TÜSİAD-KOÇ UNIVERSITY ECONOMIC RESEARCH FORUM
WORKING PAPER SERIES

CYCLICAL DYNAMICS OF INDUSTRIAL PRODUCTION AND EMPLOYMENT: MARKOV CHAIN-BASED ESTIMATES AND TESTS

Sumru Altuğ
Barış Tan
Gözde Gencer

Working Paper 1101
January 2011

TÜSİAD-KOÇ UNIVERSITY ECONOMIC RESEARCH FORUM
Rumeli Feneri Yolu 34450 Sarıyer/Istanbul

Cyclical Dynamics of Industrial Production and Employment: Markov Chain-based Estimates and Tests

Sumru Altug
Koç University and CEPR

Barış Tan
Koç University

Gözde Gencer
Yapıkredi Bank*

January 24, 2011

Abstract

This paper characterizes the business cycle as a recurring Markov chain for a broad set of developed and developing countries. The objective is to understand differences in cyclical phenomena across a broad range of countries based on the behavior of two key economic times series – industrial production and employment. The Markov chain approach is a parsimonious approach that allows us to examine the cyclical dynamics of different economic time series using limited judgment on the issue. Time homogeneity and time dependence tests are implemented to determine the stationarity and dependence properties of the series. Univariate processes for industrial production and employment growth are estimated individually and a composite indicator that combines information on these series is also constructed. Tests of equality of the estimated Markov chains across countries are also implemented to identify similarities and differences in the cyclical dynamics of the relevant series.

Keywords: Markov chain models, economic indicators, cross-country analysis
JEL Codes: C22, E32, E37.

*We are grateful to Peter Benczur for providing us with the multi-country data set that formed the basis of their paper "Business Cycles around the Globe".

1 Introduction

Modeling business cycles dynamics using Markov processes and Markov chains has an important tradition. In early work, Neftci (1984) investigated the issue of asymmetry between expansions and contractions of a business cycle using a framework of discrete Markov chains. Neftci (1984) argued that the behavior of unemployment rate in the United States can be characterized by sudden jumps and slower drops. Hamilton (1989) proposed a simple nonlinear framework for modeling economic time series with a permanent component which follows a Markov switching process as an alternative to a stationary linear autoregressive model. In his framework, recessions are due to permanent negative shocks. Another type of business cycle asymmetry is due to Kim and Nelson (1999). This is known as the "plucking model" of business cycles. Here recessions occur as temporary deviations from the long-run level of GDP as occasional "plucks" whereas expansions reflect permanent shocks. Kim and Piger (2002) propose a framework which allows for infrequent asymmetric transitory shocks which come from a Markov process as well as continuous transitory symmetric shocks. Markov chain-based approaches have also been used in the labor economics literature to model labor market dynamics. Flinn and Heckman (1982) use Markov chain methods to develop a structural model of labor market search and to estimate its parameters. Eckstein and van den Berg (2007) present an up-to-date survey of empirical labor market search. In a developing economy context, Alvarez, Ciocchini and Konwar (2008) use discrete Markov chain methods to characterize the dynamics of Argentinian labor markets in a period that also encompasses the Argentinian crises of 1995 and 1998-2002.

In this paper, we characterize the business cycle as a recurring Markov chain for a broad set of developed and developing countries. Our objective is to understand differences in cyclical phenomena across a broad range of countries based on the behavior of two key economic times series – industrial production and employment. The Markov chain approach is a parsimonious approach that does not require an extensive set of assumptions regarding the distribution, homoscedasticity, serial correlation properties of the time series under consideration. In a series of papers, Harding and Pagan (2002a,b) have argued that the approach based on the Markov switching model may produce different business cycle characteristics relative to linear models depending on assumed features such as conditional heteroscedasticity, persistence, and non-normality of the process. More importantly, the Markov chain approach used in this paper allows a test of the time-dependency and time-homogeneity of the estimated Markov chains, a feature which is typically absent from applications of the Markov-switching model. One disadvantage of the Markov chain approach, however, is that some of the details of the underlying stochastic process are lost when a continuous state space of a given time series is aggregated into a discrete one. Tan and Yilmaz (2002) implemented Markov chain-based tests of time dependence and time homogeneity in the context of tests of market efficiency and examined the efficacy of the Markov chain approach using simulation methods. In this study, we extend their approach to the analysis of cyclical phenomena in a cross-country basis. Our approach is also related the work of Neftci (1984), who used a discrete Markov chain approach to model the behavior of US unemployment over the postwar period.

