	0.5288	0.5210
2	0.3141	0.3039
3	0.5256	0.4456
4	0.2056	0.3189
5	0.3188	0.2521
6	0.1449	0.1782
7	0.4435	0.5321
8	0.2403	0.3204
9	0.7418	0.7512
10	0.5391	0.5963

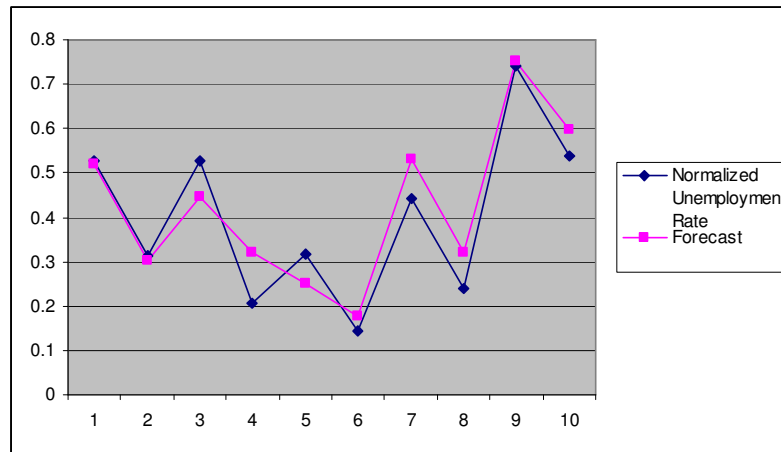


Figure 6.7: Plot of real normalized unemployment rates and forecasted unemployment rates

The best network in deseasonalized unemployment rates is found to be the model 8 with a hidden unit number of 13, with a test error and a training error of 0.00147 and 0.00297. The minimum test error reached using the deseasonalized unemployment data is lower than the half of the test error reached in the original unemployment data. However, the training error is higher compared to the unemployment rate data. The deseasonalized unemployment rates and the forecasted deseasonalized unemployment rates are given in Table 6.9 and plotted in Figure 6.8 below.

Table 6.9: Real Normalized Deseasonal Unemployment Rates and Forecasted Deseasonal Unemployment Rates

Sample	Real Value	Forecast
1	0.51173	0.42792
2	0.49578	0.4564
3	0.46677	0.43974
4	0.49206	0.53342
5	0.31526	0.3063
6	0.25543	0.2634
7	0.23045	0.27642
8	0.39815	0.43847
9	0.36372	0.33411
10	0.73947	0.74838
11	0.78110	0.79835

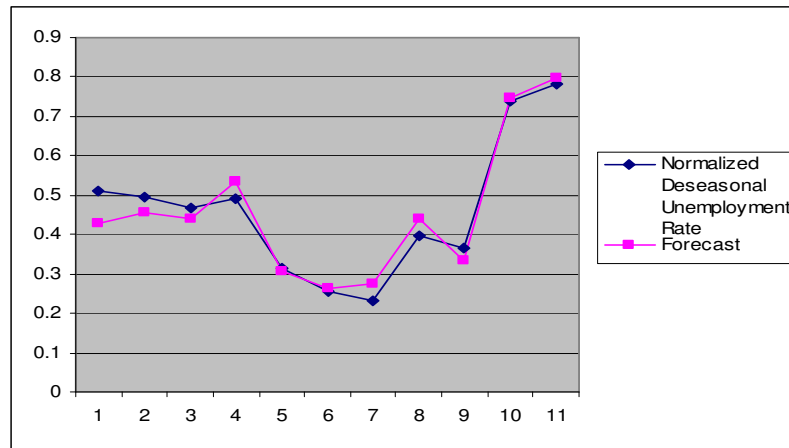


Figure 6.8: Plot of normalized deseasonal unemployment rates and forecasted deseasonal unemployment rates

The best model found for the data set in per cent changes of unemployment is found to be model 28 with 12 hidden units and the best model for the data set in per cent changes of deseasonal unemployment rates is found to be model 32 with 16 hidden units. Model 32 uses lagged variables as the inputs, nonlinear output activation function and a scaling range of 0.1-0.9 while model 28 uses all the inputs and the per cent change in unemployment rate in one past period as the input, a nonlinear output activation function and a scaling range of 0.1-0.9. The test error for model 28 with unemployment per cent change data is 0.00465 and the test error for deseasonalized unemployment per cent change data is 0.00284. The best test MSE results obtained for each model in the unemployment rate analysis are summarized below in Table 6.10.

The results show that the models using the results of the linear regression analysis and principal component analysis as the inputs result with the worse average MSEs compared to the other models. Furthermore, considering unemployment rate analysis, only the lagged models and the model using all variables plus unemployment of the past period end up with the smallest MSEs. However, this result is expectable since some information is lost when the number of inputs are decreased. The best test errors obtained in each model also indicate that input scales, output activation functions and deseasonalization may have significant affect on the network performance.

Table 6.10: The Best Test MSEs for Different Scale Ranges and Different Activation Functions

Unemployment	All Variables		All Variables + U(T-1)		Lagged		Regressed		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0202	0.043	0.023	0.031	0.041	0.025	0.0784	0.0778	0.028	0.016
Scale 0.1;0.9	0.0097	0.0086	0.0157	0.035	0.0042	0.0067	0.015	0.0147	0.006	0.007
Unemployment % Change	All Variables		All Variables + U(T-1)		Lagged (a)		Regressed		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0312	0.0094	0.0182	0.0084	0.0316	0.0175	0.1666	0.153	0.084	0.082
Scale 0.1;0.9	0.0079	0.0046	0.0071	0.0038	0.003	0.0043	0.031	0.0318	0.030	0.0212
Deseasonalized Unemployment	All Variables		All Variables + U(T-1)		Lagged		Regressed		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0271	0.02	0.0071	0.0061	0.0087	0.0093	0.0561	0.0536	0.015	0.014
Scale 0.1;0.9	0.0043	0.0056	0.0022	0.00147	0.00143	0.00243	0.0120	0.0125	0.0055	0.0066
Deseasonalized Unemployment % Change	All Variables		All Variables + U(T-1)		Lagged		Regressed		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.028	0.0217	0.0146	0.023	0.001	0.0124	-	-	0.076	0.071
Scale 0.1;0.9	0.0034	0.0024	0.0034	0.0049	0.0021	0.0028	-	-	0.016	0.014

In unemployment rate prediction, the networks using data scaled to 0.1-0.9, give better test MSE results compared to data scaled to -0.9-0.9. As an example, consider the model using all the inputs in their current period values in the unemployment data set and the output activation function of purelin, the upper left corner in Table 6.10. While the average MSEs found using a scale range of -0.9;0.9 is 0.0202, the same average MSE is found to be 0.0097 when a scaling range of 0.1;0.9 is used. The same relationship in the different scale ranges is observed in all the other models in the analysis. Table 6.10 also gives information about the best test MSEs found with using different output activation functions when the columns are compared to each other. The results show that in some of the models tansig activation function gives better test MSEs in others purelin activation function gives better MSEs e.g.(a). To test the affects of activation functions, input scales and deseasonalization on network performance, the tranining performances and the test performances of the best networks obtained for all the hidden units and the models in the analysis are averaged and this average MSE is used as an indicator of the overall network performance. The overall average MSEs obtained for each model in the analysis are given below in Table 6.11.

Table 6.11: The Overall Network Performance for Different Scale Ranges and Different Activation Functions for Unemployment Rate Prediction Study

Unemployment	All Variables		All Variables + U(T-1) *		Lagged		Regressed		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0443	0.0453	0.0289	0.0343	0.0365	0.0378	0.1026	0.1025	0.047	0.0417
Scale 0.1;0.9	0.011	0.0104	0.038	0.0381	0.0096	0.0087	0.0202	0.0200	0.014	0.0143
Unemployment % Change	All Variables		All Variables + U(T-1)		Lagged (b)		Regressed (a)		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0538	0.0388	0.0335	0.0204	0.0882	0.0398	0.1477	0.1511	0.1118	0.0095
Scale 0.1;0.9	0.0172	0.0145	0.0117	0.009	0.0126	0.0097	0.0294	0.0299	0.0321	0.0313
Deseasonalized Unemployment	All Variables		All Variables + U(T-1)		Lagged		Regressed		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0395	0.0354	0.0145	0.0159	0.0114	0.0119	0.0965	0.0948	0.0278	0.0274
Scale 0.1;0.9	0.011	0.0085	0.0039	0.0035	0.0038	0.0033	0.0194	0.0195	0.0134	0.0131
Deseasonalized Unemployment % Change	All Variables		All Variables + U(T-1)		Lagged		Regressed		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0326	0.0307	0.0455	0.0406	0.0196	0.0228	-	-	0.11	0.111
Scale 0.1;0.9	0.0091	0.0086	0.0099	0.0096	0.0084	0.0079	-	-	0.0231	0.0231

The affect of input scaling, deseasonalization and output activation functions are tested using pairwise t test in SPSS. The results show that the performances obtained by using the two input scaling ranges statistically differ for a significancy level of 0.05. The models using a scaling range of 0.1;0.9 gives lower average MSEs compared to the models using a scaling range of -0.9;0.9. The affects of two activation functions on network performance however do not differ from each other statistically for a significancy level of 0.05. The pairwised t test also shows that deseasonalization has a significant affect on the performance. The models using deseasonalized data give significantly lower average MSEs compared to the models using seasonal unemployment rate data for a significancy level of 0.05. The results of the pairwise t tests are given in Appendix H.

The relative importance of each input in a neural network may be calculated to illuminate the black box in a neural network analysis. To identify the relative importance of inputs, the three methods showing the highest performance when applied to a dataset simulated from a dataset with prior known correlation structure, in a recent study of Olden et.al, 2004 are applied . These methods are the widely applied Connection Weight Approach, the Improved stepwise selection 1 method and

Improved selection 2 methods. These methods are described in Section 5.5. The average per cent changes in MSEs for each input variable is calculated using each of the three methods and the average of the results of the three methods are used as a reference in quantifying the importance of each input variable.

Input importance evaluation analysis is applied to the deseasonalized unemployment in levels data set in the study. Model 8 is used in the relative importance evaluation analysis as it has the highest performance within selected best models summarized in Table 6.7.

Table 6.12: Relative Importance of Inputs for Deseasonalized Unemployment Rate Data in Levels with respect to Three Input Evaluation Methods

Input variable	Improved Selection 1	Improved Selection 2	Connection Weight	Average
unemployment (t-1)	0.22302247	0.232005	0.186311	0.21378
GNP	0.008658	0.00577	0.068527	0.02765
Capacity utilization	0.08983965	0.045874	0.044491	0.06007
Effective exchange rates	0.05122275	0.016148	0.114615	0.06066
Inflation	0.04037953	0.078144	0.007543	0.04202
Real deposit rates	0.09336897	0.057892	0.105419	0.08556
Real wages	0.02053045	0.011477	0.119809	0.05061
Total export	0.01299617	0.080538	0.056085	0.04987
Total import	0.09055918	0.268687	0.187389	0.18221
Productivity	0.345712	0.158595	0.048652	0.18432
Private investments/GDP	0.00012453	0.00273	0.032533	0.01180
Public investments/GDP	0.02358631	0.042139	0.028626	0.03145

The relative importance analysis for deseasnalized unemployment rate in levels identifies unemployment(t-1), productivity, and total import as the three most important factors for deseasonalized unemployment rate prediction in levels. The degree of importance of each variable for the different input variable importance evaluation methods are given above in Table 6.12 and variables are plotted below in Figure 6.9 with respect to their average importance scores. In the improved selection method, where each variable and its weights are eliminated from the network in an iterative way, a value of “0” is given to each variable and its affect on the network importance is evaluated. In the improved selection 2 method each variable is given its average value, 0.5 in this study, and the affect of this change in the network is evaluted. In the third approach the connection weight method is adopted and the average of this three methods are calculated.

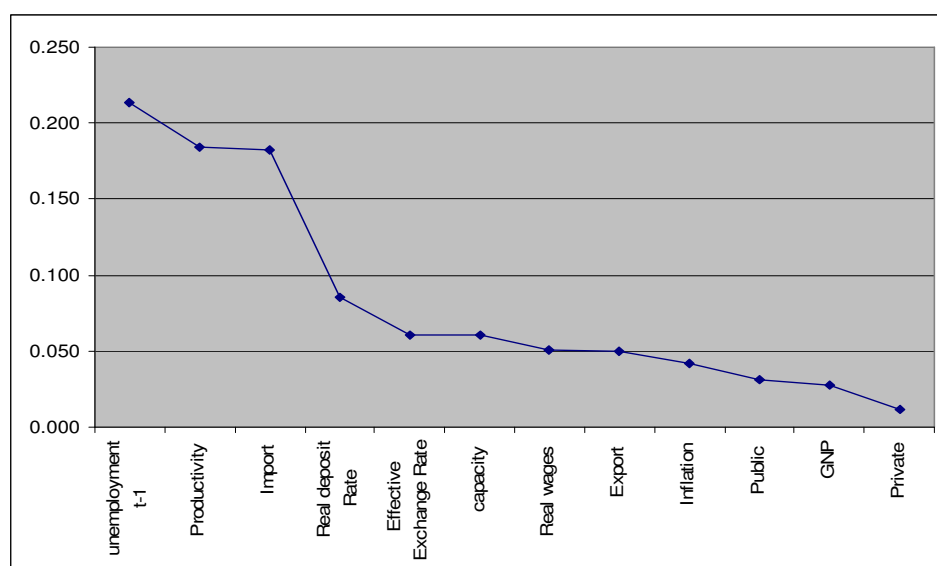


Figure 6.9: Relative Importance of Variables with respect to Deseasonalized Unemployment Rate in Levels

The selected model, Model 8 is further applied to a recent data set covering 2005Q1 and 2005Q4 and the whole test set results are compared with an ARIMA and a VAR model applied to the same data set. The results of the comparison are summarized below in Table 6.13.

Table 6.13 : Comparison of Artificial Neural Network Results with ARIMA and VAR Model Results for The Test Set.

	Actual data	ARIMA forecast	VAR forecast	NN forecast	SE ARIMA	SE VAR	SE NN
1989Q2	8.71	8.74	8.73	8.679095	0.000798	0.000336	0.001044
1990Q4	8.60	8.67	8.61	8.865778	0.004283	0.00015	0.070851
1992Q2	8.40	8.42	8.42	8.902515	0.000653	0.000604	0.256224
1993Q4	8.57	8.65	8.62	9.302936	0.005216	0.001897	0.531989
1995Q2	7.33	7.36	7.35	7.773499	0.000426	0.000135	0.192677
1996Q4	6.92	6.97	6.92	7.581513	0.002983	9.37E-05	0.443906
1998Q2	6.74	6.76	6.74	7.755131	0.000416	7.46E-06	1.030105
1999Q4	7.92	7.98	7.93	8.891679	0.00421	0.000153	0.953003
2001Q2	7.67	7.61	7.64	7.982932	0.003731	0.001262	0.095359
2002Q4	10.31	10.26	10.27	10.88509	0.00238	0.00128	0.333755
2004Q2	10.60	11.21	10.62	11.3344	0.376894	0.000398	0.540616
2005Q1	11.70	9.45	10.12	11.11236	5.049234	2.483097	0.345323
2005Q2	9.20	12.04	10.24	11.68025	8.053561	1.07958	6.15163
2005Q3	9.40	8.69	8.72	10.12207	0.505293	0.463735	0.521382
2005Q4	10.60	10.06	10.23	10.14989	0.292933	0.138723	0.202599
MSE whole test data					0.953534	0.278097	0.778031
MSE 2005 data					3.475255	1.041284	1.805233

The comparison results indicate that within the three models VAR model gives the best test results for both the whole test data set and the data set for year 2005.

ARIMA model gives the worst results within the three models with an MSE of 0.95 for the whole test set and 3.47 for 2005 data. Artificial neural networks perform better compared to the ARIMA model both in the whole data set and in the data set covering 2005 data.

6.2.2 Employment Index Prediction in Manufacturing Industry of Turkey with Artificial Neural Networks

In addition to the unemployment rate prediction study, neural networks are also used to predict the employment index level in manufacturing industry in Turkey. The reason for this second analysis is that, it is possible to find more accurate and reliable data about labour issues in the manufacturing sector in Turkey. The real wages, capacity utilization rates, productivity levels available, are all about manufacturing sector and in the previous unemployment prediction analysis study, as mentioned in section 6.2.1, they are assumed to be representatives of the other sectors in Turkey. The analysis covers the period 1988Q3 to 2004Q4, since the data before 1988Q3 is unreliable. The data for the variables are obtained from SIS. The data on manufacturing sector is available quarterly for the whole analysis period therefore there was no need for an early interpolation analysis. The dependent and independent variables used in the study are summarized below in Table 6.14.

Similar to the analysis made in predicting unemployment rates in Turkey, an input preparation study is made as a first step. The lag analyses, regression analyses and principal component analyses are all re-applied to the employment data.

Table 6.14: Dependent and Independent Variables used in the Employment Index Analysis

Dependent Variable	Employment index level for manufacturing industry in Turkey
Independent Variables	GNP % growth
	capacity utilization rate in manufacturing industry
	real effective exchange rates
	inflation
	real deposit rates
	index level of real wages in manufacturing industry
	export level of manufacturing industry
	import level of manufacturing industry
	productivity in manufacturing industry
	private investments/GDP
	public investments/GDP

In order to find the best performing model for employment rate prediction, similar to the analysis made in unemployment study, a total of 40 models are analyzed. In the models through 1 to 4, 11 of all the 11 variables are used as the inputs to the network analysis. In the models through 5 to 8, in addition to the 11 variables in the current period, employment index level in one past period is included into the independent variable list to understand the affect of employment in one past period on employment in the current period. In the models through 9 to 12 a lag analysis is performed initially on the variables and the lagged variables are used as the inputs to the network, the reason for the lagged models is that macroeconomic variables affect each other after a time delay and lagged models take these delays of the variables into consideration while predicting the unemployment rates. In the models through 13 to 16, initially a regression analysis is performed and the outcomes of the regression analysis, the significant variables, are used as the inputs to the network analysis. In the models through 17 to 20, initially a principal component analysis is performed and the outcoming factors are used as the inputs to the network analysis. Regression analysis and principal component analysis are again used in order to reduce the number of inputs and identify the performance of the network with a considerably lower number of inputs. In the models through 1 to 20, the data about the output variable and all the input variables except GNP are taken in their real values. GNP is used as the per cent change in GNP level. The networks using the per cent change values in employment data, are analyzed in models through 21 to 40.

As mentioned in section 6.2.1, recent research states that deseasonalization may have a significant impact on prediction analyses with neural networks especially in the studies of unemployment data where, seasonality is obvious. Especially during the summer periods the requirement for daily labour increases and unemployment rates decline, this demand for seasonal labour is observed through all the years in the study naturally. In the winter terms, as the demand for seasonal labours decline significantly, the unemployment rates seem to incline. Although seasonality in employment in manufacturing industry would be less significant compared to unemployment rates , it is also taken into consideration and the prediction analysis for employment index is once again repeated using the deseasonalized data. The specifications of the models are summarized above in section 6.2.1. in Table 6.3.

6.2.2.1 Employment Index Data- Seasonal Adjustment

The deseasonalization analysis is repeated for the employment index data as defined in section 6.2.1.1. The seasonally adjusted series is given below in Appendix F. The seasonal indexes for employment are, 9.7, 1.00, 1.02 and 1.00 for quarter 1 to 4 respectively. The whole models are once more trained and tested using the deseasonalized series.

6.2.2.2 Employment Index Data - Lag analysis

According to the lag analysis as described in 6.2.2.1, the following results are obtained for the different types of employment data. The outputs of the analysis is given in Appendix C, and the lag lengths for the independent variables for employment index level data and employment index per cent change data are given in Table 6.15 and Table 6.16, respectively.

Table 6.15: Lag Lengths for Independent Variables for Employment Index Level Data and Deseasonalized Employment Index Level Data

VARIABLE	Lag lengths for employment index level	Lag lengths for deseasonalized employment index level
GNP % growth	4	4
Exportation in manufacturing industry	5	1
Importation in manufacturing industry	6	6
Public investments /GDP	5	5
Private investments/GDP	1	1
Capacity utilization rate in manufacturing industry	1	1
Productivity in manufacturing industry	5	4
Real exchange rates	5	2
Real wages in manufacturing industry	1	1
Real deposit rates	1	1
Inflation	1	1
Employment	1	2

The results of the lag analysis indicate that GNP % growth back to 4 periods behind has an affect on current period employment index level. Exportation back to 5 periods behind has an affect on current period employment index level. The lag lengths for each input variable for unemployment rate data are given in Table 6.15 coloumn 1, and the lag lengths for each input variable in deseasonalized unemployment rate data are given in Table 6.15 coloumn 2.

In the lagged input models through models 9 to 12 in the employment index level prediction analysis, GNP % growth (t-4), exportation in manufacturing industry(t-5), importation in manufacturing industry (t-6), public investments/GDP(t-5), private investments/GDP(t-1), capacity utilization rate in manufacturing industry(t-1), productivity in manufacturing industry(t-5), real exchange rates(t-5), real wages(t-1),

real deposit rates (t-1), inflation(t-1) and employment(t-1) are used as the inputs to the neural network.

Through the models 9 to 12 in the deseasonalized employment index level prediction analysis, GNP % growth (t-4), exportation in manufacturing industry(t-1), importation in manufacturing industry (t-6), public investments/GDP(t-5), private investments/GDP(t-1), capacity utilization rate in manufacturing industry(t-1), productivity in manufacturing industry(t-4), real exchange rates(t-2), real wages in the manufacturing industry(t-1), real deposit rates (t-1), inflation(t-1) and employment(t-2) are used as the inputs to the neural network.

Table 6.16: Lag Lengths for Independent Variables for Employment Index per cent change Data and Deseasonalized Employment Index per cent change Data

VARIABLE	Lag lengths for employment index in per cent changes	Lag lengths for deseasonalized employment index in per cent changes
GNP % growth	4	4
% change in export level of manufacturing industry	4	0
% change in import level of manufacturing industry	5	1
% change in public investments/GDP	4	4
% change in private investments/GDP	0	1
% change in capacity utilization rate in manufacturing industry	4	2
% change in productivity in manufacturing industry	4	3
% change in real exchange rates	0	0
% change in real wages	0	0
% change in real deposit rates	0	0
Inflation	0	1
% change in employment	2	1

The inputs used in the models through 29 to 32 in the employment index per cent change prediction analysis are GNP % growth (t-4), per cent change in exportation in the manufacturing industry(t-5), per cent change in importation in the manufacturing industry(t-5), per cent change in public investments/GDP(t-4), per cent change in private investments/GDP(t), per cent change in capacity utilization rate in manufacturing industry(t-4), per cent change in productivity in manufacturing industry(t-4), per cent change in real exchange rates(t), per cent change in real wages in the manufacturing industry(t), per cent change in real deposit rates(t), inflation(t), and finally per cent change in employment index(t-2).

The inputs used in the models through 29 to 32 in the deseasonalized employment index per cent change prediction analysis are GNP % growth (t-4), per cent change in exportation in the manufacturing industry(t), per cent change in importation in the manufacturing industry(t-1), per cent change in public investments/GDP(t-4), per

cent change in private investments/GDP(t-1), per cent change in capacity utilization rate in manufacturing industry(t-2), per cent change in productivity in manufacturing industry(t-3), per cent change in real exchange rates(t), per cent change in real wages in the manufacturing industry(t), per cent change in real deposit rates(t), inflation(t-1), and finally per cent change in employment index(t-1).

6.2.2.3 Input Preparation- Regression Analysis

Similar to the regression analysis applied in section 6.2.1.3, a regression analysis is applied to the employment index data. In the models through 13 to 16 the outputs of the regression analysis applied to employment index level data are used as the network inputs and in the models through 32 to 35, the outputs of the regression analysis applied to employment index data in per cent changes are used as the network inputs.

Table 6.17: Significant variables for different types of unemployment data

employment index level	employment index in per cent changes	deseasonalized employment Index level	deseasonalized employment index in per cent changes
Productivity in manufacturing industry	GNP	GNP	per cent change in capacity utilization rates
Real wages in manufacturing industry	Per cent change in capacity utilization rates	capacity utilization rates	per cent change in real wages in manufacturing industry
inflation	Per cent change in importation in manufacturing industry	Real effective exchange rates	per cent change in importation in manufacturing industry
Public investments/GDP	Per cent change in productivity in manufacturing industry	Real wages in manufacturing industry	per cent change in productivity rates in manufacturing industry
GNP	-	Productivity in manufacturing industry	-
-	-	Public investments/GDP	-

The same approach is also applied to the deseasonalized employment index data. The significant variables identified in the regression analysis for each type of employment data are summarized below in Table 6.17. The regression study is previously described in section 6.2.1.3. in detail. The SPSS outputs for each of the regression analyses are given in Appendix D.

6.2.2.4 Input Preparation- Principal Component Analysis

The principal component analysis applied to the employment data in levels and per cent changes identifies four factors when the factors with eigenvalues greater than 1 are considered. The four components are also shown in the scree plot in Appendix

7.0. These four component factors accounts for the % 78.85 of the total variance between variables. Table below shows that component 1 is highly correlated to the variables export, import and productivity, public investments/GDP and real effective exchange rates; the second component is highly correlated to real deposit rates, inflation and capacity utilization; the third component is highly correlated to realwages and private investment/GDP and the fourth component is highly correlated to GNP, the same components identified in the unemployment analysis. In the models through 17 to 20, the four components are used as the input to the network analysis. The outputs of the PCA analysis is given in Appendix E and the rotated component matrix for employment index data is given in Figure 6.10

Rotated Component Matrix ^a

	Component			
	1	2	3	4
GNP	-,060	-,028	-,023	,959
capacity	,275	,645	,359	,097
reefexrate	,632	,538	,113	-,209
inflation	-,135	-,914	,197	,059
realdeprate	,161	,941	-,143	-,044
realwage	,032	-,060	,852	,074
exportihr	,845	,369	-,222	-,129
importith	,835	,440	-,056	-,095
productivity	,904	,298	-,049	-,079
privinvgdp	-,374	-,057	,591	-,200
publicinvvgdp	-,670	,217	,042	-,209

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Figure 6.10: Rotated Component Matrix for employment index data

The principal component analysis performed on the data in per cent changes however, identifies five components. Component 1 is highly related to per cent change in capacity, per cent change in productivity, per cent change in importation, per cent change in public investments/GDP, per cent change in exportation. Component 2 is highly related top er cent change in inflation and per cent change in realwages. Component 3 is highly related top er cent change in GNP, per cent change in private investment/GDP. Components 4 and 5 are highly related to per cent change is real Exchange rates and real deposit rates respectively. In the models through 29 to 32, these five components are used as the inputs to the neural network analysis. The outputs of the PCA analysis is given in Appendix E and the rotated

component matrix for employment index data for per cent changes is given in Figure 6.11.

