Cyclical Dynamics of Industrial Production and Employment: A Markov Chain Approach

by

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This is to certify that I have examined this copy of a master's thesis by

Gözde Gencer

and have found that it is complete and satisfactory in all respects,
and that any and all revisions required by the final
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ABSTRACT

Understanding the dynamics of business and growth cycles received considerable attention in the literature. In this study, we provide a methodology based on representing economic time series such as industrial production index growth, employment growth and capacity utilization rates as Markov chains and testing these series for time-dependence and homogeneity. Then we use a first passage time analysis to evaluate the expected passage times between below the trend and above the trend states of these Markov process. These times can be used to analyze the recession and recovery durations as well as the times from a trough to a peak and from a peak to a trough of growth cycles. We use this analysis to study the growth cycles of 24 countries which thus allows us to compare cyclical dynamics of these countries and relate the differences to institutional changes that were put in place. As a result, we present Markov chain-based tests as an easy-to-implement nonparametric methodology to study cyclical dynamics of economic time series.

ÖZET

İş devirlerinin ve büyüme çevrimlerinin dinamiklerini çözümlemek, litaratürde oldukça yer almış ve ilgi toplamıştır. Biz bu çalışmada, kapasite üretim oranları, üretim endeksindeki ve istihdamdaki büyüme gibi ekonomik zaman serilerinin Markov zincirleri halinde incelenmesine ve bu serilerin zamansal bağlılık ve zamansal türdeşlik özelliklerinin test edilmesine dayanan bir metodoloji önermekteyiz. Böylece, ilk geçiş zamanı analizini kullanarak bu ekonomik verilerin her birinin izlediği trendin altındaki büyümelerden, trendin üzerindeki büyümelere; ayrıca trendin üzerindeki büyümelerden, trendin altındaki büyümelere geçiş zamanlarını değerlendirmekteyiz. Belirlenen bu geçiş zamanları, ekonomik durgunlukların ve gelişmelerin sürelerinin tahmin edilmesinde kullanılabileceği gibi, aynı zamanda bir büyüme çevriminde görülebilecek maksimum büyümenin gözlemlendiği bir dönemden, maksimum daralmanın yaşandığı diğer bir döneme geçiş süresi ve maksimum daralmanın gözlemlendiği bir dönemden maksimum büyümenin gözlemlendiği bir sonraki döneme geçiş süresinin de analiz edilmesinde kullanılabilmektedir. Bu yöntemden, farklı 24 ülkenin büyüme çevrimlerinin analizinde faydalanıyoruz, böylece bu ülkelerin döngüsel dinamiklerini karşılaştırabilme ve ülkeler arasında görünen farklılıkları ortaya çıkarılan ekonomik ve politik değişimlerle ilişkilendirebilmekteyiz. Sonuç olarak Markov zincir testlerini, ekonomik zaman serilerinin döngüsel dinamiklerinin incelenmesinde kolayca uygulanabilen ve parametre kullanımına ihtiyaç duyulmayan etkin bir metodoloji olarak sunmaktayız.

to my family...

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Chapter 1

INTRODUCTION

The notion that market economies are subject to repetitive fluctuations in a large set of variables was explained by Burns and Mitchell (1946) in their work titled “Measuring Business Cycles” as:

“Business cycles are a type of fluctuation found in aggregate economic activity of nations that organize their work mainly in business enterprises; a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic, in duration business cycles vary from one year to ten or twelve years, they are not divisible into shorter cycles of similar cycles with amplitudes approximating their own.”

This definition has formed the basis of modern thinking about business cycles. Historically, the periods of depression and crises of various types which had direct effects on market economies of the nineteenth century initiated the research of business cycles as recurrent movements in a large set of variables. In this frame, The Great Depression and World War II were two major events in the development of business cycle analysis. The period following World War II was an era of high and sustained growth in many countries. The oil shocks of the 1970s, which caused high inflation and high unemployment rates, also led researchers to account for the observations using new mechanisms for the effects of money on performance of economic activities (Altug, 2010).

The desire to explain the general economic activity aroused great interest to examine aggregate economic activity as recurrent phenomena and characterize the functioning of economies with optimizing agents. Another important channel which affected the study of business cycles was the development of statistical and time series methods. In the last few decades, new techniques of dissecting business cycles have been introduced to the literature which has contributed to new insights, perspectives and approaches in the field of business cycle analysis (Altug, 2010).

Our greatest motivation during this study is to understand the differences among the cyclical growth behavior of diverse economies. These growth cycles represent the fluctuations around the long-term trend of aggregate economic activity. Thus, the comparison of cyclical movements in smoothed growth rates of the principal measures of aggregate economic activity enables us to analyze the growth cycles of different economies.

During our work, we are concentrated on a number of questions as they constituted the key issues of this study:

- Which economic time series are appropriate to study the cyclical behavior of an economy?
- How can we model an economic time series as a Markov chain?
- What are the transition probabilities between different states of economic time series?
- What are the time dependence and time homogeneity properties of these economic time series modeled as a Markov chain?
- What are the expected passage times between different states of these Markov chains?
- What are the probabilities of these transitions to be observed in a certain time interval?

- How do the answers to these questions differ from country to country?
- What are the effects of institutional changes in growth performance of economies?

In order to make an efficient study where accurate results to these questions are clearly served, we use a systematic Markov chain based testing methodology and analyze the cyclical dynamics of growth in economic time series like industrial production index and employment rates to examine the economic growth performances of different countries. In contrast to parametric Markov switching models used to analyze business and growth cycles, the implementation of this methodology does not require any parameterizations of the stochastic models. Prejudgments about the behavior of the studied economic time series are also eliminated via a systematic testing procedure of time-dependence and time-homogeneity of the series in question. This systematic Markov chain testing procedure thus enables us to conduct a comparative study of 24 countries via an objective approach and relate the findings to the institutional changes and other developments observed in these diverse economies.

Chapter 2 of this study provides necessary background and literature review on the use of Markov chains in order to study economic time series. The fundamentals of parametric and non-parametric approaches to detect business cycles and growth cycles and previous studies using Markov switching models are also reviewed.

Chapter 3 describes the Markov chain based testing methodology used during this study. A detailed framework to use this methodology as a test of time-dependence and homogeneity of economic time series is also presented in this chapter.

The role of analyzing economic indicators when dissecting growth cycles are briefly explained in Chapter 4, where we also explain the characteristics of these economic indicators which should be analyzed by Markov chain based testing methodology in order to make predictions about the patterns of growth cycles.

A detailed explanation of the methodology is given in Chapter 5 where the Markov chain based testing methodology is applied to certain economic time series like Capacity Utilization Rates, Unemployment Rates and Industrial Production Index growths. The results of these tests are also given in this chapter and these theoretical results are compared with the empirical ones which are obtained by the observation of historical data.

Chapter 6 includes the analysis of growth cycles of various countries due to the results acquired by the application of the methodology to Industrial Production Index growth and Employment growth of these nations. These are the main economic indicators depicting the overall economic performance of a nation, thus are chosen to be combined in order to make predictions about turning points of growth cycles of these countries.

In Chapter 7, our predictions on growth cycles are compared with the NBER inferences on business cycles. The difference of approaches used when detecting business cycles and growth cycles is thus signified. Chapter 8 gives a short summary of the performed study and conclusions.

Chapter 2

LITERATURE REVIEW

2.1 Overview

Until now, various approaches, parametric and nonparametric, have been proposed in order to study business and growth cycles. Research on business cycles is mostly concentrated on the sporadic periods of expansion and contraction in the level of economic activities while growth cycle studies involve analyses of the alternating periods observed in the growth rate of the economies. The parametric approaches used in these studies generally concern the use of statistically defined multivariate frameworks, while nonparametric approaches favor the combination of results obtained by separate analysis of leading economic indicators.

Differences and similarities in economic growth performances of nations can be stated by the information acquired via the analyses of several economic time series recorded in these countries. Furthermore, the combination of those economic time series which are leading in relation to the general economic behavior thus should be considered to be very utile in dissecting these similarities and differences in growth performances.

2.2 Dating Business Cycles with Nonparametric Approach

When using the nonparametric approach to dissect business and growth cycles, the change in monotonicity of an economic time series is taken into account by the investigator. Thus, this approach works even when reliable information on the parametric function is not provided. Nonparametric approaches extract the information about how an economic time series is supposed to evolve directly from the observation of the historical data. While using nonparametric approach, there is no need to make the assumption that all expansions (or recession phases) have the same level and parametric shape. The possibility that the behavior of the economic time series may have changed in past is also taken into consideration and the predictions are made through that philosophy (Andersson, Bock and Frisén, 2004).

Burns and Mitchell (1946) were the first investigators who set out the nonparametric methods to learn the characteristics of the cycles observed in economic time series. They laid the foundations of documenting recurrent cycles of quantities and prices. Their data analysis was mostly focused on expansions, contractions and turning points of business cycles. Their view that output alternates between periods of expansion and contraction of varying durations is consistent with recent empirical research of asymmetric output fluctuations (Brock and Sayers, 1988).

Burns and Mitchell (1946) indicated that “Aggregate economic activity can be given a definite meaning and made conceptually measurable by identifying it with gross national product.” This means the level of GNP can be examined as a measure of economic activity. Though, in the absence of measures of GNP, Burns and Mitchell (1946) proposed the combination of a variety of economic series in order to measure the economic activity. In such case, the best combination of economic indicators is to be chosen to detect the behavior of “the cycle” under investigation (Harding and Pagan, 2005).

The nonparametric approach which is still used by National Bureau of Economic Research (NBER) in order to detect turning points of business cycles is essentially derived from Bry and Boschan’s influential work where no formal statistical model is used during the process (Bry and Boschan, 1971). Bry and Boschan’s approach is a nonparametric procedure which is set out to be applied to a single monthly time series adjusted for seasonality. This approach corresponds the identification of major cyclical patterns and then representing the neighborhoods of maxima and minima of the economic time series in consideration. Then the search for these turning points is narrowed from these neighborhoods into specific calendar dates. This approach is still known as the best algorithm for determining the potential set of turning points, peaks and troughs in a series.

According to the NBER methodology, six different economic variables which are esteemed to be significant in the name of defining the business cycle (such as GDP) are examined critically in order to detect their turning points with the regular procedure suggested by Bry and Boschan (1971). Thus, a dating for the overall economy is proposed by the aggregation of the turns of these single time series. An alternative for this procedure is also represented by the aggregation of these six economic variables into a composite coincident indicator (Bruno and Otranto, 2004).

2.3 Dating Business Cycles with Parametric Approach

Many authors prefer using parametric models in order to detect the regime shifts in business and growth cycles. Using a parametric model may improve the performance of a method if the parameter information is reliable. On the other hand, a wrongly specified parametric model can cause serious effects.

There exist several approaches using parametric procedures in order to detect business cycles. Stock and Watson (1991) developped an explicit probability model of the four coincident variables (industrial production, real person income, real manufacturing and trade sales and employment in nonagricultural establishments). This probability model enabled the computation of an alternative coincident index which is supposed to represent the general state of the economy. In this study, Stock and Watson stated that estimations about this unobserved index may well be used to predict business cycle turning points.

Diebold and Rudebusch (1996) made an important contribution to this study by adding a Markov switching dynamics to the coincident indicator model proposed by Stock and Watson.

Krolzig (1997, 2001) extended the Markov switching model to the multivariate case by using vector autoregressive models and proposed a multivariate Markov switching model in order to analyze the regime shifts in the stochastic process of economic growth in the US, Japan and Europe over the last four decades. Kim and Nelson (1999) proposed a Bayesian approach to detect and identify structural and abrupt changes in a Markov switching model of the business cycle. The Bayesian approach they used in this study enabled the calculation of the marginal likelihood for the model under consideration. In this study, they took the asymmetric nature of the business cycle into consideration.

Some other researchers like Neftci (1984) also investigated the issue of asymmetry between expansions and contractions of a business cycle using a framework of finite state Markov processes. In this frame, Neftci (1984) implemented a statistical test to see if the behavior of unemployment rate of United States in 1959-1978 could be characterized by sudden jumps and slower drops. The result of this research proved that it is possible to observe that the average length of expansions differ from that of the recessions. We can say that our work shows similarity to Neftci's study. On the other hand, the difference is that in this study, a formal time-dependency and time-homogeneity test is proposed and a first passage time methodology is used to study the asymmetric behavior instead of the comparison of transition probabilities.

Artis, Marcellino and Proietti (2003) brought the nonparametric and parametric approaches together in order to observe their performance in detecting business cycles. They analyzed the business cycle in Europe by comparing the commonly used nonparametric dating approach where the probability of a phase change in a business cycle could be directly computed with the model-based approach.

A statistical turning point dating procedure which is considered as a milestone in the literature was suggested by Hamilton (1989). In his study, Hamilton (1989) used a parametric model based on estimating a two-regime Markov switching specification which allowed the dating of a time series and enabled the identification of turning points in the series under investigation. First, a statistical model was fit to the GNP data of United States and then the estimated parameters of the model were used in order to analyze the characteristic behaviors of the long term trend in this economic time series.

Beyond these, the robustness of Hamilton's (1989) Markov switching model in detection of business cycles was rejected by Boldin (1996). After analyzing the same time interval of United States GNP data with Hamilton, Boldin found two local maxima which were not displayed as turning points in Hamilton's (1989) study although they had higher likelihood values. Boldin (1996) also indicated that a three-regime Markov switching Model for GNP growth was much more convenient and robust in the name of detecting business cycle dynamics over the time period 1952-1984.

What catches the attention in such Markov switching approaches is that the parameterization to characterize the nonlinear model is definitely not simple (Harding and Pagan, 2002). In such models, a variety of estimations with numerous assumptions which cause lack of transparency are also required to obtain accurate results. In contrast to these approaches, our study does not include any complex parameterization to characterize the stochastic models of the time series analyzed. Beyond, our methodology enables direct estimation of transition probabilities between different levels of growth of economic time series directly.

According to Harding and Pagan (2002), the Markov switching model alternative generally includes judgments about how many states are included in the model and what critical value should be used for the estimated probabilities to produce a set of cycle states. The issue about whether the transition probabilities are constant during the observed time interval or not even relies on judgments and assumptions. This means the time-homogeneity of observed series is not properly tested. On the other hand, our work does not involve such assumptions about the stationarity of the time series in consideration: A formal tests of time-homogeneity of the series is proposed so that we can reveal if the transition probabilities between the states of the Markov model are stationary or not. The systematic time-dependence and time-homogeneity testing procedure thus enables us to make realistic inferences about the growth patterns of economic time series in an objective approach and with limited judgment on the issue.

In this frame, Markov switching models may be considered as an alternative way to elucidate the moments of growth of an economic indicator but not as a dating rule adopted to analyze the overall economic growth performance. In order to study growth cycles of diverse economies in an objective approach; this study offers a simple and systematic methodology which is not only released from assumptions and judgments but also based on empirical and measurable evidence.

Chapter 3

MARKOV CHAIN BASED TESTING METHODOLOGY

3.1 Overview of the Methodology

In this study, we analyze the time dependence and time homogeneity properties of given time series by applying a Markov chain based methodology that is a nonparametric testing procedure. This method is presented in detail in (Tan and Yilmaz, 2002).

Markov chain based tests require the transformation of a continuous state-space process associated with a given time series into a discrete state space sequence. If only the time dependency and homogeneity properties of a time series are of interest, observations can be aggregated into a finite number of states. Hence we aggregate the continuous state space of the time series into a discrete state space with a number of finite states. That means, a given continuous state space stochastic process $y(t)$ i.e. $\{y(t), t = 0,1,2,...\}$ is mapped into a discrete state space stochastic process defined as $\{X_t, t = 0,1,2,...\}$ on the state space S of size n_s. This state-space representation is thus used to investigate the time dependence and time homogeneity properties of the time series in question.

Here, the discrete state space includes the set of alternative categorization of the given time series of prespecified intervals. These possible values depend on the statistical properties of the time series under investigation. To analyze economic time series (e.g.

capacity utilization rates, industrial production indices, stock prices) as a Markov chain, numerous studies prefer to focus on the direction of movements of the time series which indicate whether the data elements increase or decrease by time. Alike other researches, in this study, the continuous state space of a stationary economic time series are mapped into a discrete state space $S = \{U, D\}$ where U corresponds to an upward movement of $y(t)$ at time t, D corresponds to a downward movement of $y(t)$ with respect to its average during the full period $[0,T]$, $\bar{y} = \frac{1}{1+T}\sum_{t=0}^{T} y(t)$, i.e.,

$$X_t = \begin{cases} U & \text{if} \quad y(t) \geq \bar{y} \\ D & \quad\quad y(t) \leq \bar{y} \end{cases} \tag{3.1}$$

When the magnitude of the movements is of interest, then the number of states may be increased to gain more information about the given time series. Such an approach may require a three-state process - “Up,” “Down,” and “No Change”. Alternatively, one can use more states in S to include more information on $y(t)$ in X_t. However, the increased number of states requires a greater probability transition matrix to estimate and reduces the testing power when the number of observations is limited.

In general, when $X_n = i$ the stochastic process is said to be in state i at time n. Whenever the stochastic process is in state i at time n, there is a probability $p_{ij}(n)$ that it will be next in state j at time $n+1$. That is, we suppose that:

$$P\{X_{n+1} = j \mid X_n = i, X_{n-1} = i_{n-1}, \ldots, X_1 = i_1, X_0 = i_0\} = p_{ij}(n). \tag{3.2}$$

When the transition probabilities between states do not vary over time, then the underlying Markov chain is time homogeneous. In this case, when the process is in state i at time n, the probability that the process will next make a transition into state j is independent of time n. This implies, for a time homogeneous Markov chain:

$$p_{ij}(n) = p_{ij}\,. \tag{3.3}$$

Let P denote the matrix of one-step transition probabilities for a time homogeneous (stationary) Markov chain. Since these probabilities are nonnegative and since the process must make a transition into some state, we have that:

$$\begin{gathered} p_{ij} \geq 0 \\ \sum_i p_{ij} = 1;\ \ i, j \in S\,. \end{gathered} \tag{3.4}$$

As already indicated, in this study we define $S = \{U, D\}$ to make accurate analyses of time dependence and time homogeneity properties of economic time series. Thus we focus on the transition probabilities between states U and D when analyzing the movements of these series. In the next chapter, we explain the time dependence testing methodology where we will also indicate the transition probabilities estimation procedure.

3.2 Testing time Dependence

If a given sequence is an independent process or random walk, then the movements at any given time are independent of each other. By definition, a given sequence

$\{X_t, t = 0,1,2,...\}$ is an independent process if for all *t, t=0, 1, 2, ...,* the probability law of the process is given by,

$$P[X_t = j \mid X_{t-1} = i_1,..., X_0 = i_t] = P[X_t = j]. \tag{3.5}$$

If the above condition does not hold, then determining the degree of dependency, that is, whether a given movement depends on the last movement, last two movements, etc. is of interest. If $\{X_t, t = 0,1,2,...\}$ is a first order Markov chain, or simply a Markov chain, then

$$P[X_t = j \mid X_{t-1} = i_{1,...,} X_0 = i_t] = P[X_t = j \mid X_{t-1} = i_1]. \tag{3.6}$$

Similarly, if $\{X(t), t = 0,1,2,...\}$ is a Markov chain of order u, then

$$P[X_t = j \mid X_{t-1} = i_1,..., X_{t-u} = i_u,..., X_0 = i_t] = P[X_t = j \mid X_{t-1} = i_1,..., X_{t-u} = i_u]. \tag{3.7}$$

$$t = u, u+1, u+2,...$$

A time homogeneous Markov chain of order *u* is completely characterized with its state transition matrix $P = \{P_{ij}\}$ where

$$p_{i,j} = P[X_t = j \mid X_{t-1} = i_1,..., X_{t-u} = i_u] \tag{3.8}$$

$$i = (i_i,..., i_u) \in S^u,\ j \in S,\ t = 0,1,2,....$$

In this representation state i includes more than one state if the order of time dependency is greater than one. For example, for a second order Markov chain defined on the state space $\{U, D\}$; $i \in \{UU, UD, DU, DD\}$ and $j \in \{U, D\}$.

Once it is assured that state transition probabilities do not change with time, i.e., the Markov chain is time homogenous, over a given period, and the order of the Markov chain is set then these probabilities can be estimated directly from the observed transitions. For each subinterval of the given time period, the transition probabilities are estimated by,

$$p_{i,j} = n_{i,j} / n_i, \quad i \in S^u, \ j \in S^u \tag{3.9}$$

$$\text{Subject to } \sum_j p_{ij} = 1$$

where $n_{i,j}$ represents the total number of observed transitions from state $i \in S$ to $j \in S$ and n_i symbolizes the total number of transitions from state i during the given time period.

During the procedure, we will be testing the null hypothesis that the Markov chain is of order u versus order v such that $v > u$. Here, we assume that $P = \{p_{i,j}\}$ denote the time homogeneous state transition matrix of Markov chain of order u and $Q = \{q_{i,j}\}$ represents the transition matrix for order v.

As indicated in Tan and Yilmaz (2002), an asymptotically equivalent test statistic for the likelihood ratio test statistic is given by,

$$-2\ln(\Lambda) = 2\sum_{i,j}\left[\ln(q_{i,j}) - \ln(\tilde{q}_{i,j})\right], \tag{3.10}$$

$$i \in S^v, j \in S,$$

with Λ : maximum likelihood ratio test statistic subject.

with

$$\tilde{Q} = \{\tilde{q}_{i,j}\} = \left[\underbrace{P^T, P^T, \ldots, P^T}_{2^{v-u}}\right]^T .$$

This test statistic has a χ^2 asymptotic distribution with $(n_s^v - n_s^u)(n_s - 1)$ degrees of freedom. The order-test procedure starts with testing the null hypothesis that the given time series is a random walk (with *u=0*) versus alternative hypothesis that the time series is a Markov chain of first order (with *v=u+1*). If the null hypothesis is not rejected at this first step, then we can come to the conclusion that the given time series is a random walk. In case of rejecting the random walk hypothesis, we continue to the procedure by increasing *u* by one and apply the same test with order *u* versus *u+1*. This procedure lasts until the null hypothesis is not rejected. As explained, we need the Markov Chain to be time homogeneous to apply this order test. The following part includes the details of time homogeneity testing procedure.

3.3 Testing Time Homogeneity

In order to test a time series for time homogeneity, we divide $\{X_t, t = 0,1,2,...\}$ into K different equal sub-intervals. This test involves testing whether the transition probabilities of each subinterval are statistically different from the transition probabilities estimated for the full time period.

The state transition probability of a u^{th} order Markov chain corresponding to period *k, k=1, 2,…, K* is given by

$$p_{i,j}(k) = P\left[X_t = j \mid X_{t-1} = i_1,..., X_{t-u} = i_u\right] . \tag{3.11}$$

$$i = (i_1,..., i_u) \in S^u, \quad j \in S, \quad t \in \left[(k-1)\Delta, k\Delta\right]$$

$$\Delta = \lfloor (T+1)/K \rfloor$$

During this procedure, we would like to test the null hypothesis that the transition probabilities for each subinterval are not statistically different from the transition probabilities determined for the whole period versus the alternative hypothesis that they are different.