Burns and Mitchell (1946) were the first investigators who set out the nonparametric methods to determine the characteristics of cycles in economic time series. They laid the foundations of documenting recurrent cycles of quantities and prices. Nonparametric approaches extract information about the evolution of an economic time series directly from the observation of the historical data. Thus, this approach works even when reliable information on the parametric function is not provided. The possibility that the behavior of the economic time series may have changed in the past is also taken into consideration, and predictions are made by taking into account such changes (see Andersson, Bock and Frisen, 2004). The nonparametric approach which is used by NBER in order to detect turning points of business cycles is derived from Bry and Boschan's (1971) influential work where no formal statistical model is used during the process. Bry and Boschan's approach is a nonparametric procedure which is applied to a single monthly time series adjusted for seasonality. As we discussed above, there are numerous parametric approaches to modeling business cycles. Implementation of parametric models such as the Markov-switching model involve judgments about how many states are included in the model and whether the transition probabilities are constant during the observed time interval. This means that the time-homogeneity of observed series is not properly tested. On the other hand, the simple Markov chain approach does not involve such assumptions about the stationarity of the time series in consideration.

In this paper, we implement formal tests of time-homogeneity of the series to determine if the transition probabilities between the states of the Markov model are invariant over time or not. The systematic time-dependence and time-homogeneity testing procedure thus enables us to make realistic inferences about the cyclical dynamics of economic time series using limited judgment on the issue. Our study permits the detection of breaks in the estimated transition probabilities. This approach leads to using different transition probabilities for different time periods depending on the determined breaks in the period under investigation. 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. In recent years, a number of studies have investigated the impact of various institutional factors on business cycle characteristics. See, for example, Canova, Cicarrelli and Ortega (2009) or De Pace (2010). In our study, we used information about such underlying institutional, political or policy changes when testing for time-homogeneity of the economic time series. Hence, our approach relates such factors to potential nonlinearities in the underlying series.

Another contribution of our study is that we can use Markov chain-based tests to identify similarities and differences in the cyclical dynamics of the relevant series. By comparing the estimated transition probabilities of two countries by using a Markov chain-based test, we formally test whether the cyclical dynamics of one country can be differentiated from another one. Furthermore, we use a first passage time analysis to determine the mean and the coefficient of variation of the first passage times between the states above and below the trend. These first passage times also give additional information regarding the similarities and differences between the cyclical dynamics of different countries.

The rest of this paper is organized as follows. Section 2 describes the methodology while Section 3 discusses the notion of economic indicators as well as the data used in this study. Section 4 describes how to implement tests of time homogeneity and time dependence while Section 5 describes the results of implementing such tests. Section 6 implements tests of the statistical difference of the estimated Markov chains between the different countries while Section 7 examines the expected first passage times between the different states. Section 8 shows how the analysis can be extended to derive composite indicators. Section 9 concludes.

2 Methodology

In this study, we propose and use a Markov chain-based methodology for investigating the cyclical behavior of key economic aggregates. More specifically, we view a business cycle as a recurring Markov chain. The length of time this process is expected to spend in each state before switching to the other state gives statistical information regarding this alternating process.