Rotated Component Matrix ^a					
	Component				
	1	2	3	4	5
GNP	,308	-,028	,753	-,092	,189
capacitych	,771	,256	,175	,315	,044
realexratech	,082	,021	-,041	,974	,015
inflation	-,234	-,813	,006	-,140	-,028
realdepositrch	-,038	,055	-,001	,018	,974
realwagech	-,144	,879	,047	-,088	,034
exportch	,783	-,086	-,195	-,052	-,105
importch	,877	,097	-,050	,154	,134
productivitych	,899	,102	,097	,067	-,094
privinvgdpch	,268	-,070	-,781	-,043	,174
publicinvgdpch	,807	-,118	,038	-,111	,024

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Figure 6.11: Rotated Component Matrix for employment index data in per cent changes

6.2.2.5 Data Scaling-Neural Network Structure and Analysis

The data used in the neural network prediction analyses for employment index is scaled to (-0.1,0.9) and (0.1,0.9) by using equation 6.1 and the network structure is organized as described in section 6.2.1.6. The error used in the analysis is the widely used MSE. In the hidden layer the activation function is selected as the tansig. Both a linear activation function –purelin-, and a nonlinear activation function -tangent sigmoid- are in the output node to identify the performances of these two activation functions.

Approximately 20 % of the 68 samples are taken as the test set and the remaining samples are used as the training set. The networks are trained by MATLAB version 6.5 using the TRAINGDX algorithm that adapts the learning rate and momentum by itself. The MATLAB code (the Matlab m. file) used in the neural network training and analysis is given in Appendix G.

6.2.2.6 Results of the Neural Network Prediction Analysis of Employment Index in Turkey

Similar to the unemployment rate analysis study, during the analyses for employment rate prediction a total of 80 models have been tested and 17220 runs have made. For each model and for each unit the runs are performed by starting 10 different initial weights in order to avoid getting stuck in local minimum. Since the data set is not

large enough to use a validation set, training is stopped at epoch 1000, and the model is tested using the test set; and for each model-hidden unit combination, the minimum test errors found and their corresponding training errors are summarized. Similar to the results obtained during the unemployment rate analyses, it is observed that, the networks get overtrained as the hidden units increase. Therefore, to avoid selecting an overtrained model as the best model, once again it is decided to discard the results obtained with more than 20 hidden units from the analysis and the best model for each data set is selected as the model having the minimum average value of test and training MSE. The selected models are summarized below in Table 6.18.

Table 6.18: Best networks found for different employment index data sets

DATA ANALYZED	BEST MODEL	STRUCTURE OF THE BEST MODEL	TEST ERROR (MSE)	TRAINING ERROR (MSE)
Employment index	MODEL 8	T-1 Tansig 0.1-0.9 Scale	0.00067	0.00083
Employment % Change	MODEL 28	T-1 Tansig 0.1-0.9 Scale	0.00639	0.00318
Deseasonalized Employment in Levels	MODEL 8	T-1 Tansig 0.1-0.9 Scale	0.00053	0.00073
Deseasonalized Employment % Change	MODEL 28	T-1 purelin 0.1-0.9 Scale	0.0097	0.0062

The results of the neural networks analysis applied to employment index data in manufacturing industry in Turkey indicates that the best network having the minimum test MSE is found in the model using all the variables plus the employment index level in one past period as the input. Model 8, with a scaling range of 0.1-0.9, a tansig output activation function and 19 hidden units has the minimum test error with a value of 0.00067. The training error for the same network is found to be 0.00083. The normalized test set and the outputs of the network analysis are given below in Table 6.19 and plotted below in Figure 6.12.

Table 6.19: Real normalized employment index data and forecasted employment index data

Sample	Normalized Employment Index	Forecast
1	0.7496	0.7593
2	0.8267	0.8353
3	0.3737	0.4022
4	0.4373	0.4322
5	0.2619	0.2427
6	0.4566	0.4682
7	0.4875	0.4733
8	0.3641	0.4085
9	0.2118	0.1518
10	0.2176	0.2193
11	0.1887	0.1979

The best network in deseasonalized employment index is again found to be model 8 with a hidden unit number of 5, with a test error and a training error of 0.00053 and 0.00073 respectively. This result is very similar to the result in the seasonal data set. The normalized deseasonalized employment index data and the forecasted deseasonalized employment index data are given in Table 6.20 and plotted in Figure 6.13 below.

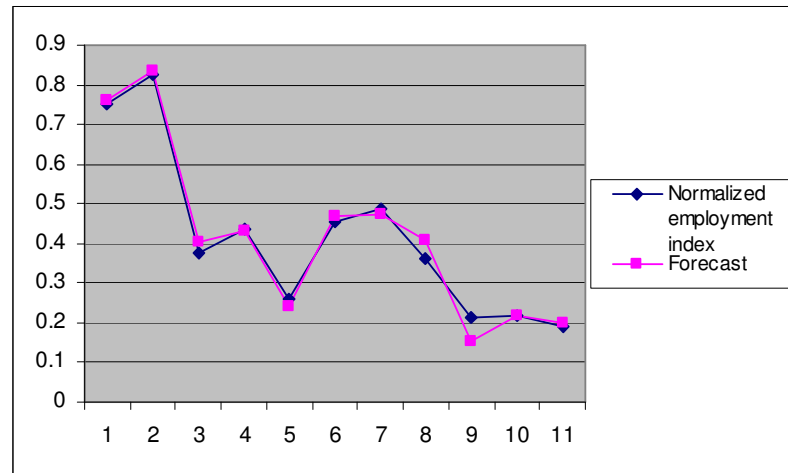


Figure 6.12: Plot of real normalized employment index data and forecasted employment index data

Considering the prediction analysis of employment index in per cent changes, the results reveal that the test errors obtained are considerably high compared to the results obtained in the prediction analysis of employment index data in levels. The results also indicate that deseasonalization does not improve the network performance in the prediction of employment index values significantly contrary to the results obtained in the unemployment rate analysis. This result can be attributed to the characteristics of manufacturing industry. Seasonality is not significantly observed in the manufacturing industry.

The best model found for the data set in per cent changes is found to be Model 28 for employment per cent change data. Model 28 uses all the variables plus the employment index per cent change in one past period as the input the inputs to the neural network analysis. The network used in model 28 uses tansig activation function and a scaling range of 0.1;0.9. The test error found for the employment

index per cent change data is 0.00639 with a network using 9 hidden units and a training error of 0.00318.

Table 6.20: Real normalized deseasonal employment index data and forecasted deseasonal employment index data

Sample	Real Value	Forecast
1	0.8536	0.8839
2	0.8226	0.8337
3	0.4372	0.4113
4	0.4116	0.3751
5	0.3134	0.3163
6	0.4319	0.4377
7	0.5632	0.5421
8	0.3342	0.3081
9	0.2578	0.2526
10	0.1796	0.2177
11	0.2322	0.2184

In the deseasonalized employment index per cent change prediction analysis the best network is reached in model 28. This model uses current period values of the input variables with a scaling range of 0.1;0.9 and a training function of tansig in the output node. The test error in this model is 0.0097 and the training error is 0.0062. The minimum test errors obtained in the 80 models analyzed in the employment index prediction are summarized in Table 6.21 below.

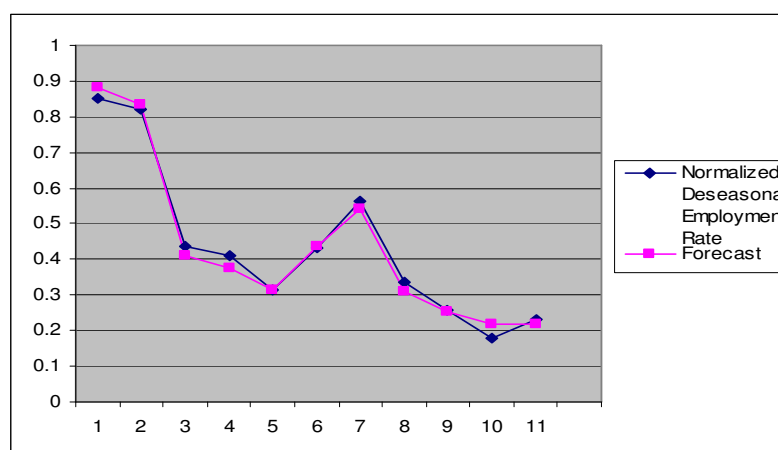


Figure 6.13: Plot of normalized deseasonal employment index data and forecasted deseasonal employment index data

The results show that similar to the results obtained in unemployment rate prediction the models using the results of the linear regression analysis and principal component analysis as the inputs result with the worse average MSEs compared to the other models (Table 6.21). This result is expectable since some information is lost when the number of inputs are decreased.

Table 6.21: The Best test MSEs for different scale ranges and different activation functions

Employment index	All Variables		All Variables + E(T-1)		Lagged		Regressed		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0024	0.003	0.0028	0.0048	0.0051	0.0065	0.023	0.015	0.0183	0.0027
Scale 0.1;0.9	0.0012	0.002	0.00071	0.00067	0.0012	0.00064	0.0045	0.0045	0.0051	0.0056
Employment index % Change	All Variables		All Variables + E(T-1)		Lagged		Regressed (a)		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0349	0.0279	0.033	0.0235	0.071	0.082	0.0221	0.0069	0.037	0.0346
Scale 0.1;0.9	0.0050	0.0041	0.0038	0.0064	0.018	0.012	0.0052	0.0044	0.0094	0.008
Deseasonalized employment index	All Variables		All Variables + E(T-1)		Lagged		Regressed(b)		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0041	0.0031	0.0025	0.0018	0.007	0.005	0.0074	0.0068	0.0152	0.0154
Scale 0.1;0.9	0.0015	0.0020	0.0007	0.0005	0.0018	0.0015	0.0025	0.0025	0.0059	0.0053
Deseasonalized employment index % Change	All Variables		All Variables + E(T-1)		Lagged		Regressed		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.061	0.058	0.058	0.0336	0.1367	0.091	0.062	0.058	0.1288	0.105
Scale 0.1;0.9	0.057	0.015	0.0126	0.0097	0.0195	0.0132	0.0112	0.0116	0.0277	0.0245

The best test errors obtained in each model also indicate that input scales and output activation functions. In employment index prediction, the networks using data scaled to 0.1-0.9, give better test MSE results compared to data scaled to -0.9-0.9. As an example, consider the model using all the inputs in their current period values in the unemployment data set and the output activation function of purelin, the upper left corner in Table 6.21. The same relationship in the different scale ranges is observed in all the other models in the analysis. In terms of the differences in the test MSEs with respect to activation functions, the results show that in some of the models tansig e.g.(a) in Table 6.21 activation function gives better test MSEs in others purelin activation function gives better MSEs e.g.(b) in Table 6.18. In most of the models (30 out of 40) nonlinear output activation function, tansig, gives smaller , in two of the models the average MSEs are almost equal and in eight models a linear activation function gives smaller MSEs compared to a nonlinear activation output function.

To further analyze the affect of output activation functions, input scaling and deseasonalization on network performance, the tranining performances and the test

performances of the best networks obtained for all the hidden units and the models in the analysis are averaged and this average MSE is used as an indicator of the overall network performance. The overall average MSEs obtained for each model in the analysis are given below in Table 6.22

Table 6.22: The Overall network performance for different scale ranges and different activation functions for employment index prediction study

Employment index	All Variables		All Variables + E(T-1)		Lagged		Regressed		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0064	0.0048	0.0034	0.0034	0.0072	0.0062	0.0253	0.0226	0.022	0.021
Scale 0.1;0.9	0.0026	0.0025	0.0014	0.0012	0.002	0.0017	0.0061	0.0058	0.0075	0.0072
Employment index % Change	All Variables		All Variables + E(T-1)		Lagged		Regressed (a)		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0284	0.0265	0.0334	0.0292	0.0602	0.0647	0.0325	0.0298	0.0473	0.0446
Scale 0.1;0.9	0.0069	0.0066	0.00665	0.00647	0.0144	0.0135	0.0076	0.0075	0.0145	0.013
Deseasonalized employment index	All Variables		All Variables + E(T-1)		Lagged		Regressed(b)		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0062	0.005	0.0027	0.0026	0.0071	0.0068	0.0114	0.0083	0.024	0.0218
Scale 0.1;0.9	0.0026	0.0025	0.0013	0.001	0.0022	0.0022	0.0038	0.0037	0.0085	0.0076
Deseasonalized employment index % Change	All Variables		All Variables + E(T-1)		Lagged		Regressed		PCA Models	
	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig	Purelin	Tansig
Scale -0.9;0.9	0.0613	0.0633	0.0617	0.0550	0.1134	0.0886	0.0795	0.0794	0.1132	0.1137
Scale 0.1;0.9	0.0505	0.0139	0.0125	0.0115	0.0188	0.0185	0.0148	0.0148	0.0252	0.0239

The affect of input scaling, deseasonalization and output activation functions are tested using pairwise t tests in SPSS. The results show that similar to the results obtained in the application of pairwise t tests in unemployment rate prediction analysis, the performances obtained by using the two input scaling ranges statistically differ for a significancy level of 0.05. The models using a scaling range of 0.1;0.9 gives lower average MSEs compared to the models using a scaling range of -0.9;0.9. The two activation functions also differ from each other statistically for a significancy level of 0.05, however this difference is not statistically significant for a significancy level of 0.01. Nonlinear output activation function,tansig, ends up with lower average MSEs compared to the linear output activation function.

The pairwised t test also shows that contrary to the results obtained in the pairwise t tests applied in unemployment rate prediction analysis, deseasonalization has a

significant negative affect on the performance. The models using deseasonalized data give significantly higher average MSEs compared to the models using seasonal unemployment rate data for a significancy level of 0.05. The results of the pairwise t tests are given in Appendix H. The reason for the negative affect of deseasonalization on network performance may be attributed to the characteristic of the employment data. Employment index in manufacturing industry does not show an evident seasonality. Therefore deseasonalization does not improve but worsens the overall neural networks prediction performance.

The results also reveal that deseasonalization does not have a significant impact on tperformance in employment index analysis contrary to the results obtained in unemployment rate analysis. The reason for the lower affect of deseasonalization on prediction performance may be attributed to the characteristic of the employment data. Employment index in manufacturing industry does not show an evident seasonality. Therefore deseasonalization does not improve the prediction performance.

It is possible to find the relative importance of inputs using the neural network analysis as stated in section 5.5. To identify the relative importance of inputs, the three methods showing the highest performance when applied to a dataset simulated from a dataset with prior known correlation structure, in a recent study of Olden et.al, 2004 are applied. These methods are the widely applied Connection Weight Approach, the Improved stepwise selection 1 method and Improved selection 2 methods. The average per cent change in MSE for each input variable is calculated using each of the three methods and the average of the results of the three methods are used as a reference in quantifying the importance of each input variable.

Input importance evaluation analysis is applied to the best model obtained for the employment index prediction. Model 8 is used in the analysis as the base model. The degree of importance of each variable for the different input variable importance evaluation methods are given below in Table 6.23 and the variables are plotted below in Figure 6.14 with respect to their average imortance scores. In the improved selection method, where each variable and its weights are eliminated from the network in an iterative way, a value of “0” is given to each variable and its affect on the network importance is evaluated. In the improved selection 2 method each variable is given its average value, 0.5 in this study, and the affect of this change in

the network is evaluated. In the third approach the connection weight method is adopted and the average of this three methods are calculated.

Table 6.23: Relative importance of inputs for deseasonalized employment index data with respect to three input evaluation methods

Input variable	Improved Selection 1	Improved Selection 2	Connection Weight	Average
Employment (t-1)	0.51971231	0.349249	0.186311	0.35176
GNP	0.00162008	5.86E-05	0.068527	0.02340
Capacity utilization	0.07096196	0.007334	0.044491	0.04093
Effective exchange rates	0.01182385	0.002768	0.114615	0.04307
Inflation	0.01095431	0.079859	0.007543	0.03279
Real deposit rates	0.07464434	0.037413	0.105419	0.07249
Real wages	0.06703504	0.018076	0.119809	0.06831
Export	0.1354016	0.444235	0.056085	0.21191
Import	0.09178166	0.044741	0.187389	0.10797
Productivity	0.00756358	0.0037	0.048652	0.01997
Private investments/GDP	0.00076844	0.010108	0.032533	0.01447
Public investments/GDP	0.00773282	0.002457	0.028626	0.01294

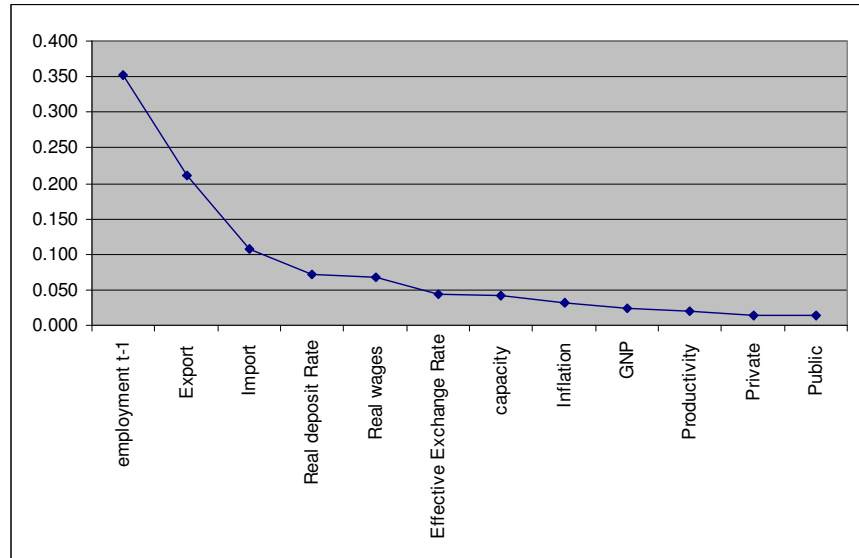


Figure 6.14: Relative importance of variables with respect to deseasonalized employment index prediction

The relative importance analysis for deseasonalized employment index data identifies five inputs to be more important. These are deseasonalized employment in one past period, export in manufacturing industry in current period, import in manufacturing industry in current period, real deposit rates in current period and finally real wages in current period.

The selected model, Model 8 is further applied to a recent data set covering 2005Q1 and 2005Q4 and the whole test set results are compared with an ARIMA and a VAR

model applied to the same data set. The results of the comparison are summarized below in Table 6.24.

Table 6.24 : Comparison of artificial neural networks results with ARIMA and VAR model results for the test set of deseasonalized employment data, model 8.

	Actual data	ARIMA forecast	VAR forecast	NN forecast	SE ARIMA	SE VAR	SE NN
1989Q2	115.08	114.20	114.88	115.5947	0.7746	0.0400	0.2623
1990Q4	113.59	117.79	115.44	113.6409	17.6311	3.4190	0.0025
1992Q2	95.03	96.24	95.34	94.26834	1.4683	0.0982	0.5770
1993Q4	93.79	90.85	93.26	92.53493	8.6723	0.2825	1.5829
1995Q2	89.06	87.85	88.61	89.61553	1.4731	0.2096	0.3053
1996Q4	94.77	92.54	92.76	95.51550	5.0059	4.0400	0.5511
1998Q2	101.10	101.84	101.38	100.7953	0.5572	0.0808	0.0903
1999Q4	90.07	90.65	90.49	89.55435	0.3407	0.1749	0.2646
2001Q2	86.39	87.90	86.63	86.89119	2.2725	0.0569	0.2521
2002Q4	82.62	82.66	82.66	85.05887	0.0019	0.0013	5.9471
2004Q2	85.15	82.85	84.17	84.4134	5.3047	0.9727	0.5498
2005Q1	83.91	84.20	84.02	84.26116	0.0818	0.0111	0.1233
2005Q2	83.11	83.32	83.23	85.70568	0.0436	0.0145	6.7376
2005Q3	85.67	82.55	84.81	86.38837	9.7128	0.7405	0.5161
2005Q4	86.49	86.16	86.18	85.38411	0.1104	0.0990	1.2230
MSE whole test data					3.5634	0.6827	1.2657
MSE 2005 data					2.4871	0.2163	2.1500

The comparison results indicate that within the three models VAR model gives the best test results for both the whole test data set and the data set for year 2005. ARIMA model gives the worst results within the three models with an MSE of 3.56 for the whole test set and 2.48 for 2005 data. Artificial neural networks perform better compared to the ARIMA model both in the whole data set and in the data set covering 2005 data.

6.3 Summary of Analyses and Results

Unemployment is one of the most serious problems that nations face. The rise of unemployment reduces personal and social income; increases the inequality of the income distribution and poverty, causes production losses since labor force cannot be fully utilized, and increases transfer expenditures of the nations. In addition to economic problems unemployment causes socio-psychological problems. It deteriorates social morale and responsibility. Unemployed person loses his human capital capacities and skills by time and gets rejected from the society. With respect to these given outcomes of high levels of unemployment, understanding the reasons

of unemployment and defining policies to avoid high unemployment rates becomes crucial for nations.

Forecasting is accepted as an important tool in the development and application of macro policies. Considering the fact that accurate forecasts help decision makers take better decisions, forecasting studies have started to take growing interest of researchers. By the developments in the computer specifications, artificial intelligence techniques have gained more attention as decision support tools. Among the artificial intelligence techniques, artificial neural networks are seen as promising techniques especially in forecasting applications. In this study, cognitive mapping methodology and artificial neural networks methodology is integrated in order to define a prediction model framework. The framework is applied to two data sets in Turkey in order to understand the important factors that affect unemployment and employment in Turkey and to forecast unemployment rate and employment index in manufacturing industry in Turkey.

Cognitive mapping methodology is used in capturing the cause-effect relationships in complex causal systems and facilitate understand the interconnections within the elements of the systems by gathering expert knowledge. In the first phase of the study cognitive mapping methodology is used in the identification of the factors that affect unemployment in Turkey by taking the views of five different experts who have made research on macroeconomic problems of Turkey. The eleven variables identified by the experts are used in the second phase of the study as the input data set in developing a multi-variate forecasting model by using artificial neural networks.

The framework of the study is applied both to unemployment rate data in Turkey and the employment index data in manufacturing industry in Turkey. The research period covers 1988 and 2004. Quarterly data is used in the analysis. Since unemployment rates were available through 1988 and 2000 semi annually, the data was interpolated to quarterly data in this period. Employment index data in manufacturing industry was readily available as quarterly data therefore original values are used in the study.

Previous research (Zhang and Qi (2005), Zhang et.al, (1998), Masters (1993), Gately (1996), Haykin(1999), and others.) show that factors like different output activation functions, different scaling ranges, using per cent change data rather than level data and deseasonalization may have affect on network performance. To find the best

network to forecast the output variables, a design of experiment is made and two different output activation functions; (linear and nonlinear tangent sigmoid functions), two different scaling ranges (-0.9;0.9 and 0.1;0.9), both per cent change data and level data and both seasonal and deseasonalized data is used in the study. Additionally, five different input data structure is used in the study. In the first data structure, all variables identified by the experts are used in the analysis. In the second structure, unemployment rate/employment index data in one past period is added to the 11 input variables. In the third input structure, all input variables and unemployment rate/employment index data are used in their lagged values as the inputs to the network. In the fourth and fifth structures, widely applied input dimension reducing methods regression and principal component analysis results are used as the input data set respectively. A total of 80 different models are tested for both unemployment rate data and employment index data.

The networks are trained using Matlab software, TRAINGDX training algorithm and to train each network, different numbers of hidden units are tested to find the best network and almost 80 % of the data set is used as the training set. Each run is replicated ten times with different initials weights in order to avoid getting stuck with local minima.

Since the data set was not large enough to use a validation set, training is stopped at epoch 1000, and the model is tested using the test set; and for each model-hidden unit combination, the minimum test errors found and their corresponding training errors are listed. The results showed that similar to the findings in literature (Gately,1996; Zhang et.al.,1998), the networks tend to get overtrained as the hidden units increase. Therefore, to avoid selecting an overtrained model as the best model, it is decided to discard the results obtained with more than 20 hidden units from the analysis and the best model for each data set is selected as the model having the minimum average value of test and training MSE.

The results of the study show that the best networks found for both the unemployment rate data and employment index data are found using the level values in deseasonalized data sets. They both use tangent sigmoid function as the output activation function and a scaling range of 0.1;0.9. The structure of the input set is the second structure which includes all the 11 variables identified by the expert and the on past period value of the dependent variable itself.

To identify the relatively most important variables in each model, three different methods have been applied. In the first method, improved selection method, each variable and its weights are eliminated from the network in an iterative way, a value of “0” is given to each variable and its affect on the network importance is evaluated. In the second method, improved selection 2 method, each variable is given its average value, 0.5 in this study, and the affect of this change in the network is evaluated. In the third approach the connection weight method is adopted. The average per cent changes in MSEs for each input variable is calculated using each of the three methods and the average of the results of the three methods are used as a reference in quantifying the importance of each input variable. For the unemployment rate model, deseasonalized unemployment in one past period, productivity and total import in current period are found to be relatively important. When combined with the views of the experts as identified in the cognitive map, these results indicate that the increase in labor productivity causes an increase in unemployment, similarly the rise in total import rises unemployment rates; the demand for products in the market is supplied by the imported goods rather than the locally produced goods. For the employment index model, deseasonalized employment index in one past period, export in manufacturing industry in current period, import in manufacturing industry in current period, real deposit rates in current period and finally real wages in current period. When these results are combined with the expert views, it can be said that when exportation affects employment in manufacturing industry in a positive manner, the rise of exportation increases employment; importation on the other hand decreases employment in manufacturing industry similar to the result of the increases in real wages. Deposit rates affect employment index in manufacturing industry in a negative manner; the increase in deposit rates decreases employment index, this result may be explained by the fact that laborers tend to choose investing their money in the banks rather than getting involved in production. The best networks found for unemployment rate data set and employment index data set and their properties are summarized below in Table 7.1; the relatively important variables for each data set are shown with (*).

Table 7.1: Input structures for the best models of unemployment rate data and employment index data.