To conduct the hypothesis test, an asymptotically equivalent test statistic for the likelihood ratio test statistic is given in (Tan and Yilmaz, 2002) as:

$$-2\ln(\Lambda) = 2\sum_{k}\sum_{i,j} n_{i,j}(k)\left[\ln(p_{i,j}(k)) - \ln(p_{i,j})\right], \tag{3.12}$$

$$i \in S^u, \ j \in S, \ k = 1,2,..., K .$$

This test statistic has a χ^2 asymptotic distribution with $(K-1)n_s(n_s-1)$ degrees of freedom.

In case the null hypothesis is not rejected, one can admit the time series analyzed is time homogeneous. Otherwise, the time dependence test cannot be done by using a single probability transition matrix estimated by observation of the empirical data.

In order to test time homogeneity and time dependence together, first we assume the given time series is time homogeneous and conduct the time dependence test with a single probability transition matrix obtained from the empirical data. Then we test time homogeneity with this order determined in the previous step. At the end of these two tests, if time homogeneity is accepted, we can conclude that the given time series is a homogeneous stochastic process following a Markov chain of the specified order.

It is also possible that the whole process cannot be accepted as time homogeneous. In this case, the order of dependence cannot be estimated for the given time series by using Markov chains. Thus, we need to divide the whole process into 2 subseries. This division process may conclude the determination of a “breakpoint” which stands for a time sequence where the behavior of the data analyzed may have changed due to the alternations in political and economic institutions. In such case, the whole analysis involving the time dependence and time homogeneity tests is conducted for the second time subseries which represents the most recent data. Thus, the time dependence and time homogeneity properties are revealed by the results obtained at the end of this process.

The third case, in which all orders of dependence equal to or less than the maximum order specified by the researcher are rejected for the sample (or the subinterval) analyzed, is considered as inconclusive. In such a situation, no accurate result about the time dependence can be obtained; thus the researcher cannot proceed with the time homogeneity test. Figure 3.1 illustrates the flow chart of the Markov chain based testing methodology.

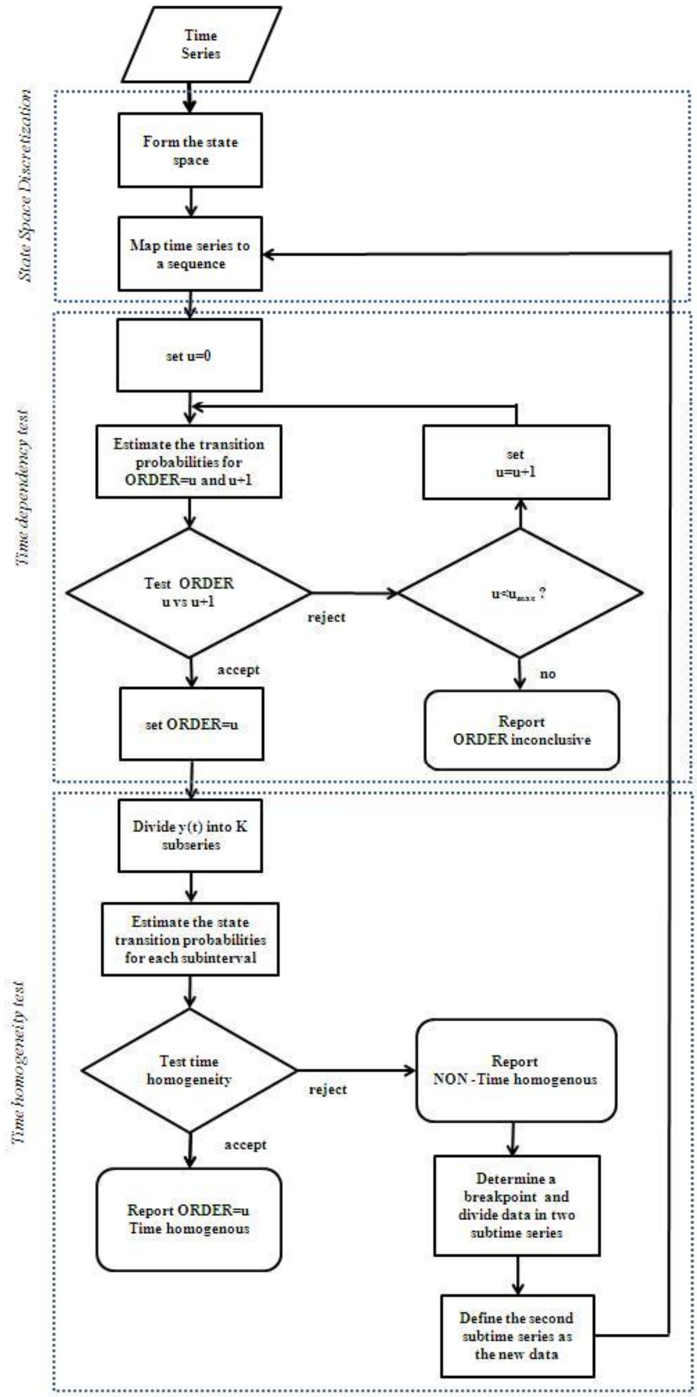

Figure 3.1: Flow Chart of Combined Time Dependence and Homogeneity Test (Tan and Yilmaz, 2002)

3.3.1 Analyses Conducted via Time Homogeneity Test

As well, we can use time homogeneity test in order to observe if the transition probabilities of two different time series are statistically different or not. The difference here is that, we consider each time series as a subinterval of a larger time series which, in fact, consists the combination of both time series as a whole.

In order to conduct such analysis, first of all we should reveal the time dependence and time homogeneity properties of each time series separately as explained in the previous part. To precede the analysis, the order of time dependence of each time series should be equal. Time homogeneity property for each time series is also a must. In case these conditions are satisfied, then we conduct the hypothesis test by revealing the same asymptotically equivalent test statistic given in (3.12).

As this testing process involves taking each time series as a subinterval of the whole time interval, we define $p_{(i,j)}(k)$ with $k = \{1,2\}$ where $p_{(i,j)}(1)$ stands for the transition probabilities of the first time series while $p_{(i,j)}(2)$ denotes the transition probabilities for the second one. Similarly, $p_{(i,j)}$ represents the transition probabilities acquired for the combination of both data.

Expected First Passage Time Analysis

3.4.1 Expected First Passage Times

First passage time stands for the length of time to go from a state i to a state j for the first time. In this part of our study, we will indicate the general approach used to find these first passage times between states of a Markov chain. Let us denote T_{ij} the first passage time from state *i* to state *j*.

Assume that f_i the probability that, starting from state i, the process will ever reenter state i. When $f_i < 1$, state i is classified as transient; while in case $f_i = 1$, state i said to be recurrent. Absorbing states, on the other hand, are defined as the states which once entered can never be left (Ross, 2003). Thus, the transition probabilities between absorbing states is defined with an identity matrix I which is a square matrix with ones on the main diagonal and zeros elsewhere. Let the transient and absorbing states are ordered in such a way that the probability matrix is represented in Figure 3.2.

$$\begin{array}{cc} & \begin{array}{cc} \text{Transient} & \text{Absorbing} \end{array} \\ P = & \left[\begin{array}{c|c} Q & R \\ \hline 0 & I \end{array}\right] \end{array}$$

Fig 3.2: Illustration of a Matrix with Transient and Absorbing States

In such representation of a transition probability matrix, we can find the expected number of periods spent in each of the transient states until absorption. Let T_i be the first passage time from state i to an absorbing state.

When the initial state is i, the expected number of periods spent in a transient state j can be obtained by calculating the ij^{th} element of matrix $(I - Q)^{-1}$. Thus, the sum of the number of periods spent in each transient state when initial state is i, i.e., the i^{th} element of

$(I-Q)^{-1}\underline{u}$ where $\underline{u}$ is a column vector of 1s with the appropriate size, gives us the first expected passage time from state i to an absorbing state.

3.4.2 Steady State Probabilities

For any irreducible ergodic Markov chain, it is possible to find the fraction of time that the process is in one of the states in the long run. These time fractions are also called steady state probabilities. Thus, for an irreducible ergodic Markov chain,

$$\lim_{n\to\infty} p_{ij}^{(n)} = \pi_j \tag{3.13}$$

where π_j stands for the steady state probability of being in state j in the long run and $p_{ij}^{(n)}$ represents the probability that a process in state i will be in state j after n additional transitions (Ross, 2003).

Suppose that there exist M defined states in a Markov chain. In order to find the steady state probabilities of these states, we need to find the probabilities which satisfy the conditions defined as:

$$\sum_{j=1}^{M} \pi_j = 1 \tag{3.14}$$

$$\pi_j = \sum_{i=1}^{M} \pi_i p_{ij} \text{ for all } j = 1,\ldots,M$$

$$\pi_j > 0 \text{ for all } j = 1,\ldots,M$$

3.4.3 Special Cases

Expected Passage Times for a Two-State First Order Markov Chain

Whenever time dependence between the components of a given stochastic time series is determined as a first order Markov chain, then the expected passage times between states U and D can be estimated by using the transition probability matrix directly.

The probability transition matrix for a stochastic process following a first order Markov chain can be defined as:

$$P = \begin{array}{c c} & \begin{array}{cc} U & D \end{array} \\ \begin{array}{c} U \\ D \end{array} & \begin{bmatrix} p & 1-p \\ q & 1-q \end{bmatrix} \end{array}. \tag{3.15}$$

The probability that the first passage time from state U to state D is k periods is:

$$P(T_{UD} = k) = p^{(k-1)}(1-p). \tag{3.16}$$

Thus, the expected first passage time to state D from state U can be represented as the following;

$$E[T_{UD}] = \sum_{k=1}^{\infty} kp^{(k-1)}(1-p). \tag{3.17}$$

where n represents the number of time periods analyzed in the historical data.

For a relatively large historical data, the expected first passage time from state U to state D is thus as follows:

$$E[T_{UD}] = 1/(1-p) \quad (3.18)$$

Similarly, the probability that the first passage time from state D to state U is k periods is defined as:

$$P(T_{DU} = k) = (1-q)^{(k-1)} q \, . \quad (3.19)$$

This equation implies that the expected first passage time from state D to state U is as:

$$E[T_{DU}] = 1/q \quad (3.20)$$

Expected Passage Times for a Second Order Markov Chain

The transition probability matrix for a stochastic process following a second order Markov chain is defined as:

$$P = \begin{array}{c} \\ UU \\ DU \\ UD \\ DD \end{array} \begin{array}{c} \begin{array}{cccc} UU & DU & UD & DD \end{array} \\ \begin{bmatrix} p_{UU,UU} & 0 & p_{UU,UD} & 0 \\ p_{DU,UU} & 0 & p_{DU,UD} & 0 \\ 0 & p_{UD,DU} & 0 & p_{UD,DD} \\ 0 & p_{DD,DU} & 0 & p_{DD,DD} \end{bmatrix} \end{array} \quad (3.21)$$

Derived from (3.21), matrix A stands for the transient matrix for state U before absorption in state D. Similarly, matrix C represents the transient matrix for state D before the stochastic process evolves by moving from state D to state U.

$$A = \begin{array}{c} \\ UU \\ DU \end{array}\begin{array}{c} \begin{array}{cc} UU & DU \end{array} \\ \begin{bmatrix} p_{UU,UU} & 0 \\ p_{DU,UU} & 0 \end{bmatrix} \end{array} \qquad C = \begin{array}{c} \\ DD \\ UD \end{array}\begin{array}{c} \begin{array}{cc} DD & UD \end{array} \\ \begin{bmatrix} p_{DD,DD} & 0 \\ p_{UD,DD} & 0 \end{bmatrix} \end{array} \tag{3.22}$$

Let $W_{UD} = (I - A)^{-1}$ and $W_{DU} = (I - C)^{-1}$ where I is a $2x2$ identity matrix. The total number of periods to be spent in transient states thus gives us the expected first passage times to absorbing states.

$$\begin{aligned} E[T_{UU,UD}] &= [1 \quad 0] W_{UD} \cdot \underline{u} \\ E[T_{DU,UD}] &= [0 \quad 1] W_{UD} \cdot \underline{u} \\ E[T_{DD,DU}] &= [1 \quad 0] W_{DU} \cdot \underline{u} \\ E[T_{UD,DU}] &= [0 \quad 1] W_{DU} \cdot \underline{u} \end{aligned} \tag{3.23}$$

where $\underline{u} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$

We see that expected first passage times to absorbing states also depend on the state of the previous time period. To obtain the first passage times independent of previous states, we need to find the steady state probabilities satisfying the conditions (3.14). These steady state probabilities thus give the long run proportion of time that the stochastic process is in any of these transient states.

Once the steady state probabilities π_{UU}, π_{UD}, π_{DU} and π_{DD} are calculated, then the first passage times independent of the previous states of the Markov chain can be obtained by,

$$\begin{aligned} E[T_{UD}] &= \pi_{UU} E[T_{UU,UD}] + \pi_{DU} E[T_{DU,UD}] \\ E[T_{DU}] &= \pi_{DD} E[T_{DD,DU}] + \pi_{UD} E[T_{UD,DU}] \end{aligned} \tag{3.24}$$

This method of finding expected first passage times between different states of the Markov chain will be used in the forthcoming chapters to study the cyclical dynamics of economic series of different countries.

Chapter 4

ECONOMIC INDICATORS

4.1 Overview

Economic indicators present economic statistics showing the general trends in the economy. These indicators play a major role in understanding the macro picture of the economy and the economic performance of a nation.

Economic indicators can be classified as leading or lagging. Leading factors involve statistical data which give information about the possible changes in the future of the general economy, while, on the other hand, lagging factors are those which record an economical activity that has already taken place. Leading economic factors are generally used in predicting the business and growth cycles as they reflect economical changes before the whole economy starts to follow a particular pattern or trend.

The leading indicator approach is totally based on the view that market-oriented economies experience business cycles where repetitive sequences are observed. These sequences not only underlie the generation of business and growth cycles but also constitute the most useful data to forecast the turning points of the economic activity. So we can say that the leading economic indicator approach is then to find the repetitive sequences, to explain them, and to use them in order to identify and anticipate the upcoming stages of the business cycles (Lahiri and Moore, 1992).

The significance of an economic indicator depends on the timeliness, the accuracy and the importance of the concerning data. As long as an economic indicator is considered to be significant, it can be thus used for analyzing the overall performance of the economy and making forecasts about the upcoming economic performance of a nation.

According to the National Bureau of Economic Research, one of the most important criteria taken into consideration while determining the usefulness of an economic indicator is "Economic Significance". This criterion indicates the meaning and importance of an indicator when detecting the turning points of a growth or business cycle. Other criteria taken into consideration while measuring the performance of an economic indicator are as follows:

- Statistical adequacy: Concerns how well the indicator measures the economic process.
- Timing: Indicates the consistency of the indicator in leading the economy at turning points.
- Conformity: Points out the regularity of the indicator adapted to the business cycle i.e the economic time series which tend to move in broad swings whose duration and timing match well the business cycles as dated by NBER ensure this criterion.
- Smoothness: Indicates if the nonrandom movements and the irregular components of the time series can be discriminated in an easy and efficient way.
- Currency: Involves the availability of the time series.

In this study, we analyze Capacity Utilization Rates, Employment Growth, and Industrial Production Index Growth as the most important leading indicators which compromise all these six criteria. We believe studying the statistical properties of Industrial Production Index growths and Employment growths gives us significant information about growth cycles. Combining the important changes in their directions will provide us important clues in determination of turning points in order to forecast the future growth trends in economy.

4.2 Properties of Capacity Utilization Rates

Capacity utilization rate is the ratio of the actual level of output over a related capacity index which stands for the sustainable maximum level of output or capacity of a nation. Though the fact that capacity utilization data itself does not give information about growth cycles, we allocated a chapter in order to study the properties of this index as these data provides us information about the overall economic performance of a nation.

The Federal Reserve calculates capacity and capacity utilization measures for the nation's industrial subsectors involving manufacturing, mining and electric and gas utilities (Corrado and Mattey, 1997). Although these subsectors do not cover a great part of overall activity within the economy, the manufacturing sector often sets the tone for the entire economy. That's the reason why these measures are extensively used to explain changes in rate of investment, labor productivity and inflation (Berndt and Morrison, 1981).

The information obtained with the help of capacity utilization rates helps illuminate structural developments in the economy. Movements in capacity utilization can be efficiently used to explain changes in business cycles and describe to what extent various industries are participating in the progress of economic growth. An efficient estimation of future capacity utilization rates can be considered to be very fundamental to predict the rate of investment, labor productivity and inflation of the upcoming periods. In this frame, essential information about the possible growth in the economy and the investment level in business can also be provided by the information that is obtained by capacity utilization data.

In case that a sharp decline in capacity utilization rate is estimated for the future, descends in growth periods within the economy can also be foreseen which affect the future planning of industries. All these prove that capacity utilization rates can be regarded as a key to assess the current and future performance of the economy.

In the general case, 70-80% of capacity utilization can proclaim growth potential and softness in the economy, while 85% of capacity utilization is comprehended as an important sign of an upward pressure on prices (Brausch and Taylor, 1997). In a superficial approach, full capacity utilization may seem optimal. However, 100% capacity utilization is considered as too tight because it leaves no room for absorbing additional economic demand. Instead, a rate which leaves some cushion in order to maximize output while deadening the negative effects of inflation is sought. In a general sense, this optimal capacity utilization rate is figured as 80%. Yet, we should consider that this rate may vary by industry (Schwab Center for Financial Research, 2007).

Historical data certifies that rising rates of capacity utilization actuates investment in capital equipment which is regarded as fixed assets as they have an extended life. On the other hand, falling levels of capacity utilization result is a pronounced slowdown in business investment. It is difficult to make general comments about capacity utilization levels that characterize cyclical downturns, but sharp declines in capacity utilization rates are generally related to recessionary or descend in growth of the economy (Brausch and Taylor, 1997).

4.3. Properties of Employment Data

Unemployed population can be defined as the group of people who are above a specified age and who are able to work but did not take part in the production of goods and services, while employed population definitely stands for the productive population.

Employment data indicates a major role when determining the industrial output capacity of a nation. As emphasized by International Labor Organization, unemployment data is also widely and particularly used as an overall indicator of the current performance of a nation's economy (www.ilo.org). For this reason, growth in employment rates may be considered as an appropriate data to be used to serve our purpose, which is to make forecasts about the economic activities and estimate the turning points of growth cycles.

Employment data is generally considered as a lagging factor by many economists, as it is destined to peak after the official end of the recession in economy and displays a sharp decrease after the peak of the business cycle. On the other hand, historically, the unemployment rate has peaked more often fairly close to recessions' end. That is why employment data should be considered more than a lagging indicator (Schaik, 2009).

The effects of unemployment in economic performance of a nation can be observed when the statistical time series in interest rates, stock prices or exchange rates are analyzed. Low unemployment rate signals a strong economy with higher potential profits in stock markets. It may also lead to higher wage inflation which causes stock market prices to fall. Unemployment rates which are lower than expected also tend to appreciate the exchange rate as it is expected to lead to higher interest rates (Roubini, 1998).

So, as it involves the properties of a leading economic indicator, employment data should be considered not only as an economic measure of short-term trends in labor market to make predictions about the nation's economy but also as an important input to long-term planning, such as the provision of training facilities, identifying unused labor supply and forecasting the future levels of unemployment (Sapsford and Jupp, 1996).

Statistical analysis of employment data can provide us a deep understanding of citizens' relationship with economic activity in that nation. However, in order to intensify statistical analysis of growth in employment rates, a large quantity of detailed data is required. That means statistical relationships which denote the nature of employment rate movements can only be derived by analyzing readily available aggregate data. In case a sufficiently long time series of employment rate is available, we can examine the extent of statistical dependence of rate movements by applying various techniques of statistical analysis (Dryden, 1969).

In this study, we are concentrated on analyses made through the valuation of employment growth in order to prevent the seasonal effects of the data and analyze growth cycles accurately. Such an analysis involves taking the logarithm of the data because the linear logarithmic function gives an adequate description of employment growth in range. Such an approach also makes us enable to make accurate predictions concerning the turning points of growth cycles in a country when employment growth and industrial production index growth are analyzed as a composite indicator in the following chapters of this study.

4.4 Properties of Industrial Production Index

Industrial production index is widely known as an economic indicator which measures the real growth rate in industrial production of a nation. The reference year for this index is determined according to the year 2002 and a level of %100. It represents the industrial capacity measure and the availability of resources among factories, utilities and mines (Chenery, 1960). The aim of this indicator is not to quantify the actual production level but to assess the average change in the value of production between two points of time. If the index is growing month-over-month for a particular industry, this is a sign that the companies in the industry are performing well.

It is known that the largest component of industrial output is generated by manufacturing and manufacturing itself is considered to be one of the major cyclical sectors of the economy. Thus, growth in industrial production plays a key role in defining turning points of a growth cycle. Furthermore, industrial production is a significant factor in cyclical changes in personal income growth since it leads employment in the high wage manufacturing sector.

Analysts and economists are generally interested in the change in the percent of the industrial production level rather than the level itself and how the industrial index evolves compared to the comprehended trend of the economy at that time (Schwab Center for Financial Research, 2007). A rise in the share of industrial output is generally interpreted as an increase in per capita income in a country. These interrelationships are the main features why growth in industrial production must be analyzed in a detailed way. Thus, in this study we will be concentrated on the industrial production index growth data which is also constructed as the logarithm of the indices as done in our analysis for employment growth.

In the next section, we apply Markov chain based time-dependence and time-homogeneity tests to these economic time series and reveal their characteristics for different countries. We also show how the results obtained via these applications enable us to detect the differences between economic performances of diverse nations.

Chapter 5

DETAILED EXPLANATION OF THE METHODOLOGY

As Zarnowitz (1992) indicates, growth cycle dates are derived from the observed consensus of the corresponding turning points in the deviations from the trend, whereas business cycle dates are derived from the consensus of the turning points in the levels of the same indicators. Thus, when examining a growth cycle, stochastic shifts between high and low growth states of the time series are taken into full account (Evans, Honkapohja, Romer; 1996).

In this study, we analyze capacity utilization and unemployment rates in order to visualize the difference in general economic performances of Turkey and United States. We also examine the cyclical behaviors of industrial production index growths in these countries in order to provide a basis to study the growth cycles of these economies.

5.1 Capacity Utilization Rates as an Economic Indicator

Application and Test Results

Time dependence and time homogeneity properties of capacity utilization permit us to understand the proceeding of this data accurately. Beyond, an efficient analysis of the pattern that capacity utilization rates have followed provides us useful information in overall economic performance and helps us understand the cyclical dynamics of an economy.

In this part of our study, we will be analyzing the time dependence and time homogeneity properties of capacity utilization rates of United States and Turkey and will compare the expected upcoming trends in these two countries.

Case 1: United States

When we observe the capacity utilization rates of United States in 1967-2009, we see that this stochastic process has not followed a particular trend (Figure 5.1). Thus, the Markov states for this time series are determined according to the average capacity utilization rate calculated for this time interval: In case the capacity utilization rate of a time period is higher than the average capacity utilization level, the process is said to be in state *U*; else, in state *D*.