Formally, we view a given economic time series $y(t)$ as a discrete parameter, continuous state space stochastic process $\{y(t), t = 1, 2, \ldots\}$. In order to utilize the Markov chain methodology, we aggregate the continuous state space of the time series into a discrete state space with a finite number of states. That is, the process $\{y(t), t = 1, 2, \ldots\}$ is mapped into a discrete parameter, discrete state space stochastic process defined as $\{X_t, t = 1, 2, \ldots\}$ on the state space S.

The aggregation of the state space and the definition of the state space depend on the statistical properties of the time series under investigation. To analyze cyclical dynamics of economic time series (e.g. capacity utilization rates, industrial production indices, stock prices) as a Markov chain, it is sufficient to focus on the direction of movements of the time series which indicate whether the consecutive states show an increase or decrease over time. This approach has been used extensively in the literature. One can use more states in S to include more information on $y(t)$ in X_t to study not only the direction of change but also the magnitude of change. However, the increased number of states requires a greater probability transition matrix to estimate and reduces the power of the tests power when the number of observations is limited. It is shown that analyzing a time series as a two-state recurring Markov chain is sufficient to analyze its cyclical dynamics (Tan and Yilmaz 2002).

In this study, the continuous state space of a stationary economic time series is 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 $[0, T]$, $\bar{y} = 1/(T+1)\sum_{t=0}^{T} y(t)$, i.e.,

$$X_t = \begin{cases} U & \text{if } y(t) \geq \bar{y} \\ D & \text{if } y)t) < \bar{y}. \end{cases}$$

In economic time series which exhibit a trend over the sample period, the movements in the series are defined relative to this trend.

Our methodology starts with determining the time-dependency and time-homogeneity properties of the two-state Markov chain obtained from the economic time series that is being investigated. The first step of our methodology tests whether the time series under investigation can be represented as a time-homogeneous Markov chain of a determined order. The outcome of this step is a time-homogeneous probability transition matrix that gives the estimated transition probabilities between the states depending on the determined order of time dependency. Alternatively, we can conclude that the time series cannot be represented as a time-homogeneous time series in the time period being investigated. In this case, we can continue with searching another starting point for the time series that may yield a time-homogeneous Markov chain representation.

Once we ensure the time homogeneity and determine the order of time dependency, we use the estimated probability matrix to analyze the statistical properties of the time series. We also use the estimated probability matrices of two countries to test whether the Markov chains of these countries are statistically different. Furthermore, we use a first-passage time analysis to determine the expected times the process spends in state U until it switches to state D and the expected time it spends in state D until it switches to state U. This analysis also gives us information about the distribution of the switching times and thus answers questions on the probability of observing a transition into another state within a given time period.

Unlike other parametric approaches, this methodology allows us to directly test the time-dependency and homogeneity properties of the underlying time series without making distributional assumptions.

Our discussion follows from Tan and Yilmaz (2002). For a more detailed discussion of the procedures, the reader is referred to Anderson and Goodman (1957) and Kemeny and Snell (1976). In the next section, first the methodology to test for time-dependency and time-homogeneity given in (Tan and Yilmaz 2002) is summarized. Then the methodology to test the statistical difference between two time series, and also the methodology to analyze the passage times between the up and the down states are presented.

2.1 Definitions

A Markov chain of order u is completely characterized with its state transition matrix $P(t) = \{p_{i,j}(t)\}$ where

$$\begin{aligned} &p_{i,j}(t) = P(X_{t+1} = j | X_t = i_1, \ldots, X_{t-u+1} = i_u), \\ &i = (i_1, \ldots, i_u)' \in S^u, j \in S, t = u-1, u, u+1, \ldots \end{aligned} \tag{1}$$

In this representation the 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 $j \in \{U, D\}$.

The above definition shows that whenever the stochastic process is in state i, there is a probability $p_{i,j}(t)$ that it will be in state j at time $t+1$. When the transition probabilities between states do not vary over time, then the underlying Markov chain is *time homogeneous.* In this case, when in state i at time t, the probability that the process will next make a transition into state j is independent of time t. This implies, for a time homogeneous Markov chain $p_{i,j}(t) = p_{i,j}$ and therefore $P(t) = P$.