	Unemployment Rate Analysis	Employment Index in Manufacturing Industry Analysis
Dependent variable	Deseasonalized Unemployment rate	Deseasonalized Employment Index
Independent variables	* Deseasonalized Unemployment rate in one past period	*Deseasonalized Employment Index in one past period
	GNP % change	GNP % change
	Capacity utilization rate in manufacturing industry	Capacity utilization rate in manufacturing industry
	Real effective exchange rates	Real effective exchange rates
	Inflation	Inflation
	Real deposit rates	*Real deposit rates
	Index level of real wages in manufacturing industry	*Index level of real wages in manufacturing industry
	Total export	*Export level of manufacturing industry
	*Total import	*Import level of manufacturing industry
	* Productivity in manufacturing industry	Productivity in manufacturing industry
	Private investments/GDP	Private investments/GDP
	Public investments/GDP	Public investments/GDP
Output activation function	Tangent sigmoid	Tangent sigmoid
Scaling range	0.1;0.9	0.1;0.9
Number of Hidden Units	13	5
TEST MSE	0.00147	0.00053
TRAIN MSE	0.00297	0.00073

In a previous study, (Tekin, 1993), has analyzed the main factors of unemployment in Turkey during the period 1970-1992 by Generalized Least Squares Method. The researcher has used ten variables as the regressor variables. These variables are namely, unemployment with one lag, energy supply, credits, money supply, capital investments, investments realized by receiving subsidies from the government, inflation, GNP, real wages and total labor force. It was found that unemployment rate is positively affected by productivity, and the import-export wedge. The results also reveal that inflation does not affect unemployment in Turkey. The importance of productivity is similar to the findings in the study. Moreover inflation is found to be unimportant in this study and Tekin's study. However, it should be noted that Tekin uses a linear method in analyzing the factors that affect unemployment rate in comparison to the nonlinear method in this study.

The results also show that it is not possible to expect fast decreases in unemployment. Therefore it is not rational to expect a rapid recovery in unemployment rates in Turkey. The lag lengths up to 4 periods in the explanatory variables indicate that the affects of these explanatry variables are long period affects.

The results indicate that, total import and productivity have long term affects of unemployment rates in Turkey. One of the reasons why total import is more

important for unemployment rates in Turkey compared to GNP is that, Turkish economy is highly import oriented especially in manufacturing sector.

The intermediate goods and capital goods import which is directly related to production, accounts for approximately 90 % of total importation of Turkey. Therefore, the increase in importation may be seen as an indicator for an increase in total production in Turkey. The relatively low level affect of GNP variable on unemployment rates may be attributed to the labor market structure in Turkey and high levels of black economy. It is highly accepted that almost 50 % of Turkish economy is unregistered. Unregistered economy is especially seen in agricultural sector and services sector. While the proportion of agricultural sector within GNP is low, the proportion of services sector in GNP is 50 %. This value also indicates the importance of services sector in Turkey. Unemployment rates in Turkey, reflect especially the current structure in production sector, the unemployment situation in services sector can not be officially reflected by the current unemployment rates.

The reason behind the relatively low affect of real wages on unemployment rates is also unregistered economy. Especially in the unregistered economy, there are employees that earn lower than real wage or even the minimum wage. Therefore, the real wage variable can not be functional in the economy and in the unemployment rate prediction analysis.

In addition to the importance analysis of variables, in the study, the effects of the different activation functions and different scaling ranges and deseasonalization on neural network performance are tested with using pairwised t-tests in SPSS. The results showed that for both the employment index data and the unemployment rate data; models using a scaling range of 0.1;0.9 give significantly better average MSE results compared to the models using a scaling range of -0.9;0.9 for a significance level of 0.01. For the output activation functions the test results reveal that in the unemployment rate analysis, the mean performances of the models using tangent sigmoid function are not different from each other statistically for a significance level of 0.05; in the employment index data however, for a significance level of 0.05 the tangent sigma output activation function gives better average MSE results compared to the models using linear output activation function.

Zhang et.al, 1998, state that so far no research has investigated the relative performance of using linear and nonlinear activation functions for output nodes and

there have been no empirical results to support preference of one over the other. The findings in this study may be an empirical evidence for the affects of output activation functions on network performance. The results show that while in one analysis there is no difference between the affects of the two functions on the network performance, in the second data set, tangent sigma output activation function gives moderately better MSEs. The test results also show that deseasonalization significantly improves network performance in unemployment rate data; however in the employment index data set the results show that when the average performances of the whole models are considered, deseasonalization significantly worsens the network performance. This result may be attributed to the fact that unemployment rate is a seasonal variable; however, it is not possible to say that employment in manufacturing industry shows seasonality. Although the best model found for employment index data uses deseasonalized data set; in the overall analysis, deseasonalized models give worse results compared to the models using original employment index data set.

Lastly in the study, the performance of the best models identified for each data set is further compared with an AR(2) and VAR model for the test set and a recent data set covering 2005Q1 and 2005Q4. The results showed that for both of the data sets neural network models are able to forecast the 2005 data accurately and the results are satisfactory for this new data set. The results also show that neural network models give better MSEs when compared to the AR(2) model; however they give worse MSEs when compared with the VAR model.

7. CONCLUSION

The aim of this study is to develop a prediction framework with the use of artificial intelligence methods. The framework is applied to two data sets in Turkey in order to understand the important factors that affect unemployment and employment in Turkey and to forecast unemployment rate and employment index in manufacturing industry in Turkey.

In the first phase of the study cognitive mapping methodology is used in the identification of the factors that affect unemployment in Turkey and in the second phase of the study these factors are used as the input data set in developing a multivariate forecasting model by using artificial neural networks. Different input structures and neural network parameters are used in the study in order to find the best prediction networks and finally the results are compared with two linear models AR (2) and VAR models.

The study is unique in the sense that the factors that affect unemployment in Turkey are aggregated in different experts' views and are used as inputs to a multivariate nonlinear prediction model. The results of the study indicate that artificial neural network methodology may be seen as a promising methodology in forecasting macroeconomic time series. Their ability to learn from examples and capture functional relationships among the data even if the underlying relationship are unknown or hard to describe (Zhang et.al., 1998); their nonlinearity, their ability to deal with fuzzy, problematic data make them advantageous over linear models and models that require explicit knowledge on the relationship between input and output variables. With the use of artificial neural networks in prediction, it is possible to overcome the restrictions in model specifications that exist in traditional models.

Furthermore, the results of the analysis of the affects of two different scaling ranges; two different output functions and deseasonalization of the can be used as an evidence of the discussed topics in literature about how factors like different output activation functions, different scaling ranges, using per cent change data rather than

level data and deseasonalization may have affect on network performance research (Zhang and Qi (2005), Zhang et.al., (1998), Masters (1993), Gately (1996), Haykin(1999), and others). The results show that for both the employment index data and the unemployment rate data; models using a scaling range of 0.1;0.9 give significantly better average MSE results compared to the models using a scaling range of -0.9;0.9 for a significancy level of 0.01. For the output activation functions the test results reveal that in the unemployment rate analysis, the mean performances of the models using tangent sigmoid function are not different from each other statistically for a significance level of 0.05; in the employment index data however, for a significancy level of 0.05 the tangent sigma output activation function gives better average MSE results compared to the models using linear output activation function. The test results also show that deseasonalization significantly improves network performance in unemployment rate data; however in the employment index data set the results show that when the average performances of the whole models are considered, deseasonalization significantly worsens the network performance.

The disadvantages of artificial neural networks are however, they are data dependent, therefore they may require larger data sets and more computer time to learn the relationships and that they may get overtrained.

Finally, the following suggestions can be made for future study:

- This study may be repeated when larger data set on unemployment rates in Turkey is available, and the results may be compared to the current findings. As the stopping criteria when enough data is available, early stopping may be used rather than a target performance level or a target epoch level.
- Recurrent neural network model can be used as an alternative to multilayer feedforward neural networks and the performances of these two different neural network structures may be compared.
- The prediction framework developed in this study with the use of cognitive maps and artificial neural networks may be applied to other forecasting problems.
- System dynamics methodology may be applied to this problem domain depending on the complex dynamic nature of the problem.

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APPENDIX A– (DATA)

Period	Unemployment rate	Employment index	GNP % change	capacity utilization rate	real effective exchange rates	Inflation	real deposit rates	real wage index	Export in manufacturing industry (000)
1988Q2	-	123,5	33,34	74,7	92,70	13,73	3,88	55,1	2221,07
1988Q3	7,85	119,7	52,74	73,6	90,5	6,75	8,31	60,8	2198,56
1988Q4	9,03	115,9	-11,69	74,6	85,3	13,56	6,18	67,9	2789,54
1989Q1	9,79	111,9	-7,75	71,0	91,8	12,43	1,52	66,6	2093,09
1989Q2	7,64	117,3	31,62	69,3	99,6	16,14	2,25	72	2175,03
1989Q3	7,84	117,9	75,78	72,0	104,5	14,08	4,35	80,3	2123,49
1989Q4	9,02	114,3	-13,55	78,9	106,5	14,98	4,69	89,1	2778,50
1990Q1	7,83	112,1	-9,68	74,4	111	7,61	0,00	85,6	2411,58
1990Q2	6,11	117,7	35,92	75,6	113	9,48	5,75	89,9	2342,26
1990Q3	8,01	115,9	55,01	74,5	111,9	6,39	6,10	102,7	2382,73
1990Q4	9,21	111,6	-11,65	76,4	117	13,61	1,67	95	3212,00
1991Q1	9,61	103,7	-17,27	71,3	113,8	10,20	3,33	115,7	2707,53
1991Q2	7,50	103,2	32,98	74,5	115,5	12,81	2,15	120,2	2478,35
1991Q3	7,29	100,1	67,46	74,8	112,2	11,74	8,85	134,7	2552,50
1991Q4	8,39	97,3	-9,91	75,5	112,9	11,36	5,55	142,5	2947,46
1992Q1	9,43	92,4	-7,92	73,8	116,4	16,38	-3,51	126,5	2877,39
1992Q2	7,37	95,5	26,01	74,9	103	15,23	11,20	139,3	2795,04
1992Q3	7,97	93,6	60,33	77,5	104,3	12,28	10,77	139	3251,58
1992Q4	9,17	94,4	-5,93	79,3	114,9	13,28	2,89	135,2	3362,27
1993Q1	10,32	89,4	-9,67	76,5	123,1	9,25	4,06	142,2	2958,79
1993Q2	8,06	92,5	33,45	78,6	121,8	10,99	8,32	143,5	3056,25
1993Q3	7,98	95,7	63,60	80,9	122,2	12,11	7,09	135,8	3062,74
1993Q4	9,18	92,2	-8,46	82,3	125,7	13,10	5,29	141,8	3716,11
1994Q1	9,29	90,8	-16,62	75,9	98,1	18,89	3,86	141,9	3070,79
1994Q2	7,25	88,8	56,75	66,2	85,3	50,64	-22,49	108,8	3369,60
1994Q3	8,21	88,9	62,78	73,0	85	12,35	15,72	101,3	4270,56
1994Q4	9,45	87,7	-2,30	76,6	95,7	21,41	4,11	102,4	4806,90
1995Q1	8,24	86,6	-2,15	75,3	93,9	20,76	-0,49	99,9	4118,21
1995Q2	6,44	91,6	33,66	79,4	99,5	11,17	10,63	98,9	4674,20
1995Q3	7,37	94,5	57,53	79,8	107,3	12,30	14,13	94,3	4821,27
1995Q4	8,48	94,3	-11,56	79,8	103,1	11,41	9,79	96,2	5475,63
1996Q1	7,10	91,0	-3,77	76,8	102,8	16,51	3,96	95	4816,09
1996Q2	5,55	93,8	33,96	77,8	101,8	17,63	3,22	93,7	4680,98
1996Q3	6,44	96,7	65,58	78,1	102,4	13,98	13,89	100	5254,70
1996Q4	7,41	98,4	-3,03	79,4	101,7	13,56	7,23	97	5774,24
1997Q1	8,11	95,7	-11,81	76,9	107,1	14,61	6,07	99,9	5352,56
1997Q2	6,34	99,0	38,41	79,4	106,1	16,23	6,41	102	5679,03
1997Q3	5,96	103,8	68,73	80,9	111,3	17,62	7,53	101,6	5957,01
1997Q4	6,86	101,5	-4,89	80,3	115,9	19,36	4,35	96	6324,20
1998Q1	7,57	98,3	-7,43	77,5	116,2	15,28	7,78	99,8	5915,01

1998Q2	5,91	101,4	29,59	76,1	115,5	11,73	12,50	101,4	5951,35
1998Q3	6,51	103,0	55,67	77,3	121,1	8,97	14,96	100,7	6060,46
1998Q4	7,49	98,1	-9,14	75,3	120,9	7,18	12,41	97,4	6137,77
1999Q1	8,30	90,6	-23,41	70,3	121,8	7,50	12,38	112	5668,72
1999Q2	6,48	92,4	35,30	75,7	121,5	11,66	10,25	110,2	5737,90
1999Q3	7,37	91,9	56,97	71,6	124,1	10,55	10,05	115,4	5988,91
1999Q4	8,48	89,8	-9,27	72,0	127,3	13,40	-4,45	106,1	6562,28
2000Q1	8,25	85,1	-9,12	72,6	132,4	16,28	-6,30	111,6	6134,13
2000Q2	6,12	90,5	28,67	76,3	132,3	8,94	1,94	109,4	6581,75
2000Q3	5,53	91,7	47,09	76,6	139	6,82	6,54	113,2	6326,31
2000Q4	6,24	89,0	-10,83	78,1	147,6	6,75	4,65	111,1	6475,35
2001Q1	8,49	84,0	-30,53	69,8	113,5	7,51	10,04	107	6726,00
2001Q2	6,73	82,4	51,44	69,9	111,8	25,36	-15,27	93,4	7503,17
2001Q3	7,82	81,5	54,23	71,1	98,5	11,93	4,22	95,3	7039,39
2001Q4	10,40	78,9	-6,59	72,8	116,3	16,19	0,17	88,3	7557,46
2002Q1	11,55	78,2	-10,70	73,8	138,4	10,23	4,90	90	7324,74
2002Q2	9,32	82,5	16,37	75,9	118,9	4,73	7,79	89,5	8064,29
2002Q3	9,56	84,3	53,01	77,1	115,2	4,08	5,80	92,7	8798,95
2002Q4	11,04	83,6	-5,65	74,9	125,4	6,74	4,36	87,9	9513,67
2003Q1	12,32	82,2	-17,73	75,0	123,5	8,55	1,43	89,2	9680,34
2003Q2	10,03	84,0	16,60	78,1	140,6	4,36	7,81	84,8	10780,39
2003Q3	9,41	85,5	43,52	80,7	151,5	2,05	9,65	89,2	11586,47
2003Q4	10,32	83,2	-14,08	79,7	140,6	3,88	5,72	90	12331,23
2004Q1	12,40	82,8	-17,15	78,5	154,2	3,01	-0,89	89,6	12719,75
2004Q2	9,30	86,3	18,81	82,8	137,5	3,22	1,90	89,2	14753,68
2004Q3	9,50	87,4	39,34	83,6	138,1	0,00	6,12	91,9	15155,68
2004Q4	10,00	85,0	-10,34	81,7	143,2	2,79	5,52	91,1	16903,81
2005Q1	10,39	84,4	-21,07	78,03	154,70	0,93	3,87	92,3	16228,44
2005Q2	10,48	84,8	16,42	81,34	159,50	1,58	3,47	91	17195,18
2005Q3	10,15	85,8	35,59	81,53	162,20	0,61	4,43	93,7	16937,85
2005Q4	9,9	84,1	-11,10	76,55	171,30	1,43	1,22	92	18375,29

Period	Import in manufacturing industry (000)	Total export	Total import	productivity index	Private investments/GDP	Public investments/GDP
1988Q2	2456,1	-	-	49,1	20,43	7,97
1988Q3	2845,03	2584,98	3246,39	49,8	17,03	8,29
1988Q4	3214,56	3547,92	3816,47	55,6	14,74	13,56
1989Q1	2421,67	2803,27	3319,05	52,9	18,92	8,66
1989Q2	2947,40	2573,87	3807,26	51,4	18,47	6,82
1989Q3	2975,40	2568,12	3994,41	54,3	15,38	6,59
1989Q4	3491,78	3679,43	4671,43	60,1	12,34	9,54
1990Q1	3376,28	2994,33	4706,62	58,5	16,13	5,37
1990Q2	3903,70	2745,46	4875,28	56,2	20,92	6,66
1990Q3	4262,09	2858,71	5434,65	60,1	14,16	6,79
1990Q4	5389,38	4360,79	7285,57	67,1	54,68	9,48
1991Q1	3938,34	3378,66	4915,89	60,6	16,47	5,78
1991Q2	3761,24	2904,93	4745,65	65,3	22,93	7,29
1991Q3	4261,29	3208,71	5243,98	74	13,97	6,59
1991Q4	5079,69	4101,16	6141,51	79,1	53,40	9,30
1992Q1	4094,34	3549,95	4942,12	74,4	16,32	5,43
1992Q2	4413,07	3303,35	5484,92	73,3	17,28	7,39
1992Q3	4657,10	3701,31	5856,47	81,1	14,41	6,49
1992Q4	5433,17	4160,02	6587,55	83,1	15,49	8,87
1993Q1	4739,09	3673,27	5908,03	78,1	18,75	3,93
1993Q2	6494,78	3477,29	7778,20	85,5	20,55	6,91
1993Q3	6302,70	3561,98	7465,87	87,1	16,95	6,33
1993Q4	7172,64	4632,53	8276,28	93,8	18,55	9,37
1994Q1	4922,70	3826,36	5887,09	81,1	21,08	3,76
1994Q2	4090,75	3830,78	4953,89	76	21,20	4,57
1994Q3	4259,13	4815,19	5416,28	82	17,22	4,90
1994Q4	5758,61	5633,54	7012,76	89,4	15,64	7,54
1995Q1	5537,76	4756,36	6853,75	85,1	17,94	2,17
1995Q2	7159,85	5199,12	8615,33	90	20,90	3,64
1995Q3	7543,56	5288,13	9134,79	92,6	18,19	3,63
1995Q4	9465,18	6393,44	11105,15	93,7	20,71	5,17
1996Q1	7734,70	5541,41	9757,80	88,9	21,37	1,84
1996Q2	8849,17	5197,54	10985,29	94	23,23	4,58
1996Q3	8732,10	5753,83	10754,43	94,2	20,22	4,48
1996Q4	9891,22	6731,68	12129,13	98,1	20,18	6,89
1997Q1	8207,30	6077,79	10545,11	93,5	21,08	2,49
1997Q2	9606,68	6349,25	11695,22	99,5	22,68	5,01
1997Q3	10517,87	6511,88	12650,04	99,9	20,27	5,37
1997Q4	11470,45	7322,15	13668,34	107,1	19,98	8,11
1998Q1	9459,69	6735,19	11344,31	97,8	19,84	2,93
1998Q2	10371,90	6596,93	11975,92	98,7	20,98	4,71
1998Q3	9764,79	6654,78	11581,68	100,4	18,33	5,22
1998Q4	9428,56	6987,05	11019,48	102,9	14,30	9,55
1999Q1	6666,20	6480,03	8059,76	95,7	15,58	2,98
1999Q2	8659,53	6300,92	10329,91	108,9	15,81	5,26
1999Q3	8652,46	6468,57	10440,14	105	15,18	4,56
1999Q4	9957,65	7337,70	11841,46	111	14,05	7,61
2000Q1	8995,04	6703,43	11324,62	104,5	15,56	2,97
2000Q2	11492,47	7102,59	14154,04	116,6	16,14	5,78
2000Q3	11904,19	6735,71	14200,06	117,1	17,13	5,33

2000Q4	11808,54	7233,17	14824,11	119,6	14,76	8,29
2001Q1	8352,08	7298,28	10775,03	105,1	13,53	2,84
2001Q2	7827,31	8062,37	9895,74	112,1	13,17	4,67
2001Q3	8169,02	7658,99	10363,69	117,7	12,55	4,65
2001Q4	8337,70	8314,58	10364,63	117,6	9,42	7,82
2002Q1	8056,27	7910,04	10409,06	117	10,34	2,39
2002Q2	9991,03	8513,88	12453,79	127,4	11,71	4,42
2002Q3	10989,07	9297,95	13528,63	126,9	11,22	5,48
2002Q4	12346,65	10337,23	15162,32	127	11,43	7,74
2003Q1	10974,99	10365,42	14367,13	123,4	10,69	1,42
2003Q2	13248,48	11318,77	16470,20	131,4	11,18	3,38
2003Q3	14937,73	12179,52	18447,73	138,2	11,01	3,75
2003Q4	16528,57	13389,13	20054,64	142,1	12,26	7,33
2004Q1	16871,80	13500,14	20921,29	136,8	14,51	1,19
2004Q2	20332,87	15519,09	24390,35	150,1	15,44	2,84
2004Q3	20746,06	15968,39	25098,38	147,1	14,35	3,34
2004Q4	22496,57	18133,33	27129,75	145,2	12,68	6,97
2005Q1	20773,09	17240,80	25732,14	141,7	15,46	1,57
2005Q2	24033,58	18139,84	29273,97	156	17,69	3,78
2005Q3	24261,92	18129,82	30227,29	156,1	14,44	3,80
2005Q4	24935,31	19879,40	31303,71	157,6	14,23	7,05

APPENDIX B – (AGGREGATED COGNITIVE MAP MATRIX)

		Demographic (Labour Supply)			Macro					
		Participation rate in Employment	Population growth rate	Literacy Rate	Urbanization Rate	Export	Import	Real Wages	Country Competitiveness	Unregistered (Informal) Employment
Demographic (Labour Supply)	Participation rate in Employment	x	0	+	+	0	0	-	+	-
	Population growth rate	+	x	-	+	0	0	-	-	+
	Literacy Rate	+	-	x	+	0	0	+	+	-
Macro	Urbanization Rate	+	-	+	x	0	0	+	+	+
	Export Intensity	0	0	0	0	x	+	+	+	+
	Import Intensity	0	0	0	0	+	x	-	0	0
	Real Wages	+	0	0	+	-	+	x	-	+
	Country Competitiveness	+	0	0	0	+	-	+	x	0
	Unregistered Employment	0	0	0	0	0	0	-	0	x
Macro - Demand Side	Technological Improvements	0	0	+	+	+	+	+	+	-
	Capital Cost	0	0	0	0	-	-	-	-	0
	GDP	+	-	+	+	+	+	+	+	-
	Per capita Income	+	-	+	+	+	+	+	+	-
	Agricultural Sector/GDP	+	+	-	-	0	0	-	0	+
	Services Sector /GDP	+	-	+	+	+	+	+	0	0
	Manufacturing Sector/GDP	+	-	+	+	+	+	+	+	0
	Income Distribution	+	-	+	+	0	0	0	0	-
	Public Investments / GDP	+	0	+	+	0	0	0	0	-
	Private sector Investments /GDP	+	0	0	+	0	+	+	+	0
	Capacity Usage	+	0	0	0	0	+	+	0	0
	Labour Productivity	0	0	0	0	+	-	+	+	-
	Inflation	+	0	0	0	-	-	-	-	+
	Uncertainty	0	0	0	0	0	0	-	-	+
	Domestic Demand	+	0	0	+	-	+	+	0	+

		Macro-Demand Side														
		Technological Improvements	Capital Cost	GDP	Per capita income	Agricultural Sector/GDP	Service Sector /GDP	Manufacturing Sector/GDP	Income Distribution	Public Investments / GDP	Private Investments /GDP	Capacity Usage	Labour Productivity	Inflation	Uncertainty	Domestic Demand
Demographic (Labour Supply)	Participation rate in Employment	0	0	+	+	-	+	+	+	+	+	0	0	0	0	0
	Population growth rate	0	0	-	-	+	0	0	-	0	0	0	0	0	0	0
	Literacy Rate	+	0	+	+	-	+	+	+	0	0	0	+	0	0	0
Macro	Urbanization Rate	+	0	+	+	-	+	+	+	0	0	0	0	0	0	+
	Export	+	0	+	+	0	0	+	0	0	+	+	+	0	0	0
	Import	+	0	+	+	0	0	0	0	0	0	-	0	0	0	0
	Real Wages	+	0	+	+	0	0	0	+	0	-	0	+	+	0	+
	Country Competitiveness	+	-	+	+	0	+	+	0	0	+	+	+	-	-	+
	Unregistered Employment	-	0	-	-	0	0	0	-	0	-	0	-	0	+	0
Macro-Demand Side	Technological Improvements	x	0	+	+	-	+	+	+	+	+	+	+	-	-	+
	Capital Cost	-	x	-	-	+	-	-	-	0	-	0	0	+	0	-
	GDP	+	0	x	+	-	+	+	+	+	+	+	+	-	0	+
	Per capita Income	+	0	+	x	-	+	+	+	+	+	+	+	-	0	+
	Agricultural Sector/GDP	0	0	+	+	x	0	0	0	0	0	0	0	0	0	0
	Service sector /GDP	0	0	+	+	-	x	+	0	0	+	0	0	0	0	0
	Manufacturing Sector/GDP	+	0	+	+	-	+	x	0	0	+	+	+	0	0	+
	Income Distribution	0	0	+	+	-	+	+	x	0	+	0	0	-	0	+
	Public Investments / GDP	+	-	+	+	+	+	+	+	x	+	+	+	-	-	+
	Private sector Investments /GDP	+	0	+	+	-	+	+	+	+	x	+	+	-	-	+
	Capacity Usage	0	0	+	+	0	+	+	+	+	+	x	+	-	0	+
	Labour Productivity	+	0	+	+	0	+	+	+	+	+	+	x	-	-	0
	Inflation	-	+	-	-	0	0	0	-	-	-	-	0	x	+	-
	Uncertainty	-	+	-	-	0	-	-	-	-	-	-	-	+	x	-
	Domestic Demand	+	+	+	+	+	+	+	+	+	+	+	+	+	-	x