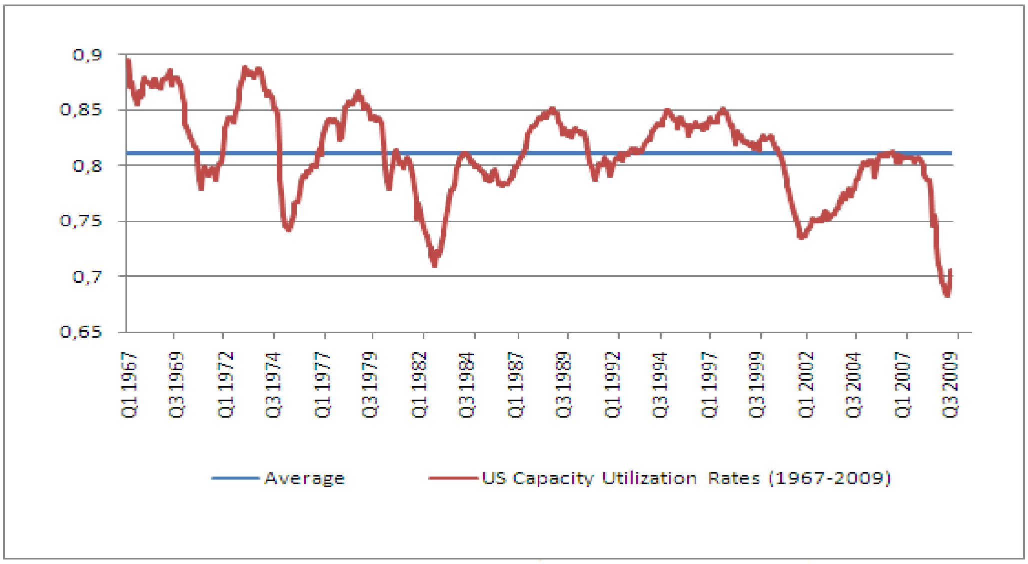

Figure 5.1: Capacity Utilization Rates of United States (1967-2009)

When the time dependence and time homogeneity tests are applied to capacity utilization rates of United States, we see that these rates follow a time homogenous second order Markov chain. Here is the transition probability matrix of capacity utilization rates which is obtained empirically when the time series is observed:

$$P = \begin{array}{c} \\ UU \\ DU \\ UD \\ DD \end{array} \begin{array}{c} \begin{array}{cccc} UU & DU & UD & DD \end{array} \\ \begin{bmatrix} 0.9753 & 0 & 0.0247 & 0 \\ 0.625 & 0 & 0.375 & 0 \\ 0 & 0.1111 & 0 & 0.8889 \\ 0 & 0.0279 & 0 & 0.9721 \end{bmatrix} \end{array} . \tag{5.1}$$

By using the analysis given in (5.1), we can find the expected first passage times between states U and D which are independent of the previous states by using the transition probability matrix above.

$$E[T_{UD}] = 39.93 \approx 40 \text{ Months}$$

$$E[T_{DU}] = 35.74 \approx 36 \text{ Months}$$

These results show that if the current capacity utilization rate of United States is above the average level, one can expect the rate to fall below the average in 40 months (nearly 3.5 years). An opposite change in pattern is expected to occur in 36 months (3 years). As it can be seen, the expected passage times to switch from expansion to contraction and from contraction to expansion are not the same. However, the difference between these two passage times is only 4 months which cannot be considered as extreme. That is why regardless of whether the current capacity utilization rate is below or above the average level, one should not expect a sharp change in capacity utilization rate trend of United States during 3 years unless there occurs an exceptional economical or industrial development or a crisis in macro levels.

Case 2: Turkey

When the capacity utilization rates of Turkey are observed in 1991-2009, we see that the seasonal effects are not removed from this historical data (Figure 5.2). This situation causes a conflict in our time dependence analysis as the result of the test will be misleading due to the existence of periodic trends in the aggregate data. Thus Markov chain based time dependence and time homogeneity tests are conducted on the seasonally adjusted capacity utilization rates of Turkey (Figure 5.3).

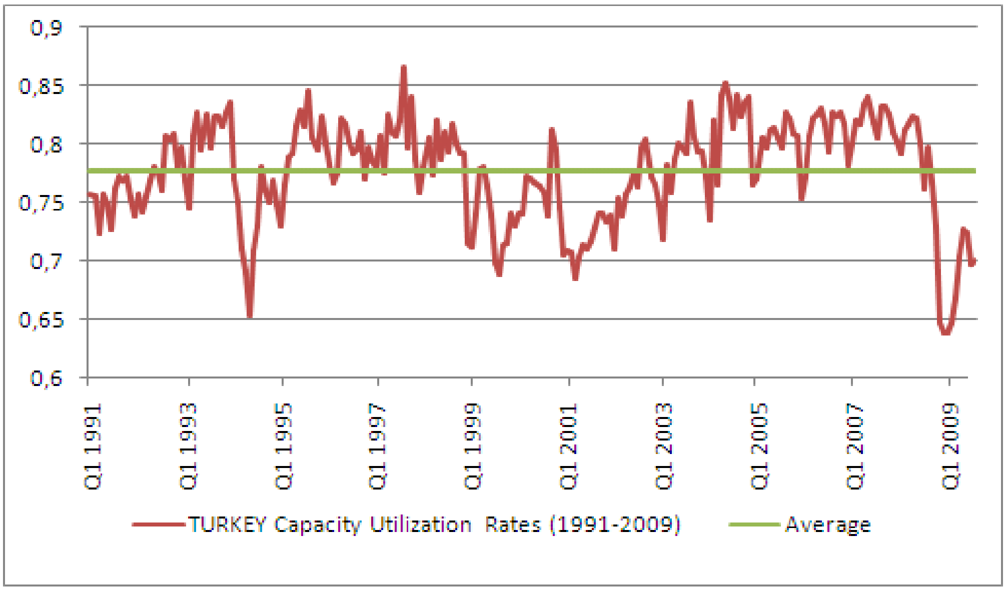

Figure 5.2: Capacity Utilization Rates of Turkey (1991-2009)
(Seasonally Unadjusted Data)

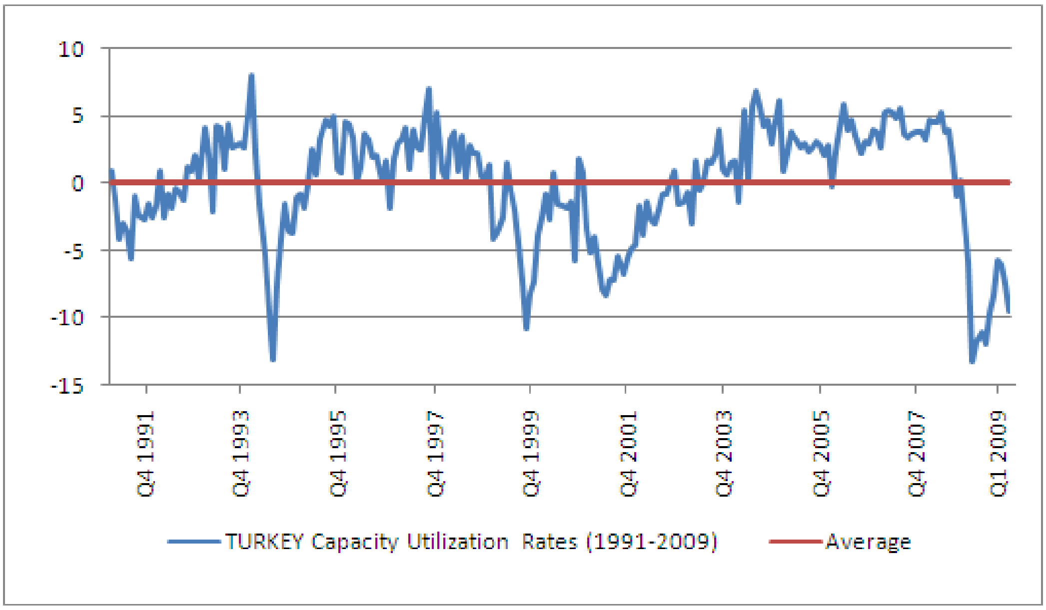

Figure 5.3: Capacity Utilization Rates of Turkey (1991-2008)
(Seasonally Adjusted Data)

As the capacity utilization rates of Turkey do not follow a particular trend either, *U* and *D* states are also determined with the respect to the historical average capacity utilization rate as done for the United States.

When time dependence and time homogeneity tests are applied to adjusted capacity utilization rates of Turkey, we see that this time series also follows a time homogeneous second order Markov chain with the transition probabilities indicated below.

$$P = \begin{array}{c} \\ UU \\ DU \\ UD \\ DD \end{array} \begin{array}{c} \begin{array}{cccc} UU & DU & UD & DD \end{array} \\ \begin{bmatrix} 0.9115 & 0 & 0.0885 & 0 \\ 0.625 & 0 & 0.375 & 0 \\ 0 & 0.4706 & 0 & 0.5294 \\ 0 & 0.1053 & 0 & 0.8947 \end{bmatrix} \end{array}$$

With the same method used for United States, it is also possible for capacity utilization data of Turkey to find the expected first passage times between states U and D. Numerical results give us:

$$E[T_{DU}] = 8.92 \approx 9 \text{ Months}$$

$$E[T_{UD}] = 10.89 \approx 11 \text{ Months.}$$

As noticed, the expected first passage time from capacity utilization rates which are below the average level to rates which are above this average (from state D to U) is nearly 4 times longer in United States than it is in Turkey. The same situation exists when the issue is to find the expected first passage time in reverse direction. In United States, when the current capacity utilization rate is above the average level, we expect this rate to fall below the average in 40 months while this period is expected to be 11 months in Turkey.

This difference shows that there is more stability in labor productivity and investment levels in United States as capacity utilization rates in this country are less likely to change in short time periods. In such a case, we can also say that in United States, slowdowns in economy and the upcoming effects of industrial developments on business activity are much easier to predict.

A General View of the Capacity Utilization Data

Second order time dependence of capacity utilization rates of both United States and Turkey prove that current capacity utilization rate concerning this month has effect not only on the capacity utilization movement of the next month but also the following month. As long as we have information about the capacity utilization levels of the past two months, efficient estimation about capacity utilization rate of the next month is also available for these countries.

In the big picture, we see that both in Turkey and in United States, if the capacity utilization rates of the last two months are both above/below the average level, the rate does not tend to display an enormous change and fall below/rise above the average level for the next month.

Validation and Accuracy of Results

In order to show the efficiency of our approach and the accuracy of our results, we conducted a validation study by using the capacity utilization data of United States.

During our validation study, first we examine the capacity utilization series of United States in 1967-2009 (Figure 5.1) and determine when peaks and troughs are observed in the historical data (Table 5.1). Then, we calculate the average passage times between peaks and troughs of this series during the time period we analyze. The aim is to see if these passage times between peaks and troughs which we calculate by observing the historical data are consistent with the estimated passage times between states *U* and *D* we obtain by our Markovian approach.

Table 5.1: Observed Turning Points in Capacity Utilization Cycle of United States

Trough	-	11/1970	05/1975	12/1982	01/1992	02/2002	06/2009
Peak	01/1967	11/1973	12/1978	01/1989	12/1994	08/2006	-

Based on the recorded turning points in Table 5.1, we see that the average passage time from a peak to a trough in capacity utilization series of United States is 44.5 months while a reverse passage is 48.4 months on average. In Table 5.2, we can see both the estimated passage times and the observed average passage times obtained by observation of the historical capacity utilization data.

Table 5.2: Average Observed and Estimated Passage Times for United States Data

United States Capacity Utilization Series	**Peak-Trough** $E[T_{UD}]$	**Trough-Peak** $E[T_{DU}]$
Estimated Passage Times	39.93 months	35.74 months
Observed Passage Times	44.50 months	48.40 months

As seen in the table, the observed passage times between peaks and troughs of United States capacity utilization series are very close to the estimated first passage times between states U and D obtained by our methodology. The similar results show that our predictions are consistent with the historical data.

5.2 Industrial Production Index Growth as an Economic Indicator

Application and Test Results

As emphasized in previous sections, growth in industrial production index is a better indicator than the index itself and should be taken into consideration when analyzing growth cycles. Time dependence and time homogeneity properties of “changes” in industrial production index can provide us knowledge about how growth cycles evolve. Industrial production index growth can be obtained by logarithmic differences of industrial production indices for the same quarter of each respective two years. Such approach also provides the removal of seasonal effects from the industrial production index data.

Case 1: United States

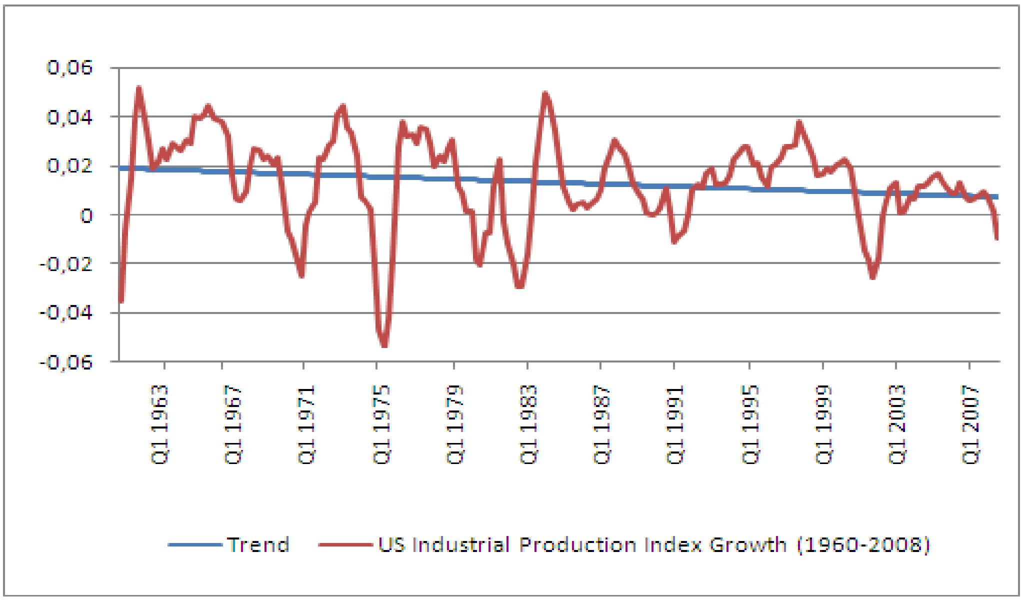

Figure 5.4: Industrial Production Growths of United States (1960-2008)

In contrast to capacity utilization rates of United States, we see that industrial production index growths follow a particular trend in 1960-2008. Thus, the states *U* and *D* are determined with respect to this trend instead of an average growth level. If the growth recorded in a quarter is above the growth trend of industrial production index, then the process is said to be in state *U*; otherwise, in state *D*.

When the time dependence and time homogeneity tests are applied to industrial production index growths of United States, we see that these rates follow a time homogeneous first order Markov chain.

Here is indicated the transition probability matrix of industrial production index growths which is obtained via the historical data:

$$P = \begin{array}{c} \\ U \\ D \end{array} \begin{array}{c} \begin{array}{cc} U & D \end{array} \\ \begin{bmatrix} 0.8929 & 0.1071 \\ 0.1538 & 0.8462 \end{bmatrix} \end{array}$$

This transition probability matrix implies:

$$E[T_{UD}] = 9.337 \approx 10 \text{ Quarters}$$

$$E[T_{DU}] = 6.5 \approx 7 \text{ Quarters.}$$

Case 2: Turkey

When the time dependence test is applied to industrial production index growths of Turkey, we obtain the result that the series follow a first order Markov chain. Whereas, the time homogeneity test result indicates that the transition probability matrix of this stochastic process is not stationary when the data is examined in two subintervals, which means the first order time dependence of growth series cannot be directly accepted. In such case, the breakpoint in the historical pattern of industrial production index growths of Turkey must be detected. Only with such approach, an effective and healthy analysis is enabled.

As known, the Turkish economy was hit by two crises in the last two decades, one of which occurred in 1994 and the second in 2001. The 1994 crisis may be thought as due to the 1994 Currency Crisis which caused the highest level of annual output loss in the history of the Turkish Republic. In the first quarter of 1994, Turkish Lira was devalued more than 50% against USD, the Central Bank lost half of its reserves, interest rates increased enormously and inflation reached three digit levels (Celasun, 1998). On the other hand, the second crisis in 2001 was preceded by a chaos that appeared suddenly in the second half of November 2000 in the middle of an exchange rate based stabilization program. Since December 2000, the average interest rates were almost four times higher than their levels defined at the beginning of November and more than five times higher than the pre-announced year-end depreciation rate of the lira (Özatay and Sak, 2002).

In this frame, both 1994 and 2001 may be considered as breakpoints in the Turkish economy. However, the analyses show that during the time period 1994-2008, homogeneous behavior of industrial production index growth is not observed. This observation leads us to find another breakpoint in 1994-2008 as time homogeneity of the time interval we analyze is indispensable.

In such case, we consider November 2001 Crisis as the potential breakpoint in the pattern followed by industrial production index growths of Turkey and divide the whole time series into two subintervals (1994-2001 and 2002-2008). In case we conduct the Markov chain based time dependence and time homogeneity tests, we see that industrial production index growths of Turkey follow a homogeneous Markov chain in both subintervals. This result leads us to analyze the time dependence and time homogeneity properties of industrial production index growths in 1980-2001 and 2002-2008 separately (Figure 5.5).

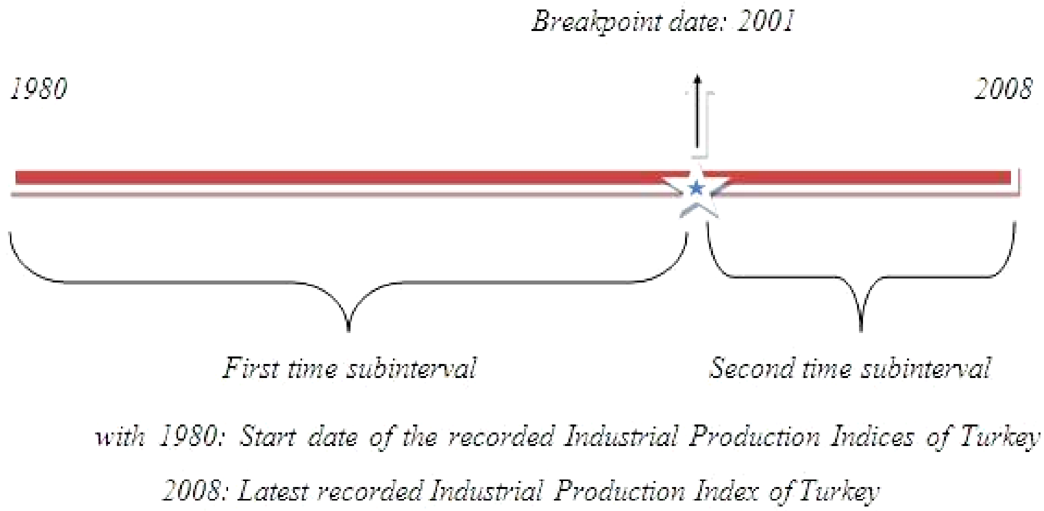

Figure 5.5: Analysis of Industrial Production Index Growth of Turkey in Two Subintervals

Here as illustrated above, the whole time interval is separated by 2001 crisis and Markov chain based time dependence and time homogeneity tests are applied to both of these time intervals. As no specific trend is followed during each of these subintervals, the average industrial production index growth is once more taken as the reference level to define when the process is in state *U* and *D*. However, in this case, the average industrial production index growth is specified for each subinterval separately. Such an approach is necessary as these time intervals should be considered as independent stochastic processes which may display different time dependence properties.

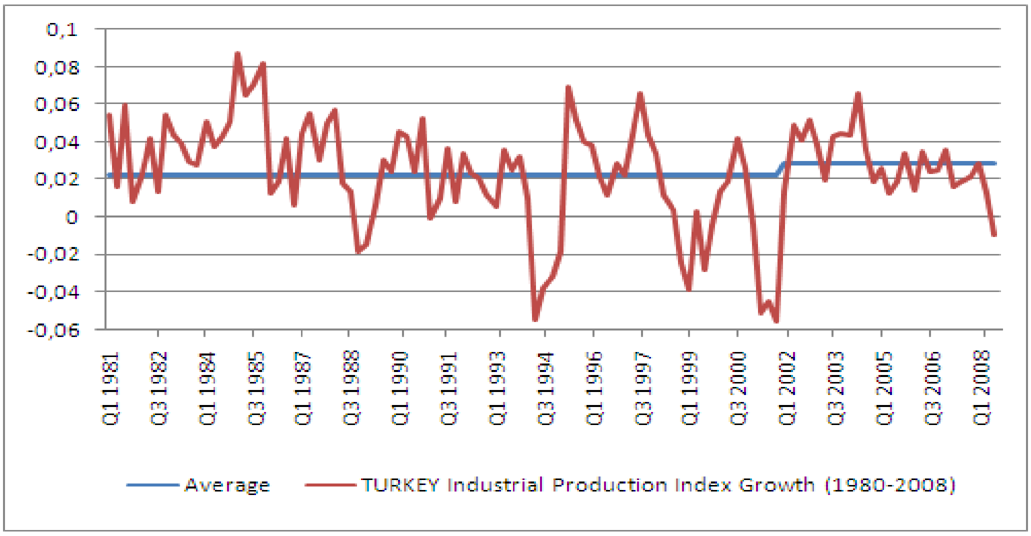

Figure 5.6: Industrial Production Index Growths of Turkey (1980-2008)

The test results show that industrial production index growths of Turkey follow homogeneous first order Markov chain in 1980-2001. The probability matrix for this first subinterval is as indicated below:

$$P = \begin{array}{c} \\ U \\ D \end{array} \!\!\begin{array}{c} \begin{array}{cc} U & \quad D \end{array} \\ \begin{bmatrix} 0.6957 & 0.3034 \\ 0.3514 & 0.6486 \end{bmatrix} \end{array}.$$

Estimated passage times between states U and D are also as:

$$E[T_{UD}] = 3.28 \approx 4 \text{ Quarters}$$

$$E[T_{UD}] = 2.84 \approx 3 \text{ Quarters}.$$

On the other hand, we see that the industrial production index growth of Turkey follows a random walk during 2002-2008, which means the growth of the current quarter is independent from the growth of the last quarter. Such result also shows that the information about the industrial production index growth of this quarter does not provide any information when estimating the change in industrial production growth of the next quarter. The transition probability matrix and the estimated first passage times between states *U* and *D* for this subinterval is as:

$$\begin{array}{cc} U & D \end{array}$$

$$P = \begin{bmatrix} 0.4815 & 0.5185 \end{bmatrix}$$

$$E[T_{UD}] = 1.92 \approx 2\,\text{Quarters}$$

$$E[T_{UD}] = 2.07 \approx 2\,\text{Quarters.}$$

We see that the estimated passage times between states *U* and *D* are much shorter for this time interval. This shows that the industrial production index growth of Turkey is much less predictable in 2002-2008 as a result of the time independence of the increments of this series.