Consequently, for a given sequence $\{X_t, t = 0.1, 2, \ldots\}$ is an independent process then the probability law of the process is given by:

$$P(X_t = j | X_{t-1} = i_1, \ldots, X_0 = i_t) = P(X_t = j).$$

Similarly, for a first-order Markov chain,

$$P(X_t = j | X_{t-1} = i_1, \ldots, X_0 = i_t) = P(X_t = j | X_{t-1} = i_1);$$

and for a second-order Markov chain,

$$P(X_t = j | X_{t-1} = i_1, \ldots, X_0 = i_t) = P(X_t = j | X_{t-1} = i_1, X_{t-2} = i_2).$$

2.2 Estimation of State Transition Probabilities

For a time-homogeneous Markov chain order u, the transition probabilities can be estimated directly from the observed transitions. The maximum likelihood estimates of the state transition probabilities are given as

$$\hat{p}_{i,j} = \frac{n_{i,j}}{\sum_i n_{i,j}}, \; i \in S^u, j \in S, \tag{2}$$

where $n_{i,j}$ represents the total number of observed transitions from state i to j during the given time period (Anderson and Goodman 1957). Once the transition probabilities have been estimated, they can be used to construct tests of time dependence and time homogeneity of the Markov chain in question. We present the relevant tests in Section 4. In that section, we also show such tests can be extended to test for the equality of the transition probabilities of two different Markov chains. Finally, using the results of Appendix A, we calculate the expected first passage times for the different economic indicators considered in this study.

3 Economic indicators

In this study, we analyze the behavior of industrial production and employment growth as economic indicators which provide information about the underlying trends of the economy. Economic indicators can be classified as leading or lagging. As Lahiri and Moore (1992) argue, it may be useful to identify series as leading indicators since market-oriented economies experience business cycles where repetitive sequences are observed. These sequences not only underlie the generation of business cycles but also constitute the most useful data to forecast the turning points of economic activity.

The industrial production index is an economic indicator which measures the real growth rate in industrial production of a nation. It represents the industrial capacity measure and the availability of resources among factories, utilities and mines. It is well 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 business cycle. Unemployment data is generally considered as a lagging indicator by many economists, as it is destined to increase after the official end of a recession in the 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 the end of recessions. Hence, there are those who argue that employment data should be considered more than a lagging indicator.

Existing business cycle studies have examined the behavior of industrial production as much as they have concentrated on the behavior of aggregate real GDP. Artis, Kontolemis and Osborne (1997) and Artis, Krolzig and Toro (2004) use industrial production data to examine business cycles in G7 and the Euro area, respectively, using both parametric and nonparametric approaches. The cyclical behavior of aggregate employment has been one of the key issues around which the debate about the efficacy of the Real Business Cycle model in replicating aggregate fluctuations has evolved. (See, for example Hodrick and Prescott, 1997, and Gali, 1999.) In his influential study, Neftci (1984) argues that economic time series such as the unemployment rate are related to the production side of the economy. Hence, they give a better indication of business cycles than other variables that are not directly linked real economic decisions.

In this paper, we analyze the cyclical dynamics of industrial production and employment of a broad set of countries playing key roles in the global economy. The full set of countries used in our study is similar to the set considered by Altug and Bildirici (2010), and it comprises a set of developed countries including Australia, Canada, the UK, the US and Japan plus the EU countries of Finland, France, Germany, Italy, the Netherlands and Spain as well as a set of developing countries including the East Asian countries of Malaysia, Philippines, and S. Korea, the Latin American countries of Argentina, Chile, and Mexico and a set of countries typically considered among the emerging economies including China, S. Africa and Turkey. Data on the industrial production index is typically available from the International Financial Statistics (IFS) database of the IMF. Data on aggregate employment can be obtained from the International Labor Office (ILO), Eurostat or Bank of International Settlements (BIS).