		Union Power	Skill Mismatch	Tax Burden	Minimum wage	Unemployment rate in the previous period	Current period unemployment rate
Demographic (Labour Supply)	Participation rate in Employment	+	-	0	0	0	+
	Population growth rate	0	+	0	0	0	+
	Literacy Rate	0	-	0	0	0	-
Macro	Urbanization Rate	+	-	0	0	0	+
	Export	0	0	0	0	0	-
	Import	0	0	0	0	0	+
	Real Wages	+	0	0	0	0	+
	Country Competitiveness	0	0	0	0	0	-
	Unregistered Employment	-	0	0	0	0	0
Macro-Demand Side	Technological Improvements	-	+	0	0	0	+
	Capital Cost	0	0	0	0	0	+
	GDP	+	0	0	0	0	-
	Per capita Income	+	0	0	0	0	-
	Agricultural Sector/GDP	-	0	0	0	0	-
	Service Industries /GDP	-	0	0	0	0	-
	Manufacturing Sector/GDP	+	0	0	0	0	-
	Income Distribution	-	0	0	0	0	+
	Public Investments / GDP	+	0	0	0	0	-
	Private sector Investments /GDP	+	0	0	0	0	-
	Capacity Usage	+	0	0	0	0	-
	Labour Productivity	+	-	0	0	0	+
	Inflation	0	0	0	0	0	+
	Uncertainty	0	+	0	0	0	+
	Domestic Demand	0	0	0	0	0	-

		Demographic (Demand Side)			Macro						Labour Market					
		Participation rate in Employment	Population growth rate	Literacy Rate	Urbanization Rate	Export	Import	Real Wages	Country Competitiveness	Unregistered Employment	Union Power	Skill Mismatch	Tax Burden	Minimum wage	Unemployment rate in the previous period	Current period unemployment rate
Labour Market	Union Power	+	0	0	0	0	0	+	-	-	x	0	0	0	0	0
	Skill Mismatch	-	0	0	0	0	0	-	-	0	0	x	0	0	0	+
	Tax Burden	-	0	0	0	0	0	-	-	+	0	0	x	0	0	+
	Minimum wage	+	0	0	+	-	+	+	-	+	0	0	0	x	0	0
	Unemployment rate in the previous period	+	-	0	-	0	0	-	0	0	+	0	0	0	x	+
	Current period unemployment rate	-	-	0	-	0	0	-	0	0	+	0	0	0	0	x

		Macro Demand Side														
		Technological Improvements	Capital Cost	GDP	Per capita Income	Agricultural Sector/GDP	Service Sector /GDP	Manufacturing Sector/GDP	Income Distribution	Public Investments / GDP	Private Investments /GDP	Capacity Usage	Labour Productivity	Inflation	Uncertainty	Domestic Demand
Labour Market	Union Power	0	0	0	0	0	0	0	+	0	-	0	+	0	0	0
	Skill Mismatch	0	0	0	0	0	0	0	-	0	-	0	-	0	0	0
	Tax Burden	-	0	-	-	0	0	-	-	0	-	-	0	0	0	0
	Minimum wage	0	0	+	+	0	0	0	+	0	0	0	+	0	0	+
	Unemployment rate in the previous period	0	0	-	-	0	0	0	-	+	+	-	+	-	0	-
	Current period unemployment rate	0	0	-	-	0	0	0	-	+	-	-	+	-	0	-

APPENDIX C- (EViews 4.0 OUTPUTS FOR LAG ORDER SELECTION ANALYSES)

LAG ORDER SELECTION FOR UNEMPLOYMENT RATES IN LEVELS

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT GNP						
Exogenous variables: C						
Date: 10/20/05 Time: 12:54						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-393.6162	NA	1828.879	13.18721	13.25702	13.21451
1	-368.0359	48.60260	890.9386	12.46786	12.67730	12.54978
2	-311.9031	102.9101	156.8239	10.73010	11.07916	10.86664
3	-296.7319	26.80243	108.2140	10.35773	10.84641	10.54888
4	-281.0718	26.62221	73.54275	9.969059	10.59736*	10.21482
5	-274.2509	11.14070	67.19931	9.875031	10.64296	10.17541
6	-266.8653	11.57089*	60.36312*	9.762175*	10.66972	10.11717*
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT EXPORT						
Exogenous variables: C						
Date: 10/20/05 Time: 12:55						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-679.6140	NA	25259605	22.72047	22.79028	22.74777
1	-570.3941	207.5176	757327.4	19.21314	19.42257	19.29506
2	-551.3852	34.84981	459484.0	18.71284	19.06190	18.84937
3	-516.0270	62.46605	161772.8	17.66757	18.15625	17.85872
4	-511.0557	8.451263	156999.4	17.63519	18.26349	17.88095
5	-494.8969	26.39275*	105085.2*	17.22990*	17.99782*	17.53027*
6	-491.3473	5.560921	107271.1	17.24491	18.15246	17.59990
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT IMPORT						
Exogenous variables: C						
Date: 10/20/05 Time: 12:56						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-708.6455	NA	66481643	23.68818	23.75800	23.71549
1	-614.4205	179.0275	3285723.	20.68068	20.89012	20.76261
2	-602.2842	22.24995	2506741.	20.40947	20.75853	20.54601
3	-576.3615	45.79674	1208751.	19.67872	20.16740	19.86987
4	-567.6928	14.73676	1037062.	19.52309	20.15140*	19.76886
5	-560.1766	12.27651*	925897.1	19.40589	20.17381	19.70626
6	-554.2879	9.225682	874258.8*	19.34293*	20.25048	19.69792*
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT PUBLICINVGDP						
Exogenous variables: C						
Date: 10/20/05 Time: 12:57						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-243.4783	NA	12.26638	8.182610	8.252422	8.209917
1	-217.9627	48.47965	5.988471	7.465423	7.674858	7.547345
2	-193.9428	44.03656	3.074409	6.798092	7.147149	6.934628
3	-166.5280	48.43282	1.410549	6.017599	6.506279	6.208748
4	-123.8276	72.59066	0.389221	4.727586	5.355889*	4.973350
5	-116.8802	11.34737*	0.354152*	4.629340*	5.397266	4.929718*
6	-115.7739	1.733142	0.392194	4.725798	5.633347	5.080790
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT PRIVINVGDP						
Exogenous variables: C						
Date: 10/20/05 Time: 12:57						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-319.0283	NA	152.2001	10.70094	10.77076	10.72825
1	-304.1931	28.18698	106.0788	10.33977	10.54920	10.42169
2	-298.0041	11.34644	98.67427	10.26680	10.61586	10.40334
3	-286.3828	20.53090	76.64176	10.01276	10.50144	10.20391
4	-275.5551	18.40719	61.18959	9.785169	10.41347	10.03093
5	-263.2047	20.17234*	46.50008*	9.506822*	10.27475*	9.807201*
6	-262.1299	1.683823	51.54899	9.604330	10.51188	9.959322
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT CAPACITY						
Exogenous variables: C						
Date: 10/20/05 Time: 12:59						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-273.4700	NA	33.33423	9.182333	9.252144	9.209640
1	-243.4859	56.96977	14.02174	8.316196	8.525631	8.398118
2	-235.8043	14.08286	12.40995	8.193478	8.542535	8.330013
3	-220.0638	27.80833	8.402305	7.802126	8.290806	7.993275
4	-211.8972	13.88320	7.330523	7.663239	8.291543	7.909003
5	-202.8095	14.84323*	6.210748*	7.493650*	8.261576*	7.794028*
6	-201.6212	1.861718	6.859090	7.587372	8.494921	7.942364
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT PRODUCTIVITY						
Exogenous variables: C						
Date: 10/20/05 Time: 12:59						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-383.9313	NA	1324.288	12.86438	12.93419	12.89169
1	-285.1657	187.6548	56.25729	9.705523	9.914957	9.787444
2	-270.6758	26.56479	39.68133	9.355860	9.704917	9.492396
3	-252.2630	32.52929	24.57707	8.875433	9.364113	9.066583
4	-238.9758	22.58824	18.07749	8.565860	9.194163	8.811624
5	-230.4287	13.96033*	15.59453*	8.414288*	9.182215*	8.714667*
6	-228.0038	3.798964	16.52700	8.466793	9.374342	8.821785
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT REEFFEXCRATE						
Exogenous variables: C						
Date: 10/20/05 Time: 13:01						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-358.0888	NA	559.5947	12.00296	12.07277	12.03027
1	-314.9424	81.97816	151.7893	10.69808	10.90752	10.78000
2	-314.1794	1.398890	169.1863	10.80598	11.15504	10.94252
3	-301.7029	22.04178	127.7162	10.52343	11.01211	10.71458
4	-290.4905	19.06108	100.6677	10.28302	10.91132	10.52878
5	-273.2839	28.10407*	65.06780*	9.842798*	10.61072*	10.14318*
6	-272.3547	1.455844	72.48350	9.945156	10.85271	10.30015
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT REALWAGES						
Exogenous variables: C						
Date: 10/20/05 Time: 13:01						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-369.6340	NA	822.2558	12.38780	12.45761	12.41511
1	-304.9484	122.9026	108.7835	10.36495	10.57438	10.44687
2	-303.3567	2.918134	117.9480	10.44522	10.79428	10.58176
3	-289.7209	24.08997	85.66203	10.12403	10.61271	10.31518
4	-282.4409	12.37595	76.97683	10.01470	10.64300	10.26046
5	-266.4106	26.18284*	51.74450*	9.613686*	10.38161*	9.914065*
6	-265.4362	1.526497	57.55517	9.714541	10.62209	10.06953
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT REALDEPOSITRATE						
Exogenous variables: C						
Date: 10/20/05 Time: 13:02						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-309.5951	NA	111.1362	10.38650	10.45632	10.41381
1	-292.7294	32.04479	72.38949	9.957648	10.16708	10.03957
2	-289.3061	6.276069	73.83936	9.976871	10.32593	10.11341
3	-277.9500	20.06252	57.86121	9.731667	10.22035	9.922816
4	-272.6672	8.980802	55.57388	9.688906	10.31721	9.934670
5	-258.5055	23.13079*	39.75811*	9.350182*	10.11811*	9.650560*
6	-257.0371	2.300417	43.50053	9.434570	10.34212	9.789563
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT INFLATION						
Exogenous variables: C						
Date: 10/20/05 Time: 13:03						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-314.2506	NA	129.7929	10.54169	10.61150	10.56900
1	-295.1163	36.35517	78.38434	10.03721	10.24665	10.11913
2	-289.3370	10.59538	73.91547	9.977901	10.32696	10.11444
3	-278.7686	18.67096	59.46174	9.758953	10.24763	9.950102
4	-271.3881	12.54674	53.25432	9.646271	10.27457	9.892035
5	-257.4092	22.83234*	38.33143*	9.313639*	10.08156*	9.614017*
6	-256.1522	1.969190	42.23618	9.405074	10.31262	9.760067
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

Dependent Variable: UNEMPLOYMENT				
Method: Least Squares				
Date: 10/20/05 Time: 13:17				
Sample(adjusted): 1988:4 2004:4				
Included observations: 65 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.256817	0.850170	3.830783	0.0003
UNEMPLOYMENT(-1)	0.608741	0.101406	6.003017	0.0000
R-squared	0.363869	Mean dependent var		8.272390
Adjusted R-squared	0.353772	S.D. dependent var		1.576663
S.E. of regression	1.267453	Akaike info criterion		3.342182
Sum squared resid	101.2055	Schwarz criterion		3.409086
Log likelihood	-106.6209	F-statistic		36.03622
Durbin-Watson stat	1.833308	Prob(F-statistic)		0.000000

Dependent Variable: UNEMPLOYMENT				
Method: Least Squares				
Date: 12/25/05 Time: 22:29				
Sample(adjusted): 1989:1 2004:4				
Included observations: 64 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.615396	0.953759	3.790680	0.0003
UNEMPLOYMENT(-1)	0.682273	0.127093	5.368296	0.0000
UNEMPLOYMENT(-2)	-0.119280	0.127691	-0.934128	0.3539
R-squared	0.376800	Mean dependent var		8.260584
Adjusted R-squared	0.356368	S.D. dependent var		1.586229
S.E. of regression	1.272579	Akaike info criterion		3.365709
Sum squared resid	98.78689	Schwarz criterion		3.466907
Log likelihood	-104.7027	F-statistic		18.44099
Durbin-Watson stat	1.868212	Prob(F-statistic)		0.000001

Dependent Variable: UNEMPLOYMENT				
Method: Least Squares				
Date: 12/25/05 Time: 22:30				
Sample(adjusted): 1989:2 2004:4				
Included observations: 63 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.535189	0.897894	1.709767	0.0926
UNEMPLOYMENT(-1)	0.740855	0.108234	6.844928	0.0000
UNEMPLOYMENT(-2)	-0.482254	0.129675	-3.718940	0.0004
UNEMPLOYMENT(-3)	0.556968	0.108245	5.145415	0.0000
R-squared	0.567393	Mean dependent var		8.236344
Adjusted R-squared	0.545396	S.D. dependent var		1.586976
S.E. of regression	1.070008	Akaike info criterion		3.034596
Sum squared resid	67.55012	Schwarz criterion		3.170668
Log likelihood	-91.58978	F-statistic		25.79412
Durbin-Watson stat	2.355897	Prob(F-statistic)		0.000000

Dependent Variable: UNEMPLOYMENT				
Method: Least Squares				
Date: 12/25/05 Time: 22:32				
Sample(adjusted): 1989:3 2004:4				
Included observations: 62 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.602107	0.867429	0.694127	0.4904
UNEMPLOYMENT(-1)	0.524624	0.120749	4.344744	0.0001
UNEMPLOYMENT(-2)	-0.262393	0.135345	-1.938688	0.0575
UNEMPLOYMENT(-3)	0.236468	0.136065	1.737904	0.0876
UNEMPLOYMENT(-4)	0.436608	0.129513	3.371142	0.0013
R-squared	0.645948	Mean dependent var		8.245903
Adjusted R-squared	0.621103	S.D. dependent var		1.598101
S.E. of regression	0.983705	Akaike info criterion		2.882226
Sum squared resid	55.15754	Schwarz criterion		3.053769
Log likelihood	-84.34902	F-statistic		25.99838
Durbin-Watson stat	1.519608	Prob(F-statistic)		0.000000

LAG ORDER SELECTION FOR UNEMPLOYMENT RATES IN PER CENT CHANGES

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPCCH CAPACITYCH						
Exogenous variables: C						
Date: 11/15/05 Time: 14:05						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-413.6232	NA	4506.036	14.08892	14.15935	14.11641
1	-407.2343	12.12803	4156.229	14.00794	14.21922	14.09042
2	-386.4713	38.00683	2356.107	13.43971	13.79183	13.57716
3	-377.3950	15.99887*	1986.480	13.26763	13.76060*	13.46007*
4	-371.9564	9.218013	1896.768*	13.21886*	13.85269	13.46628
5	-371.4778	0.778708	2145.875	13.33823	14.11291	13.64063
6	-370.4410	1.616768	2386.579	13.43868	14.35420	13.79606
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPCCH REALDEPOSITRATECH						
Exogenous variables: C						
Date: 11/15/05 Time: 14:06						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-914.2745	NA	1.06E+11	31.06015	31.13058	31.08764
1	-912.2960	3.755812	1.13E+11	31.12868	31.33995	31.21115
2	-897.1771	27.67513	7.78E+10	30.75177	31.10389*	30.88922
3	-891.7317	9.598684	7.41E+10	30.70277	31.19575	30.89521
4	-882.7572	15.21103*	6.28E+10*	30.53414*	31.16797	30.78156*
5	-879.0741	5.992935	6.37E+10	30.54488	31.31956	30.84729
6	-878.5413	0.830740	7.21E+10	30.66242	31.57794	31.01980
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPCCH EXPORTCH						
Exogenous variables: C						
Date: 11/15/05 Time: 14:07						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-481.6887	NA	45273.68	16.39623	16.46665	16.42372
1	-471.3713	19.58563	36552.32	16.18208	16.39335	16.26455
2	-434.4410	67.60117	11978.38	15.06580	15.41792	15.20325
3	-428.4916	10.48712	11228.47	14.99972	15.49269	15.19215
4	-412.5903	26.95134*	7520.052*	14.59628*	15.23011*	14.84370*
5	-410.0579	4.120603	7935.499	14.64603	15.42070	14.94843
6	-407.4963	3.994273	8381.066	14.69479	15.61032	15.05217
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPCCH REEFFEXRATECH						
Exogenous variables: C						
Date: 11/15/05 Time: 14:08						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-453.6438	NA	17497.35	15.44555	15.51598	15.47304
1	-453.5063	0.261082	19948.41	15.57648	15.78776	15.65896
2	-435.2259	33.46228	12301.37	15.09240	15.44453	15.22986
3	-428.5202	11.82027	11239.36	15.00069	15.49366	15.19312
4	-414.5055	23.75383*	8024.443*	14.66120*	15.29503*	14.90862*
5	-413.8060	1.138030	9010.607	14.77309	15.54776	15.07549
6	-413.6897	0.181398	10338.97	14.90474	15.82026	15.26212
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPCCH GNP						
Exogenous variables: C						
Date: 11/15/05 Time: 14:08						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-529.9702	NA	232614.8	18.03289	18.10331	18.06038
1	-487.2483	81.09923	62611.30	16.72028	16.93155	16.80275
2	-456.3385	56.58049	25163.43	15.80809	16.16021	15.94554
3	-444.5246	20.82452	19335.52	15.54321	16.03618	15.73565
4	-421.7711	38.56538	10265.45	14.90749	15.54132	15.15491
5	-411.8382	16.16189*	8429.157*	14.70638*	15.48106*	15.00878*
6	-408.3377	5.458481	8623.536	14.72331	15.63884	15.08069
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPCCH IMPORTCH						
Exogenous variables: C						
Date: 11/15/05 Time: 14:09						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-490.7841	NA	61623.44	16.70455	16.77497	16.73204
1	-483.7477	13.35721	55605.54	16.60162	16.81289	16.68409
2	-456.0025	50.78784	24878.40	15.79669	16.14882*	15.93415
3	-448.5376	13.15838	22153.12	15.67924	16.17222	15.87168*
4	-443.4410	8.638348	21399.31	15.64207	16.27589	15.88949
5	-437.4979	9.670172*	20116.00*	15.57620*	16.35087	15.87860
6	-435.8759	2.529139	21933.07	15.65681	16.57234	16.01420
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPCCH INFLATION						
Exogenous variables: C						
Date: 11/15/05 Time: 14:10						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-449.1842	NA	15042.45	15.29438	15.36480	15.32187
1	-441.0791	15.38583	13090.56	15.15523	15.36650	15.23770
2	-422.0342	34.86186	7865.878	14.64523	14.99735*	14.78268
3	-418.5165	6.200804	8006.966	14.66158	15.15455	14.85401
4	-408.8671	16.35493*	6628.381*	14.47007*	15.10390	14.71749*
5	-407.3292	2.502371	7234.397	14.55353	15.32821	14.85593
6	-406.2261	1.719975	8027.854	14.65173	15.56726	15.00912
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPCCH PRIVINVGDPCH						
Exogenous variables: C						
Date: 11/15/05 Time: 14:11						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-569.9431	NA	901805.0	19.38790	19.45833	19.41539
1	-563.9232	11.42760	842266.4	19.31943	19.53071	19.40190
2	-545.5968	33.54669	518579.9	18.83379	19.18591*	18.97124
3	-542.5429	5.383094	536248.1	18.86586	19.35884	19.05830
4	-530.7888	19.92221*	413352.2*	18.60301*	19.23683	18.85043*
5	-528.6282	3.515514	441721.4	18.66536	19.44004	18.96776
6	-527.6750	1.486315	492664.8	18.76864	19.68417	19.12603
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPCCH PRODUCTIVITYCH						
Exogenous variables: C						
Date: 11/15/05 Time: 14:12						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-441.1095	NA	11440.49	15.02066	15.09109	15.04815
1	-428.8850	23.20588	8658.408	14.74186	14.95314	14.82434
2	-404.5533	44.53936	4349.064	14.05265	14.40478	14.19011
3	-392.3188	21.56598	3294.499	13.77352	14.26649*	13.96596
4	-386.5073	9.849884*	3106.212*	13.71211*	14.34594	13.95953*
5	-384.2958	3.598489	3313.664	13.77274	14.54741	14.07514
6	-380.7542	5.522400	3385.370	13.78828	14.70380	14.14566
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPCCH PUBLICINVGDPCCH						
Exogenous variables: C						
Date: 11/15/05 Time: 14:13						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-570.0921	NA	906371.0	19.39295	19.46338	19.42044
1	-538.0713	60.78524	350640.1	18.44309	18.65437	18.52557
2	-509.4943	52.31032	152518.1	17.60998	17.96210	17.74743
3	-495.4208	24.80762	108552.9	17.26850	17.76148	17.46094
4	-472.2929	39.19985*	56905.29*	16.62010*	17.25392*	16.86752*
5	-470.8197	2.396979	62244.50	16.70575	17.48043	17.00816
6	-467.8271	4.666439	64785.83	16.73990	17.65543	17.09729
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPCCH REALWAGECH						
Exogenous variables: C						
Date: 11/15/05 Time: 14:13						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-446.2147	NA	13601.98	15.19372	15.26414	15.22121
1	-444.3569	3.526618	14628.94	15.26634	15.47761	15.34881
2	-423.2505	38.63552	8196.949	14.68646	15.03858*	14.82391
3	-418.7528	7.928075	8071.368	14.66959	15.16256	14.86202
4	-408.5449	17.30158*	6556.381*	14.45915*	15.09297	14.70657*
5	-407.0539	2.425953	7167.215	14.54420	15.31888	14.84660
6	-404.5687	3.875187	7589.266	14.59555	15.51108	14.95293
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

Dependent Variable: UNEMPCCH				
Method: Least Squares				
Date: 11/15/05 Time: 14:25				
Sample(adjusted): 1989:1 2004:4				
Included observations: 64 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.670102	2.098760	0.795757	0.4292
UNEMPCCH(-1)	-0.066079	0.126115	-0.523955	0.6022
R-squared	0.004408	Mean dependent var		1.557102
Adjusted R-squared	-0.011650	S.D. dependent var		16.60476
S.E. of regression	16.70119	Akaike info criterion		8.499589
Sum squared resid	17293.65	Schwarz criterion		8.567054
Log likelihood	-269.9868	F-statistic		0.274529
Durbin-Watson stat	2.093494	Prob(F-statistic)		0.602178

Dependent Variable: UNEMPCH				
Method: Least Squares				
Date: 12/26/05 Time: 10:59				
Sample(adjusted): 1989:2 2004:4				
Included observations: 63 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.715062	1.644458	1.651038	0.1040
UNEMPCH(-1)	-0.115090	0.098322	-1.170533	0.2464
UNEMPCH(-2)	-0.642592	0.097815	-6.569487	0.0000
R-squared	0.421400	Mean dependent var		1.448235
Adjusted R-squared	0.402114	S.D. dependent var		16.71509
S.E. of regression	12.92463	Akaike info criterion		8.002594
Sum squared resid	10022.76	Schwarz criterion		8.104648
Log likelihood	-249.0817	F-statistic		21.84932
Durbin-Watson stat	2.332566	Prob(F-statistic)		0.000000

Dependent Variable: UNEMPCH				
Method: Least Squares				
Date: 12/26/05 Time: 11:00				
Sample(adjusted): 1989:3 2004:4				
Included observations: 62 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.913838	1.635369	2.393245	0.0200
UNEMPCH(-1)	-0.310410	0.124809	-2.487072	0.0158
UNEMPCH(-2)	-0.666367	0.095276	-6.994075	0.0000
UNEMPCH(-3)	-0.312632	0.126586	-2.469726	0.0165
R-squared	0.470021	Mean dependent var		1.824910
Adjusted R-squared	0.442608	S.D. dependent var		16.57978
S.E. of regression	12.37825	Akaike info criterion		7.932100
Sum squared resid	8886.824	Schwarz criterion		8.069334
Log likelihood	-241.8951	F-statistic		17.14607
Durbin-Watson stat	1.714754	Prob(F-statistic)		0.000000

Dependent Variable: UNEMPCH				
Method: Least Squares				
Date: 12/26/05 Time: 11:01				
Sample(adjusted): 1989:4 2004:4				
Included observations: 61 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.153760	1.577041	1.365697	0.1775
UNEMPCH(-1)	-0.177209	0.120328	-1.472717	0.1464
UNEMPCH(-2)	-0.361525	0.120082	-3.010647	0.0039
UNEMPCH(-3)	-0.188018	0.120326	-1.562574	0.1238
UNEMPCH(-4)	0.451934	0.122445	3.690923	0.0005
R-squared	0.573939	Mean dependent var		1.813056
Adjusted R-squared	0.543507	S.D. dependent var		16.71711
S.E. of regression	11.29480	Akaike info criterion		7.764974
Sum squared resid	7144.059	Schwarz criterion		7.937996
Log likelihood	-231.8317	F-statistic		18.85918
Durbin-Watson stat	1.838834	Prob(F-statistic)		0.000000

Dependent Variable: UNEMPCH				
Method: Least Squares				
Date: 12/26/05 Time: 11:01				
Sample(adjusted): 1990:1 2004:4				
Included observations: 60 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.537646	1.620166	1.566288	0.1231
UNEMPCH(-1)	-0.099475	0.134336	-0.740493	0.4622
UNEMPCH(-2)	-0.388926	0.123176	-3.157492	0.0026
UNEMPCH(-3)	-0.258379	0.131992	-1.957533	0.0555
UNEMPCH(-4)	0.427083	0.124183	3.439137	0.0011
UNEMPCH(-5)	-0.180204	0.136871	-1.316596	0.1935
R-squared	0.582758	Mean dependent var		1.592378
Adjusted R-squared	0.544125	S.D. dependent var		16.76835
S.E. of regression	11.32174	Akaike info criterion		7.785966
Sum squared resid	6921.819	Schwarz criterion		7.995401
Log likelihood	-227.5790	F-statistic		15.08428
Durbin-Watson stat	1.956337	Prob(F-statistic)		0.000000