A General View of the Industrial Production Growth Series

First order time dependence of industrial production index growth series in United States show that it is possible to make predictions about future growth levels by observing the most recent growth behavior. Our analyses also show that in United States, imitational behavior of industrial production index growth is highly observed. This may be due to the fact that United States has an economy with fairly constant output growth and low and stable inflation. On the other hand, we see that such imitational behavior is not observed in Turkey in 2002-2008.

Figure 5.7 and Figure 5.8 display the different growth behaviors of industrial production index of United States and Turkey. Let $P(T_{ij} < t)$ denote the probability that the first passage time from state i to state j is smaller than t quarters. Thus $P(T_{UD} < t)$ represents the probability that, starting in state *U*, the first passage into state *D* will be observed in *t* quarters and similarly; $P(T_{UD} < t)$ signifies the probability to observe the first passage into state *U* in *t* quarters when starting from state *D*.

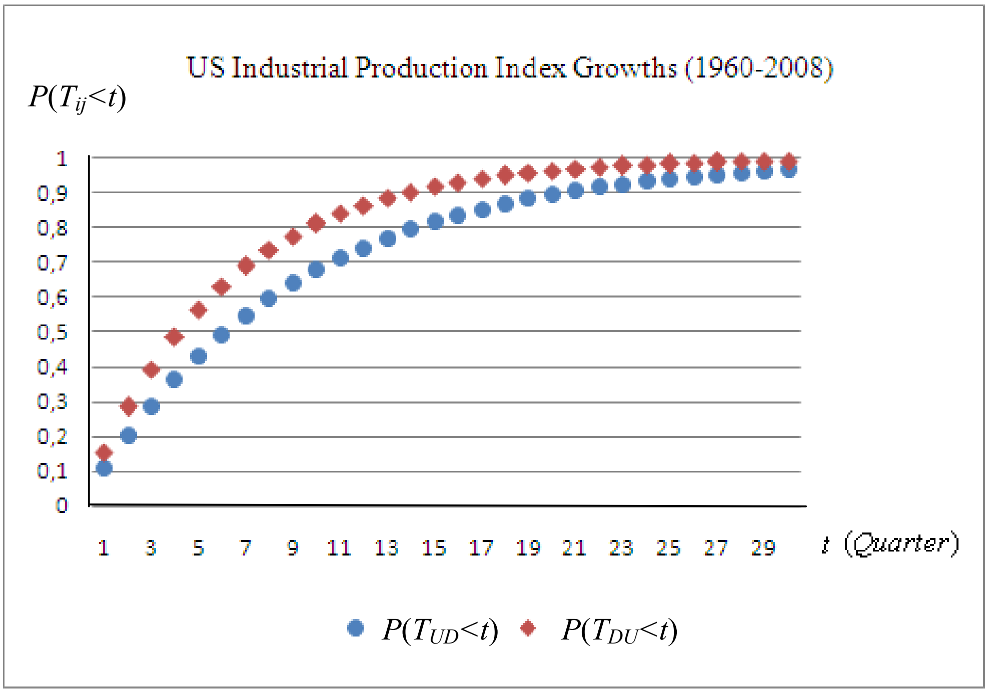

Figure 5.7: $P(T_{UD} < t)$ and $P(T_{DU} < t)$ Values for Industrial Production Index Growths of United States (1960-2008)

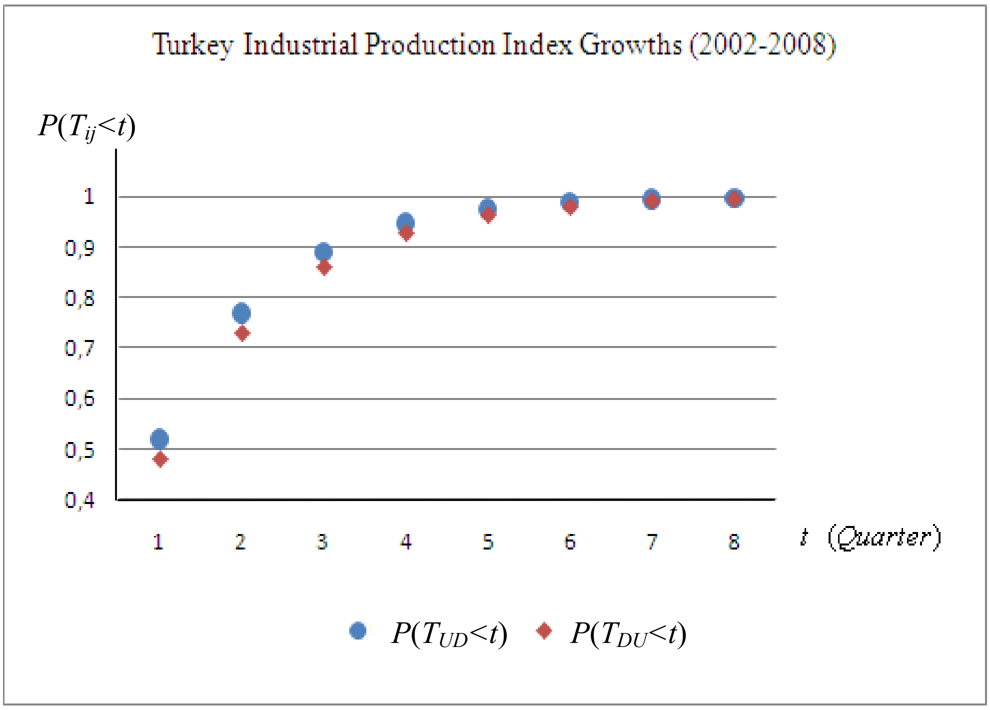

Figure 5.8: $P(T_{UD} < t)$ and $P(T_{DU} < t)$ Values for Industrial Production Index Growths of Turkey (2002- 2008)

In Figure 5.8, we see the probability that a first passage between states *U* and *D* will be observed in 5 quarters is more than 90% for industrial production index growth series of Turkey while this probability is less than 60% for United States. What is more, we expect to observe a passage between states *U* and *D* at most in 8 quarters for Turkey, while there is still a probability about %2 that a sharp change in industrial production index growth behavior of United States will not be observed in 28 quarters (7 years).

With the help of interdependence between industrial production index growths, one can make predictions for the upcoming quarter about the rises in manufacturing industry and the change in the sources of supply which are used for the production of commodities. As an increase in industrial production index growth in industrialized countries can also be considered as a sign of an increase in the average income, possible growth in economy and higher investments can be expected.

Validation and Accuracy of Results

In the following chapters of this study, we will have made thorough analyses of industrial production index growth of various countries one of which is Australia. In order to prove the validation of our studies on growth of this index, we choose to observe industrial production index growths of this country as this time series follows short time trends and includes numerous fluctuations (Figure 5.9). In this part of our study, we will see that our predictions are consistent with the historical data even when the series does not follow a smooth pattern.

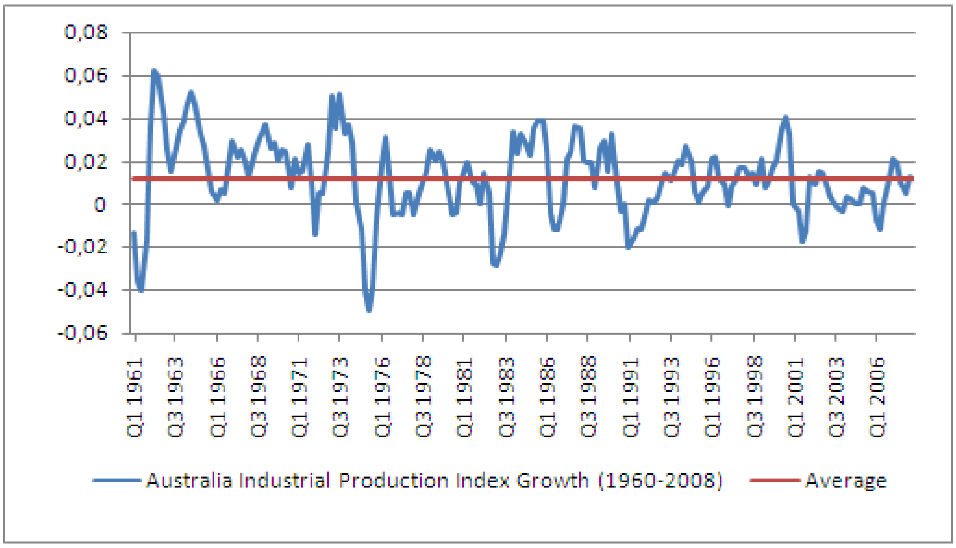

Figure 5.9: Industrial Production Index Growths of Australia (1960-2008)

Here in Table 5.3, the recorded turning points of industrial production index growths of Australia can be seen.

Table 5.3: Recorded Turning Points of Industrial Production Index Growths of Australia

Peak	-	Q2/1962	Q1/1969	Q3/1971	Q3/1973	Q2/1976	Q1/1979	Q2/1981
Trough	Q3/1961	Q1/1966	Q3/1970	Q1/1972	Q2/1975	Q4/1976	Q3/1980	Q1/1982

Peak	Q2/1982	Q4/1985	Q4/1987	Q1/1990	Q2/1993	Q3/1994	Q2/1996	Q3/1998
Trough	Q1/1983	Q4/1986	Q1/1989	Q1/1991	Q3/1993	Q2/1995	Q1/1997	Q4/1998

Peak	Q1/1999	Q3/2000	Q1/2002	Q3/2002	Q1/2007	Q1/2008
Trough	Q2/1999	Q3/2001	Q2/2002	Q2/2006	Q4/2007	-

When we compare the observed passage times and the estimated first passage times obtained by our methodology, we see once more that our predictions are in agreement with the historical data of industrial production index growths of Australia (Table 5.4).

Table 5.4: Average Observed and Estimated Passage Times for Australia Data

Australia Industrial Production Index Growths	**Peak-Trough** $E[T_{UD}]$	**Trough-Peak** $E[T_{DU}]$
Estimated Passage Times	4.61 quarters	4.38 quarters
Observed Passage Times	4.45 quarters	4.52 quarters

Hence, we can say that the Markovian approach we have been using in this study gives us consistent and accurate results also when analyzing the growth of economic indicators. Thus, our study now can be developed by making the same analyses for various countries to compare the future trends of industrial production index and employment growths.

5.3 Unemployment Rates as an Economic Indicator

Application and Test Results

When the time dependence and time homogeneity tests are applied to the unemployment rates of United States seen in Figure 5.10, we obtain some interesting results which enable us have information about the labor supply and labor trends of United States in 1948-2009. This application also enables us to compare our results with the assumptions which are indicated in the study of Neftci (1984) concerning the stationary and time dependence of unemployment rates of United States in 1959-1978.

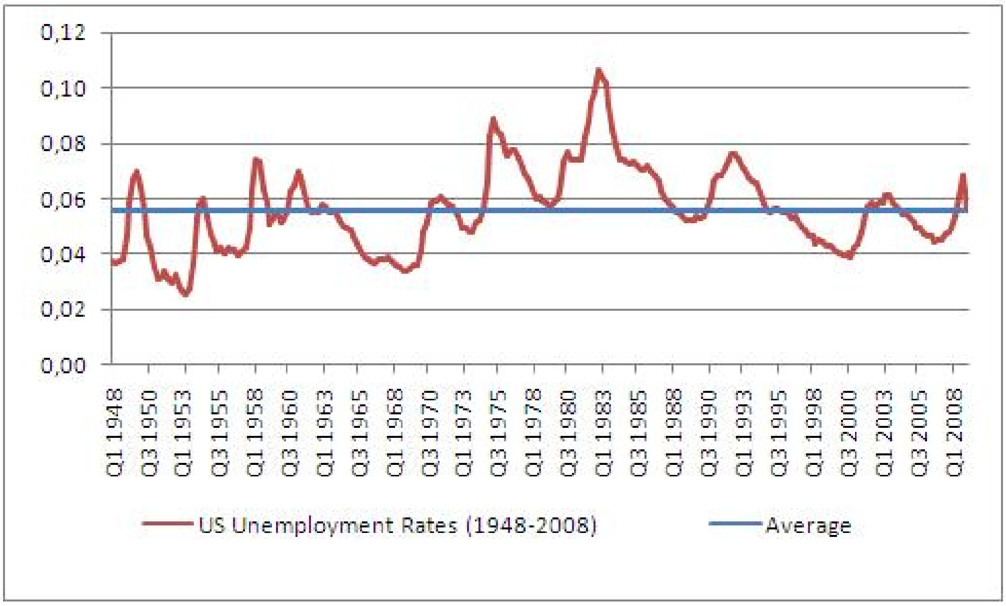

Figure 5.10: Unemployment Rates of United States (1948-2008)

During our analyses, states U and D are also determined with respect to the average unemployment rate of United States in 1948-2008 as these unemployment rates do not follow a trend during the time interval in question (Figure 5.10). The time dependence and time homogeneity tests show that the quarterly unemployment rates of United States in 1948-2008 is a homogeneous stochastic process following a first order Markov chain. The empirical probability transition matrix concerning the frequency of transitions between states U and D is as:

$$P = \begin{array}{c} \\ U \\ D \end{array} \begin{array}{c} \begin{array}{cc} U & D \end{array} \\ \begin{bmatrix} 0.9027 & 0.0973 \\ 0.0923 & 0.9077 \end{bmatrix} \end{array}.$$

The expected passage times between states U and D are also defined as:

$$E[T_{UD}] = 1.1077 \text{ Quarters}$$
$$E[T_{DU}] = 1.1016 \text{ Quarters}.$$

Neftci (1984) also examines the behavior of quarterly unemployment rate data of United States in 1959-1978 by using the statistical theory of finite state Markov processes in order to discover whether the unemployment rates display an asymmetric behavior or not. As mentioned in that article, there are several reasons why the applications are limited to unemployment series. First of all, Neftci believes that economic time series like unemployment data which are related to the production side give a better indication of business cycles. Furthermore, the unemployment rates data allow him to use either monthly or quarterly data, as indicated in his paper.

In his study, Neftci (1984) assumes that the quarterly unemployment rate movements follow a second order Markov chain. During the application, he also supposes that the unemployment rate movements are stationary. This claim leads us to the thought that there are no breakpoints during these years and the labor trend does not show up a very sharp change. On the other hand, Neftci does not use any time homogeneity or time dependence tests in order to justify these assumptions. Our aim in this study is to provide a basis in order to see if these assumptions are reliable or not. When it is considered that Neftci uses the unemployment rates in 1959-1978, the properties of the unemployment rates of this time interval should be examined distinctly from the whole interval.

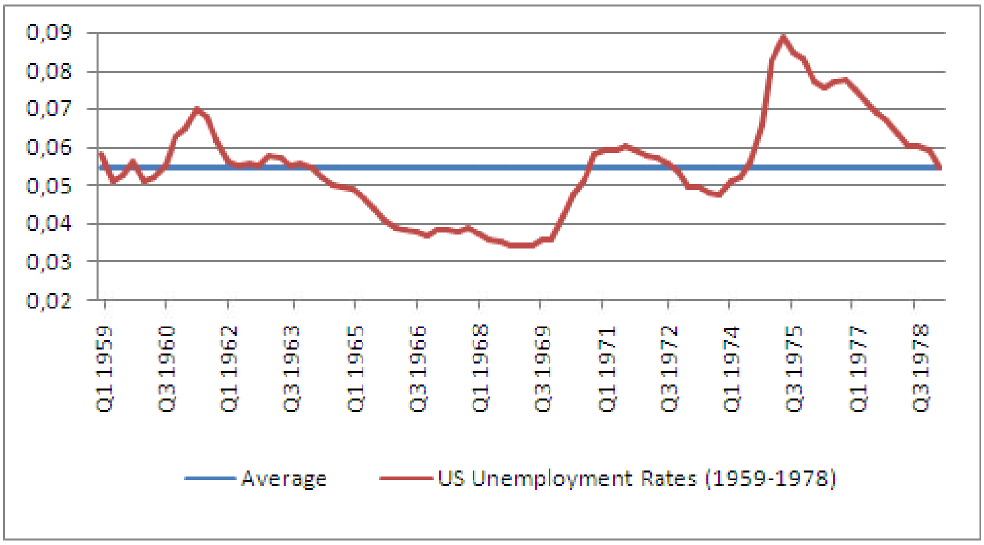

Figure 5.11: Unemployment Rates of United States (1959-1978)

The time dependence tests show that the unemployment rate movements in 1959-1978 follow a stochastic process of first order Markov chain with the empirical probability transition matrix defined as below:

$$P = \begin{array}{c c} & \begin{array}{cc} U & D \end{array} \\ \begin{array}{c} U \\ D \end{array} & \begin{bmatrix} 0.9024 & 0.0976 \\ 0.1053 & 0.8947 \end{bmatrix} \end{array}.$$

The expected passage times between these states are also indicated as:

$$E[T_{UD}] = 1.1081 \text{ Quarters}$$
$$E[T_{DU}] = 1.1176 \text{ Quarters.}$$

Time homogeneity test result we conduct also shows that there exists no breakpoint in the unemployment series of United States in 1959-1978. Thus, the assumption used by Neftci (1984) that this process is time homogeneous is validated by our approach. However, as seen, the time dependence test we apply to this time series gives us a different result than the assumption used by Neftci (1984): Our results show that this series follow a first order Markov chain while Neftci assumes that the unemployment rate in 1959-1978 follow a stochastic process of a second order chain.

The statistical analysis of unemployment rates should be considered as a key to evaluate the current and future performance of the economy. As long as the dependence of unemployment rates is proven, we can make predictions about future labor trends and long-term planning of facilities. Thus, detailed and systematic study of economic time series like unemployment rates is indispensable to make accurate predictions about the future economic performance of a nation. In this case, we suggest using Markov chain based time dependence and time homogeneity tests in order to derive statistical properties of patterns these economic time series follow. We believe Markov chain based testing methodology provides us better information about statistical properties of economic time series other than assumptions which are put forward without approval.

Chapter 6

ANALYSES OF BUSINESS CYCLES IN 24 COUNTRIES

6.1 Overview of Approach

In this part of our study, we analyze the time-homogeneity and time-dependence properties of industrial production growths and employment growths of 24 countries playing key roles in the dynamic global economy.

While revealing these properties, homogeneity of these time series' behaviors is a very important issue for our analysis as indicated before. Thus, we may need to divide the whole data into subintervals and search for the properties of these time series separately if homogeneity cannot be obtained for the whole time period we analyze. In order to achieve accurate results about the future tendencies of industrial production index growth and employment growth of each country, diligent analysis of each time interval where homogeneity can be obtained is absolutely needed.

During the analyses of these countries, we came across with such homogeneity problems. For some countries, these time series did not follow a particular trend during the whole time period and obviously changed their behaviors and started to follow a brand new pattern depending upon replaced economical and political institutions which constituted "breakpoints". The detection of these breakpoints has been enabled by diligent analysis of not only economic but also political history of the countries in question.

Thus, these subintervals defined by:

- First time interval: Start of the recorded historical data - Breakpoint date
- Second time interval: Breakpoint date- Latest recorded data date

For a meticulous analysis, Markov chain based time-dependence and time-homogeneity tests should be applied to both of these subintervals in case a breakpoint exists. With respect to the test results, the transition probabilities between different levels of industrial production index growths and employment growths for each subinterval can be determined and thus be used to detect the behaviors of these economic indicators in both time periods. In cases when homogeneous behavior of the time series for both subintervals cannot be accepted, taking another breakpoint as a reference should be considered.

In this analysis, when homogeneity cannot be obtained for the whole time period, the behavior of the time series during the *second time interval* is taken into consideration in order to predict their future pattern. That is via to the fact that recent data is more informative about the latest trends of a pattern that an economic time series follow. As a result of this approach, the beginning years of our analysis for each county may differ.

6.2 Analysis Results of Industrial Production Index and Employment Growth

In this part of our study, we share the acquired transition probabilities and expected passage times between peaks and troughs of industrial production index and employment growths of each country as shown in Table 6.1 and Table 6.2. The beginning year of analyzed data for each country is also indicated in the first columns of the tables.