Let $y_{i,t} = \ln(Y_{i,t})$ where $Y_{i,t}$ denotes the industrial production index (or total employment) of country i in quarter t. We take the annual quarter-to-quarter growth rate of GDP for country i as $\Delta y_{i,t} = \ln(Y_{i,t}) - \ln(Y_{i,t-4})$. For seasonally unadjusted data, this transformation tends to eliminate any seasonal effects that might exist at the quarterly frequency. In some cases the underlying growth series may exhibit a trend – typically a negative trend – over the sample period. In this case, we calibrate the Markov chain relative to this time-varying trend, and not the simple sample average described in Section 2.1.

4 Tests of time homogeneity and time dependence

In this section we describe how to test for time dependence and time homogeneity of the estimated Markov chains for each country individually. These tests allow us to determine the order of the Markov chain and also whether it follows a stationary process.

4.1 Testing for time dependence

In order to test time dependence, we first assume that the Markov Chain is time homogeneous in the time period that is being investigated.

Let $P = \{p_{i,j}\}$ denote the time homogeneous state transition matrix of Markov chain of order u and $Q = \{q_{i,j}\}$ denote the transition matrix for order v. In order to test the null hypothesis that the Markov chain is of order u versus order v such that $v > u$, an asymptotically equivalent test statistic for the likelihood ratio test statistic is given in (Tan and Yilmaz 2002) as

$$-2\ln(\Lambda) = 2\sum_{i,j} n_{i,j}\left[\ln(q_{i,j}) - \ln(\tilde{q}_{i,j})\right], \quad i \in S^v, j \in S, \tag{3}$$

with

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

where A^{T} denotes the transpose of matrix A.

This test statistic has a χ^2 asymptotic distribution with $2^v - 2^u$ degrees of freedom. The order-test procedure starts with testing the null hypothesis that the given time series is an independent process (with $u = 0$) versus the alternative hypothesis that the time series is a Markov chain of first order (with $v = u + 1$), and if it is rejected continues by increasing u by one and applying the same test with order u versus $u + 1$. This procedure lasts until the null hypothesis is not rejected.

Since it is assumed that the Markov chain is time homogeneous to perform this task, this assumptions must be tested to finalize the time-dependency test.

4.2 Testing for time homogeneity

In order to test a time series for time homogeneity, we divide observations on $\{X_t, t = 0, 1, 2, \ldots\}$ into K different equal sub-intervals. This test involves testing whether the estimated 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

$$\begin{aligned} &p_{i,j}(k) = P(X_t = j | X_{t-1} = i_1, \ldots, X_{t-u} = i_u), \\ &\quad i = (1_i, \ldots, i_u) \in S^u, j \in S, t \in [(k-1)\Delta, k\Delta], \end{aligned} \tag{4}$$

where $\Delta = \lfloor (T + 1)/K \rfloor$. We would like to test the null hypothesis that the transition probabilities for each subinterval $P(k) = \{p_{i,j}(k)\}$ are not statistically different from the transition probabilities determined for the whole period $P = \{p_{i,j}\}$ 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:

$$\begin{aligned} &-2\ln(\Lambda) = 2 \sum_k \sum_{i,j} n_{i,j}(k) \left[\ln(p_{i,j})(k) - \ln(p_{i,j}) \right], \\ &\quad i \in S^u, j \in S, k = 1, 2, \ldots, K \end{aligned} \tag{5}$$

where $n_{i,j}(k)$ is the number of observed transitions from state i to state j for subinterval k. This test statistic has a ξ^2 asymptotic distribution with $2(K - 1)$ 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.

5 Results

Tables 1 and 2 provide the estimated transition probabilities for the behavior of industrial production (IP) growth and employment growth for the entire sample of countries. The results of tests for time homogeneity and time dependence are also reported in these tables. Column 1 shows the beginning year for which time homogeneity of the series can be established while Column 2 shows the order of the estimated Markov chain. In our analysis, we typically report the time series properties of the economic indicators in the period after a break is detected, if such a break exists. By focusing on the most recent period for which time-homogeneity can be established, we also ensure that the estimated Markov models in this paper have predictive power for future developments in the economy.