LAG ORDER SELECTION FOR DESEASONALIZED UNEMPLOYMENT RATES

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT_DESEASON CAPACITY						
Exogenous variables: C						
Date: 04/03/06 Time: 15:20						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-263.9864	NA	24.29975	8.866214	8.936025	8.893521
1	-200.6697	120.3017	3.364920*	6.888991*	7.098426*	6.970913*
2	-200.1555	0.942723	3.781818	7.005184	7.354242	7.141720
3	-194.1888	10.54113*	3.546669	6.939628	7.428309	7.130778
4	-192.1265	3.505916	3.792501	7.004218	7.632522	7.249982
5	-189.5975	4.130713	3.998355	7.053251	7.821178	7.353629
6	-187.9764	2.539766	4.352498	7.132547	8.040096	7.487539
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT_DESEASON EXPORT						
Exogenous variables: C						
Date: 04/03/06 Time: 15:20						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-668.2158	NA	17275131	22.34053	22.41034	22.36783
1	-531.0686	260.5797	204168.1	17.90229	18.11172	17.98421
2	-523.7910	13.34224	183148.8	17.79303	18.14209	17.92957
3	-517.0923	11.83433	167620.5	17.70308	18.19176	17.89423
4	-497.6967	32.97250	100579.0	17.18989	17.81819	17.43566
5	-483.2558	23.58680*	71288.69*	16.84186*	17.60979*	17.14224*
6	-481.0874	3.397290	76199.84	16.90291	17.81046	17.25790
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT_DESEASON GNP						
Exogenous variables: C						
Date: 04/03/06 Time: 15:21						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-393.4575	NA	1819.230	13.18192	13.25173	13.20922
1	-348.1565	86.07189	459.2659	11.80522	12.01465	11.88714
2	-303.4314	81.99598	118.2422	10.44771	10.79677	10.58425
3	-296.4069	12.41000	107.0480	10.34690	10.83558	10.53805
4	-271.1801	42.88548*	52.88637	9.639338	10.26764*	9.885102*
5	-266.0983	8.300377	51.20861	9.603276	10.37120	9.903654
6	-261.9146	6.554456	51.18035*	9.597153*	10.50470	9.952145
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT_DESEASON IMPORT						
Exogenous variables: C						
Date: 04/03/06 Time: 15:22						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-698.0336	NA	46674417	23.33445	23.40427	23.36176
1	-574.3525	234.9942	864144.8	19.34508	19.55452*	19.42700
2	-570.4815	7.096726	868398.0	19.34938	19.69844	19.48592
3	-566.0883	7.761365	858256.1	19.33628	19.82496	19.52743
4	-560.2223	9.972267	808457.6	19.27408	19.90238	19.51984
5	-553.2512	11.38604	735034.5	19.17504	19.94297	19.47542
6	-546.0543	11.27523*	664426.0*	19.06848*	19.97603	19.42347*
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT_DESEASON INFLATION						
Exogenous variables: C						
Date: 04/03/06 Time: 15:22						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-304.2389	NA	92.96414	10.20796	10.27777	10.23527
1	-255.4323	92.73239*	20.88067*	8.714411	8.923846*	8.796332*
2	-252.4117	5.537851	21.58669	8.747056	9.096114	8.883592
3	-247.3766	8.895305	20.88297	8.712554*	9.201234	8.903703
4	-245.9047	2.502225	22.77427	8.796824	9.425127	9.042588
5	-245.8851	0.032098	26.10518	8.929502	9.697428	9.229880
6	-244.2842	2.508038	28.43656	9.009473	9.917022	9.364465
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT_DESEASON PRIVINVGDP						
Exogenous variables: C						
Date: 04/03/06 Time: 15:23						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-308.7280	NA	107.9700	10.35760	10.42741	10.38491
1	-263.3905	86.14125	27.22396	8.979685	9.189119*	9.061606*
2	-260.2961	5.673213	28.07528	9.009869	9.358926	9.146404
3	-256.7293	6.301282	28.52243	9.024310	9.512990	9.215460
4	-247.0914	16.38440*	23.69321*	8.836381*	9.464684	9.082145
5	-246.2534	1.368793	26.42766	8.941779	9.709706	9.242158
6	-244.7525	2.351344	28.88398	9.025084	9.932634	9.380077
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT_DESEASON PRODUCTIVITY						
Exogenous variables: C						
Date: 04/03/06 Time: 15:23						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-372.2883	NA	898.3213	12.47628	12.54609	12.50358
1	-249.5280	233.2446	17.15023	8.517599	8.727033*	8.599520
2	-242.5499	12.79307	15.53898	8.418331	8.767388	8.554867
3	-237.2621	9.341837	14.90630	8.375403	8.864084	8.566553
4	-226.3904	18.48191*	11.88353	8.146346	8.774649	8.392110*
5	-221.1325	8.587862	11.43923	8.104417	8.872343	8.404795
6	-216.6191	7.071038	11.30794*	8.087303*	8.994852	8.442295
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT_DESEASON PUBLICINVGNP						
Exogenous variables: C						
Date: 04/03/06 Time: 15:24						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-234.3469	NA	9.047439	7.878230	7.948041	7.905537
1	-188.7960	86.54662	2.265089	6.493201	6.702636	6.575123
2	-186.6402	3.952405	2.410161	6.554673	6.903730	6.691208
3	-183.6895	5.212875	2.499350	6.589650	7.078330	6.780800
4	-128.4855	93.84687	0.454597	4.882849	5.511152	5.128613
5	-114.3029	23.16488*	0.324997*	4.543429*	5.311356*	4.843807*
6	-110.4879	5.976799	0.328835	4.549597	5.457146	4.904589
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT_DESEASON REALDEPOSITRATE						
Exogenous variables: C						
Date: 04/03/06 Time: 15:24						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-300.9848	NA	83.40798	10.09949	10.16930	10.12680
1	-254.6129	88.10650*	20.31806*	8.687097*	8.896532*	8.769018*
2	-253.0703	2.828161	22.06583	8.769009	9.118067	8.905545
3	-249.4862	6.331891	22.40432	8.782873	9.271553	8.974023
4	-247.8011	2.864694	24.26035	8.860036	9.488339	9.105800
5	-247.1399	1.079849	27.22030	8.971331	9.739258	9.271710
6	-242.8255	6.759351	27.08694	8.960849	9.868398	9.315841
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT_DESEASON REALWAGES						
Exogenous variables: C						
Date: 04/03/06 Time: 15:24						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-360.2145	NA	600.6843	12.07382	12.14363	12.10112
1	-265.3178	180.3037*	29.03033*	9.043928*	9.253363*	9.125850*
2	-263.2237	3.839344	30.95319	9.107455	9.456513	9.243991
3	-259.2655	6.992816	31.03853	9.108849	9.597529	9.299998
4	-253.9283	9.073118	29.75762	9.064278	9.692581	9.310042
5	-251.7435	3.568491	31.73488	9.124785	9.892711	9.425163
6	-249.8368	2.987152	34.21843	9.194562	10.10211	9.549554
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENT_DESEASON REEFFEXCRATE						
Exogenous variables: C						
Date: 04/03/06 Time: 15:25						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-349.0600	NA	414.1604	11.70200	11.77181	11.72931
1	-276.0421	138.7341*	41.50510*	9.401403*	9.610838*	9.483325*
2	-274.8196	2.241268	45.55895	9.493986	9.843044	9.630522
3	-271.9488	5.071786	47.37082	9.531626	10.02031	9.722775
4	-266.6836	8.950824	45.52494	9.489453	10.11776	9.735217
5	-264.3755	3.769914	48.35070	9.545849	10.31378	9.846227
6	-262.3803	3.125708	51.98113	9.612678	10.52023	9.967670
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

Dependent Variable: UNEMPLOYMENT_DESEASON				
Method: Least Squares				
Date: 04/03/06 Time: 15:26				
Sample(adjusted): 1988:4 2004:4				
Included observations: 65 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.946677	0.497472	1.902977	0.0616
UNEMPLOYMENT_DESEASON(-1)	0.886879	0.059530	14.89795	0.0000
R-squared	0.778908	Mean dependent var		8.264660
Adjusted R-squared	0.775398	S.D. dependent var		1.338773
S.E. of regression	0.634473	Akaike info criterion		1.958243
Sum squared resid	25.36106	Schwarz criterion		2.025147
Log likelihood	-61.64290	F-statistic		221.9489
Durbin-Watson stat	1.715895	Prob(F-statistic)		0.000000

Dependent Variable: UNEMPLOYMENT_DESEASON				
Method: Least Squares				
Date: 04/03/06 Time: 15:27				
Sample(adjusted): 1989:1 2004:4				
Included observations: 64 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.113866	0.518307	2.149047	0.0356
UNEMPLOYMENT_DESEASON(-1)	1.023820	0.127861	8.007287	0.0000
UNEMPLOYMENT_DESEASON(-2)	-0.157682	0.130197	-1.211104	0.2305
R-squared	0.784057	Mean dependent var		8.262105
Adjusted R-squared	0.776977	S.D. dependent var		1.349196
S.E. of regression	0.637162	Akaike info criterion		1.982155
Sum squared resid	24.76449	Schwarz criterion		2.083352
Log likelihood	-60.42895	F-statistic		110.7412
Durbin-Watson stat	1.897826	Prob(F-statistic)		0.000000

LAG ORDER SELECTION FOR DESEASONALIZED UNEMPLOYMENT RATES IN PER CENT CHANGES

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENTDESEASONCH CAPACITYCH						
Exogenous variables: C						
Date: 12/17/05 Time: 13:51						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-373.3462	NA	1150.386	12.72360	12.79403*	12.75109*
1	-371.1956	4.082438	1225.023	12.78629	12.99757	12.86877
2	-362.7155	15.52295*	1053.091*	12.63442*	12.98655	12.77188
3	-359.0337	6.490050	1066.034	12.64521	13.13818	12.83765
4	-357.2982	2.941399	1154.035	12.72197	13.35580	12.96939
5	-354.9574	3.808784	1225.727	12.77822	13.55289	13.08062
6	-352.3171	4.117165	1291.096	12.82431	13.73983	13.18169
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENTDESEASONCH EXPORTCH						
Exogenous variables: C						
Date: 12/17/05 Time: 13:51						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-442.6225	NA	12042.55	15.07195	15.14237	15.09944
1	-438.1916	8.411166	11869.94	15.05734	15.26862	15.13982
2	-426.8593	20.74396	9263.618	14.80879	15.16091	14.94624
3	-416.2568	18.68914	7416.536	14.58498	15.07795	14.77741
4	-398.5593	29.99580*	4673.664*	14.12065*	14.75448*	14.36807*
5	-396.5167	3.323431	5014.453	14.18701	14.96168	14.48941
6	-394.0162	3.899146	5306.971	14.23784	15.15336	14.59522
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENTDESEASONCH GNP						
Exogenous variables: C						
Date: 12/17/05 Time: 13:52						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-492.6807	NA	65715.39	16.76884	16.83926	16.79633
1	-492.5042	0.334947	74822.17	16.89845	17.10972	16.98092
2	-448.4878	80.57236	19283.82	15.54196	15.89409	15.67942
3	-446.5795	3.363872	20730.38	15.61286	16.10584	15.80530
4	-415.4826	52.70651	8294.706	14.69433	15.32815*	14.94175
5	-408.3585	11.59183*	7491.284*	14.58842*	15.36310	14.89083*
6	-406.4576	2.964133	8091.090	14.65958	15.57510	15.01696
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENTDESEASONCH IMPORTCH						
Exogenous variables: C						
Date: 12/17/05 Time: 13:52						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-449.8756	NA	15399.18	15.31782	15.38824*	15.34531*
1	-446.5272	6.356290	15745.76	15.33990	15.55118	15.42238
2	-441.5937	9.030766	15265.07	15.30826	15.66039	15.44572
3	-438.3149	5.779681	15665.23	15.33271	15.82568	15.52514
4	-431.1054	12.21938*	14086.31	15.22391	15.85774	15.47133
5	-425.4290	9.236306	13361.79*	15.16708*	15.94176	15.46948
6	-424.9971	0.673401	15168.50	15.28804	16.20356	15.64542
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENTDESEASONCH INFLATION						
Exogenous variables: C						
Date: 12/17/05 Time: 13:52						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-408.5737	NA	3797.142	13.91775	13.98818*	13.94524
1	-401.9717	12.53263	3477.154	13.82955	14.04082	13.91202
2	-395.8792	11.15221*	3241.137*	13.75862*	14.11074	13.89607*
3	-393.6953	3.849636	3451.872	13.82018	14.31316	14.01262
4	-392.6449	1.780299	3824.616	13.92017	14.55399	14.16759
5	-392.0003	1.048934	4302.621	14.03391	14.80858	14.33631
6	-391.1878	1.266976	4821.776	14.14196	15.05748	14.49934
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENTDESEASONCH PRIVINVGDPCH						
Exogenous variables: C						
Date: 12/17/05 Time: 13:53						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-528.2933	NA	219761.4	17.97605	18.04647*	18.00354*
1	-523.2697	9.536384	212302.5	17.94135	18.15262	18.02382
2	-519.4113	7.062843	213460.5	17.94615	18.29827	18.08360
3	-516.7219	4.740599	223477.4	17.99057	18.48355	18.18301
4	-510.3636	10.77678*	206835.1*	17.91063*	18.54446	18.15805
5	-507.8200	4.138759	218179.3	17.96000	18.73468	18.26240
6	-506.8822	1.462392	243468.3	18.06380	18.97933	18.42119
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENTDESEASONCH PRODUCTIVITYCH						
Exogenous variables: C						
Date: 12/17/05 Time: 13:53						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-400.9680	NA	2934.183	13.65993	13.73036*	13.68742
1	-395.7343	9.935212	2814.478	13.61811	13.82939	13.70058
2	-388.6306	13.00324	2535.039	13.51290	13.86503	13.65036
3	-381.0804	13.30891	2250.815	13.39256	13.88553	13.58499
4	-373.3315	13.13370*	1987.278*	13.26548*	13.89930	13.51289*
5	-371.6997	2.655191	2162.075	13.34575	14.12043	13.64815
6	-370.1543	2.409821	2363.496	13.42896	14.34448	13.78634
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENTDESEASONCH PUBLICINVGDP						
Exogenous variables: C						
Date: 12/17/05 Time: 13:54						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-532.4215	NA	252769.7	18.11598	18.18641	18.14347
1	-513.0500	36.77294	150142.0	17.59492	17.80619	17.67739
2	-508.0359	9.178402	145161.1	17.56054	17.91266	17.69799
3	-496.0898	21.05746	111042.9	17.29118	17.78416	17.48362
4	-462.3981	57.10469*	40689.51*	16.28468*	16.91850*	16.53210*
5	-461.8693	0.860346	45955.13	16.40235	17.17702	16.70475
6	-460.6630	1.881049	50817.16	16.49705	17.41258	16.85443
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENTDESEASONCH REALDEPRATECH						
Exogenous variables: C						
Date: 12/17/05 Time: 13:54						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-873.8436	NA	2.69E+10	29.68961	29.76004*	29.71710
1	-867.1267	12.75078*	2.45E+10*	29.59751*	29.80879	29.67999*
2	-864.6564	4.521787	2.58E+10	29.64937	30.00150	29.78683
3	-863.3934	2.226418	2.84E+10	29.74215	30.23512	29.93459
4	-862.7182	1.144436	3.18E+10	29.85485	30.48868	30.10227
5	-862.1989	0.844938	3.60E+10	29.97284	30.74752	30.27524
6	-861.8685	0.515105	4.10E+10	30.09724	31.01276	30.45462
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENTDESEASONCH REALWAGECH						
Exogenous variables: C						
Date: 12/17/05 Time: 13:54						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-404.9341	NA	3356.420	13.79438	13.86480*	13.82187*
1	-402.9394	3.786672	3593.109	13.86235	14.07363	13.94483
2	-396.9623	10.94117*	3362.338	13.79533	14.14746	13.93279
3	-392.8192	7.303075	3350.859*	13.79048*	14.28346	13.98292
4	-390.4422	4.028752	3549.437	13.84550	14.47932	14.09292
5	-389.1796	2.054425	3910.274	13.93829	14.71297	14.24069
6	-385.9209	5.081298	4033.383	13.96342	14.87895	14.32081
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: UNEMPLOYMENTDESEASONCH REEFFEXRATECH						
Exogenous variables: C						
Date: 12/17/05 Time: 13:55						
Sample: 1988:4 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-413.2698	NA*	4452.380*	14.07694*	14.14737*	14.10443*
1	-412.8632	0.771806	5029.994	14.19875	14.41003	14.28123
2	-407.8560	9.165754	4864.263	14.16461	14.51673	14.30206
3	-404.0015	6.794406	4895.310	14.16954	14.66252	14.36198
4	-399.7750	7.163445	4870.302	14.16187	14.79569	14.40929
5	-399.4635	0.506820	5541.229	14.28690	15.06157	14.58930
6	-399.3731	0.141001	6363.713	14.41943	15.33495	14.77681
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

Dependent Variable: UNEMPLOYMENTDESEASONCH				
Method: Least Squares				
Date: 12/17/05 Time: 13:55				
Sample(adjusted): 1989:1 2004:4				
Included observations: 64 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.449091	1.049089	0.428077	0.6701
UNEMPLOYMENTDESEASONCH(-1)	0.073275	0.127992	0.572494	0.5691
R-squared	0.005258	Mean dependent var		0.495054
Adjusted R-squared	-0.010786	S.D. dependent var		8.323331
S.E. of regression	8.368097	Akaike info criterion		7.117481
Sum squared resid	4341.553	Schwarz criterion		7.184946
Log likelihood	-225.7594	F-statistic		0.327749
Durbin-Watson stat	1.932601	Prob(F-statistic)		0.569058

Dependent Variable: UNEMPLOYMENTDESEASONCH				
Method: Least Squares				
Date: 12/17/05 Time: 13:56				
Sample(adjusted): 1989:2 2004:4				
Included observations: 63 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.606603	1.024416	0.592146	0.5560
UNEMPLOYMENTDESEASONCH (-1)	0.094258	0.123884	0.760850	0.4497
UNEMPLOYMENTDESEASONCH (-2)	-0.312872	0.124084	-2.521464	0.0144
R-squared	0.100672	Mean dependent var		0.452079
Adjusted R-squared	0.070694	S.D. dependent var		8.383026
S.E. of regression	8.081279	Akaike info criterion		7.063425
Sum squared resid	3918.424	Schwarz criterion		7.165479
Log likelihood	-219.4979	F-statistic		3.358236
Durbin-Watson stat	1.908261	Prob(F-statistic)		0.041452

Dependent Variable: UNEMPLOYMENTDESEASONCH				
Method: Least Squares				
Date: 12/17/05 Time: 13:56				
Sample(adjusted): 1989:3 2004:4				
Included observations: 62 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.528826	1.051310	0.503017	0.6169
UNEMPLOYMENTDESEASONCH (-1)	0.127990	0.132535	0.965706	0.3382
UNEMPLOYMENTDESEASONCH (-2)	-0.321605	0.126041	-2.551596	0.0134
UNEMPLOYMENTDESEASONCH (-3)	0.103041	0.132927	0.775169	0.4414
R-squared	0.110071	Mean dependent var		0.456908
Adjusted R-squared	0.064040	S.D. dependent var		8.451371
S.E. of regression	8.176282	Akaike info criterion		7.102693
Sum squared resid	3877.392	Schwarz criterion		7.239927
Log likelihood	-216.1835	F-statistic		2.391240
Durbin-Watson stat	1.929569	Prob(F-statistic)		0.077831

LAG ORDER SELECTION FOR EMPLOYMENT INDEX LEVEL

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENT EXPORTIHR						
Exogenous variables: C						
Date: 07/28/05 Time: 13:55						
Sample: 1988:2 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-759.4811	NA	5.56E+08	25.81292	25.88334	25.84041
1	-593.8231	314.4695	2320766.	20.33299	20.54426	20.41546
2	-585.2868	15.62584	1991250.	20.17921	20.53134	20.31667
3	-582.8710	4.258354	2104115.	20.23291	20.72589	20.42535
4	-577.6996	8.765019	2027375.	20.19321	20.82703	20.44063
5	-555.2438	36.53824*	1088878.	19.56759	20.34226*	19.86999*
6	-551.0671	6.512808	1088745.	19.56160	20.47712	19.91898
7	-546.6179	6.636059	1081023.	19.54637	20.60275	19.95874
8	-542.1810	6.317010	1076677.*	19.53156*	20.72878	19.99891
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENT CAPACITY						
Exogenous variables: C						
Date: 07/28/05 Time: 13:59						
Sample: 1988:2 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-366.0874	NA	899.4564	12.47754	12.54796	12.50503
1	-280.1573	163.1216	55.96168	9.700246	9.911521*	9.782719
2	-276.8643	6.027734	57.35587	9.724214	10.07634	9.861670
3	-267.9840	15.65337	48.68023	9.558781	10.05176	9.751219
4	-264.0077	6.739610	48.84383	9.559582	10.19341	9.807002
5	-250.4134	22.11957	35.42518	9.234351	10.00903	9.536753*
6	-246.1788	6.603074	35.35142	9.226399	10.14192	9.583783
7	-239.3410	10.19869*	32.37064*	9.130204*	10.18658	9.542570
8	-236.9074	3.464784	34.50601	9.183303	10.38053	9.650651
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENT GNP						
Exogenous variables: C						
Date: 07/28/05 Time: 14:00						
Sample: 1988:2 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-491.8352	NA	63858.77	16.74018	16.81060	16.76767
1	-420.1677	136.0468	6443.228	14.44636	14.65764	14.52884
2	-370.7329	90.49088	1381.964	12.90620	13.25832	13.04366
3	-345.7136	44.10175	678.6965	12.19368	12.68666	12.38612
4	-329.0795	28.19346	443.3911	11.76541	12.39923*	12.01283
5	-323.1649	9.623771*	417.2043*	11.70050	12.47518	12.00291*
6	-320.1505	4.700397	433.9175	11.73392	12.64944	12.09130
7	-316.5186	5.417109	442.9425	11.74639	12.80277	12.15876
8	-311.0883	7.731242	426.5541	11.69791*	12.89513	12.16526
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENT IMPORTITH						
Exogenous variables: C						
Date: 07/28/05 Time: 14:01						
Sample: 1988:2 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-779.5671	NA	1.10E+09	26.49380	26.56423	26.52129
1	-643.4986	258.2996	12501045	22.01690	22.22818	22.09937
2	-638.9010	8.415879	12258203	21.99665	22.34877	22.13410
3	-631.9345	12.28004	11101326	21.89608	22.38906	22.08852
4	-619.6249	20.86375	8397525.	21.61440	22.24823	21.86182
5	-602.2959	28.19621	5366280.	21.16257	21.93725	21.46498
6	-587.0592	23.75904*	3688040.*	20.78167*	21.69719*	21.13905*
7	-584.3609	4.024564	3885801.	20.82579	21.88217	21.23816
8	-579.5656	6.827121	3823458.	20.79883	21.99606	21.26618
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENT INFLATION						
Exogenous variables: C						
Date: 07/28/05 Time: 14:01						
Sample: 1988:2 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-409.2512	NA	3885.357	13.94072	14.01114	13.96821
1	-343.5092	124.7983	479.2355	11.84777	12.05905*	11.93024
2	-339.2928	7.718157	476.0372	11.84044	12.19256	11.97789
3	-336.1105	5.609559	490.1169	11.86815	12.36113	12.06059
4	-332.3798	6.323133	495.8773	11.87728	12.51111	12.12470
5	-315.3671	27.68168	320.2961	11.43617	12.21085	11.73858
6	-310.9064	6.955812	317.1877	11.42055	12.33608	11.77794
7	-302.6657	12.29118*	276.9536	11.27680	12.33318	11.68917*
8	-297.5737	7.249657	269.7824*	11.23978*	12.43701	11.70713
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: PRIVINGNP EMPLOYMENT						
Exogenous variables: C						
Date: 07/28/05 Time: 14:02						
Sample: 1988:2 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-404.1980	NA	3273.704	13.76942	13.83985	13.79692
1	-342.4529	117.2111	462.3783	11.81196	12.02324*	11.89444
2	-339.4332	5.527476	478.3083	11.84519	12.19732	11.98265
3	-332.6664	11.92790	436.1109	11.75141	12.24438	11.94384
4	-327.6025	8.582991	421.7380	11.71534	12.34916	11.96276
5	-317.0856	17.11222	339.5084	11.49443	12.26910	11.79683*
6	-313.3216	5.869258	344.2497	11.50243	12.41795	11.85981
7	-308.7276	6.852082	340.1339	11.48229	12.53867	11.89466
8	-301.4553	10.35385*	307.7217*	11.37136*	12.56859	11.83871
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENT PRODUCTIVITY						
Exogenous variables: C						
Date: 07/28/05 Time: 14:02						
Sample: 1988:2 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-458.5077	NA	20633.72	15.61043	15.68085	15.63792
1	-330.6221	242.7659	309.6178	11.41092	11.62219	11.49339
2	-324.1049	11.92979	284.4761	11.32559	11.67771	11.46304
3	-320.8408	5.753616	292.0797	11.35054	11.84351	11.54297
4	-302.8272	30.53145	182.0980	10.87550	11.50932	11.12292
5	-285.8473	27.62829*	117.7513	10.43550	11.21018*	10.73790*
6	-280.7116	8.008264	113.9709*	10.39700*	11.31253	10.75439
7	-277.3505	5.013160	117.4143	10.41866	11.47504	10.83103
8	-274.8718	3.528974	124.9686	10.47023	11.66746	10.93758
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: PUBLICINGNP EMPLOYMENT						
Exogenous variables: C						
Date: 07/28/05 Time: 14:03						
Sample: 1988:2 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-333.1651	NA	294.6477	11.36153	11.43195	11.38902
1	-255.6260	147.1929	24.36379	8.868676	9.079951	8.951150
2	-252.1522	6.358724	24.81818	8.886516	9.238641	9.023971
3	-246.8069	9.422185	23.74577	8.840913	9.333888	9.033350
4	-190.4946	95.44468	4.041671	7.067612	7.701437	7.315032
5	-181.6610	14.37325*	3.444692	6.903763	7.678438*	7.206165*
6	-178.2164	5.371282	3.530814	6.922589	7.838114	7.279973
7	-172.7203	8.197474	3.383544*	6.871876*	7.928251	7.284242
8	-171.4779	1.768919	3.755356	6.965352	8.162577	7.432700
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: REALDEPOSITRATE EMPLOYMENT						
Exogenous variables: C						
Date: 07/28/05 Time: 14:04						
Sample: 1988:2 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-412.6664	NA	4362.242	14.05649	14.12691	14.08398
1	-345.9985	126.5561	521.4292	11.93215	12.14343*	12.01463
2	-342.4888	6.424420	530.5082	11.94877	12.30090	12.08623
3	-339.4056	5.434911	548.0365	11.97985	12.47283	12.17229
4	-335.5109	6.601150	551.4032	11.98342	12.61725	12.23084
5	-317.6359	29.08473	345.9013	11.51308	12.28776	11.81548
6	-313.7498	6.059639	349.2832	11.51694	12.43247	11.87433
7	-305.2499	12.67785*	302.3096	11.36440	12.42078	11.77677*
8	-300.4445	6.841670	297.3563*	11.33710*	12.53433	11.80445
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: REALWAGES EMPLOYMENT						
Exogenous variables: C						
Date: 07/28/05 Time: 14:04						
Sample: 1988:2 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-459.5741	NA	21393.28	15.64658	15.71700	15.67407
1	-348.6136	210.6369	569.7630	12.02080	12.23207*	12.10327*
2	-347.1657	2.650287	621.6478	12.10731	12.45944	12.24477
3	-342.4286	8.350111	607.1760	12.08233	12.57530	12.27476
4	-341.2336	2.025494	669.4498	12.17741	12.81124	12.42483
5	-327.0634	23.05668*	476.1475*	11.83266	12.60733	12.13506
6	-325.0196	3.186798	511.7880	11.89897	12.81450	12.25635
7	-318.9950	8.985863	481.7319	11.83034*	12.88672	12.24271
8	-316.6864	3.286922	515.6892	11.88767	13.08490	12.35502
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: REEFEXCRATE EMPLOYMENT						
Exogenous variables: C						
Date: 07/28/05 Time: 14:05						
Sample: 1988:2 2004:4						
Included observations: 59						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-451.6515	NA	16354.67	15.37802	15.44844	15.40551
1	-363.9296	166.5228	957.5801	12.53999	12.75126	12.62246
2	-361.9647	3.596796	1026.628	12.60897	12.96110	12.74643
3	-356.7972	9.108907	988.2023	12.56940	13.06237	12.76183
4	-350.5433	10.59985	917.8535	12.49299	13.12682	12.74041
5	-331.2975	31.31514*	549.6370*	11.97619*	12.75086*	12.27859*
6	-330.5715	1.131990	617.7665	12.08717	13.00270	12.44456
7	-326.5534	5.993228	622.4120	12.08655	13.14293	12.49892
8	-325.7695	1.116007	701.6307	12.19558	13.39280	12.66292
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