Table 6.1: Transition Probabilities and Estimated Passage Times Between Peaks and Troughs of Industrial Production Index Growths

COUNTRIES	Beginning Year	Order	Probabilities p_{UU}	p_{UD}	p_{DU}	p_{DD}	Expected Passage Times (Quarters) E[UD]	E[DU]
AUSTRALIA	1960	1	0.7835	0.2165	0.2283	0.7717	4.6189	4.3802
CANADA	1980	1	0.8545	0.1455	0.1481	0.8519	6.8728	6.7521
USA	1960	1	0.8929	0.1071	0.1538	0.8462	9.337	6.5000
JAPAN	1993	1	0.8158	0.1842	0.2917	0.7083	5.4288	3.4281
GERMANY	1960	1	0.8300	0.1700	0.1910	0.8090	5.8823	5.2356
ITALY	1960	1	0.7978	0.2022	0.1700	0.8300	4.9455	5.8823
FRANCE	1960	1	0.7957	0.2043	0.1875	0.8125	4.8947	5.3333
FINLAND	1960	1	0.7419	0.2581	0.2371	0.7629	3.8744	4.2176
SINGAPORE	1966	1	0.8317	0.1683	0.2462	0.7538	5.9417	4.0617
S.KOREA	1980	1	0.6800	0.3200	0.2667	0.7333	3.125	3.7495
PHILIPPINES	1981	1	0.7045	0.2955	0.2500	0.7500	3.3841	4.0000
MEXICO	1995	1	0.8387	0.1613	0.2273	0.7727	6.1996	4.3994
CHILE	1960	1	0.8689	0.1311	0.2576	0.7424	2.8336	3.6670
MALAYSIA	1998	1	0.8182	0.1818	0.2000	0.8000	5.5005	5.0000
TURKEY	2002	0	0.4815	0.5185	0.4815	0.5185	1.9286	2.0768
S.AFRICA	1983	1	0.8519	0.1481	0.1915	0.8085	6.7521	5.3333
CHINA	1992	1	0.6667	0.3333	0.2917	0.7083	3.0003	3.4281
ARGENTINA	1997	1	0.8788	0.1212	0.1739	0.8261	8.2508	5.7504
SPAIN	1960	1	0.8642	0.1358	0.0962	0.9038	7.3638	10.3950
NETHERLANDS	1963	2		*(1)			6.7305	6.3145
UK	1960	2		*(2)			5.2335	4.1110

(*1)

$$\begin{array}{cc} & \begin{array}{cccc} UU & DU & UD & DD \end{array} \\ \begin{array}{c} UU \\ DU \\ UD \\ DD \end{array} & \begin{bmatrix} 0.8592 & 0 & 0.1408 & 0 \\ 0.5882 & 0 & 0.4118 & 0 \\ 0 & 0.25 & 0 & 0.75 \\ 0 & 0.1558 & 0 & 0.8442 \end{bmatrix} \end{array}$$

(*2)

$$\begin{array}{cc} & \begin{array}{cccc} UU & DU & UD & DD \end{array} \\ \begin{array}{c} UU \\ DU \\ UD \\ DD \end{array} & \begin{bmatrix} 0.8235 & 0 & 0.1765 & 0 \\ 0.5217 & 0 & 0.4783 & 0 \\ & 0.1304 & & 0.8696 \\ & 0.2533 & & 0.7467 \end{bmatrix} \end{array}$$

Table 6.2: Transition Probabilities and Estimated Passage Times Between Peaks and Troughs of Employment Growths

COUNTRIES	Beginning Year	Order	Probabilities				Expected Passage Times (Quarters)	
			p_{UU}	p_{UD}	p_{DU}	p_{DD}	E[UD]	E[DU]
AUSTRALIA	1978	1	0.8919	0.1081	0.1739	0.8261	9.2506	5.7504
CANADA	1960	1	0.8283	0.1717	0.1828	0.8172	5.8241	5.4704
USA	1960	1	0.8761	0.1239	0.1772	0.8228	8.0710	5.6433
JAPAN	1993	1	0.8108	0.1892	0.2222	0.7778	5.2854	4.5004
GERMANY	1962	1	0.8913	0.1087	0.1209	0.8791	9.1996	8.2713
ITALY	1993	1	0.9118	0.0882	0.1111	0.8889	11.3378	9.0009
UK	1975	1	0.9438	0.0562	0.1064	0.8936	17.7935	9.3984
FRANCE	1980	1	0.8269	0.1731	0.1525	0.8475	5.7770	6.5574
SPAIN	1980	1	0.9565	0.0435	0.0714	0.9286	22.9885	14.0056
NETHERLANDS	1984	1	0.8222	0.1778	0.1633	0.8367	5.6243	6.1236
ARGENTINA	2002	1	0.9333	0.0667	0.0833	0.9167	14.9925	12.0048
CHILE	1999	1	0.6471	0.3529	0.2727	0.7273	2.8336	3.6670
MEXICO	2000	0	0.6250	0.3750	0.6250	0.3750	2.6666	1.6000
VENEZUELA	1988	1	0.6829	0.3171	0.3421	0.6579	3.1535	2.9231
S.KOREA	1983	1	0.8571	0.1429	0.1818	0.8182	6.9979	5.5006
TURKEY	2000	0	0.5455	0.4545	0.5455	0.4545	2.2002	1.8331
S. AFRICA	1970	1	0.8209	0.1791	0.1294	0.8706	5.5834	7.7280
PHILIPPINES	1990	1	0.6471	0.3529	0.3333	0.6667	2.8337	3.0030
MALAYSIA	1997	0	0.4889	0.5111	0.4889	0.5111	1.9565	2.0454
CHINA	1999	1	0.8667	0.1333	0.1111	0.8889	7.5019	9.0009
FINLAND	1992	2		*(3)			8.9018	6.3333
TAIWAN	1988	2		*(4)			5.7721	5.1574

*(3):

$$P = \begin{array}{c} \\ UU \\ DU \\ UD \\ DD \end{array} \begin{array}{c} \begin{array}{cccc} UU & DU & UD & DD \end{array} \\ \begin{bmatrix} 0.8947 & 0 & 0.1053 & 0 \\ 0.8 & 0 & 0.2 & 0 \\ 0 & 0.75 & 0 & 0.25 \\ 0 & 0.125 & 0 & 0.875 \end{bmatrix} \end{array}$$

*(4):

$$P = \begin{array}{c} \\ UU \\ DU \\ UD \\ DD \end{array} \begin{array}{c} \begin{array}{cccc} UU & DU & UD & DD \end{array} \\ \begin{bmatrix} 0.8378 & 0 & 0.1622 & 0 \\ 0.5556 & 0 & 0.4444 & 0 \\ 0 & 0.5 & 0 & 0.5 \\ 0 & 0.1739 & 0 & 0.8261 \end{bmatrix} \end{array}$$

By using the transition probabilities given in Table 6.1 and Table 6.2. we can also define the probabilities $P(T_{UD} \leq t)$ and $P(T_{DU} \leq t)$ in terms of different number of t values. Thus. the probabilities of observing a passage from a peak to a trough or vice-versa in t quarters for both industrial production index and employment growth series of diverse countries can be acquired (Table 6.3 and Table 6.4).

Table 6.3: $P(T_{UD} \leq t)$ and $P(T_{DU} \leq t)$ values for t=2,4 and 8 quarters for Industrial Production Index Growth Series of Different Countries

IPI Growths	Probabilities					
COUNTRIES	$P(T_{UD} \leq 2)$	$P(T_{DU} \leq 2)$	$P(T_{UD} \leq 4)$	$P(T_{DU} \leq 4)$	$P(T_{UD} \leq 8)$	$P(T_{DU} \leq 8)$
AUSTRALIA	0.3861	0.4044	0.6231	0.6453	0.8579	0.8742
CANADA	0.2698	0.2742	0.4668	0.4733	0.7157	0.7225
JAPAN	0.3344	0.4983	0.5570	0.7483	0.8038	0.9366
SINGAPORE	0.3082	0.4317	0.5215	0.6771	0.7710	0.8957
MEXICO	0.2965	0.4029	0.5052	0.6435	0.7551	0.8729
KOREA	0.5376	0.4622	0.7861	0.7108	0.9542	0.9163
CHINA	0.5555	0.4983	0.8024	0.7483	0.9609	0.9366
GERMANY	0.3111	0.3455	0.5254	0.5716	0.7747	0.8160
FRANCE	0.3668	0.3398	0.5991	0.5641	0.8393	0.8100
ITALY	0.3635	0.3111	0.5948	0.5254	0.8358	0.7747
FINLAND	0.4495	0.4179	0.6970	0.6612	0.9082	0.8852
MALAYSIA	0.3305	0.3600	0.5518	0.5904	0.7991	0.8322
PHILIPPINES	0.5036	0.4375	0.7536	0.6835	0.9390	0.8998
S. AFRICA	0.2742	0.3398	0.4733	0.5641	0.7225	0.8100
CHILE	0.2450	0.4488	0.4299	0.6962	0.6750	0.9077
TURKEY	0.7681	0.7311	0.9462	0.9277	0.9971	0.9947
USA	0.2027	0.2839	0.3643	0.4872	0.5959	0.7371
NETHERLANDS	0.3067	0.3010	0.4882	0.5018	0.7211	0.7470
UK	0.3847	0.4116	0.5827	0.6719	0.8081	0.8980
SPAIN	0.2532	0.1831	0.4422	0.3327	0.6889	0.5548
ARGENTINA	0.2277	0.3176	0.4036	0.5343	0.6443	0.7831

Table 6.3: $P(T_{UD} \leq t)$ and $P(T_{DU} \leq t)$ values for t=2,4 and 8 quarters for Employment Growth Series of Different Countries

Employment Growths	Probabilities					
COUNTRIES	$P(T_{UD} \leq 2)$	$P(T_{DU} \leq 2)$	$P(T_{UD} \leq 4)$	$P(T_{DU} \leq 4)$	$P(T_{UD} \leq 8)$	$P(T_{DU} \leq 8)$
AUSTRALIA	0.2045	0.3176	0.3672	0.5343	0.5996	0.7831
CANADA	0.3139	0.3322	0.5293	0.5540	0.7784	0.8011
JAPAN	0.3426	0.3950	0.5678	0.6340	0.8132	0.8660
MEXICO	0.6094	0.8594	0.8474	0.9802	0.9767	0.9996
KOREA	0.2654	0.3305	0.4603	0.5518	0.7088	0.7991
CHINA	0.2488	0.2099	0.4357	0.3757	0.6816	0.6102
UK	0.1092	0.2015	0.2065	0.3624	0.3704	0.5934
GERMANY	0.2056	0.2272	0.3689	0.4028	0.6017	0.6433
FRANCE	0.3162	0.2817	0.5325	0.4841	0.7814	0.7339
ITALY	0.1686	0.2099	0.3088	0.3757	0.5223	0.6102
NETHERLANDS	0.3240	0.2999	0.5430	0.5099	0.7912	0.7598
SPAIN	0.0851	0.1377	0.1630	0.2564	0.2994	0.4471
MALAYSIA	0.7610	0.7388	0.9429	0.9318	0.9967	0.9953
PHILIPPINES	0.5813	0.5555	0.8247	0.8024	0.9693	0.9610
S. AFRICA	0.3261	0.2421	0.5459	0.4255	0.7938	0.6700
ARGENTINA	0.1290	0.1597	0.2413	0.2938	0.4243	0.5013
CHILE	0.5813	0.4710	0.8247	0.7202	0.9693	0.9217
VENEZUELA	0.5336	0.5672	0.7825	0.8127	0.9527	0.9649
TURKEY	0.7024	0.7934	0.9115	0.9573	0.9922	0.9982
US	0.2324	0.3230	0.4109	0.5417	0.6529	0.7899

6.3 Economical and Political Institutions Evolutions Effecting Nations' Economies

In this part of our study. we focus on the economical and political institutional changes observed in these countries which are meaningful in order to define the breakpoints of industrial production index growth and employment growth data.

AUSTRALIA. CANADA and USA: Markov chain based time-homogeneity test results show that both industrial production index growths and employment growths of Australia, Canada and USA are homogeneous when the time intervals are considered in two periods. This may be due to the existence of stable economies and political systems in these three countries. Moreover. industrial production index growth behaviors of USA and Canada, as two examples of stable and strong economies compared to the South America and Asia, show similarities as seen in the transition probabilities segment of the tables above.

JAPAN: Markov chain based time homogeneity test shows that industrial production index growth and employment growth of Japan do not follow a homogeneous pattern when the time intervals 1960-2008 are considered as two equal subintervals.

Based on his preliminary examinations, Meltzer (2001) claims that there occurred two types of change in Japan in the 1990s: The maintained growth rate of Japan slowed and Japan's cost of production rose relative to U.S production costs. In order to reach the 1980s' growth rate again, increase in productivity growth, real currency depreciation or deflation was necessary. Japans' policy makers, willingly or not, chose deflation instead of currency depreciation. However, monetary growth was not high enough to avoid deflation by adjusting asset prices and the real exchange rate. Even industries such as automobiles and electronics that have experienced extraordinary growth in 1980s entered a recession period in 1992 until before the period of zero or negative real base growth ended and in 1993, the monetary base started to expand. That is why 1993 can be considered as the breakpoint of the Japan Economy which affected not only industrial production indices but also employment levels.

GERMANY. ITALY. FRANCE and SPAIN: When Markov chain based time-homogeneous and time-dependence tests are applied to Germany, France and Italy; we see that industrial production index growths of these three countries follow a homogeneous pattern. The expected passage times between troughs and peaks of industrial production index growths are also close due to their mutual historical data and organized proximities since the early 1940s.

On the other hand. employment growth shows homogeneous behavior in Germany and France and Spain but not in Italy. It is not wrong to consider that this unstable behavior of employment growth in Italy is due to the 23 July 1993 agreement signed by the social parties and the Italian Government. This agreement was based on the will to bring pay settlements into line with rigorous incomes policy in order to combat inflation and was considered as a base step for entry into EU Economic and Monetary Union (EMU) (Tiraboschi and Del Conte, 2004). However, following the agreement, wage increases were initially lower than the inflation rate and dependent workers' share of the national income reduced significantly. The situation worsened by the growing weight of the tax burden on workers' incomes and of the social security contributions paid by employers. This combination of factors gave rise to an unemployment rate of 11.3% marginally and an inflation rate (5%) higher than that of Italy's main trading partners (Biagioli, 1998) .In the middle of 1990s, the unemployment rate started to decrease again due to 28 November 1996 legislations where the procedures were totally reformed to promote access to employment (Tiraboschi and Del Conte, 2004).

UNITED KINGDOM: Following the end of World War II, no major economic recession was observed in United Kingdom until 1973. Though, the annual growth rate in 1960-1973 was far below the rates of other European countries like France,West Germany and Italy. What is more, the severe shock of 1973 oil crisis had caused United Kingdom to enter a recession period and GDP had fallen by 1.1%. Even when the recession ended in 1975, growth in United Kingdom was much lower than other European nations and unemployment was increasing (Dow. 2000).

By the election of Margaret Thatcher in 1979, a new period of neo-liberal economics began. However, Thatcher's modernization of the British economy including a battle against inflation resulted in mass unemployment (3.000.000 by the start of 1982) and rose until 1987. - When we observe the employment data of United Kingdom, we also observe a shocking decrease in the employment rate starting from 1979.

On the other hand, unemployment fell dramatically during the final 3 years of 1980s and stood at about 1.500.000 by the end of 1989 until a global crisis due to savings and loan crisis in the United States caused the economy to shrink and the unemployment peaked at 3.000.000 in 1993. This recession period ended at the turn of 1993 and substantial fall in unemployment was succeeded thanks to a subsequent economic recovery (International Monetary Fund, 2009; Office for National Statistics, 2010).

Since elected in 1997, Tony Blair had stayed in power for 10 years and during his rule, many successive quarters of economic growth had been seen. The highest economic growth rate of major developed countries was reached and United Kingdom became the strongest of any European nation. The United Kingdom economy had been one of the strongest European Union economies in terms of inflation, interest and unemployment all of which remained relatively low until 2008-2009 recessions due to the global financial crisis (Tang, 2008).

When this economic stability and growth are taken into consideration, it is not surprising that the employment growth of United Kingdom shows homogeneous behavior during the time period 1960-2008 in spite of the rising unemployment growth in 1979-1982.

NETHERLANDS: Netherlands, known with its open economy heavily depending on foreign trade, plays a very important role in European transoceanic transportation. Netherlands has stable industrial relations and a much lower unemployment rate compared to other European countries. The highly mechanized agricultural sector in Netherlands employs less than 2% of the labor force. Moreover, international trading and foreign investments play an important role in the recruitment (CIA World Factbook, 2008). However, by 1960s, we observe weakness in Dutch economy which also caused a sharp decline in employment in manufacturing in 1962 (De Smidt and Wever, 1990). On the other hand, the employment data concerning the time interval 1984-2008 shows us that there has been no sharp decline or increase during the last 3 decades in the growth of employment rates of Netherlands.

FINLAND: Finland can be considered as a perfect example of a very successful transformation from agriculture oriented economy to a very advanced and more diversified economic structure. As a country which was not more than a supplier of simple intermediate products. Finland had shown high performance in economic activities and became able to upgrade the level of its raw material based industries (Blomström and Kokko, 2002). Despite the retard of this development, Finland succeeded to become one of the wealthiest countries in the world where very high income levels were reached in a short time. Inflow of major foreign capitals as a result of huge expansion of bank lending had also played an important role during the rapid advance of industrial development. Though, Finland also suffered from the depression because of speculative currency attacks and a major banking crisis (Honkapohja and Koskela, 1999). However, Finland prospered a stable and consistent industrial production index growth like most of the other European countries.

SINGAPORE: Singapore had been one of the richest countries in Asia, even before 1965 when the country became independent. After 1965, Singapore had a modern economy focused on industry, education and urban planning. Despite its small physical size, Singapore has the world's ninth largest foreign reserves and is the fourth wealthiest country in terms of GDP per capita. With its economy heavily depending on exports, Singapore is also known with its huge sectors in biomedical and chemicals (Murphy, 2006).

Relying on these facts, it is not surprising that Singapore was not significantly affected by the 1997 crisis, which had a big impact on many Asian countries like Malaysia.

SOUTH KOREA: Before 1960s, Korea had one of the poorest economies. Though, thanks to industrial developments. South Korea had experienced relatively high increases in per capita income (6.8%) and left not only African countries behind but also Mexico and Argentina who had been richer (Rodrik, 1994). Today, Korea is one of the world's fastest growing economies since the early 1960s through the late 1990s and now, classified as a high-income economy by the World Bank and an advanced economy by the IMF. According to the data collected in 1980-2008, we do not observe a breakpoint in industrial output performance of Korea. Our analyses also show that industrial production index growth of Korea follows a homogeneous first order Markov chain.

PHILIPPINES: During 1970s, Philippines had shown a continuous expansion, with 5.8% average growth in GDP and in every year during that decade, both growth in GDP and GDP per capita had been observed with a peak (8%) both in 1974 and 1977. On the other hand, by the late 1970s, this rate had fallen down nearly to 6% and finally collapsed in 1984 (Balisacan and Hill, 2003). Negative industrial production index growths observed in 1985 and 1984 can also be considered due to the effects of this collapse.

Unlike many neighbors, Philippines had not experienced a long-term rapid growth since 1970s due to the weak political and institutional foundations. Even in 1990s, at the peak years for Asian countries, growth higher than 6% had not been observed in Philippines. A state of strong economic prosperity growth had been visualized for a short time just before the 1997 Asian Financial Crisis when decline of the peso was gradually observed for a long time. Besides, neglect of the land reform and weak leaderships in economic matters affected Philippines economy in a very negative way.

As no strong improvement had been observed in Philippines, industrial production index growths were generally low and stable during the last two decades of the 20th century.

TAIWAN: Taiwan, having few natural resources other than its dense population, specialized in labor-intensive agriculture and industry for meeting domestic needs thus increasing employment and equalizing income (Winkler and Greenhaigh, 1988).

The development program implemented by Japan before 1945 provided Taiwan not only the modernization of agriculture and industry but also guaranteed a market for them. Later on, Taiwan transformed itself to a major foreign investor with investment especially in Asia. (CIA World Factbook, 2008) During 1980s, Taiwan gave weight to technological productions and capital-intensive commodities rather than labor-intensive goods. Deregulation of various financial areas (banking, stock market, trade, finance, etc.) during the 1990s was also an attempt to liberalize the economy and was a sign of Taiwan's desire to join the World Trade Organization (Taipei Economic and Cultural Office, 2006).

Cultural and linguistic similarities also helped to facilitate the economic integration of Taiwan with other Asian countries like China, Japan and Hong Kong (Ash and Kueh, 1993). Due to the strong economic structure, low inflation and unemployment rates observed in Taiwan, it is not unexpected that the employment growths of Taiwan follow a smooth pattern with very small variations.

MEXICO: Mexico’s industrial development should be considered as the consequence of a persistent and difficult process of adjustment which started at the beginning of 1980s, rather than a rapid policy fix made in a short time.

In 1976, Mexico faced a financial crisis and the total external debt rose to 88 billion $ from 1975 to 1982. During 1980-1982, foreign borrowing increased and the rate of inflation averaged 37% and finally rose up to 100% at the end of 1982. As a result of this worsening economy, Mexican government decided to adopt a new economic program giving a start both to the development of the country and the depreciation of high interest rates. Thus, liberal trading and private public sector enterprises had been made available. Though, the authorities needed to introduce a more developing economic program based on The Pact of Economic Solidarity providing financial policies to be tightened and structural reforms to be instituted. In addition to reforming tax system and divesting public sector enterprises, Mexico took measures to liberalize its external trade and investment system. These reforms had helped Mexico to create the conditions for sustainable economic growth (Loser and Kalter, 1992).

In 1994, NAFTA (North American Free Trade Agreement) between Canada., USA and Mexico had been a very important turning point in Mexican economy. This agreement had contributed much to the size of the free trade area. Not only had this agreement covered the merchandize trade but also the issues related to the investment, labor markets and environmental policies. Mexico had been given decline in trade barriers and increase market access. As a result of this agreement, increase in trade and financial flows among NAFTA partners had been stimulated and NAFTA contributed to making North America one of the most economically integrated regions in the world. This increase in regional integration among NAFTA partners also affected business cycles in Mexico and a significant increase in the comovement of business cycles within the NAFTA region had been observed. The role of country-specific shocks driving the Mexican business cycles was decreased and the role of region-wide shocks had been increased. NAFTA also had favorable effect on Mexico's growth performance and over the past decade. Investment in GDP growth and total factor productivity had sharply increased (Kose, Meredith and Towe, 2004). That is why when analyzing industrial production index growth of Mexico, 1994 should be considered as the year changing the whole behavior of Mexico economy.

As seen, industrial production index growth of Mexico became relatively more stable after NAFTA, which means the growth cycle of Mexico has been more predictable.

CHILE: Like most of other countries in Latin America. Chile had experienced economic crisis in the early 1980s which caused sharp decreases in industrial output. On the other hand, unlike Mexico, Chile economy succeeded to recover rapidly and 1980 did not constitute a lost decade for this country. Instead, Chile grew consistently during 1980s and its economy began to grow spectacularly. This success may be due to the early reforms undertaken in the 1970s which set the stage for the successful performance of Chile in the 1980s (Bergoeing, Kehoe and Soto, 2001).

During the early 1990s, Chile had the reputation of being a dynamic market-oriented economy by a high level of foreign trade. The democratic government of Patricio Aylwin strengthened the economic reforms and growth in real GDP averaged 8% during the period

1991-1997. As a result of this recover, Chile economy had seen growth rates of 5-7% over the past years. In 2006, Chile had the reputation of having the highest nominal GDP per capita in Latin America (Vardy, 2010).

ARGENTINA: Argentina has been known as a country with rich natural resources and an export-oriented agricultural sector with a relatively diversified industrial base. However, domestic instability and global trends constitute the main factors affecting the decline of Argentine economy. Systematic problems including increasingly oppressive debt, uncertainty over the monetary system, excessive regulation, barriers to free trade and a weak rule of law coupled with corruption and a bloated bureaucracy (Eiras and Schaefer. 2001). Recovering slightly the era of decline in 1930-1980, though, Argentina suffered from a series of economic crises in 1981-2002.

Argentina entered 2001 with an economy already mired in a long recession period due to plenty factors one of which was Russia's debt default in August 1998. This caused investors to avoid emerging markets and also raised the cost of Argentina's foreign borrowing (Lucchin, 2002). By 2002, economy suffered its sharpest decline since 1930: Argentina had defaulted on its debt; its GDP had decreased enormously.

In 2003 policies supporting development and commodity exports contributed the rise in GDP. This trend has been largely maintained, creating millions of jobs and encouraging internal consumption. The socio-economic situation was steadily improving and the economy grew around 9% annually for five consecutive years between 2003 and 2007 and 7% in 2008. Inflation, however, though officially hovering around 9% since 2006, has been privately estimated at over 15%, becoming a contentious issue again (Rigobon and Cavallo, 2010). The urban income poverty rate has decreased to 18% as of mid-2008 which is a rated equal to a third of the peak level observed in 2002 according to the Worldbank data.

As a result of these, our approach to analyze the employment growths of Argentina includes taking year 2002 as a breakpoint in the name of analyzing the data into two homogeneous subintervals. The results concerning the time interval 2002-2008 are thus useful to make predictions about the future trend of growth cycle in Argentina as a country recovering from an arduous crisis.

VENEZUELA: The petroleum sector dominates Venezuela's mixed economy, accounting for roughly a third of GDP which is more than the half of government revenues. Venezuelan workers have the highest wages in Latin America due to this existence of the largest oil and natural gas reserves in this country. However, the collapse of oil prices in 1980s reversed this situation and the number of people living in poverty rose from 36% in 1984 to 66% in 1995 (McCaughan, 2004).

Though these conflicts, when the growth in employment rates of Venezuela in 1988-2008 is analyzed, we see sustainable growth in employment with little fluctuations recorded in 1996. The inflation rate of this year is also nearly %100, but it decreases to 50% in 1997 and growth in employment is then observed again; thus we can say that this was a short economic recession period for Venezuela which does not constitute a significant sharp change in the behavior of employment growth (International Monetary Fund, 2009).