Method: Least Squares				
Date: 02/12/06 Time: 14:18				
Sample(adjusted): 1988:3 2004:4				
Included observations: 66 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.406290	3.295967	2.247077	0.0281
EMPLOYMENT(-1)	0.916293	0.034298	26.71557	0.0000
R-squared	0.917708	Mean dependent var		94.86364
Adjusted R-squared	0.916423	S.D. dependent var		10.76084
S.E. of regression	3.110932	Akaike info criterion		5.137556
Sum squared resid	619.3855	Schwarz criterion		5.203909
Log likelihood	-167.5394	F-statistic		713.7218
Durbin-Watson stat	1.843830	Prob(F-statistic)		0.000000

Dependent Variable: EMPLOYMENT				
Method: Least Squares				
Date: 02/12/06 Time: 14:18				
Sample(adjusted): 1988:4 2004:4				
Included observations: 65 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.115308	3.494962	2.035875	0.0460
EMPLOYMENT(-1)	0.989370	0.127233	7.776055	0.0000
EMPLOYMENT(-2)	-0.069468	0.121382	-0.572309	0.5692
R-squared	0.910833	Mean dependent var		94.48154
Adjusted R-squared	0.907957	S.D. dependent var		10.38356
S.E. of regression	3.150235	Akaike info criterion		5.177886
Sum squared resid	615.2869	Schwarz criterion		5.278243
Log likelihood	-165.2813	F-statistic		316.6617
Durbin-Watson stat	1.942488	Prob(F-statistic)		0.000000

Dependent Variable: EMPLOYMENT				
Method: Least Squares				
Date: 02/12/06 Time: 14:18				
Sample(adjusted): 1989:1 2004:4				
Included observations: 64 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.442504	3.484324	1.848997	0.0694
EMPLOYMENT(-1)	1.014320	0.122287	8.294563	0.0000
EMPLOYMENT(-2)	-0.408700	0.172067	-2.375233	0.0208
EMPLOYMENT(-3)	0.319707	0.116824	2.736669	0.0082
R-squared	0.915164	Mean dependent var		94.14688
Adjusted R-squared	0.910922	S.D. dependent var		10.10615
S.E. of regression	3.016276	Akaike info criterion		5.106385
Sum squared resid	545.8754	Schwarz criterion		5.241315
Log likelihood	-159.4043	F-statistic		215.7483
Durbin-Watson stat	2.023496	Prob(F-statistic)		0.000000

Dependent Variable: EMPLOYMENT				
Method: Least Squares				
Date: 02/12/06 Time: 14:19				
Sample(adjusted): 1989:2 2004:4				
Included observations: 63 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.606126	3.639546	1.540337	0.1289
EMPLOYMENT(-1)	0.994957	0.130420	7.628880	0.0000
EMPLOYMENT(-2)	-0.390354	0.181009	-2.156549	0.0352
EMPLOYMENT(-3)	0.286591	0.181760	1.576749	0.1203
EMPLOYMENT(-4)	0.042968	0.126029	0.340936	0.7344
R-squared	0.912208	Mean dependent var		93.86508
Adjusted R-squared	0.906154	S.D. dependent var		9.930633
S.E. of regression	3.042187	Akaike info criterion		5.139069
Sum squared resid	536.7844	Schwarz criterion		5.309159
Log likelihood	-156.8807	F-statistic		150.6634
Durbin-Watson stat	1.816653	Prob(F-statistic)		0.000000

LAG ORDER SELECTION FOR DESEASONALIZED EMPLOYMENT INDEX LEVEL

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDES CAPACITY						
Exogenous variables: C						
Date: 12/24/05 Time: 17:28						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-382.2705	NA	1015.649	12.59903	12.66824	12.62615
1	-265.8958	221.3026	25.50873*	8.914616	9.122243*	8.995987*
2	-264.7147	2.168474	27.99494	9.007041	9.353086	9.142659
3	-257.8566	12.14230*	25.52371	8.913331*	9.397794	9.103196
4	-255.3553	4.264502	26.87116	8.962469	9.585350	9.206582
5	-254.3939	1.576071	29.79425	9.062095	9.823394	9.360455
6	-252.6202	2.791422	32.22050	9.135088	10.03480	9.487695
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDES EXPORT						
Exogenous variables: C						
Date: 12/24/05 Time: 17:29						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-787.4249	NA	5.97E+08	25.88279	25.95199	25.90991
1	-590.8045	373.9012	1079236.	19.56736	19.77499*	19.64873
2	-584.0681	12.36840	987198.1	19.47764	19.82369	19.61326
3	-581.3715	4.774282	1031634.	19.52038	20.00484	19.71024
4	-578.8211	4.348258	1084349.	19.56791	20.19079	19.81202
5	-563.9864	24.31916*	762905.9*	19.21267*	19.97397	19.51103*
6	-562.1292	2.922904	822775.0	19.28292	20.18264	19.63553
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDES GNP						
Exogenous variables: C						
Date: 12/24/05 Time: 17:30						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-514.1732	NA	76723.42	16.92371	16.99292	16.95083
1	-421.7992	175.6619	4232.760	14.02620	14.23383	14.10758
2	-377.0751	82.11655	1114.285	12.69099	13.03703	12.82660
3	-366.8093	18.17549	908.5288	12.48555	12.97001	12.67542
4	-339.6298	46.33872*	425.8781	11.72557	12.34845*	11.96968*
5	-335.2584	7.166260	422.2557*	11.71339*	12.47469	12.01175
6	-333.7261	2.411439	460.2707	11.79430	12.69402	12.14691
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDES IMPORT						
Exogenous variables: C						
Date: 12/24/05 Time: 17:31						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-808.0444	NA	1.17E+09	26.55883	26.62804	26.58596
1	-647.8015	304.7241	6993702.	21.43612	21.64374	21.51749
2	-639.3968	15.43165	6056735.	21.29170	21.63774	21.42732
3	-634.1847	9.227903	5828298.	21.25196	21.73642	21.44182
4	-630.9782	5.466905	5995732.	21.27797	21.90085	21.52209
5	-615.8466	24.80592	4177499.	20.91300	21.67430	21.21136
6	-606.2416	15.11606*	3494662.*	20.72923*	21.62895*	21.08184*
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDES INFLATION						
Exogenous variables: C						
Date: 12/24/05 Time: 17:32						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-426.4579	NA	4324.499	14.04780	14.11701	14.07492
1	-327.3475	188.4723	191.2975	10.92942	11.13705*	11.01080
2	-319.2935	14.78766*	167.5849	10.79651	11.14255	10.93213*
3	-314.0620	9.262254	161.1617*	10.75613*	11.24059	10.94600
4	-313.0661	1.697994	178.2541	10.85463	11.47751	11.09874
5	-312.5307	0.877710	200.4248	10.96822	11.72952	11.26658
6	-310.6656	2.935249	216.0976	11.03822	11.93793	11.39082
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDES PRIVINVGDP						
Exogenous variables: C						
Date: 12/24/05 Time: 17:32						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-424.0756	NA	3999.582	13.96969	14.03890	13.99682
1	-331.3648	176.3027	218.2289	11.06114	11.26877*	11.14251*
2	-326.2623	9.368525	210.6031	11.02499	11.37104	11.16061
3	-324.0735	3.875226	223.7777	11.08438	11.56884	11.27424
4	-316.3007	13.25188*	198.1977*	10.96068*	11.58356	11.20479
5	-315.8361	0.761767	223.3663	11.07659	11.83789	11.37495
6	-314.9181	1.444659	248.4292	11.17764	12.07736	11.53025
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDES PRODUCTIVITY						
Exogenous variables: C						
Date: 12/24/05 Time: 17:33						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-474.2361	NA	20713.70	15.61430	15.68351	15.64142
1	-321.9203	289.6498	160.1144	10.75148	10.95911	10.83285
2	-312.8378	16.67604	135.6161	10.58484	10.93089	10.72046
3	-305.9679	12.16300	123.5973	10.49075	10.97521	10.68062
4	-293.4799	21.29101	93.78847	10.21246	10.83534*	10.45657
5	-287.3779	10.00328*	87.86130*	10.14354*	10.90484	10.44190*
6	-284.2408	4.937086	90.86232	10.17183	11.07155	10.52444
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: PUBLICINVGDP EMPLOYMENTDES						
Exogenous variables: C						
Date: 12/24/05 Time: 17:34						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-350.2735	NA	355.7403	11.54995	11.61916	11.57707
1	-256.0684	179.1441	18.48224	8.592406	8.800033	8.673777
2	-251.1633	9.005981	17.95225	8.562732	8.908777	8.698351
3	-245.8643	9.381916	17.22596	8.520141	9.004603	8.710006
4	-203.5710	72.10665	4.919499	7.264622	7.887503	7.508735
5	-188.1452	25.28815*	3.394739*	6.890006*	7.651305*	7.188366*
6	-186.6245	2.393263	3.701763	6.971294	7.871011	7.323902
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDES REALDEPOSITRATE						
Exogenous variables: C						
Date: 12/24/05 Time: 17:35						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-419.0368	NA	3390.513	13.80448	13.87369	13.83161
1	-324.8745	179.0626*	176.3993*	10.84835*	11.05597*	10.92972*
2	-321.8798	5.498528	182.4157	10.88131	11.22735	11.01692
3	-318.0627	6.758081	183.7507	10.88730	11.37177	11.07717
4	-317.7986	0.450367	208.1741	11.00979	11.63267	11.25390
5	-316.4928	2.140704	228.2277	11.09812	11.85942	11.39648
6	-314.8694	2.554867	248.0324	11.17604	12.07576	11.52865
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDES REALEXRATE						
Exogenous variables: C						
Date: 12/24/05 Time: 17:35						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-470.1153	NA	18095.92	15.47919	15.54840	15.50631
1	-348.4357	231.3908	381.9333	11.62084	11.82847	11.70221
2	-340.0612	15.37601*	331.0933*	11.47742*	11.82346*	11.61304*
3	-336.1948	6.845406	332.9774	11.48180	11.96626	11.67166
4	-334.0596	3.640397	354.7889	11.54294	12.16582	11.78705
5	-329.4840	7.501067	349.4235	11.52406	12.28536	11.82242
6	-329.1243	0.566079	395.8096	11.64342	12.54314	11.99603
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: REALWAGES EMPLOYMENTDES						
Exogenous variables: C						
Date: 12/24/05 Time: 17:36						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-480.4228	NA	25371.75	15.81714	15.88635	15.84426
1	-333.6345	279.1383*	235.0888*	11.13556*	11.34319*	11.21693*
2	-329.7888	7.061011	236.4176	11.14062	11.48666	11.27623
3	-327.8552	3.423417	253.3177	11.20837	11.69283	11.39823
4	-324.6312	5.496680	260.4458	11.23381	11.85669	11.47792
5	-323.3067	2.171259	285.3604	11.32153	12.08283	11.61989
6	-323.1485	0.248966	325.3846	11.44749	12.34721	11.80010
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

Dependent Variable: EMPLOYMENTDES				
Method: Least Squares				
Date: 12/24/05 Time: 17:37				
Sample(adjusted): 1988:3 2004:4				
Included observations: 66 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.128890	2.182146	2.350388	0.0218
EMPLOYMENTDES(-1)	0.940221	0.022722	41.37858	0.0000
R-squared	0.963968	Mean dependent var		94.83053
Adjusted R-squared	0.963405	S.D. dependent var		10.59867
S.E. of regression	2.027514	Akaike info criterion		4.281332
Sum squared resid	263.0920	Schwarz criterion		4.347685
Log likelihood	-139.2840	F-statistic		1712.187
Durbin-Watson stat	1.398490	Prob(F-statistic)		0.000000

Dependent Variable: EMPLOYMENTDES				
Method: Least Squares				
Date: 12/24/05 Time: 17:37				
Sample(adjusted): 1988:4 2004:4				
Included observations: 65 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.492678	2.187766	1.596459	0.1155
EMPLOYMENTDES(-1)	1.220243	0.119331	10.22571	0.0000
EMPLOYMENTDES(-2)	-0.260701	0.114179	-2.283277	0.0259
R-squared	0.965866	Mean dependent var		94.48462
Adjusted R-squared	0.964765	S.D. dependent var		10.29886
S.E. of regression	1.933191	Akaike info criterion		4.201276
Sum squared resid	231.7081	Schwarz criterion		4.301632
Log likelihood	-133.5415	F-statistic		877.1937
Durbin-Watson stat	2.066511	Prob(F-statistic)		0.000000

Dependent Variable: EMPLOYMENTDES				
Method: Least Squares				
Date: 12/24/05 Time: 17:38				
Sample(adjusted): 1989:1 2004:4				
Included observations: 64 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.700815	2.239506	1.652514	0.1037
EMPLOYMENTDES(-1)	1.182826	0.126503	9.350219	0.0000
EMPLOYMENTDES(-2)	-0.046338	0.194683	-0.238017	0.8127
EMPLOYMENTDES(-3)	-0.178425	0.118297	-1.508280	0.1367
R-squared	0.964946	Mean dependent var		94.15266
Adjusted R-squared	0.963193	S.D. dependent var		10.02366
S.E. of regression	1.923054	Akaike info criterion		4.206168
Sum squared resid	221.8883	Schwarz criterion		4.341098
Log likelihood	-130.5974	F-statistic		550.5433
Durbin-Watson stat	1.953255	Prob(F-statistic)		0.000000

LAG ORDER SELECTION FOR EMPLOYMENT IN PER CENT CHANGES

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTCH CAPACITYCH						
Exogenous variables: C						
Date: 04/10/06 Time: 22:04						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-324.9475	NA	155.0647	10.71959	10.78880	10.74671
1	-323.4149	2.914480	168.1562	10.80049	11.00812	10.88186
2	-314.6459	16.10045	143.8989	10.64413	10.99017	10.77975
3	-302.0340	22.32923	108.6409	10.36177	10.84623	10.55164
4	-287.5974	24.61326	77.33694	10.01959	10.64247*	10.26370
5	-282.4461	8.444714	74.74338	9.981840	10.74314	10.28020
6	-275.3006	11.24539*	67.77705*	9.878709*	10.77843	10.23132*
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTCH EXPORTIHRCH						
Exogenous variables: C						
Date: 04/10/06 Time: 22:04						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-388.7084	NA	1254.340	12.81011	12.87932	12.83724
1	-380.1568	16.26205	1080.614	12.66088	12.86851	12.74225
2	-372.2542	14.50970	951.3755	12.53293	12.87897	12.66854
3	-364.3258	14.03730	837.4822	12.40412	12.88859	12.59399
4	-345.9693	31.29625	524.2690	11.93342	12.55630*	12.17753
5	-340.1157	9.596030	495.1533	11.87265	12.63395	12.17101
6	-334.0781	9.501802*	465.6132*	11.80584*	12.70556	12.15845*
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTCH GNP						
Exogenous variables: C						
Date: 04/10/06 Time: 22:05						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-440.8103	NA	6923.121	14.51837	14.58758	14.54549
1	-437.3220	6.633459	7041.331	14.53515	14.74277	14.61652
2	-376.4643	111.7388	1092.193	12.67096	13.01700	12.80658
3	-368.1572	14.70754	949.5821	12.52975	13.01421	12.71961
4	-347.2098	35.71368	546.0313	11.97409	12.59697*	12.21820*
5	-343.4922	6.094402	553.1180	11.98335	12.74465	12.28171
6	-337.3620	9.647489*	518.5435*	11.91351*	12.81323	12.26612
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTCH IMPORTCH						
Exogenous variables: C						
Date: 04/10/06 Time: 22:05						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-402.4795	NA	1970.166	13.26162	13.33083	13.28875
1	-397.3188	9.813772	1896.890	13.22357	13.43119	13.30494
2	-390.5311	12.46252	1732.207	13.13217	13.47821	13.26779
3	-376.5912	24.68060	1252.059	12.80627	13.29073	12.99613
4	-365.4516	18.99212	993.0365	12.57218	13.19506	12.81630
5	-351.6421	22.63854	722.5452	12.25056	13.01186*	12.54892
6	-344.3843	11.42201*	652.7951*	12.14375*	13.04347	12.49636*
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTCH INFLATION						
Exogenous variables: C						
Date: 04/10/06 Time: 22:06						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-365.7312	NA	590.5249	12.05676	12.12597*	12.08388
1	-358.9559	12.88409	539.2465	11.96577	12.17340	12.04714
2	-352.4941	11.86435	497.7189	11.88505	12.23110	12.02067
3	-351.3767	1.978340	547.7619	11.97956	12.46403	12.16943
4	-334.6371	28.53966	361.5704	11.56187	12.18475	11.80598
5	-329.8730	7.809934	353.9095	11.53682	12.29812	11.83518
6	-320.2199	15.19184*	295.5939*	11.35147*	12.25119	11.70408*
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTCH PRIVINVGDPCH						
Exogenous variables: C						
Date: 04/10/06 Time: 22:06						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-489.9218	NA	34642.49	16.12858	16.19779*	16.15571
1	-482.4195	14.26671	30889.11	16.01375	16.22138	16.09513
2	-477.0494	9.859875	29549.31	15.96883	16.31488	16.10445
3	-472.5452	7.974576	29102.50	15.95230	16.43677	16.14217
4	-461.9285	18.10059	23481.00	15.73536	16.35824	15.97947*
5	-457.7142	6.908797	23401.47	15.72833	16.48963	16.02669
6	-451.3978	9.940557*	21805.14*	15.65239*	16.55210	16.00499
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTCH PRODUCTIVITYCH						
Exogenous variables: C						
Date: 04/10/06 Time: 22:07						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-354.6326	NA	410.3964	11.69287	11.76208	11.72000
1	-349.2202	10.29241	391.8851	11.64656	11.85419	11.72793
2	-342.7800	11.82471	361.9620	11.56656	11.91260	11.70217
3	-323.2477	34.58165	217.8005	11.05730	11.54177	11.24717
4	-312.5383	18.25872	175.1961	10.83732	11.46020*	11.08143
5	-305.5103	11.52136	159.2160	10.73804	11.49934	11.03640
6	-296.7549	13.77888*	136.9538*	10.58213*	11.48185	10.93474*
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTCH PUBLICINVGDPC						
Exogenous variables: C						
Date: 04/10/06 Time: 22:07						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-487.9348	NA	32457.58	16.06344	16.13265	16.09056
1	-459.7601	53.57817	14694.50	15.27082	15.47845	15.35219
2	-452.0762	14.10821	13030.16	15.15004	15.49608	15.28566
3	-441.7434	18.29408	10600.79	14.94241	15.42687	15.13227
4	-410.6370	53.03390	4368.858	14.05367	14.67655*	14.29778
5	-406.3795	6.979487	4347.909	14.04523	14.80653	14.34359
6	-399.3084	11.12829*	3952.300*	13.94454*	14.84425	14.29715*
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTCH REALDEPRATECH						
Exogenous variables: C						
Date: 04/10/06 Time: 22:08						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-845.4089	NA	3.99E+09	27.78390	27.85311*	27.81102*
1	-845.0528	0.677068	4.50E+09	27.90337	28.11100	27.98474
2	-841.2118	7.052423	4.53E+09	27.90858	28.25463	28.04420
3	-838.6736	4.493749	4.76E+09	27.95651	28.44098	28.14638
4	-827.8950	18.37661*	3.82E+09*	27.73426*	28.35714	27.97838
5	-824.6058	5.392272	3.92E+09	27.75757	28.51886	28.05593
6	-820.7730	6.031947	3.96E+09	27.76305	28.66276	28.11566
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTCH REALEXRATECH						
Exogenous variables: C						
Date: 04/10/06 Time: 22:08						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-370.7741	NA	696.6994	12.22210	12.29131*	12.24923
1	-369.3739	2.662643	758.8066	12.30734	12.51497	12.38871
2	-363.0680	11.57806	703.9602	12.23174	12.57778	12.36736
3	-360.1777	5.117280	730.9891	12.26812	12.75258	12.45799
4	-345.1522	25.61722*	510.4106	11.90663	12.52951	12.15074*
5	-339.5912	9.116480	486.7103	11.85545	12.61675	12.15381
6	-334.5184	7.983426	472.3827*	11.82027*	12.71999	12.17288
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTCH REALWAGECH						
Exogenous variables: C						
Date: 04/10/06 Time: 22:08						
Sample: 1988:2 2004:4						
Included observations: 61						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-362.9840	NA	539.6605	11.96669	12.03590*	11.99381*
1	-362.4784	0.961379	605.2643	12.08126	12.28889	12.16263
2	-356.4758	11.02123	567.1271	12.01560	12.36165	12.15122
3	-355.0271	2.564921	617.4055	12.09925	12.58371	12.28911
4	-343.0798	20.36923	476.8805	11.83868	12.46156	12.08279
5	-339.8307	5.326264	490.5483	11.86330	12.62460	12.16166
6	-333.0490	10.67284*	450.1653*	11.77210*	12.67182	12.12471
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

Dependent Variable: EMPLOYMENTCH				
Method: Least Squares				
Date: 04/10/06 Time: 22:11				
Sample(adjusted): 1988:3 2004:4				
Included observations: 66 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.492385	0.415790	-1.184217	0.2407
EMPLOYMENTCH(-1)	0.043235	0.123255	0.350772	0.7269
R-squared	0.001919	Mean dependent var		-0.509685
Adjusted R-squared	-0.013676	S.D. dependent var		3.331341
S.E. of regression	3.354044	Akaike info criterion		5.288045
Sum squared resid	719.9752	Schwarz criterion		5.354398
Log likelihood	-172.5055	F-statistic		0.123041
Durbin-Watson stat	1.913724	Prob(F-statistic)		0.726911

Dependent Variable: EMPLOYMENTCH				
Method: Least Squares				
Date: 04/10/06 Time: 22:11				
Sample(adjusted): 1988:4 2004:4				
Included observations: 65 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.575568	0.401835	-1.432347	0.1571
EMPLOYMENTCH(-1)	0.079267	0.119142	0.665311	0.5083
EMPLOYMENTCH(-2)	-0.335877	0.117404	-2.860877	0.0058
R-squared	0.120071	Mean dependent var		-0.470189
Adjusted R-squared	0.091686	S.D. dependent var		3.341658
S.E. of regression	3.184784	Akaike info criterion		5.199701
Sum squared resid	628.8566	Schwarz criterion		5.300057
Log likelihood	-165.9903	F-statistic		4.230108
Durbin-Watson stat	2.046386	Prob(F-statistic)		0.018962

Dependent Variable: EMPLOYMENTCH				
Method: Least Squares				
Date: 04/10/06 Time: 22:11				
Sample(adjusted): 1989:1 2004:4				
Included observations: 64 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.598305	0.418531	-1.429536	0.1580
EMPLOYMENTCH(-1)	0.055198	0.128854	0.428380	0.6699
EMPLOYMENTCH(-2)	-0.325927	0.121465	-2.683300	0.0094
EMPLOYMENTCH(-3)	-0.061261	0.128082	-0.478293	0.6342
R-squared	0.115286	Mean dependent var		-0.427933
Adjusted R-squared	0.071050	S.D. dependent var		3.350525
S.E. of regression	3.229305	Akaike info criterion		5.242872
Sum squared resid	625.7045	Schwarz criterion		5.377802
Log likelihood	-163.7719	F-statistic		2.606171
Durbin-Watson stat	1.925317	Prob(F-statistic)		0.059926

LAG ORDER SELECTION FOR DESEASONALIZED EMPLOYMENT IN PER CENT CHANGES

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDESCH CAPACITYCH						
Exogenous variables: C						
Date: 12/24/05 Time: 19:31						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-298.0078	NA	75.52857	10.00026	10.07007	10.02757
1	-288.4998	18.06510	62.87028	9.816661	10.02610	9.898582
2	-279.6843	16.16185	53.57931	9.656142	10.00520*	9.792678
3	-273.7433	10.49567*	50.29092*	9.591444*	10.08012	9.782594*
4	-272.8278	1.556426	55.87219	9.694259	10.32256	9.940023
5	-271.2008	2.657475	60.70281	9.773358	10.54128	10.07374
6	-267.5082	5.784939	61.67081	9.783608	10.69116	10.13860
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDESCH EXPORTCH						
Exogenous variables: C						
Date: 12/24/05 Time: 19:31						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-355.1679	NA	507.6782	11.90560	11.97541*	11.93290
1	-348.8859	11.93576	470.5689	11.82953	12.03896	11.91145
2	-343.5505	9.781583	450.3553	11.78502	12.13407	11.92155
3	-337.9542	9.886706	427.6001	11.73181	12.22049	11.92296
4	-323.8244	24.02075*	305.8068*	11.39415*	12.02245	11.63991*
5	-322.7142	1.813335	338.0197	11.49047	12.25840	11.79085
6	-321.3854	2.081752	371.5621	11.57951	12.48706	11.93451
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDESCH GNP						
Exogenous variables: C						
Date: 12/24/05 Time: 19:32						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-421.1835	NA	4584.186	14.10612	14.17593	14.13342
1	-417.8394	6.353819	4686.266	14.12798	14.33741	14.20990
2	-375.1421	78.27839	1290.893	12.83807	13.18713	12.97460
3	-371.9847	5.578006	1329.472	12.86616	13.35484	13.05731
4	-341.2137	52.31063*	545.9890	11.97379	12.60209*	12.21956*
5	-336.9855	6.906156	543.9266*	11.96618*	12.73411	12.26656
6	-334.0899	4.536412	567.4765	12.00300	12.91055	12.35799
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDESCH IMPORTCH						
Exogenous variables: C						
Date: 12/24/05 Time: 19:32						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-379.4183	NA	1139.331	12.71394	12.78376	12.74125
1	-369.0404	19.71802	921.2768	12.50135	12.71078*	12.58327
2	-365.7629	6.008786	944.3068	12.52543	12.87449	12.66197
3	-359.7141	10.68621	883.1700	12.45714	12.94582	12.64829
4	-348.5281	19.01619	696.7394	12.21760	12.84591	12.46337
5	-340.8962	12.46540*	619.6612*	12.09654*	12.86447	12.39692*
6	-337.6374	5.105581	638.7084	12.12125	13.02879	12.47624
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDESCH INFLATION						
Exogenous variables: C						
Date: 04/10/06 Time: 23:10						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-333.7013	NA	248.2150	11.19004	11.25985	11.21735
1	-324.4578	17.56261	208.4446	11.01526	11.22469*	11.09718
2	-317.7734	12.25481*	190.7187*	10.92578*	11.27484	11.06231*
3	-315.0036	4.893230	198.9728	10.96679	11.45547	11.15794
4	-314.5943	0.695768	224.8168	11.08648	11.71478	11.33224
5	-312.5022	3.417234	240.4960	11.15007	11.91800	11.45045
6	-308.6393	6.051857	242.9475	11.15464	12.06219	11.50963
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDESCH PRIVINVGDPCH						
Exogenous variables: C						
Date: 12/24/05 Time: 19:33						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-457.2219	NA	15239.54	15.30740	15.37721	15.33470
1	-447.3690	18.72057*	12540.41*	15.11230*	15.32173*	15.19422*
2	-446.1962	2.150142	13788.07	15.20654	15.55560	15.34307
3	-441.8620	7.656939	13653.92	15.19540	15.68408	15.38655
4	-436.6047	8.937536	13125.29	15.15349	15.78179	15.39925
5	-435.3004	2.130305	14414.33	15.24335	16.01127	15.54372
6	-432.2626	4.759253	14967.28	15.27542	16.18297	15.63041
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDESCH PRODUCTIVITYCH						
Exogenous variables: C						
Date: 12/24/05 Time: 19:34						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-328.0487	NA	205.5885	11.00162	11.07144	11.02893
1	-318.7090	17.74545	172.0950	10.82363	11.03307	10.90556
2	-312.1540	12.01746	158.1413	10.73847	11.08753	10.87500
3	-302.1071	17.74966	129.4485	10.53690	11.02558*	10.72805
4	-295.2150	11.71653*	117.8376*	10.44050*	11.06880	10.68626*
5	-291.4981	6.070992	119.4105	10.44994	11.21786	10.75031
6	-288.0373	5.421876	122.2554	10.46791	11.37546	10.82290
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDESCH PUBLICINVGDPCH						
Exogenous variables: C						
Date: 12/24/05 Time: 19:34						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-462.2541	NA	18022.71	15.47514	15.54495	15.50244
1	-439.4156	43.39310	9620.000	14.84719	15.05662	14.92911
2	-436.7173	4.946874	10052.71	14.89058	15.23963	15.02711
3	-424.0584	22.36408	7542.636	14.60195	15.09063	14.79310
4	-394.9601	49.46718*	3275.228*	13.76534*	14.39364*	14.01110*
5	-392.4634	4.077863	3456.730	13.81545	14.58337	14.11582
6	-390.7595	2.669480	3752.530	13.89198	14.79953	14.24698
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: REALDEPRATECH EMPLOYMENTDESCH						
Exogenous variables: C						
Date: 12/24/05 Time: 19:35						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-807.9278	NA*	1.82E+09*	26.99759*	27.06740*	27.02490*
1	-804.1309	7.214091	1.83E+09	27.00436	27.21380	27.08628
2	-801.8769	4.132261	1.94E+09	27.06256	27.41162	27.19910
3	-800.3476	2.701801	2.11E+09	27.14492	27.63360	27.33607
4	-798.5718	3.018909	2.28E+09	27.21906	27.84736	27.46482
5	-797.2869	2.098558	2.51E+09	27.30956	28.07749	27.60994
6	-796.4530	1.306463	2.80E+09	27.41510	28.32265	27.77009
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDESCH REALEXRATECH						
Exogenous variables: C						
Date: 12/24/05 Time: 19:35						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-339.0908	NA	297.0636	11.36969	11.43951*	11.39700
1	-332.4850	12.55098*	272.3935	11.28283	11.49227	11.36476*
2	-328.3896	7.508411	271.6929*	11.27965*	11.62871	11.41619
3	-327.4560	1.649294	301.3423	11.38187	11.87055	11.57302
4	-324.3035	5.359293	310.7296	11.41012	12.03842	11.65588
5	-322.5982	2.785324	336.7151	11.48661	12.25453	11.78698
6	-320.3086	3.587032	358.4617	11.54362	12.45117	11.89861
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

VAR Lag Order Selection Criteria						
Endogenous variables: EMPLOYMENTDESCH REALWAGECH						
Exogenous variables: C						
Date: 12/24/05 Time: 19:36						
Sample: 1988:3 2004:4						
Included observations: 60						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-331.5194	NA*	230.8029*	11.11731*	11.18712*	11.14462*
1	-328.0697	6.554300	235.1140	11.13566	11.34509	11.21758
2	-325.6237	4.484379	247.7642	11.18746	11.53651	11.32399
3	-321.6743	6.977311	248.5200	11.18914	11.67782	11.38029
4	-319.6455	3.448942	266.0428	11.25485	11.88315	11.50061
5	-318.8476	1.303218	297.1445	11.36159	12.12951	11.66197
6	-316.8820	3.079389	319.7707	11.42940	12.33695	11.78439
* indicates lag order selected by the criterion						
LR: sequential modified LR test statistic (each test at 5% level)						
FPE: Final prediction error						
AIC: Akaike information criterion						
SC: Schwarz information criterion						
HQ: Hannan-Quinn information criterion						

Dependent Variable: EMPLOYMENTDESCH				
Method: Least Squares				
Date: 12/24/05 Time: 19:37				
Sample(adjusted): 1988:4 2004:4				
Included observations: 65 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.326202	0.262649	-1.241968	0.2189
EMPLOYMENTDESCH(-1)	0.279897	0.117596	2.380158	0.0203
R-squared	0.082504	Mean dependent var		-0.474149
Adjusted R-squared	0.067941	S.D. dependent var		2.131055
S.E. of regression	2.057389	Akaike info criterion		4.311038
Sum squared resid	266.6695	Schwarz criterion		4.377943
Log likelihood	-138.1087	F-statistic		5.665152
Durbin-Watson stat	2.107292	Prob(F-statistic)		0.020344

Dependent Variable: EMPLOYMENTDESCH				
Method: Least Squares				
Date: 12/24/05 Time: 19:37				
Sample(adjusted): 1989:1 2004:4				
Included observations: 64 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.251131	0.266596	-0.941989	0.3499
EMPLOYMENTDESCH(-1)	0.225417	0.125517	1.795908	0.0775
EMPLOYMENTDESCH(-2)	0.194621	0.122296	1.591386	0.1167
R-squared	0.116877	Mean dependent var		-0.460447
Adjusted R-squared	0.087922	S.D. dependent var		2.145013
S.E. of regression	2.048547	Akaike info criterion		4.317880
Sum squared resid	255.9893	Schwarz criterion		4.419077
Log likelihood	-135.1721	F-statistic		4.036518
Durbin-Watson stat	1.941712	Prob(F-statistic)		0.022576

APPENDIX D- (SPSS OUTPUTS FOR REGRESSION ANALYSES)

REGRESSION ANALYSIS RESULTS FOR UNEMPLOYMENT RATES

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	42,951	1	42,951	23,630	,000 ^a
	Residual	116,331	64	1,818		
	Total	159,282	65			

a. Predictors: (Constant), GNP

b. Dependent Variable: unemployment

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	8,726	,191		45,681	,000		
	GNP	-,026	,005	-,519	-4,861	,000	1,000	1,000

a. Dependent Variable: unemployment

REGRESSION ANALYSIS RESULTS FOR UNEMPLOYMENT RATE IN PER CENT CHANGES

ANOVA(b)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10759,341	11	978,122	7,635	,000(a)
	Residual	6790,244	53	128,118		
	Total	17549,585	64			

a. Predictors: (Constant), publicinvgnpch, deporatech, exratech, privinvgnpch, Inflation, GNP, realwagech, exportch, capacitych, importch, prodch

b. Dependent Variable: unempch

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	9,899	3,371		2,936	,005		
	GNP	-,076	,056	-,141	-1,363	,179	,684	1,462
	capacitych	-1,015	,606	-,257	-1,673	,100	,309	3,237
	exratech	,429	,205	,199	2,095	,041	,807	1,240
	Inflation	-,565	,238	-,239	-2,373	,021	,718	1,393
	deporatech	,000	,000	-,063	-,698	,489	,882	1,134
	realwagech	-,070	,237	-,030	-,297	,768	,726	1,377
	exportch	,930	,141	,823	6,601	,000	,470	2,127
	importch	-,312	,193	-,275	-1,616	,112	,253	3,952
	prodch	,093	,511	,036	,181	,857	,183	5,469
	privinvgnpch	-,064	,031	-,207	-2,057	,045	,718	1,392
	publicinvgnpch	-,116	,037	-,412	-3,150	,003	,427	2,339

a. Dependent Variable: unempch

REGRESSION ANALYSIS RESULTS FOR DESEASONALIZED UNEMPLOYMENT RATES

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,549 ^a	,301	,189	1,196903

a. Predictors: (Constant), publicinv/GNP, capacity, GNP, realwages, privinv/GNP, realdeposirate, reeffexcrate, productivity, Inflation

b. Dependent Variable: unemployment deseason

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	34,526	9	3,836	2,678	,012 ^a
	Residual	80,224	56	1,433		
	Total	114,751	65			

a. Predictors: (Constant), publicinv/GNP, capacity, GNP, realwages, privinv/GNP, realdeposirate, reeffexcrate, productivity, Inflation

b. Dependent Variable: unemployment deseason

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	11,717	3,883		3,017	,004		
	GNP	,001	,005	,034	,283	,778	,873	1,145
	capacity	,001	,053	,003	,021	,983	,614	1,629
	reeffexcrate	-,023	,018	-,283	-1,273	,208	,252	3,970
	Inflation	-,128	,042	-,675	-3,053	,003	,255	3,914
	realdeposirate	-,106	,039	-,496	-2,725	,009	,377	2,655
	realwages	,004	,009	,052	,400	,691	,739	1,353
	productivity	,013	,010	,254	1,342	,185	,349	2,862
	privinv/GNP	-,026	,023	-,144	-1,133	,262	,775	1,290
	publicinv/GNP	,013	,070	,024	,188	,852	,784	1,276

a. Dependent Variable: unemployment deseason

REGRESSION ANALYSIS RESULTS FOR DESEASONALIZED UNEMPLOYMENT RATES IN PER CENT CHANGES

Model Summary(b)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.325(a)	.105	-.080	8.584468

a Predictors: (Constant), publicinvdpch, realdepositrtech, reeffexratech, privinvdpch, Inflation, GNP, realwagech, exportch, capacitych, importch, productivitych

b Dependent Variable: unemploymentdesch

ANOVA(b)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	459.796	11	41.800	.567	.846(a)
	Residual	3905.734	53	73.693		
	Total	4365.529	64			

a Predictors: (Constant), publicinvdpch, realdepositrtech, reeffexratech, privinvdpch, Inflation, GNP, realwagech, exportch, capacitych, importch, productivitych

b Dependent Variable: unemploymentdesch

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.711	2.557		1.060	.294		
	GNP	.015	.042	.054	.344	.732	.684	1.462
	capacitych	-.312	.460	-.159	-.678	.500	.309	3.237
	reeffexratech	-.017	.155	-.016	-.110	.913	.807	1.240
	Inflation	-.190	.181	-.161	-1.052	.298	.718	1.393
	realdepositrtech	.000	.000	.047	.338	.737	.882	1.134
	realwagech	-.072	.180	-.061	-.401	.690	.726	1.377
	exportch	.192	.107	.340	1.795	.078	.470	2.127
	importch	-.131	.147	-.231	-.894	.375	.253	3.952
	productivitych	.092	.388	.072	.237	.813	.183	5.469
	privinvdpch	-.021	.024	-.136	-.886	.380	.718	1.392
	publicinvdpch	-.016	.028	-.115	-.581	.564	.427	2.339

a Dependent Variable: unemploymentdesch

REGRESSION ANALYSIS RESULTS FOR EMPLOYMENT INDEX DATA

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,970 ^a	,941	,931	2,95831

a. Predictors: (Constant), publicinvgdp, capacity, GNP, realwage, privinvgdp, inflation, productivity, reefexrate, export, import

ANOVA^b

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7844,424	10	784,442	89,634	,000 ^a
	Residual	490,090	56	8,752		
	Total	8334,515	66			

a. Predictors: (Constant), publicinvgdp, capacity, GNP, realwage, privinvgdp, inflation, productivity, reefexrate, exportih, importih

b. Dependent Variable: employment

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	137,406	13,097		10,492	,000		
	GNP	,052	,013	,140	4,082	,000	,888	1,126
	capacity	,035	,157	,011	,221	,826	,427	2,342
	reefexrate	,114	,042	,164	2,727	,009	,291	3,438
	inflation	-,160	,073	-,099	-2,205	,032	,520	1,925
	realwage	-,188	,024	-,339	-7,684	,000	,540	1,852
	export	-,002	,001	-,573	-3,622	,001	,042	23,853
	import	,003	,000	1,021	6,163	,000	,038	26,154
	productivity	-,552	,045	-1,300	-12,250	,000	,093	10,730
	privinvgdp	,046	,059	,030	,776	,441	,716	1,397
	publicinvgdp	,657	,173	,140	3,787	,000	,769	1,300

a. Dependent Variable: employment

REGRESSION ANALYSIS RESULTS FOR EMPLOYMENT INDEX DATA IN PER CENT CHANGES

Model Summary(b)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,881(a)	,776	,731	1,74218

a Predictors: (Constant), publicinvdpch, realdepositrch, realexratech, privinvdpch, inflationch, GNPch, realwagech, exportirch, capacitych, importch, productivitych

b Dependent Variable: employmentch

ANOVA^b

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	578,988	11	52,635	17,342	,000 ^a
	Residual	166,936	55	3,035		
	Total	745,923	66			

a. Predictors: (Constant), publicinvdpch, realdepositrch, realexratech, privinvdpch, inflationch, GNPch, realwagech, exportirch, capacitych, importch, productivitych

b. Dependent Variable: employmentch

Coefficients(a)

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-,809	,540		-1,498	,140		
	GNPch	,054	,008	,491	6,781	,000	,776	1,289
	capacitych	,319	,095	,394	3,377	,001	,299	3,341
	realexratech	-,080	,032	-,180	-2,503	,015	,785	1,274
	inflationch	-,043	,035	-,099	-1,213	,230	,616	1,623
	realdepositrch	,000	,000	-,007	-,102	,919	,867	1,153
	realwagech	-,091	,038	-,192	-2,391	,020	,633	1,580
	exportirch	-,062	,027	-,201	-2,274	,027	,518	1,929
	importch	,177	,027	,825	6,640	,000	,264	3,792
	productivitych	-,375	,072	-,721	-5,237	,000	,215	4,658
	privinvdpch	,000	,005	-,004	-,058	,954	,776	1,288
	publicinvdpch	,005	,006	,094	,910	,367	,381	2,622

a Dependent Variable: employmentch

REGRESSION ANALYSIS RESULTS FOR DESEASONALIZED EMPLOYMENT DATA IN LEVELS

Model Summary(b)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,948(a)	,899	,886	3,8004

a Predictors: (Constant), publicinv/GNP, capacity, GNP, realwages, privinv/GNP, Inflation, productivity, reeffexcrate
b Dependent Variable: employment

ANOVA^b

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7496,796	8	937,100	64,881	,000 ^a
	Residual	837,718	58	14,443		
	Total	8334,515	66			

a. Predictors: (Constant), publicinv/GNP, capacity, GNP, realwages, privinv/GNP, Inflation, productivity, reeffexcrate
b. Dependent Variable: employment

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	81,318	12,320		6,600	,000		
	GNP	,061	,016	,167	3,843	,000	,917	1,090
	capacity	,627	,161	,199	3,905	,000	,670	1,492
	reeffexcrate	,198	,050	,285	3,921	,000	,327	3,058
	Inflation	-,099	,092	-,061	-1,076	,286	,538	1,859
	realwages	-,216	,025	-,388	-8,472	,000	,824	1,213
	productivity	-,429	,030	-1,011	-14,280	,000	,346	2,892
	privinv/GNP	,145	,073	,094	1,994	,051	,774	1,292
	publicinv/GNP	,685	,222	,146	3,087	,003	,775	1,290

a. Dependent Variable: employment

REGRESSION ANALYSIS RESULTS FOR DESEASONALIZED EMPLOYMENT IN PER CENT CHANGES DATA

Model Summary(b)

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,747(a)	,558	,467	1,584024126 759382

a Predictors: (Constant), publicinvdpch, realdepratech, realexratech, privinvdpch, Inflationch, GNPch, realwagech, exporthrch, capacitych, importch, productivitych

b Dependent Variable: employmentdesch

ANOVA^b

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	170,742	11	15,522	6,186	,000 ^a
	Residual	135,493	54	2,509		
	Total	306,235	65			

a. Predictors: (Constant), publicinvdpch, realdepratech, realexratech, privinvdpch, Inflationch, GNPch, realwagech, exporthrch, capacitych, importch, productivitych

b. Dependent Variable: employmentdesch

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
1 (Constant)	,475	,491		,967	,338		
GNPch	-,006	,007	-,088	-,842	,404	,755	1,325
capacitych	,264	,086	,508	3,070	,003	,299	3,342
realexratech	-,028	,029	-,099	-,971	,336	,785	1,274
Inflationch	-,047	,032	-,170	-1,472	,147	,616	1,623
realdepratech	,000	,000	-,077	-,787	,435	,854	1,171
realwagech	-,094	,035	-,307	-2,713	,009	,640	1,562
exportihrch	-,031	,025	-,157	-1,239	,221	,510	1,961
importch	,143	,024	1,038	5,841	,000	,259	3,855
productivitych	-,300	,070	-,889	-4,314	,000	,193	5,178
privinvgdpch	-,002	,004	-,057	-,555	,581	,775	1,290
publicinvgdpch	-,012	,005	-,323	-2,188	,033	,377	2,655

a. Dependent Variable: employmentdesch

APPENDIX E- (SPSS OUTPUTS FOR FACTOR ANALYSES)

FACTOR ANALYSIS RESULTS FOR UNEMPLOYMENT RATES

Communalities

	Initial	Extraction
GNP	1,000	,881
capacity	1,000	,617
reefexrate	1,000	,729
inflation	1,000	,909
realdeprate	1,000	,943
realwage	1,000	,736
exportihr	1,000	,919
importith	1,000	,921
productivity	1,000	,914
privinvgdp	1,000	,551
publicinvgdp	1,000	,547

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4,845	44,043	44,043	4,845	44,043	44,043	3,366	30,602	30,602
2	1,555	14,135	58,179	1,555	14,135	58,179	2,828	25,705	56,307
3	1,217	11,064	69,243	1,217	11,064	69,243	1,362	12,382	68,689
4	1,050	9,543	78,786	1,050	9,543	78,786	1,111	10,098	78,786
5	,873	7,941	86,727						
6	,676	6,145	92,872						
7	,486	4,422	97,294						
8	,216	1,963	99,257						
9	,061	,559	99,816						
10	,020	,184	100,000						
11	,000	,000	100,000						

Extraction Method: Principal Component Analysis.

Component Matrix ^a

	Component			
	1	2	3	4
GNP	-,157	-,205	-,083	,899
capacity	,566	,407	,278	,233
reefexrate	,820	,119	,198	-,059
inflation	-,727	-,485	,358	-,131
realdeprate	,755	,507	-,305	,152
realwage	-,193	,318	,737	,234
exportihr	,907	-,265	,055	-,149
importith	,928	-,185	,152	-,061
productivity	,878	-,308	,214	-,042
privinvgdp	-,361	,442	,442	-,172
publicinvgdp	-,327	,587	-,250	-,181

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

Rotated Component Matrix^a

	Component			
	1	2	3	4
GNP	-,084	-,020	-,005	,935
capacity	,316	,614	,370	,058
reefexrate	,638	,535	,092	-,169
inflation	-,146	-,922	,190	,039
realdeprate	,176	,945	-,135	-,029
realwage	-,026	-,054	,847	,123
exportihr	,849	,345	-,228	-,160
importith	,858	,406	-,098	-,103
productivity	,909	,277	-,088	-,052
privinvdp	-,318	-,083	,609	-,268
publicinvdp	-,644	,226	,062	-,277

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

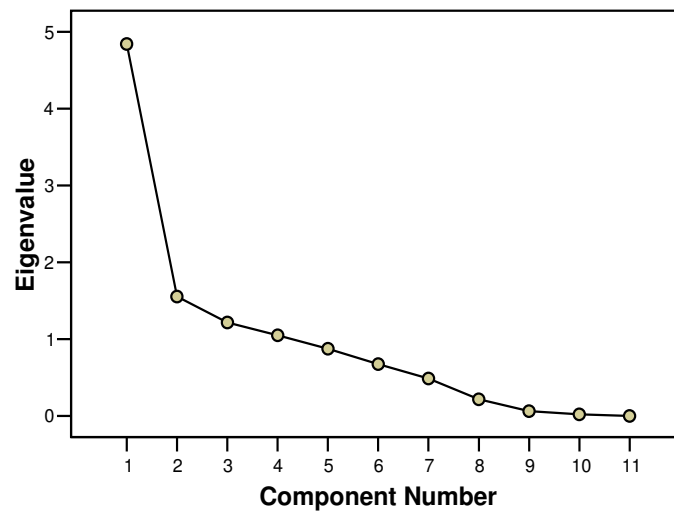
Component Transformation Matrix

Component	1	2	3	4
1	,753	,634	-,152	-,088
2	-,520	,689	,439	-,248
3	,400	-,274	,873	-,054
4	-,043	,220	,148	,963

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

Scree Plot



FACTOR ANALYSIS RESULTS FOR UNEMPLOYMENT RATES IN PER CENT CHANGES

Communalities

	Initial	Extraction
GNPch	1,000	,734
capacitych	1,000	,805
exratech	1,000	,956
Inflationch	1,000	,712
deporatech	1,000	,939
realwagech	1,000	,750
exportxh	1,000	,717
importch	1,000	,838
prodch	1,000	,889
privinvgnpch	1,000	,714
publicinvgnpch	1,000	,639

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,743	34,030	34,030	3,743	34,030	34,030	3,683	33,482	33,482
2	1,531	13,918	47,947	1,531	13,918	47,947	1,473	13,390	46,872
3	1,367	12,426	60,373	1,367	12,426	60,373	1,363	12,388	59,260
4	1,035	9,409	69,782	1,035	9,409	69,782	1,118	10,167	69,427
5	1,016	9,237	79,019	1,016	9,237	79,019	1,055	9,592	79,019
6	,749	6,813	85,832						
7	,528	4,800	90,632						
8	,388	3,523	94,155						
9	,309	2,811	96,966						
10	,200	1,818	98,784						
11	,134	1,216	100,000						

Extraction Method: Principal Component Analysis.

Component Matrix^a

	Component				
	1	2	3	4	5
GNPch	,279	-,035	,800	,107	,061
capacitych	,834	,238	,185	,041	-,130
extratech	,232	,292	-,128	,255	-,858
Inflationch	-,193	-,772	,219	,150	-,089
deporatech	-,040	,237	,109	,888	,286
realwagech	-,055	,788	-,004	-,183	,304
exportxh	,741	-,178	-,333	-,101	,123
importch	,912	,021	-,057	,048	,000
prodch	,926	-,032	,128	-,110	,037
privinvgnpch	,281	-,195	-,691	,297	,180
publicinvgnpch	,746	-,208	,097	-,025	,167

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

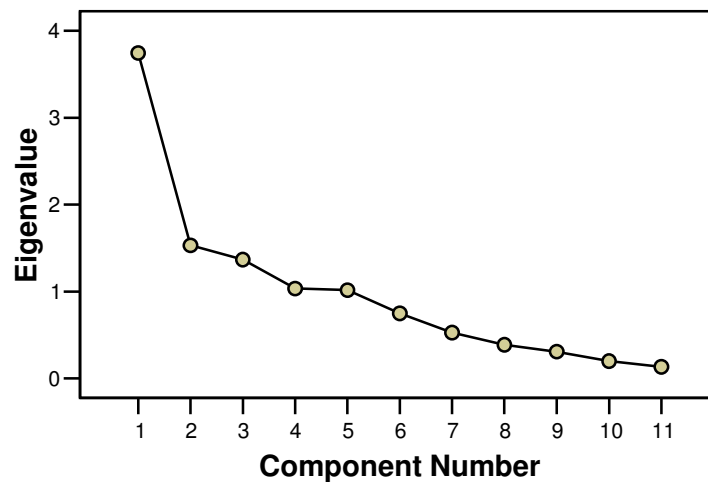
Rotated Component Matrix^a

	Component				
	1	2	3	4	5
GNPch	,325	-,135	-,745	-,082	,220
capacitych	,798	,195	-,194	,296	,073
extratech	,092	,024	,030	,972	,013
Inflationch	-,130	-,813	-,105	-,153	,002
deporatech	-,055	,061	,007	,018	,965
realwagech	-,080	,849	-,095	-,105	,061
exportxh	,747	-,031	,374	-,049	-,125
importch	,895	,060	,090	,154	,049
prodch	,933	,034	-,099	,047	-,070
privinvgnpch	,266	-,103	,768	-,031	,205
publicinvgnpch	,780	-,123	-,026	-,122	,010

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Scree Plot

FACTOR ANALYSIS RESULTS FOR EMPLOYMENT INDEX

Communalities

	Initial	Extraction
GNP	1,000	,924
capacity	1,000	,630
reefexrate	1,000	,745
inflation	1,000	,896
realdeprate	1,000	,934
realwage	1,000	,736
exportihr	1,000	,917
importith	1,000	,902
productivity	1,000	,915
privinvdp	1,000	,533
publicinvdp	1,000	,542

Extraction Method: Principal Component Analysis.