MALAYSIA: Before 1997 Asian financial crisis. Malaysia had been known as a popular investment destination which caused expectations that growth in that economy would continue. Though, in July 1997, ringgit, currency of Malaysia, was negatively affected by speculators. This caused the sell off on the stock and currency markets. In 1998, the output of the real economy of Malaysia declined and entered into its first recession for a long time period. In 1998, the ringgit decreased to the level of 3.8 dollars. Bad loans received from banks had been another factor that triggered the growth to settle down at a low rate (Athukorala, 2001).

TURKEY: Turkey suffered from two different economic crises in recent years. one of which occurred in 1994 and the other in 2001.

When the industrial production index growths of Turkey are analyzed, we notice a great decline in 1994 in growth. This may be due to the 1994 Currency Crisis in Turkey which caused the highest level of annual output loss in the history of the Turkish Republic. In the first quarter of 1994, Turkish Lira was devalued more than 50% against US dollar, the Central Bank lost half of its reserves. interest rates increased enormously and inflation reached three digit levels (Celasun, 1998).

On the other hand, the 2001 crises had deeper effects on Turkish economy. During 2001, GNP fell by 5.7% in real terms, consumer price inflation increased to 54.9% and currency lost 51% of its value against the major foreign monies. The rate of unemployment rose until to 10% and the real wages were reduced by 20% upon the impact of 2001 crisis. The recovery since then could not be assured and instability still makes its presence felt (Yeldan, 2008).

SOUTH AFRICA : In South Africa, during 1990s, the average growth rate was not much different than 1980s- 1.4 % and 2.1% increase in real GDP per annum respectively. This was highly due to the high inflation rate experienced in the former decade compared to the latter. Both nominal and real GDP growths were much more volatile during the 1980s than in the 1990s (Hodge, 2009). Furthermore, in 1982, growth in employment rate had been observed to be 3.7% and that had been the last time that employment growth was over 3% until 2004. This had been the highest employment growth rate in more than 22 years as a result of the negative effects of high interest rates and economic adjustments in

South African economy (Cape Business News, 2004). This is why 1993 can be taken as the breakpoint of economic growth in South Africa.

CHINA: Following Mao's death, gradual market reforms had been initiated and free-market system took place in China. Economical reforms provided this country to take its place as one of the most the competitive ones in the means of production outcome. Today, China is one of the fastest growing and most important economies in the world and has been most rapid industrializations in world history with positive industrial production index growths.

6.4 Comparison of Expected Passage Times

In this part of our study, we will focus on the notion of "Proximity" and study the effects of global networks in order to explain the similarities between the expected passage times of peaks and troughs of industrial production index growth and employment growth series of different countries. Proximity in general is often seen as an important pre-condition for knowledge sharing, knowledge transfer and technology acquisition (Gertler, 1995).

We believe that such interaction between these countries affect the industrial development and growth in employment directly and thus plays a key role in order to explain similar behaviors of economic time series of different countries.

Notion of Proximity

- *Geographical Proximity*

Geographical Proximity presents advances in economic theory that explains why, despite the increasing mobility of commodities, ideas and people; the diffusion of economic activity is very unequal and remains agglomerated in a limited number of spatial entities (Combes, Mayer and Thisse, 2008). In such case, similar behaviors of nations located in the same region can be explained.

- *Organized and Technological Proximity - Global Networks*

By “Organized Proximity”, the ability of an organization to make its members interact is meant. The members of such organizations are set to share the same system and the same knowledge (Torre and Rallet, 2004). Organizational proximity does not take any geographical dimensions and often exists without it. Though “organizational proximity” is generally used to define the interaction of multi-national firms located in different parts of the world, countries making economic arrangements in the name of creating an organized proximity should also be considered to be in such interaction.

Technological Proximity and Global Networks, on the other hand, refers to the shared technological experiences and knowledge bases. Technological proximity also created by the set up of global networks facilitates the acquisition and development of technological knowledge and technologies which are indispensible in the field of innovation (Oerlemans and Knoben, 2006).

Many studies concerning the importance of both geographical proximity and global networks have been done so far. In his article, Sonn and Storper (2003) indicate that economically-useful knowledge may experience considerable friction to distance. In this frame, urban economists and economic geographers suggest that geographical proximity between the people and organizations who produce knowledge may still be an important advantage in the production of economically-useful innovations (Acs 2002; Dicken 1992; Feldman 1994; Storper 1997). When analyzing local direct face-to-face contact, Storper and Venables (2004) mention that this kind of communication is not only an efficient technology of communication but also useful in the formation of projects to develop new knowledge where complete contracts are impossible and bureaucracies are too costly.

These approaches carry heavy importance in our analyses especially when industrial production index growths of countries located in the same region are in question. As known, growth in industrial productivity and economically-useful innovation are in a strong relation. Thus, interactions concerning share of such innovational knowledge contributes to all these countries in communication.

Still others claim that both long-distance and local interactions should strengthen the knowledge-based economy, especially in a world where long-distance links between nodes such as global networks are increasingly used. (Verspagen and Schoenmakers, 2002) Cairncross (1997) also points out that as long as the friction of distance dies the importance of geographical proximity decreases. According to Burmeister and Colletis-Wahl (1997), organizational proximity and global networks generate a capacity to combine information and knowledge from the collaborating parties in order to transfer tacit knowledge and other nonstandardized resources between collaborating parties.

During our analyses including the comparison of expected passage times between trough and peaks of growth of economic indicators concerning different countries, we will be taking both geographical and organization-technological proximities into consideration. In such approach, we believe to explain similar behaviors of growth cycles of different countries. Figure 6.1 puts on view the expected passage times between troughs and peaks of industrial production index growths of each country analyzed in this study while we can observe the results concerning the passage times between troughs and peaks of employment growths in Figure 6.2

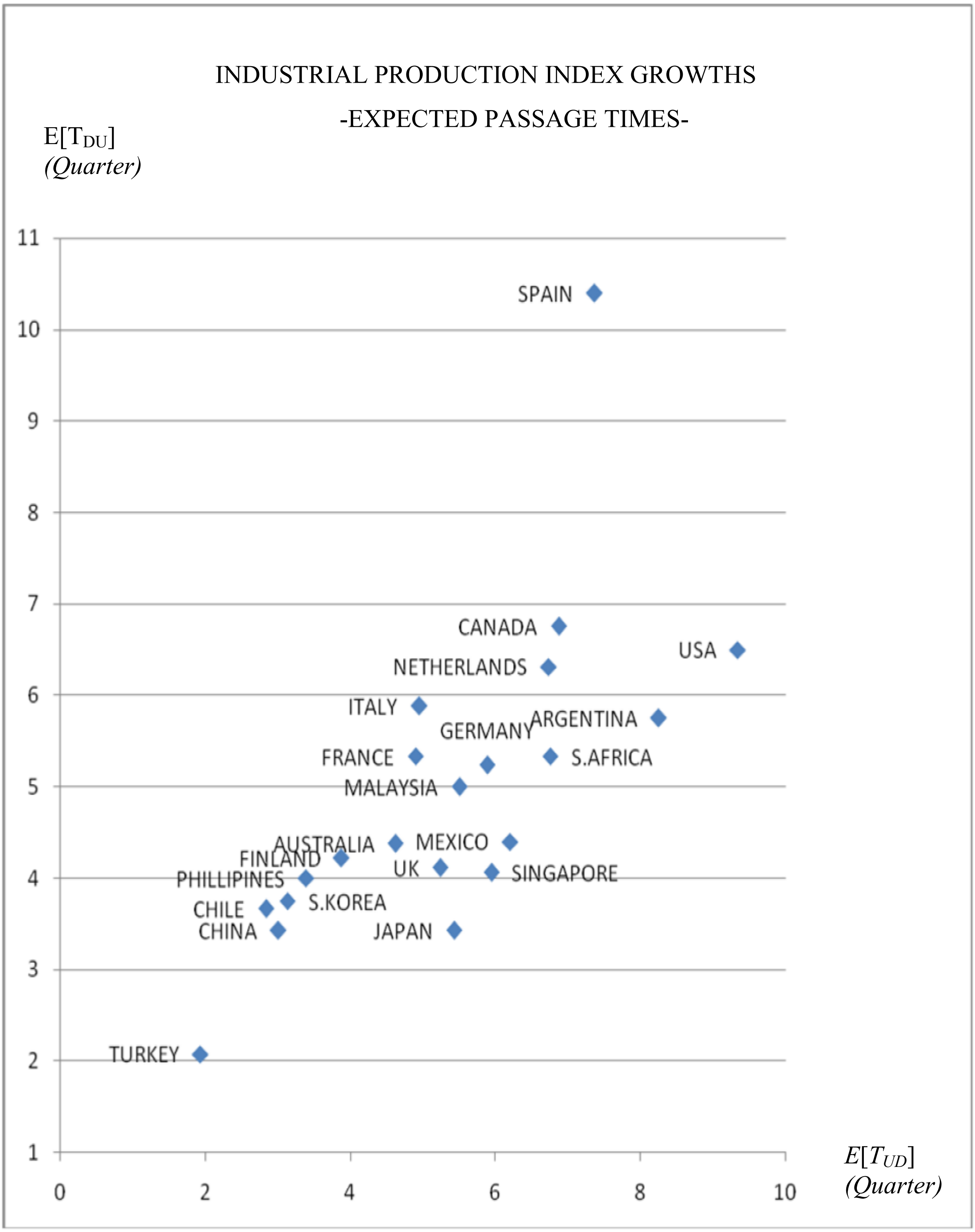

Figure 6.2: Expected Passage Times between Troughs and Peaks of Industrial Production Index Growths

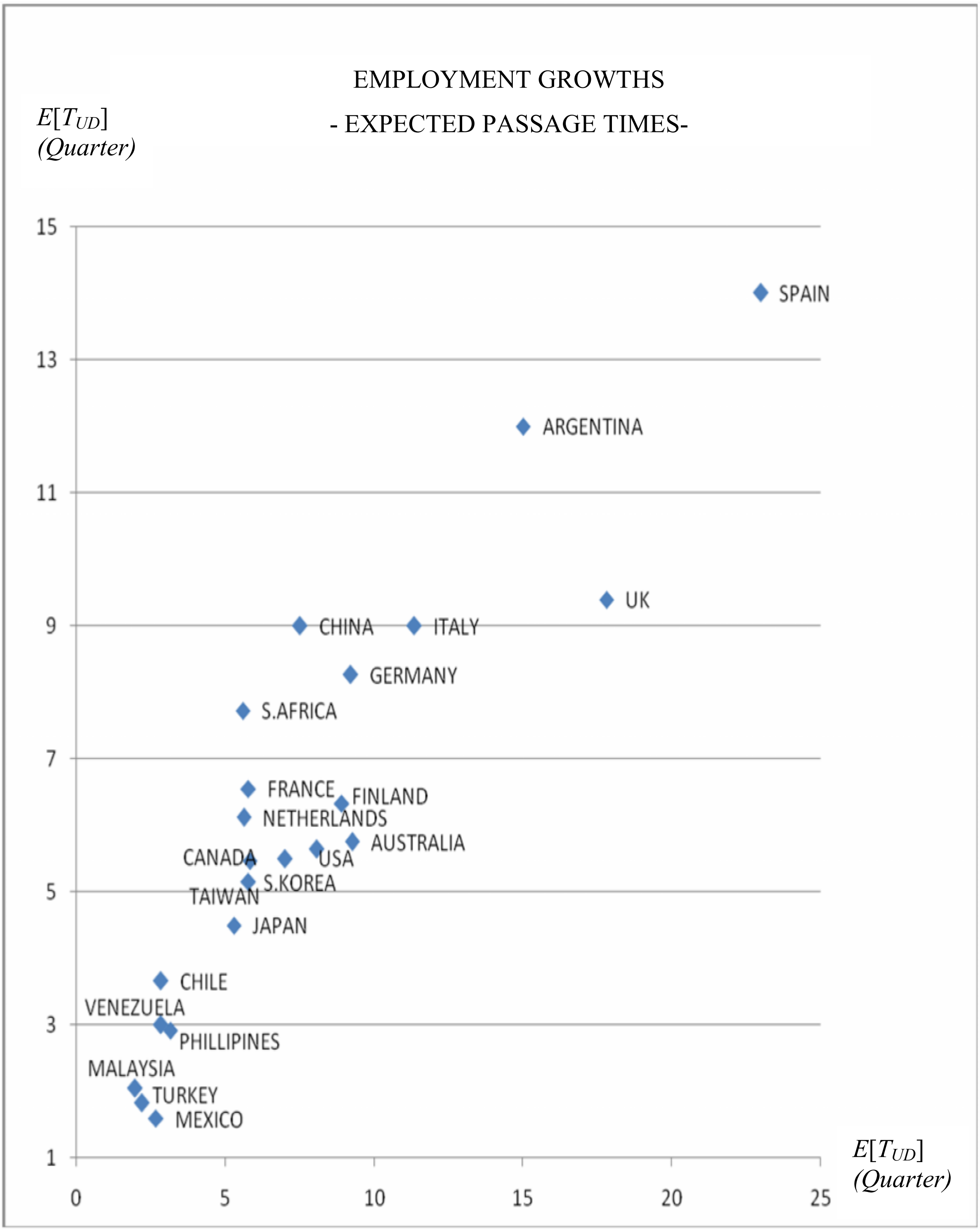

Figure 6.2: Expected Passage Times between Troughs and Peaks of Employment Growths

Agglomeration of Expected First Passage Times Values

In Figure 6.1 and Figure 6.2, we see the expected passage times between troughs and peaks observed in employment growth and industrial production index growth series of different countries are very close. What is more, the agglomeration of expected passage times between peaks and troughs of employment growth rate series is much denser. This similarity of results may be due to the issues like geographical proximity, organizational proximity, technological proximity or the global networks set up between these countries which are explained in the previous part of this study.

For European countries like France, Germany and Italy, we see the expected passage times between peaks and troughs of industrial production index growths are very close. Employment growth passage times also show such similarity. As known, these countries are located in the same region which means they have geographical proximity. In his article, Blanchard (2004) indicates that Europe practiced catch-up growth is based on imitation rather than innovation. We think this cannot be considered as the only explanation of these similarities. Also their participation in European Union committed to regional integration provides an organizational proximity and encourages innovation and the knowledge economy through the development of information and communication technologies among them. Such interaction between the members of European Union better explains the similar behaviors of these time series in these countries.

For Asian countries, we cannot talk about a systematically organized political. economic and monetary union like it exists in Europe. In many respects, Europe is unique in the name of such union and organization (Wyplosz, 2001). In the 1950s, when Europe began a long and slow union, a similar evolution could not get started due to the Chinese Revolution and the Korean War. However, the 21st century has brought rapid integration of

Asian economy and the emergence of what can be termed an informal “Asian Union” (Gresser,2004).

Similar behaviors of Asian countries like China, Japan, South Korea, Singapore, Philippines, Malaysia and Taiwan can even be observed in the results of our analyses although we are mostly concentrated on the industrial production index growths and employment growths concerning the last four decades. This time interval represents the period where international relationship and communication between Asian countries got strengthened and industrial developments got acceleration with new government policies and improved business competitiveness. Thus, these results give us relevant information about the upcoming integration of Asian countries.

The Asian challenge was first met in 1980s. In 1992, China succeeded to normalize the diplomatic relations with South Korea which then opened the gates for wealthy Korean economy to rapidly merge with the North China industrial complex. In the second half of 1990s, Taiwanese government also relaxed post-revolutionary bans on mainland investment and brought Taiwanese manufacturers and high-tech firms around China. The openings to investment and trade were followed by liberalization of telecom and trading rights. These reforms guaranteed investments in China from Asia’s richest economies like Japan, Korea, Taiwan and Singapore. Uniting Japan’s financial and technological power with China’s low costs and vast manpower reserves enabled “Asian Tigers” profit from extraordinary industrial developments.

This emergence of Asian countries made great contribution to the technological and organizational proximity of these countries. Political and economical reforms encouraging international trade also made great advantage of their geographical proximity. The Asian emergence is still proceeding at an extraordinary speed providing an informal integrated economy, though, without and a legal framework and policy coordination among governments (Gresser, 2004).

6.5 Comparison of Statistical Behaviors of Time Series

As indicated in the Methodology, the time homogeneity test procedure can be applied in order to observe if the transition probabilities of two different time series are statistically different or not. Thus, in this chapter, we use time homogeneity testing methodology to reveal if the transition probabilities concerning the Industrial Production Index Growths and Employment Growths of each country are statistically different or not than the transition probabilities estimated for the other countries.

The P values obtained as a result of this statistical significance test which has been applied to transition probabilities matrices estimated for Industrial Production Index Growths of country pairs are as shown in Table 6.5. Table 6.6 also displays if the transition probabilities estimated for Industrial Production Index Growths of country pairs are statistically different or not. In this analysis, the significance level is defined as 0.10 and 0 is assigned to country pairs where the transition probabilities are not statistically different, while 1 is assigned when the estimated transition probabilities for the Industrial Production Index Growths observed in these country pairs are statistically different. Table 6.7 and 6.8 represents, on the other hand, the same analyses for Employment Growths with the same threshold.

In case the Industrial Production Index Growths -or Employment Growths- concerning a country pair follow different orders of Markov chain, the statistical significance test cannot be conducted for the transition probabilities estimated for these series observed in each country. The yellow cells in the tables shown below stand for such country pairs.

Table 6.5: P Values Obtained after Statistical Signficance Test of Transition Probabilities Estimated for Industrial Production Index Growths

P VALUES	AUSTRALIA	CANADA	USA	JAPAN	GERMANY	ITALY	FRANCE	FINLAND	SINGAPORE	S.KOREA	PHILIPPINES	MEXICO	CHILE	MALAYSIA	TURKEY	S.AFRICA	CHINA	ARGENTINA	SPAIN	NETHERLANDS	UK
AUSTRALIA		0,2721	0,0449	0,7478	0,6040	0,5824	0,7721	0,7887	0,6674	0,3459	0,5788	0,7945	0,2270	0,9284		0,5144	0,4130	0,3892	0,0146		
CANADA	0,2721		0,7757	0,3106	0,7343	0,6430	0,5477	0,1079	0,3801	0,0299	0,0811	0,7047	0,3211	0,7774		0,8445	0,0629	0,9119	0,6232		
USA	0,0449	0,7757		0,1694	0,3246	0,1656	0,1304	0,0069	0,1650	0,0016	0,0089	0,5331	0,2582	0,5280		0,6522	0,0118	0,9498	0,4179		
JAPAN	0,7478	0,3106	0,1694		0,5733	0,4163	0,533	0,5648	0,8893	0,3382	0,4644	0,8562	0,6922	0,7795		0,5770	0,4169	0,4816	0,0519		
GERMANY	0,6040	0,7343	0,3246	0,5733		0,807	0,845	0,2566	0,7127	0,0721	0,1856	0,9228	0,4322	0,9754		0,9306	0,1403	0,7668	0,1330		
ITALY	0,5824	0,6430	0,1656	0,4163	0,807		0,9496	0,3371	0,4131	0,1083	0,2539	0,7269	0,1537	0,9437		0,6782	0,1807	0,5644	0,1512		
FRANCE	0,7721	0,5477	0,1304	0,533	0,845	0,9496		0,4798	0,5470	0,1624	0,3445	0,7948	0,2045	0,9816		0,6908	0,2381	0,5407	0,0850		
FINLAND	0,7887	0,1079	0,0069	0,5648	0,2566	0,3371	0,4798		0,307	0,6756	0,8868	0,5226	0,0591	0,7507		0,2323	0,6614	0,1877	0,0031		
SINGAPORE	0,6674	0,3801	0,1650	0,8893	0,7127	0,4131	0,5470	0,307		0,1107	0,2360	0,9798	0,7314	0,8849		0,7473	0,2033	0,6176	0,0289		
S.KOREA	0,3459	0,0299	0,0016	0,3382	0,0721	0,1083	0,1624	0,6756	0,1107		0,9481	0,2511	0,0204	0,4370		0,0738	0,9673	0,0665	0,0008		
PHILIPPINES	0,5788	0,0811	0,0089	0,4644	0,1856	0,2539	0,3445	0,8868	0,2360	0,9481		0,3865	0,0612	0,5922		0,1643	0,8829	0,1318	0,0048		
MEXICO	0,7945	0,7047	0,5331	0,8562	0,9228	0,7269	0,7948	0,5226	0,9798	0,2511	0,3865		0,876	0,942		0,9310	0,2927	0,8135	0,2621		
CHILE	0,2270	0,3211	0,2582	0,6922	0,4322	0,1537	0,2045	0,0591	0,7314	0,0204	0,0612	0,876		0,6798		0,6780	0,0733	0,6988	0,0215		
MALAYSIA	0,9284	0,7774	0,5280	0,7795	0,9754	0,9437	0,9816	0,7507	0,8849	0,4370	0,5922	0,942	0,6798			0,904	0,4308	0,7688	0,3774		
TURKEY																					
S.AFRICA	0,5144	0,8445	0,6522	0,5770	0,9306	0,6782	0,6908	0,2323	0,7473	0,0738	0,1643	0,9310	0,6780	0,904			0,1230	0,9237	0,2779		
CHINA	0,4130	0,0629	0,0118	0,4169	0,1403	0,1807	0,2381	0,6614	0,2033	0,9673	0,8829	0,2927	0,0733	0,4308		0,1230		0,0973	0,0073		
ARGENTINA	0,3892	0,9119	0,9498	0,4816	0,7668	0,5644	0,5407	0,1877	0,6176	0,0665	0,1318	0,8135	0,6988	0,7688		0,9237	0,0973		0,5802		
SPAIN	0,0146	0,6232	0,4179	0,0519	0,1330	0,1512	0,0850	0,0031	0,0289	0,0008	0,0048	0,2621	0,0215	0,3774		0,2779	0,0073	0,5802			
NETHERLANDS																					0,1616
UK																				0,1616	

Table 6.6: Statistical Difference of Transition Probabilities Estimated for Industrial Production Index Growths

P VALUES	AUSTRALIA	CANADA	USA	JAPAN	GERMANY	ITALY	FRANCE	FINLAND	SINGAPORE	S.KOREA	PHILIPPINES	MEXICO	CHILE	MALAYSIA	TURKEY	S.AFRICA	CHINA	ARGENTINA	SPAIN	NETHERLANDS	UK
AUSTRALIA		0	1	0	0	0	0	0	0	0	0	0	0	0		0	0	0	1		
CANADA	0		0	0	0	0	0	0	0	1	1	0	0	0		0	1	0	0		
USA	1	0		0	0	0	0	1	0	1	1	0	0	0		0	1	0	0		
JAPAN	0	0	0		0	0	0	0	0	0	0	0	0	0		0	0	0	1		
GERMANY	0	0	0	0		0	0	0	0	1	0	0	0	0		0	0	0	0		
ITALY	0	0	0	0	0		0	0	0	0	0	0	0	0		0	0	0	0		
FRANCE	0	0	0	0	0	0		0	0	0	0	0	0	0		0	0	0	1		
FINLAND	0	0	1	0	0	0	0		0	0	0	0	1	0		0	0	0	1		
SINGAPORE	0	0	0	0	0	0	0	0		0	0	0	0	0		0	0	0	1		
S.KOREA	0	1	1	0	1	0	0	0	0		0	0	1	0		1	0	1	1		
PHILIPPINES	0	1	1	0	0	0	0	0	0	0		0	1	0		0	0	0	1		
MEXICO	0	0	0	0	0	0	0	0	0	0	0		0	0		0	0	0	0		
CHILE	0	0	0	0	0	0	0	1	0	1	1	0		0		0	1	0	1		
MALAYSIA	0	0	0	0	0	0	0	0	0	0	0	0	0			0	0	0	0		
TURKEY																					
S.AFRICA	0	0	0	0	0	0	0	0	0	1	0	0	0	0			0	0	0		
CHINA	0	1	1	0	0	0	0	0	0	0	0	0	1	0		0		1	1		
ARGENTINA	0	0	0	0	0	0	0	0	0	1	0	0	0	0		0	1		0		
SPAIN	1	0	0	1	0	0	1	1	1	1	1	0	1	0		0	1	0			
NETHERLANDS																					0
UK																				0	