Total Variance Explained

Componen	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4,841	44,012	44,012	4,841	44,012	44,012	3,342	30,381	30,381
2	1,547	14,062	58,075	1,547	14,062	58,075	2,899	26,353	56,734
3	1,255	11,410	69,485	1,255	11,410	69,485	1,334	12,128	68,862
4	1,031	9,372	78,857	1,031	9,372	78,857	1,099	9,995	78,857
5	,875	7,955	86,812						
6	,673	6,119	92,931						
7	,483	4,391	97,322						
8	,213	1,934	99,256						
9	,059	,539	99,795						
10	,023	,205	100,000						
11	,000	,000	100,000						

Extraction Method: Principal Component Analysis.

Component Matrix^a

	Component			
	1	2	3	4
GNP	-,155	-,214	-,146	,913
capacity	,571	,390	,265	,286
reefexrate	,827	,093	,214	-,084
inflation	-,723	-,505	,329	-,095
realdeprate	,752	,524	-,279	,125
realwage	-,125	,215	,793	,212
exportihr	,908	-,283	,004	-,108
importith	,923	-,178	,133	-,030
productivity	,880	-,319	,191	-,045
privinvgdp	-,367	,428	,456	-,088
publicinvgdp	-,342	,606	-,201	-,132

Extraction Method: Principal Component Analysis.

a. 4 components extracted.

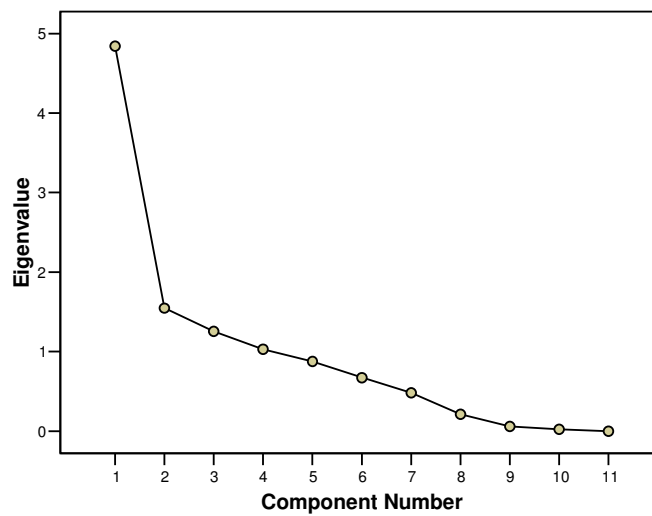
Rotated Component Matrix ^a

	Component			
	1	2	3	4
GNP	-,060	-,028	-,023	,959
capacity	,275	,645	,359	,097
reefexrate	,632	,538	,113	-,209
inflation	-,135	-,914	,197	,059
realdeprate	,161	,941	-,143	-,044
realwage	,032	-,060	,852	,074
exportihr	,845	,369	-,222	-,129
importith	,835	,440	-,056	-,095
productivity	,904	,298	-,049	-,079
privinvgdp	-,374	-,057	,591	-,200
publicinvgdp	-,670	,217	,042	-,209

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Scree Plot

FACTOR ANALYSIS RESULTS FOR EMPLOYMENT INDEX DATA IN PER CENT CHANGES

Communalities

	Initial	Extraction
GNP	1,000	,707
capacitych	1,000	,791
realexratech	1,000	,959
inflation	1,000	,736
realdepositrch	1,000	,953
realwagech	1,000	,805
exportch	1,000	,672
importch	1,000	,822
productivitych	1,000	,842
privinvdpch	1,000	,719
publicinvdpch	1,000	,679

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,783	34,389	34,389	3,783	34,389	34,389	3,685	33,501	33,501
2	1,614	14,674	49,063	1,614	14,674	49,063	1,550	14,090	47,591
3	1,245	11,318	60,380	1,245	11,318	60,380	1,263	11,486	59,077
4	1,034	9,403	69,783	1,034	9,403	69,783	1,130	10,276	69,353
5	1,010	9,182	78,965	1,010	9,182	78,965	1,057	9,612	78,965
6	,714	6,487	85,452						
7	,472	4,289	89,740						
8	,455	4,138	93,879						
9	,340	3,092	96,970						
10	,190	1,729	98,699						
11	,143	1,301	100,000						

Extraction Method: Principal Component Analysis.

Component Matrix^a

	Component				
	1	2	3	4	5
GNP	,314	,165	-,727	,192	,123
capacitych	,842	,231	-,037	-,046	,160
realexratech	,231	,201	,371	-,169	,836
inflation	-,353	-,724	-,207	,110	,179
realdepositrch	,005	,236	,093	,935	,126
realwagech	-,042	,815	,114	-,078	-,347
exportch	,738	-,294	,094	-,065	-,167
importch	,897	-,014	,082	,101	,012
productivitych	,904	-,029	-,099	-,107	-,059
privinvdpch	,228	-,319	,684	,209	-,232
publicinvdpch	,760	-,245	-,137	,072	-,132

Extraction Method: Principal Component Analysis.

a. 5 components extracted.

Rotated Component Matrix^a

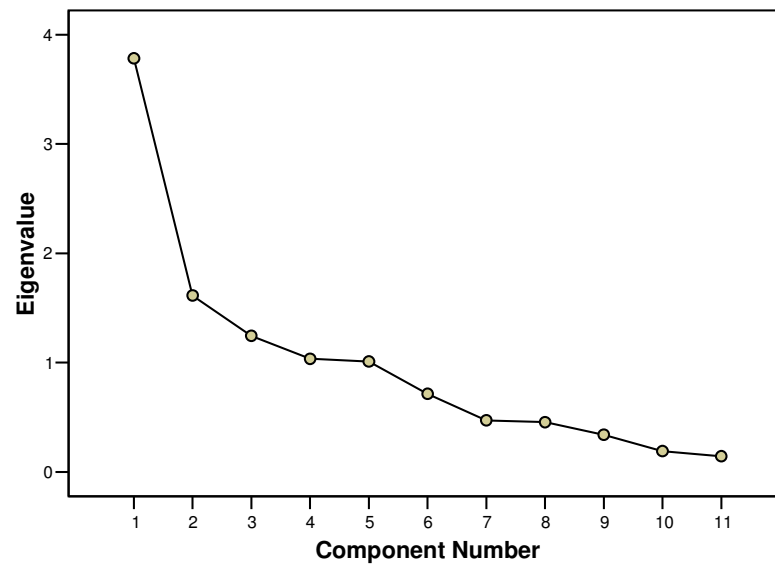
	Component				
	1	2	3	4	5
GNP	,308	-,028	,753	-,092	,189
capacitych	,771	,256	,175	,315	,044
realexratech	,082	,021	-,041	,974	,015
inflation	-,234	-,813	,006	-,140	-,028
realdepositrch	-,038	,055	-,001	,018	,974
realwagech	-,144	,879	,047	-,088	,034
exportch	,783	-,086	-,195	-,052	-,105
importch	,877	,097	-,050	,154	,134
productivitych	,899	,102	,097	,067	-,094
privinvgdpch	,268	-,070	-,781	-,043	,174
publicinvgdpch	,807	-,118	,038	-,111	,024

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Scree Plot



APPENDIX F- (DESEASONALIZATION)

DESEASONALIZATION FOR UNEMPLOYMENT DATA

MODEL: MOD_1.

—
Results of SEASON procedure for variable unemployment.
Multiplicative Model. Equal weighted MA method. Period = 4.

DATE_	unemplo	Seasonal Ratios	Seasonally factors	Smoothed averages	Moving adjusted (* 100)	trend- (* 100)	Irregular series	cycle component
Q3 1988	7,847	.	.	.	92,615	8,473	8,422	1,006
Q4 1988	9,028	.	.	.	107,116	8,428	8,533	,988
Q1 1989	9,788	8,577	114,121	112,527	8,698	8,590	1,013	
Q2 1989	7,644	8,574	89,145	87,743	8,711	8,589	1,014	
Q3 1989	7,838	8,572	91,442	92,615	8,463	8,368	1,011	
Q4 1989	9,018	8,083	111,577	107,116	8,419	7,976	1,056	
Q1 1990	7,830	7,700	101,684	112,527	6,959	7,640	,911	
Q2 1990	6,115	7,742	78,979	87,743	6,969	7,681	,907	
Q3 1990	8,006	7,791	102,767	92,615	8,645	8,063	1,072	
Q4 1990	9,212	8,235	111,859	107,116	8,600	8,409	1,023	
Q1 1991	9,607	8,582	111,945	112,527	8,537	8,492	1,005	
Q2 1991	7,502	8,404	89,277	87,743	8,551	8,323	1,027	
Q3 1991	7,293	8,199	88,960	92,615	7,875	8,146	,967	
Q4 1991	8,391	8,155	102,895	107,116	7,834	8,107	,966	
Q1 1992	9,434	8,121	116,158	112,527	8,384	8,233	1,018	
Q2 1992	7,367	8,291	88,856	87,743	8,396	8,397	1,000	
Q3 1992	7,973	8,487	93,943	92,615	8,608	8,589	1,002	
Q4 1992	9,173	8,708	105,338	107,116	8,563	8,759	,978	
Q1 1993	10,319	8,881	116,197	112,527	9,171	8,915	1,029	
Q2 1993	8,059	8,883	90,719	87,743	9,185	8,919	1,030	
Q3 1993	7,982	8,886	89,828	92,615	8,619	8,755	,984	
Q4 1993	9,184	8,627	106,448	107,116	8,574	8,545	1,003	
Q1 1994	9,285	8,425	110,202	112,527	8,251	8,435	,978	
Q2 1994	7,251	8,483	85,476	87,743	8,264	8,492	,973	
Q3 1994	8,213	8,550	96,063	92,615	8,868	8,483	1,045	
Q4 1994	9,450	8,289	114,006	107,116	8,822	8,272	1,066	
Q1 1995	8,241	8,085	101,930	112,527	7,323	7,901	,927	
Q2 1995	6,436	7,874	81,730	87,743	7,335	7,701	,952	
Q3 1995	7,371	7,632	96,581	92,615	7,959	7,557	1,053	
Q4 1995	8,481	7,348	115,420	107,116	7,917	7,328	1,080	
Q1 1996	7,103	7,126	99,687	112,527	6,313	6,925	,912	
Q2 1996	5,547	6,892	80,485	87,743	6,322	6,703	,943	
Q3 1996	6,438	6,624	97,194	92,615	6,952	6,761	1,028	
Q4 1996	7,407	6,877	107,714	107,116	6,915	6,957	,994	
Q1 1997	8,115	7,074	114,706	112,527	7,211	7,033	1,025	
Q2 1997	6,337	6,954	91,122	87,743	7,222	6,919	1,044	
Q3 1997	5,959	6,817	87,417	92,615	6,434	6,721	,957	
Q4 1997	6,856	6,681	102,615	107,116	6,401	6,610	,968	
Q1 1998	7,573	6,575	115,170	112,527	6,730	6,660	1,011	
Q2 1998	5,914	6,714	88,087	87,743	6,740	6,793	,992	
Q3 1998	6,512	6,873	94,753	92,615	7,032	6,963	1,010	
Q4 1998	7,493	7,054	106,214	107,116	6,995	7,103	,985	
Q1 1999	8,298	7,196	115,319	112,527	7,375	7,319	1,008	
Q2 1999	6,481	7,410	87,454	87,743	7,386	7,526	,981	
Q3 1999	7,369	7,657	96,246	92,615	7,957	7,687	1,035	
Q4 1999	8,479	7,645	110,901	107,116	7,915	7,632	1,037	
Q1 2000	8,252	7,554	109,241	112,527	7,334	7,300	1,005	
Q2 2000	6,117	7,094	86,225	87,743	6,971	6,807	1,024	
Q3 2000	5,528	6,535	84,599	92,615	5,969	6,487	,920	
Q4 2000	6,241	6,594	94,646	107,116	5,826	6,572	,886	
Q1 2001	8,489	6,748	125,803	112,527	7,544	7,116	1,060	
Q2 2001	6,734	7,320	91,983	87,743	7,674	7,836	,979	
Q3 2001	7,819	8,360	93,523	92,615	8,442	8,655	,975	

Q4 2001	10,399	9,125	113,964	107,116	9,708	9,426	1,030
Q1 2002	11,548	9,772	118,178	112,527	10,263	10,024	1,024
Q2 2002	9,322	10,208	91,321	87,743	10,624	10,340	1,027
Q3 2002	9,562	10,368	92,221	92,615	10,324	10,450	,988
Q4 2002	11,041	10,561	104,539	107,116	10,307	10,614	,971
Q1 2003	12,322	10,739	114,741	112,527	10,950	10,757	1,018
Q2 2003	10,031	10,701	93,741	87,743	11,432	10,718	1,067
Q3 2003	9,410	10,521	89,440	92,615	10,160	10,509	,967
Q4 2003	10,321	10,540	97,915	107,116	9,635	10,366	,929
Q1 2004	12,400	10,358	119,719	112,527	11,020	10,438	1,056
Q2 2004	9,300	10,380	89,594	87,743	10,599	10,369	1,022
Q3 2004	9,500	10,300	92,233	92,615	10,258	10,064	1,019
Q4 2004	10,000	.	.	107,116	9,336	9,644	,968

DESEASONALIZATION FOR EMPLOYMENT DATA

MODEL: MOD_2.

Results of SEASON procedure for variable employment.
 Multiplicative Model. Equal weighted MA method. Period = 4.

Moving	Seasonal	Seasonally	Smoothed				
DATE_	employe	Ratios	factors	adjusted	trend-	Irregular	
	averages						
	(* 100)	(* 100)	(* 100)				
	series	cycle	component				
Q2 1988	123,500	.	.	100,585	122,781	120,942	1,015
Q3 1988	119,700	.	.	102,033	117,315	118,609	,989
Q4 1988	115,900	117,750	98,429	100,147	115,730	116,820	,991
Q1 1989	111,900	116,200	96,299	97,235	115,083	115,868	,993
Q2 1989	117,300	115,750	101,339	100,585	116,618	115,665	1,008
Q3 1989	117,900	115,350	102,211	102,033	115,551	115,391	1,001
Q4 1989	114,300	115,400	99,047	100,147	114,132	115,301	,990
Q1 1990	112,100	115,500	97,056	97,235	115,288	115,256	1,000
Q2 1990	117,700	115,000	102,348	100,585	117,015	114,930	1,018
Q3 1990	115,900	114,325	101,378	102,033	113,591	113,290	1,003
Q4 1990	111,600	112,225	99,443	100,147	111,436	110,489	1,009
Q1 1991	103,700	108,600	95,488	97,235	106,649	106,635	1,000
Q2 1991	103,200	104,650	98,614	100,585	102,600	102,878	,997
Q3 1991	100,100	101,075	99,035	102,033	98,105	99,501	,986
Q4 1991	97,300	98,250	99,033	100,147	97,157	97,254	,999
Q1 1992	92,400	96,325	95,925	97,235	95,028	95,459	,995
Q2 1992	95,500	94,700	100,845	100,585	94,944	94,420	1,006
Q3 1992	93,600	93,975	99,601	102,033	91,735	93,399	,982
Q4 1992	94,400	93,225	101,260	100,147	94,261	93,005	1,014
Q1 1993	89,400	92,475	96,675	97,235	91,943	92,645	,992
Q2 1993	92,500	93,000	99,462	100,585	91,962	92,631	,993
Q3 1993	95,700	92,450	103,515	102,033	93,793	92,751	1,011
Q4 1993	92,200	92,800	99,353	100,147	92,065	92,310	,997
Q1 1994	90,800	91,875	98,830	97,235	93,382	91,307	1,023
Q2 1994	88,800	90,175	98,475	100,585	88,283	89,501	,986
Q3 1994	88,900	89,050	99,832	102,033	87,129	88,393	,986
Q4 1994	87,700	88,000	99,659	100,147	87,571	88,272	,992
Q1 1995	86,600	88,700	97,632	97,235	89,063	89,357	,997
Q2 1995	91,600	90,100	101,665	100,585	91,067	90,922	1,002
Q3 1995	94,500	91,750	102,997	102,033	92,617	92,329	1,003
Q4 1995	94,300	92,850	101,562	100,147	94,161	93,246	1,010
Q1 1996	91,000	93,400	97,430	97,235	93,588	93,665	,999
Q2 1996	93,800	93,950	99,840	100,585	93,254	94,322	,989
Q3 1996	96,700	94,975	101,816	102,033	94,773	95,483	,993
Q4 1996	98,400	96,150	102,340	100,147	98,255	96,982	1,013
Q1 1997	95,700	97,450	98,204	97,235	98,422	98,348	1,001
Q2 1997	99,000	99,225	99,773	100,585	98,424	99,465	,990
Q3 1997	103,800	100,000	103,800	102,033	101,732	100,474	1,013
Q4 1997	101,500	100,650	100,845	100,147	101,351	100,994	1,004
Q1 1998	98,300	101,250	97,086	97,235	101,096	101,143	1,000
Q2 1998	101,400	101,050	100,346	100,585	100,810	100,647	1,002
Q3 1998	103,000	100,200	102,794	102,033	100,948	99,405	1,016
Q4 1998	98,100	98,275	99,822	100,147	97,956	97,199	1,008
Q1 1999	90,600	96,025	94,350	97,235	93,177	94,465	,986
Q2 1999	92,400	93,250	99,088	100,585	91,862	92,189	,996
Q3 1999	91,900	91,175	100,795	102,033	90,069	90,440	,996
Q4 1999	89,800	89,800	100,000	100,147	89,668	89,558	1,001
Q1 2000	85,100	89,325	95,270	97,235	87,520	89,087	,982
Q2 2000	90,500	89,275	101,372	100,585	89,973	89,249	1,008

Q3 2000	91,700	89,075	102,947	102,033	89,873	89,024	1,010
Q4 2000	89,000	88,800	100,225	100,147	88,869	87,892	1,011
Q1 2001	84,000	86,775	96,802	97,235	86,389	85,611	1,009
Q2 2001	82,400	84,225	97,833	100,585	81,921	82,883	,988
Q3 2001	81,500	81,700	99,755	102,033	79,876	80,872	,988
Q4 2001	78,900	80,250	98,318	100,147	78,784	80,099	,984
Q1 2002	78,200	80,275	97,415	97,235	80,424	80,597	,998
Q2 2002	82,500	80,975	101,883	100,585	82,020	81,601	1,005
Q3 2002	84,300	82,150	102,617	102,033	82,620	82,646	1,000
Q4 2002	83,600	83,150	100,541	100,147	83,477	83,364	1,001
Q1 2003	82,200	83,525	98,414	97,235	84,538	83,779	1,009
Q2 2003	84,000	83,825	100,209	100,585	83,511	83,751	,997
Q3 2003	85,500	83,725	102,120	102,033	83,796	83,807	1,000
Q4 2003	83,200	83,875	99,195	100,147	83,078	84,049	,988
Q1 2004	82,800	84,450	98,046	97,235	85,155	84,741	1,005
Q2 2004	86,300	84,925	101,619	100,585	85,798	85,219	1,007
Q3 2004	87,400	85,375	102,372	102,033	85,658	85,444	1,003
Q4 2004	85,000	.	.	100,147	84,875	85,379	,994

Abbreviated Name	Extended Name
---------------------	------------------

employe	employment
---------	------------

The following new variables are being created:

Name	Label
ERR_1	Error for employment from SEASON, MOD_2 MUL EQU 4
SAS_1	Seas adj ser for employment from SEASON, MOD_2 MUL EQU 4
SAF_1	Seas factors for employment from SEASON, MOD_2 MUL EQU 4
STC_1	Trend-cycle for employment from SEASON, MOD_2 MUL EQU 4

APPENDIX G- MATLAB M. FILE FOR NETWORK TRAINING

```
%Caglas Network
clc
%clear all

revertTrue=0;
EP=1000;
for neuronC=1:25
%neuronC=25;
for j=1:10
K=[min(input(1,:)) max(input(1,:))
min(input(2,:)) max(input(2,:))
min(input(3,:)) max(input(3,:))
min(input(4,:)) max(input(4,:))
min(input(5,:)) max(input(5,:))
min(input(6,:)) max(input(6,:))
min(input(7,:)) max(input(7,:))
min(input(8,:)) max(input(8,:))
min(input(9,:)) max(input(9,:))
min(input(10,:)) max(input(10,:))
min(input(11,:)) max(input(11,:))
min(input(12,:)) max(input(12,:))];

%-----

P=[input(1,:);input(2,:);input(3,:);input(4,:);input(5,:);input(6,:);input(7,:);input(8,:);input(9,:);input(10,:);input(11,:);input(12,:)]
;
T=output;
TV.P=[tinput(1,:);tinput(2,:);tinput(3,:);tinput(4,:);tinput(5,:);tinput(6,:);tinput(7,:);tinput(8,:);tinput(9,:);tinput(10,:);tinput(11,:);tinput(12,:)]
;
TV.T=toutput;
%-----

net = newff(K,[neuronC,1] ,{'tansig' 'purelin'},'traingdx');
net.trainParam.show=100;
net.trainParam.lr=0.01;
net.trainParam.mc=0.9;
net.trainParam.lr_inc=1.05;
net.trainParam.lr_dec=0.7;
net.trainParam.epochs=EP;
net.trainParam.goal=0.00004;

if revertTrue
net.IW{1,1}=lastIW;
net.b=lastb
net.LW=lastLW
end

[net,tr]=train(net,P,T,[],[],TV)
C=tr.perf(1000)
D(neuronC,j)=C

an=sim(net,tinput)

err=0;
for i=1:11
err=err+((toutput(i)-an(i))^2);
end

err2=err/11
A(neuronC,j)=err2
```

```

inputWeights=net.IW{1,1};
bias=net.b{1,1};
bias(neuronC+1)=net.b{2,1};
bias=bias';
layerWeights=net.LW{2,1};

```

```

w1=inputWeights
w2=layerWeights
b1=bias

```

```

if revertTrue==0
net = revert(net);
lastIW=net.IW{1,1};
lastb=net.b;
lastLW=net.LW
end

```

```

end
end
wk1 write('err2.xls',A)
wk1 write('traerror.xls',D)

```

APPENDIX H- SPSS OUTPUTS FOR PAIREWISE T TESTS

RESULTS FOR UNEMPLOYMENT RATE DATA OUTPUT ACTIVATION FUNCTION

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	averagetesttrain MSEpurelin	.0365	38	.03522	.00571
	averagetesttrain MSEtansig	.0337	38	.03356	.00544

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	averagetesttrain MSEpurelin & averagetesttrain MSEtansig	38	.969	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	averagetesttrain MSEpurelin - averagetesttrain MSEtansig	.00277	.00877	.00142	-.00011	.00566	1.949	37	.059

RESULTS FOR UNEMPLOYMENT RATE DATA SCALING RANGE TESTS

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	averagetesttrainMSEm0.9_0.9	.0548	38	.03849	.00624
	averagetesttrainMSE0.1_0.9	.0153	38	.00944	.00153

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	averagetesttrainMSEm0.9_0.9 & averagetesttrainMSE0.1_0.9	38	.646	.000

Paired Samples Test

		Paired Differences				t	df	Sig. (2-tailed)	
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower				Upper
Pair 1	averagetesttrainMSEm0.9_0.9 - averagetesttrainMSE0.1_0.9	.03948	.03318	.00538	.02857	.05038	7.333	37	.000

RESULTS FOR UNEMPLOYMENT RATE DATA AFFECT OF DESEASONALIZATION

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	averagetesttrainseasonal	.0452	36	.03783	.00630
	averagetesttrain				
	MSEdeseasonal	.0273	36	.02926	.00488

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	averagetesttrainseasonal & averagetesttrain MSEdeseasonal	36	.400	.016

Paired Samples Test

		Paired Differences				t	df	Sig. (2-tailed)	
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower				Upper
Pair 1	averagetesttrainseasonal - averagetesttrain MSEdeseasonal	.01792	.03743	.00624	.00526	.03059	2.873	35	.007

RESULTS FOR EMPLOYMENT INDEX DATA OUTPUT ACTIVATION FUNCTION TEST

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	averagetesttrain MSEpurelin	.0239	40	.02876	.00455
	averagetesttrain MSEtansig	.0216	40	.02676	.00423

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	averagetesttrain MSEpurelin & averagetesttrain MSEtansig	40	.971	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	averagetesttrain MSEpurelin - averagetesttrain MSEtansig	.00235	.00692	.00109	.00013	.00456	2.143	39	.038

RESULTS FOR EMPLOYMENT INDEX DATA SCALE RANGE TEST

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	averagetesttrainMSEm0.9_0.9	.0361	40	.03309	.00523
	averagetesttrainMSE0.1_0.9	.0094	40	.00921	.00146

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	averagetesttrainMSEm0.9_0.9 & averagetesttrainMSE0.1_0.9	40	.755	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	averagetesttrainMSEm0.9_0.9 - averagetesttrainMSE0.1_0.9	.02674	.02682	.00424	.01816	.03532	6.305	39	.000

RESULTS FOR EMPLOYMENT DATA AFFECT OF DESEASONALIZATION

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	averagetesttrainseasonal	.0164	40	.01625	.00257
	averagetesttrain	.0291	40	.03462	.00547
	MSEdeseasonal				

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	averagetesttrainseasonal & averagetesttrain MSEdeseasonal	40	.904	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	averagetesttrainseasonal - averagetesttrain MSEdeseasonal	-.01277	.02111	.00334	-.01952	-.00602	-3.826	39	.000

ÖZGEÇMİŞ

Çağla Karaali was born in İstanbul in 1976. She graduated from Kadıköy Anatolian Highschool in 1994 and Istanbul University Industrial Engineering Department in 1998.

In 1998 she started an MSc. Degree in Industrial Engineering Department, Boğaziçi University and completed the degree in 2001. In 2000 she started working as a research assistant in Doğuş University, Industrial Engineering Department and worked there for six years. Çağla Karaali started her PhD degree in Istanbul Technical University in 2001. Currently she is working as a systems development engineer in Arçelik A.Ş. Turkey.