Table 6.7: P Values Obtained after Statistical Signficance Test of Transition Probabilities Estimated for Employment Growths

P VALUES	AUSTRALIA	CANADA	USA	JAPAN	GERMANY	ITALY	UK	FRANCE	SPAIN	NETHERLANDS	ARGENTINA	CHILE	MEXICO	VENEZUELA	S.KOREA	TURKEY	S. AFRICA	PHILIPPINES	MALAYSIA	CHINA	FINLAND	TAIWAN
AUSTRALIA		0,4872	0,9463	0,4533	0,7051	0,7235	0,3058	0,5559	0,1123	0,5608	0,6280	0,0445		0,0051	0,8339		0,3818	0,0033		0,7842		
CANADA	0,4872		0,6146	0,8779	0,2281	0,3084	0,0196	0,8886	0,0057	0,9545	0,3399	0,1731		0,0280	0,8942		0,6133	0,0208		0,1258		
USA	0,9463	0,6146		0,5509	0,5539	0,5946	0,1342	0,6554	0,0404	0,6735	0,5355	0,0545		0,0044	0,9411		0,4190	0,0029		0,0315		
JAPAN	0,4533	0,8779	0,5509		0,2226	0,2522	0,0368	0,7253	0,0118	0,8137	0,2687	0,4050		0,2453	0,7711		0,5235	0,1837		0,3817		
GERMANY	0,7051	0,2281	0,5539	0,2226		0,9348	0,4194	0,4785	0,2012	0,4294	0,8062	0,0148		0,0003	0,5342		0,4448	0,0003		0,0066		
ITALY	0,7235	0,3084	0,5946	0,2522	0,9348		0,8201	0,4554	0,5759	0,4173	0,9329	0,0262		0,0038	0,5281		0,4380	0,0027		0,0168		
UK	0,3058	0,0196	0,1342	0,0368	0,4194	0,8201		0,0705	0,7915	0,0674	0,9593	0,0015		0,0000	0,1270		0,0472	0,0000		0,0005		
FRANCE	0,5559	0,8886	0,6554	0,7253	0,4785	0,4554	0,0705		0,0265	0,9867	0,4390	0,1564		0,0265	0,8431		0,9222	0,0215		0,1149		
SPAIN	0,1123	0,0057	0,0404	0,0118	0,2012	0,5759	0,7915	0,0265		0,0246	0,9264	0,0004		0,0000	0,0431		0,0204	0,0000		0,0001		
NETHERLANDS	0,5608	0,9545	0,6735	0,8137	0,4294	0,4173	0,0674	0,9867	0,0246		0,4055	0,2077		0,0500	0,8680		0,8657	0,0401		0,1633		
ARGENTINA	0,6280	0,3399	0,5355	0,2687	0,8062	0,9329	0,9593	0,4390	0,9264	0,4055		0,0472		0,0183	0,4790		0,4493	0,0139		0,0385		
CHILE	0,0445	0,1731	0,0545	0,4050	0,0148	0,0262	0,0015	0,1564	0,0004	0,2077	0,0472			0,8255	0,1312		0,0981	0,8884		0,9815		
MEXICO																0,8090			0,4950			
VENEZUELA	0,0051	0,0280	0,0044	0,2453	0,0003	0,0038	0,0000	0,0265	0,0000	0,0500	0,0183	0,8255			0,0309		0,0076	0,9447		0,9090		
S.KOREA	0,8339	0,8942	0,9411	0,7711	0,5342	0,5281	0,1270	0,8431	0,0431	0,8680	0,4790	0,1312		0,0309			0,6332	0,0214		0,0983		
TURKEY													0,8090						0,8851			
S. AFRICA	0,3818	0,6133	0,4190	0,5235	0,4448	0,4380	0,0472	0,9222	0,0204	0,8657	0,4493	0,0981		0,0076	0,6332			0,0067		0,0632		
PHILIPPINES	0,0033	0,0208	0,0029	0,1837	0,0003	0,0027	0,0000	0,0215	0,0000	0,0401	0,0139	0,8884		0,9447	0,0214		0,0067			0,9323		
MALAYSIA													0,4950			0,8851						
CHINA	0,7842	0,1258	0,0315	0,3817	0,0066	0,0168	0,0005	0,1149	0,0001	0,1633	0,0385	0,9815		0,9090	0,0983		0,0632	0,9323				
FINLAND																						0,3097
TAIWAN																					0,3097	

Table 6.8: Statistical Difference of Transition Probabilities Estimated for Employment Growths

P VALUES	AUSTRALIA	CANADA	USA	JAPAN	GERMANY	ITALY	UK	FRANCE	SPAIN	NETHERLANDS	ARGENTINA	CHILE	MEXICO	VENEZUELA	S.KOREA	TURKEY	S. AFRICA	PHILIPPINES	MALAYSIA	CHINA	FINLAND	TAIWAN
AUSTRALIA		0	0	0	0	0	0	0	0	0	0	1		1	0		0	1		0		
CANADA	0		0	0	0	0	1	0	1	0	0	0		1	0		0	1		0		
USA	0	0		0	0	0	0	0	1	0	0	1		1	0		0	1		1		
JAPAN	0	0	0		0	0	1	0	1	0	0	0		0	0		0	0		0		
GERMANY	0	0	0	0		0	0	0	0	0	0	1		1	0		0	1		1		
ITALY	0	0	0	0	0		0	0	0	0	0	1		1	0		0	1		1		
UK	0	1	0	1	0	0		1	0	1	0	1		1	0		1	1		1		
FRANCE	0	0	0	0	0	0	1		1	0	0	0		1	0		0	1		0		
SPAIN	0	1	1	1	0	0	0	1		1	0	1		1	1		1	1		1		
NETHERLANDS	0	0	0	0	0	0	1	0	1		0	0		1	0		0	1		0		
ARGENTINA	0	0	0	0	0	0	0	0	0	0		1		1	0		0	1		1		
CHILE	1	0	1	0	1	1	1	0	1	0	1			0	0		1	0		0		
MEXICO																0			1			
VENEZUELA	1	1	1	0	1	1	1	1	1	1	1	0			1		1	0		0		
S.KOREA	0	0	0	0	0	0	0	0	1	0	0	0		1			0	1		1		
TURKEY													1						0			
S. AFRICA	0	0	0	0	0	0	1	0	1	0	0	1		1	0			1		1		
PHILIPPINES	1	1	1	0	1	1	1	1	1	1	1	0		0	1		1			0		
MALAYSIA													0			0						
CHINA	0	0	1	0	1	1	1	0	1	0	1	0		0	1		1	0				
FINLAND																						0
TAIWAN																					0	

6.6 Observations on Statistical Behavior of Time Series

Tables above show us that the transition probabilities concerning the Industrial Production Index Growths and Employment Growths of United States and Spain show differences than most of the other countries. According to the analyses, we can also say that the Employment Growths of United States and Spain are more persistent than most of the other countries. Our observations about United States may be explained by the fact that the United States is generally considered as the “pioneer” in the worldwide economy.

We also see that South Korea, China and Philippines show differences from other countries like Canada, Argentina, United States and Chile due to the emergence of these Asian countries and their organizational and geographical proximity.

As indicated in the previous chapters of this study, the expected passage times between states U and D of European Countries are much longer than some other South American countries like Venezuela and Chile. Supporting these results, our analyses show that the transition probabilities concerning the Industrial Production Index Growths of Chile are statistically different from the transition probabilities estimated for some European countries like Finland and Spain, while the transition probabilities concerning the Employment Growths of Venezuela are statistically different from the transition probabilities estimated for most European countries like United Kingdom, Germany, Italy, Spain and Netherlands.

Chapter 7

ANALYSIS OF GROWTH CYCLES WITH COMPOSITE INDICATORS

Until now, we revealed the time-homogeneity and time-dependence properties of important leading economic indicators like capacity utilization rates, industrial production index growths and employment growths of various countries. Thus, we were able to make accurate predictions about how these economic series evolve by time in order to estimate future behavior of business and growth cycles. On the other hand, we believe that an index composed of more than one leading economic indicator, chosen from the economic processes we have already studied, provides a healthier indication of future activity of business cycles. In this frame, an index composed of industrial production index growth and employment growth is created for further estimations about growth cycles of different countries.

In order to prevent the confusion of indices, we identified a pair of states *H* (High) and *L* (Low) for industrial production index growths. When the observed industrial production index growth is above the average growth level, then the process is in state *H*; otherwise in state *L*. For employment growths, we use the already defined states *U* and *D*- in case the observed employment growth rate is above the average growth level, then the stochastic process of employment growth is in state *U*, otherwise in state *D*.

In this frame, there exist four states where the stochastic process which this composite indicator follows can be observed over time: *HU*, *LU*, *HD* and *LD*. As an example, if the process in state *LU*, this means the process is observed in a time period where industrial production index growth is below the average level but the employment growth stays above the average employment growth. In order to reveal the time-dependence and time-homogeneity properties of this composite economic indicator, we consider the industrial production index growth and employment growth data as a whole economic time series and apply the Markov based time-dependence and time-homogeneity tests as done for single economic time series. In Table 7.1, the estimated first passage times between states *HU*, *HD*, *LU* and *LD* can be observed for each country.

Table 7.1: Expected First Passage Times between States

	Beginning Year		**Expected Passage Times (Quarter)**			
COUNTRIES			***HU***	***HD***	***LU***	***LD***
AUSTRALIA	**1978**	***HU***		24.5220	6.4646	12.1746
		HD	4.4900		9.8182	10.1164
		LU	4.900	22.3459		11.1217
		LD	7.4700	15.7170	10.5253	
CANADA	**1980**	***HU***		9.3208	10.1064	9.2991
		HD	7.5990		12.2128	8.0093
		LU	11.5752	10.6415		2.5888
		LD	11.2721	9.0566	12.1277	
JAPAN	**1960**	***HU***		7.7326	9.0258	13.1488
		HD	5.4010		8.8937	13.2706
		LU	9.3861	9.6953		8.0172
		LD	9.2876	9.0258	10.7769	
MEXICO	**2000**	***HU***		7.8750	4.1404	5.3958
		HD	1.6667		5.807	7.0625
		LU	2.5556	7.2500		4.7708
		LD	2.5556	7.2500	4.0175	
KOREA	**1983**	***HU***		10.1117	6.8784	9.9603
		HD	6.3676		9.1982	6.5105
		LU	6.6142	8.9709		9.2636
		LD	8.2123	8.1456	9.6937	
USA	**1960**	***HU***		24.1429	11.1667	14.5686
		HD	7.7899		14.1667	11.1821
		LU	8.7913	26.5476		8.4580
		LD	11.5098	24.4762	11.5000	

	Beginning Year		Expected Passage Times (Quarter)			
COUNTRIES			***HU***	***HD***	***LU***	***LD***
CHINA	**1999**	***HU***		10.5294	4.6364	5.0000
		HD	2.0000		6.6364	7.0000
		LU	2.6250	11.5882		4.6667
		LD	3.8750	9.7059	6.0909	
GERMANY	**1962**	***HU***		16.8423	8.0473	13.7867
		HD	6.9156		13.0416	11.4097
		LU	7.9633	14.4761		9.2408
		LD	11.7679	10.1892	14.5317	
FRANCE	**1980**	***HU***		15.1316	8.3793	7.7932
		HD	9.1146		11.2644	4.0475
		LU	12.1783	14.4737		6.3763
		LD	12.7834	11.5132	11.1954	
ITALY	**1980**	***HU***		9.0474	7.9957	10.1983
		HD	6.4569		10.2241	9.1379
		LU	7.5086	14.2069		8.3103
		LD	6.7155	11.5345	8.6034	
FINLAND	**1992**	***HU***		17.3814	3.5289	14.1304
		HD	3.6964		6.2314	12.5978
		LU	4.9196	16.7216		11.2065
		LD	6.7857	9.2887	6.3388	
MALAYSIA	**1997**	***HU***		4.4930	11.5211	7.3944
		HD	6.7465		9.3944	5.8592
		LU	10.9577	6.5775		2.9718
		LD	9.7606	5.9718	5.9014	
TURKEY	**2000**	***HU***		12.7778	4.1892	2.6667
		HD	1.6667		4.4595	3.4444
		LU	4.1667	13.3333		3.2222
		LD	2.7500	10.1111	5.0811	
PHILLIPINES	**1990**	***HU***		5.2632	5.6667	3.7416
		HD	7.4000		5.4286	3.9326
		LU	7.7000	6.6316		5.5843
		LD	9.5500	5.3158	4.7143	
S.AFRICA	**1970**	***HU***		5.4933	15.0167	11.2067
		HD	11.3067		15.8233	7.1133
		LU	11.2333	6.2267		8.4400
		LD	15.3933	6.1867	14.6600	
CHILE	**1998**	***HU***		5.4286	2.8824	6.6863
		HD	4.4915		3.5294	7.3333
		LU	6.7288	4.5714		3.8039
		LD	8.0508	4.1429	5.6471	

	Beginning Year		Expected Passage Times			
COUNTRIES			***HU***	***HD***	***LU***	***LD***
UK	**1960**	***HU***		16.7265	6.4885	13.6975
		HD	6.1806		11.5907	11.4438
		LU	5.5093	17.0516		13.5839
		LD	9.4967	8.6209	13.0195	
ARGENTINA	**1999**	***HU***		12.2500	14.5000	14.2000
		HD	20.0000		13.0000	8.4000
		LU	28.5000	8.5000		4.0000
		LD	24.5000	4.5000	17.5000	
SPAIN	**1980**	***HU***		53.7571	3.5	25.3333
		HD	9.8343		4.25	26.0833
		LU	14.6686	50.2571		21.8333
		LD	23.1162	28.4238	14.5024	
NETHERLANDS	**1984**	***HU***		12.9784	6.5955	7.2706
		HD	8.7582		7.2834	6.2824
		LU	5.8203	14.241		8.2176
		LD	12.2222	13.2806	8.2643	

Table 7.1 shows that for many countries, employment growths and industrial production index growths tend to show similar behavior: One can observe that for many countries, the estimated first passage times between states *HU* and *LD* are much shorter than the expected first passage times between other states where employment growth is above the average level while industrial production index growth is not or vice-versa.

In this study, we consider that when our composite indicator is in state *HU*, we are in a time period where the peak of the growth cycle is observed. Similarly, when the indicator is in state *LD*. we assume that we observe a trough in the growth cycle. Thus, we believe that the estimated passage times between states *HU* and *LD* enlighten us about the estimated passage times between a peak and a trough of growth cycles. Figure 7.1 illustrates the estimated passage times between states *HU* and *LD* for each country.

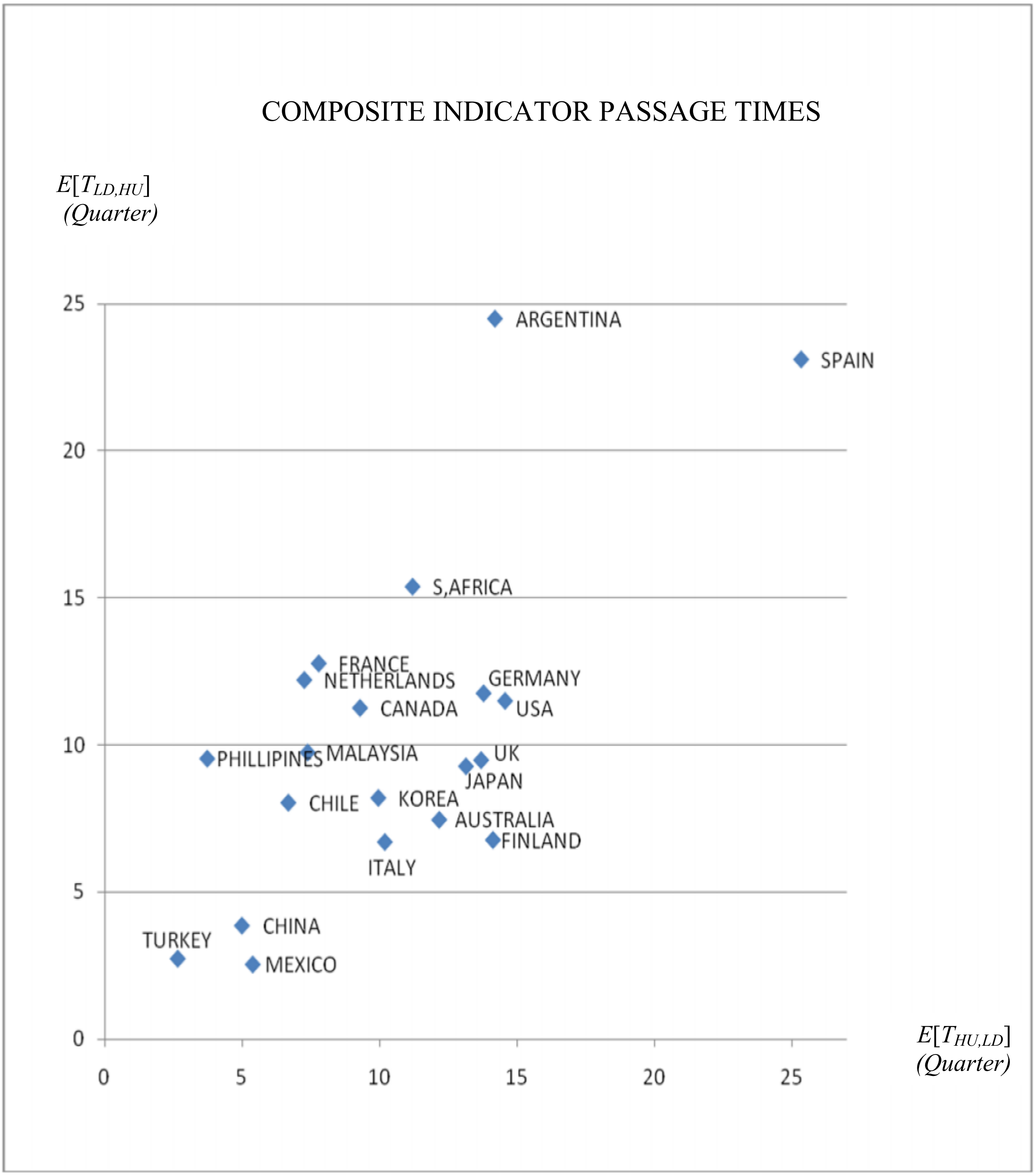

Figure 7.1 Estimated Passage Times Between States *HU* and *LD* for Each Country

Figure 7.1 displays that the estimated passage times between troughs and peaks of growth cycles exhibit symmetric behavior for most of the countries in question. What is more. we see that the expected passage times between troughs and peaks of growth cycles of industrialized economies like Germany. Japan and United States are much longer than less industrialized countries like Turkey. China and Mexico.

In Figure 7.2. we see the estimated passage times between peaks and troughs of business cycle of United States which are obtained via NBER business cycle dating methodology. For our analyses. we use the industrial production index growth and employment growth data recorded in 1960-2008. Thus. the business cycles dated by NBER during this time period are taken into consideration in order to compare our findings with NBER estimations.

BUSINESS CYCLE REFERENCE DATES		DURATION IN MONTHS			
Peak	Trough	Contraction	Expansion	Cycle	
		Peak to Trough	Previous trough to this peak	Trough from Previous Trough	Peak from Previous Peak
April 1960(II)	February 1961 (I)	10	24	34	32
December 1969(IV)	November 1970 (IV)	11	106	117	116
November 1973(IV)	March 1975 (I)	16	36	52	47
January 1980(I)	July 1980 (III)	6	58	64	74
July 1981(III)	November 1982 (IV)	16	12	20	18
July 1990(III)	March 1991(I)	8	92	100	108
March 2001(I)	November 2001 (IV)	8	120	128	128
December 2007 (IV)			73		81
Average, all cycles:					
1854-2001 (32 cycles)		17	38	55	56*
1854-1919 (16 cycles)		22	27	48	49**
1919-1945 (6 cycles)		18	35	53	53
1945-2001 (10 cycles)		10	57	67	67

* 13 cycles
** 15 cycles

Figure 7.2: NBER Business Cycle Dating in 1960-2008
(http://www.nber.org/cycles.html)

The comparison of estimated passage times between peaks and troughs of growth cycles of United States with the average passage times obtained by NBER business cycle dating methodology is indicated in Table 7.2 This comparison reveals the difference between the estimated passages between peaks and troughs of growth cycles and business cycles.

Table 7.2: Comparison of Estimated Passage Times with NBER results

United States (1960-2008) -Quarter-	**Peak to Trough ($E[T_{HU.LD}]$)**	**Trough to Peak ($E[T_{LD.HU}]$)**	**Peak from Previous Peak ($E[T_{HU.LD}] + E[T_{LD.HU}]$)**	**Trough from Previous Trough ($E[T_{LD.HU}] + E[T_{HU.LD}]$)**
NBER Dating for Business Cycle	2.67	16	18.67	18.39
Estimated Passage Times for Growth Cycle	14.55	11.50	26.05	26.05

As seen, the estimated duration of periods in the growth cycle is fairly longer than the estimated duration of periods observed in the business cycle of United States. As known, when we analyze growth cycles, we concentrate on the alternating periods of upswings and downswings in the economy's rate of growth. On the other hand, business cycle analysis involves the study of alternating periods of expansion and contraction in the level of economic activity of a nation. This different approach used when analyzing growth cycles explains why the estimated durations of periods in growth cycles and business cycles differ.

Chapter 8

CONCLUSION

In this study, we used a simple but effective nonparametric testing procedure which estimates the transition probability distribution of economic time series directly. As this testing procedure does not require any distributional assumptions which are generally involved in applications of parametric tests, we obtained accurate results about the behaviors of these time series without any judgment and any transparency problem.

By following a systematic Markov based testing procedure; we revealed the time-dependence and time-homogeneity properties of industrial production index growths and employment growths of 24 countries. The expected passage times between peaks and troughs of these economic times series were thus compared so that we could detect their similar behaviors in different countries. Our analyses showed that the estimated durations of periods observed in industrial production index growth and employment growth rate series are very close in European countries like Germany, Italy and France due to their geographical and organizational proximity sustained by their participation in European Union. Similar behavior of these economic time series is also observed in Asian countries like Japan, Taiwan, China, Singapore, Philippines, Malaysia and South Korea not only on account of their geographical proximity but also their strengthened international economic relationships as a result of new government policies permitting economic liberalization of these nations.

During our analyses indicated above, we did not need to seek a detailed methodology in order to remove the seasonal effects from the economic time series in question because we focused on the logarithm of these series which enabled us to observe the growth of adjusted data. Seasonality factor may often mislead the analysis and cause the investigator to obtain inefficient results. The issue of seasonality has also been considered by many investigators until now. Bums and Mitchell (1946), and many others afterward, defended and advanced the idea of studying business cycles after having adjusted economic time series for seasonality.

The detection of varying transition probabilities is also permitted in this study as a detailed time-homogeneity test is computed during the testing procedure. Thus, valuable and additional information whether a breakpoint exists due to a sharp change is acquired. With its nonlinear structure, the time varying transition probability model is very convenient to use in order to accurately capture and predict the expansions and contractions of economic activity. As Filardo (1994) indicates, a model with time varying transition probabilities can characterize the dynamics of business and growth cycles better than the fixed transition probability approach and standard linear time series model.

With its extra flexibility and simplicity, the Markov based approach used in this study encourages future work which involves the detection of similar behaviors of economic time series concerning different countries. The testing methodology used in this study also enables the comparison of statistical behavior of transition probabilities estimated for time series in these nations. As shown in Chapter 7 of this study, composite indicators generated by combination of significant economic indicators can permit better investigation of growth cycle patterns which thus enables effective comparison of growth performance of different nations.

BIBLIOGRAPHY

Acs Z.J. 2002. *Innovation and the Growth of Cities*. Edward Elgar Publishing, Cheltnam

Altug S. 2010. *Business Cycles: Fact, Fallacy and Fantasy*, World Scientific Publisher.

Andersson E. M., D. Bock and M. Frisén. 2004. Detection of Turning Points in Business Cycles. *Journal of Business Cycle Measurement and Analysis 1*, 93-108.

Artis M., M. Marcellino, and T. Proietti. 2003. Dating the Euro Area Business Cycle. *IGIER Working Paper 237.*

Ash R.F. and Y. Y. Kueh. 1993. Economic Integration within Greater China: Trade and Investment Flows Between China, Hong Kong and Taiwan. *The China Quarterly 136*, 711-745.

Athukorala, P. C. 2001. *Crisis and Recovery in Malaysia: The Role of Capital Controls*. Edward Elgar Publishing. Cheltenham.

Balisacan A. M. and H. Hill. 2003. *The Philippine Economy: Development, Policies, and Challenges*. Oxford University Press, Oxford.

Bergoeing R., P. J. Kehoe and R. Soto. 2001. A Decade Lost and Found: Mexico and Chile in the 1980s. *Working Papers Central Bank of Chile 107.*

Berndt E. and J. Morrison. 1981. Capacity utilization measures: Underlying Economic Theory and an Alternative Approach. *American Economic Review 71*, 48-52.

Biagioli M. 1998. Pay trends in Italy since the July 1993 agreement. *European Industrial Relations Observatory On-line.* http://www.eiro.eurofound.ie/servlet/ptconvert?IT9806326F

Blanchard O. 2004. The Economic Future of Europe. *Journal of Economic Perspectives 18(4)*, 3-26.

Blomström M. and A. Kokko. 2002. From Natural Resources to High-Tech Production: The Evolution of Industrial Competitiveness in Sweden and Finland. *EIJS Working Paper Series 139.*

Boldin M. 1996. A Check on the Robustness of Hamilton's Markov Switching Model Approach to the Economic Analysis of the Business Cycle. *Studies in Nonlinear Dynamics and Econometrics 1*, 35-46.

Brausch J. M. and T. C. Taylor. 1997. Who is Accounting for The Cost of Capacity. *Management Accounting 79*, 44-50.

Brock W.A. and C.L. Sayers. 1988. Is the Business Cycle Characterized by Deterministic Chaos?. *Journal of Monetary Economics 22*, 71-90.

Bruno G. and E. Otranto. 2004. Dating the Italian Business Cycle: A Comparison of Procedures. *ISAE Working Papers 41*.

Bry G. and C. Boschan. 1971. *Cyclical Analysis of Time Series: Selected Procedures and Computer Programs.* National Bureau of Economic Research, New York.

Burmeister. A. and K. Colletis-Wahl. 1997. Proximity in Production Networks: the Circulatory Dimension. *European Urban and Regional Studies 4(3)*, 231-241.

Burns A. F. and W. C. Mitchell. 1946. *Measuring Business Cycles*. National Bureau of Economic Research, New York.

Cairncross. F. 1997. *The death of distance: How the communications revolution will change our lives.* London: Orion.

Cape Business News. 2004. Massive employment growth at last. http://www.eprop.co.za/news/article.aspx?idArticle=4562

Celasun O. 1998. The 1994 Currency Crisis in Turkey. *World Bank Policy Research Working Paper 1913*.

Chenery H. B. 1960. Patterns of Industrial Growth. *The American Economic Review 50(4*), 625-654.

CIA World Factbook. 2008. Central Intelligence Agency of United States.
https://www.cia.gov/library/publications/the-world-factbook/geos/nl.html#Econ
https://www.cia.gov/library/publications/the-world-factbook/geos/tw.html

Combes P-P, T. Mayer and J-F Thisse. 2008. Economic Geography: *The Integration of Regions and Nations*. University Presses of California, Columbia and Princeton.

Corrado C. and J. Mattey. 1997. Capacity Utilization. *The Journal of Economic Perspectives, 11(1)*, 151-167.

Dicken. P. 1992. *Global Shift: The Internationalization of Economic Activity. 2nd ed*. Guilford Press. New York.

De Smith M. and E. Wever. 1990. *An industrial geography of the Netherlands: an international perspective.* Taylor & Francis, London

Diebold F. X. and G. D. Rudebusch. 1996. Measuring Business Cycles: A Modern Perspective. *The Review of Economics and Statistics 78(1)*, 67-77.

Dow C. 2000. *Major Recessions*. Oxford University Press, Oxford.

Dryden, M. M. 1969. Share Price Movements: A Markovian Approach. *Journal of Finance 24*, 49-60.

Eiras A.I. and B. D. Schaefer. 2001. Argentina's Economic Crisis: An `Absence of Capitalism. *Heritage Foundation Backgrounder No. 1432,* 1.

Evans G., S Honkapohja and P. Romer. 1996. Growth Cycles. *NBER Working Papers 5659*.

Feldman. M. P. 1994. *The geography of innovation*. Kluwer Academic Publishers. Boston.

Filardo A. J. 1994. Business-Cycle Phases and Their Transitional Dynamics. *Journal of Business and Economic Statistics 12(3),* 299-308.

Gertler, M.S. 1995. Being there – proximity, organization, and culture in the development and adoption of advanced manufacturing Technologies. *Economic Geography 71(1)*, 1–26.

Gresser E. 2004. The Emerging Asian Union? China Trade. Asian Investment. and New Competitive Challenge. *Policy Report*, *Progressive Policy Institute.* Washington. D.C.

Hamilton J. 1989. A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle. *Econometrica 57*, 357-384.

Harding D. and A. Pagan. 2002. A Comparison of Two Business Cycle Dating Methods. *Journal of Economic Dynamics and Control 27*, 1681-1690.

Hodge D. 2009. Growth, Employment and Unemployment in South Africa. *South African Journal of Economics 77(4),* 488-504.

Honkapohja S. and E. Koskela. 1999. The economic crisis of the 1990s in Finland. *Economic Policy, CEPR, CES, MSH*, *14(29)*, 399-436.

International Labor Organization. Overview and Topics: Employment and Unemployment. http://www.ilo.org/global/What_we_do/Statistics/topics/Employment/lang--en/index.htm

International Monetary Fund. 2009. Data and Statistics. *International Monetary Fund: Report for Selected Countries and Subjects*. http://www.imf.org/external/pubs/ft/weo/2009/01/weodata/weorept.aspx?sy=1980&ey=2014&scsm=1&ssd=1&sort=country&ds=.&br=1&c=299&s=PCPI,PCPIPCH&grp=0&a=&pr1.x=55&pr1.y=5

Kim C. and C. Nelson. 1999. Has the U.S. Economy Become More Stable?: A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle. *Review of Economics and Statistics 81*, 608-16.

Knoben. J. and L.A.G Oerlemans. 2006. Proximity and Inter-organizational Collaboration: A Literature Review. *International Journal of Management Reviews 8(2)*, 1-89.

Kose M.A., G. Meredith and M. T Christopher . 2004. How Has NAFTA Affected the Mexican Economy? Review and Evidence. *IMF Working Papers 04(59)*.

Krolzig H. M. 1997. Markov-Switching Vector Autoregressions: Modeling, Statistical Inference, and Application to Business Cycle Analysis. *Lecture Notes in Mathematical and Statistical Systems 454*.

Krolzig H. M. 2001. Markov Switching Procedures for the Dating the Euro-Zone Business Cycle. *Quarterly Journal of Economic Research 3*, 339-351.

Lahiri K. and G.H. Moore. 1992. *Leading Economic Indicators: New Approaches and Forecasting Records*. Cambridge University Press, Cambridge.

Loser C. and E. Kalter. 1992. Mexico: The Strategy to Achieve Sustained Economic Growth. *IMF Occasional Paper* 99.

Lucchin M. 2002. The Argentina's 2001 Debt Crisis. *Crossroads 2(3)*, 3-25.
http://www.webasa.org/Pubblicazioni/crossroads2002-3.pdf

McCaughan M. 2004. *The Battle of Venezuela*. Latin America Bureau, London.

Meltzer A. H. 2001. Monetary Transmission at Low Inflation: Some Clues from Japan,. *Monetary and Economic Studies 19(S-1*).

Murphy C. 2006. The United Nations Development Programme: A Better Way?. *Cambridge University Press,101*.

Neftci S. 1984. Are Economic Time Series Asymmetric Over the Business Cycle?. *Journal of Political Economy 92*, 307–328.

Office for National Statistics. 2010. Labor Market Statistics. *Statistical Bulletin: Office for National Statistics*. http://www.statistics.gov.uk/pdfdir/lmsuk0110.pdf

Pagan A. and D. Harding. 2005. A suggested framework for classifying the modes of cycle research. *Journal of Applied Econometrics 20*, 151-159.

Rigobon R. and A.Cavallo. 2010. Prices Today.
http://www.inflacionverdadera.com/

Rodrik D.1994. Getting Interventions Right: How South Korea and Taiwan Grew Rich. *NBER Working Papers 4964*.

Ross S. M. 2003. *Introduction to Probability Models, 8th ed*. Academic Press, San Diego.

Roubini N. 1998. Unemployment Rates.
http://pages.stern.nyu.edu/~nroubini/bci/Unemploymentrate.htm

Sak G. and Ozatay S. 2002. Financial Liberalization in Turkey: Why was the Impact on Growth Limited?. *Emerging Markets Finance and Trade 38(5)*, 6-22.

Sapsford R. and V. Jupp. 1996. *Data Collection and Analysis.* Sage Publications, London.

Schaik P. V. 2009. The Unemployment Rate - A Lagging Indicator?. *EzineArticles*
http://ezinearticles.com/?The-Unemployment-Rate---A-Lagging-Indicator?&id=2213853

Schwab Center for Financial Research. 2007. Schwab Guide to Economic Indicators: Industrial Production and Capacity Utilization, *Charles Schwab & Co. Inc.*
http://www.schwab.com/public/schwab/research_strategies/market_insight/1/4/schwab_guide_to_economic_indicators_industrial_production_and_capacity_utilization.htm

Stock J. H. and M. W. Watson. 1991. A simple estimator of cointegrating vectors in higher order integrated systems. *Working Paper Series, Macroeconomic Issues 91-3*.

Storper. M. 1997. *The regional world : territorial development in a global economy. Perspectives on economic change*. Guilford Press. New York.

Storper. M. and A. J. Venables. 2004. Buzz: Face-to-face contact and the economy. *Journal of Economic Geography 4(4)*, 351-370.

Taipei Economic and Cultural Office. 2006. Taiwan's Economy. *Information Division, Taipei Economic and Cultural Office.* http://www.asianinfo.org/asianinfo/taiwan/pro-economy.htm

Tan B. and K. Yilmaz. 2002. Markov chain test for time dependence and homogeneity: An analytical and empirical evaluation. *European Journal of Operational Research 137(3)*, 524-543.

Tang M.K. 2008. Twin Global Shocks Dent United Kingdom Outlook. *IMF Survey 37(9).*

Tiraboschi M. and M. Del Conte. 2004. Recent Changes in the Italian Labor Law. *Presented in JILPT Comparative Labor Law Seminar.* Tokyo, Japan. http://www.jil.go.jp/english/reports/documents/jilpt-reports/no1.pdf

Torre A. and A. Rallet. 2005. Proximity and Localization. *Regional Studies 39(1)*, 1-13.

Vardy N. 2010. Latin America's Chile: A Top Stock Market Performer. http://www.personalliberty.com/conservative-politics/liberty/latin-americas-chile-a-top-stock-market-performer/

Verspagen. B. and W. Schoenmakers. 2002. The Spatial Dimension of Patenting by Multinational Firms in Europe. *Presented at DRUID 2003 Summer Conference*. Copenhagen. Denmark.

Winckler E. A. and S. M. Greenhalgh. 1988. *Contending Approaches to the Political Economy of Taiwa*n. New York: M. E. Sharpe, Inc.

Wyplosz C. 2001. Exchange Rate Regimes: Some Lessons from Postwar Europe. *CEPR Discussion Papers 2723*.

Yeldan A.E. 2008. Turkey and the Long Decade with The IMF: 1998-2008. http://www.networkideas.org/news/jun2008/Turkey_IMF.pdf

Zarnowitz V. 1992. *Business Cycles: Theory, History, Indicators and Forecasting*. University of Chicago Press for the NBER.

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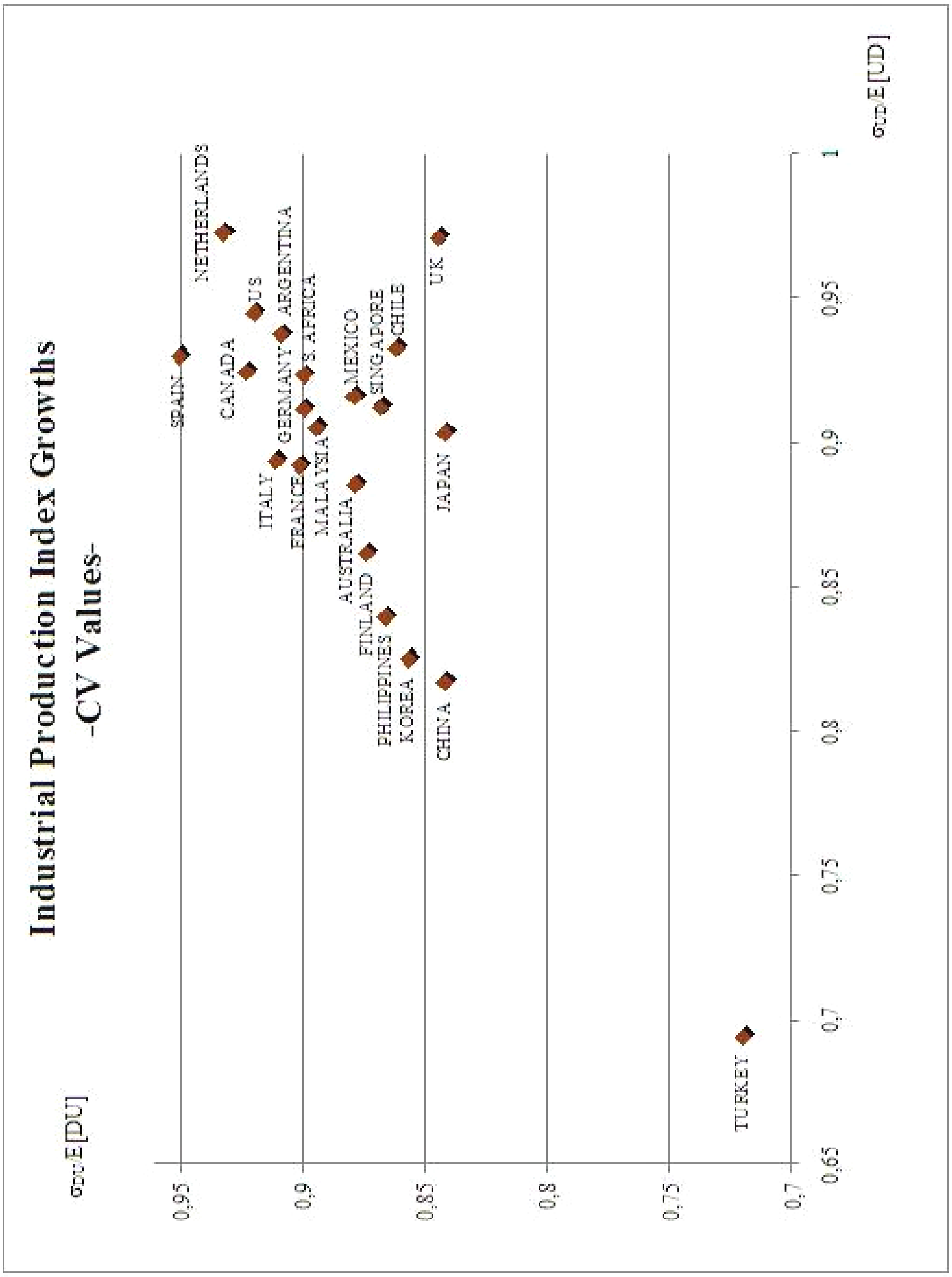
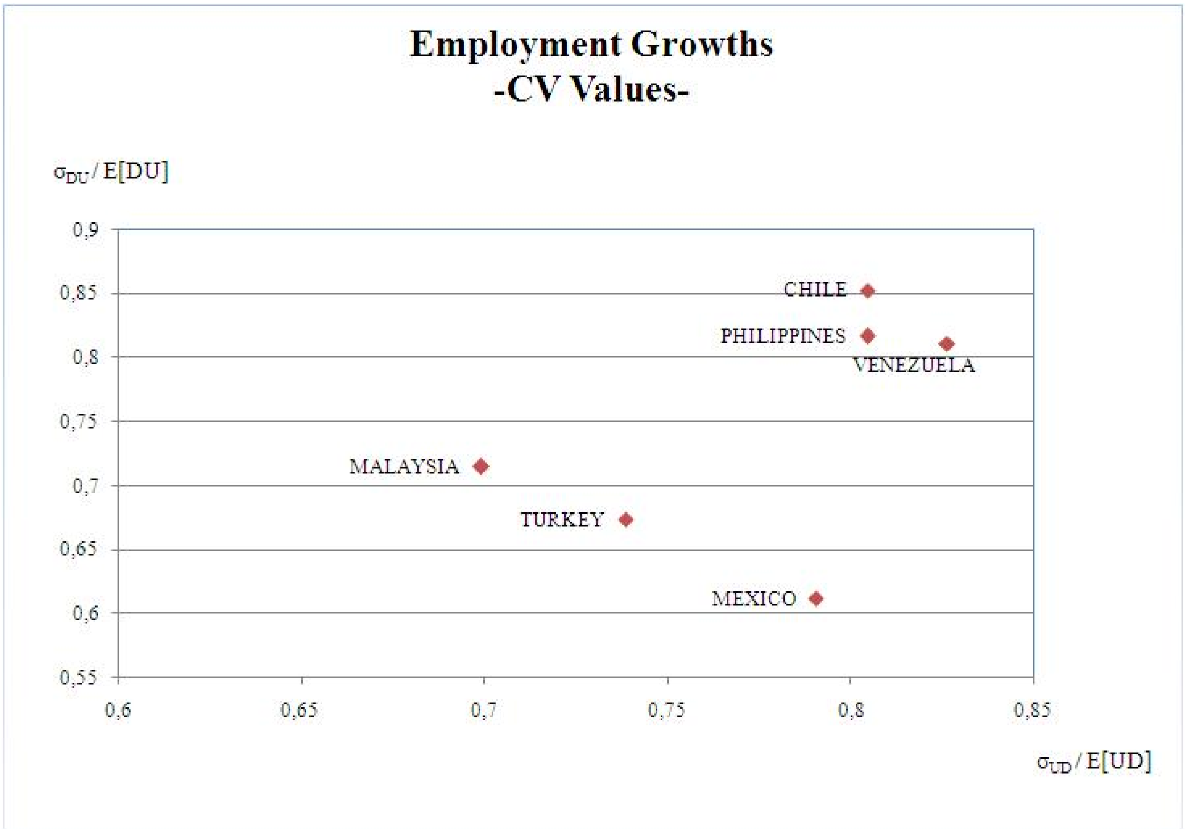
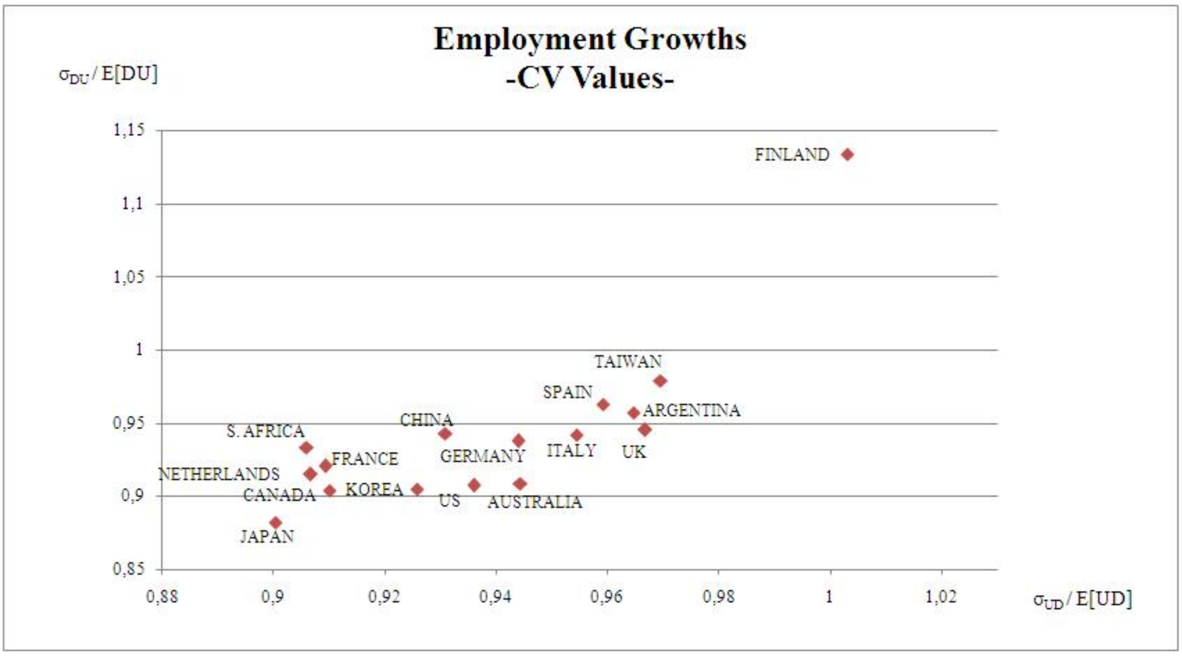
APPENDIX



CV Values of Countries for Industrial Production Index Growths





CV Values of Countries for Employment Growths

VITA

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