5.1 The developed countries

We examine cyclical phenomena for the developed countries using country groupings suggested by Altug and Bildirici (2010). Thus, one group of developed countries is termed the Anglophone countries plus Japan while the second group comprises a set of EU countries. Equivalently, the developed countries that we study may be examined in terms of the G7 countries consisting of the US, Japan, Germany, France, the UK, Italy and Canada plus a set of smaller industrialized such as the Finland, Netherlands, Spain and Sweden.

Beginning with the US, we find that both IP and employment growth both have negative trends over the sample period. Hence, the Markov chains for these variables are calibrated relative to their individual-specific trends. Tests of time homogeneity and time dependence show that time-homogeneous Markov chains of order one can be used to represent changes in IP and employment across the sample period 1960-2008 for the US.[1] We also find that IP and employment growth follow time-homogeneous processes for Australia, Canada, and the UK over the available sample periods, and that IP and employment growth follow first-order processes for Australia, Canada, and the US. This is also the case for employment growth in the UK. However, we find that IP growth in the UK follows a second-order process. Since the time-dependence properties are obtained as a result of formal testing, this result suggests a significant difference in the cyclical dynamics of the UK relative to the remaining Anglophone countries. There are also some salient differences in the expected first passage times across countries for both IP and employment growth. Specifically, the expected first passage times for US IP growth tend to be longer than those for the other Anglophone countries. More tellingly, though, we find that employment growth in the UK is a much more persistent process relative to those for the other Anglophone countries and indeed relative to those for all of the developed countries with the exception of Spain that we discuss below. In the next section, we provide results of formal tests to determine whether such differences are statistically significant or not.

Turning to EU countries, Markov chain-based time-homogeneity and time-dependence tests imply that IP growth processes for Germany, France, Italy, Finland and Spain follow homogeneous patterns across the available sample periods. However, we can estimate a time-homogeneous process for IP in the Netherlands only since 1963. Furthermore, unlike the processes in Germany, France, Italy, Finland and Spain, IP growth follows a second-order process in the Netherlands. Second, employment growth shows homogeneous behavior in Germany, France, the Netherlands, Finland, and Spain. However, the Markov chain for employment growth in Finland is of second-order, unlike the case for the other developed countries.

There are also a set of developed counties for which the Markov chain-based time homogeneity tests are rejected. A notable example in this regard is Japan. Tables 1 and 2 show

[1]It is interesting to compare this result with Neftci's (1984) results, who found that movements in the quarterly unemployment rate follow a second-order Markov chain. During the application, Neftci also supposes that the unemployment rate is a stationary series. On the other hand, Neftci does not use any time homogeneity or time dependence tests in order to justify these assumptions. Using quarterly data on unemployment rates for the U.S. over the period 1948-2008, we found that this series is a homogeneous stochastic process following a first-order Markov chain. Our results verify the validity of Neftci's results and they also show that there exists no discernible break in the behavior series such as IP and employment growth or the unemployment rate.

that both IP and employment growth follow non-homogeneous processes over the sample period. We find that 1993 appears as a natural breakpoint for the Japanese economy after which time-homogeneity of both IP and employment growth can be established. As is well known, the Japanese economy entered a long period of recession and stagnation in the early 1990's. The Economic Cycle Research Institute (ECRI) gives the date of the first Japanese recession in the 1990's as 1992:2. The "lost decade" in Japan has been studied extensively. Meltzer (2001) claims that the maintained growth rate of Japan slowed and Japan's cost of production rose relative to U.S production costs in the 1990's. "To restore 1980's growth required either increased productivity growth, real currency depreciation, or deflation. Japan's policy makers, by choice or accident, chose deflation instead of currency depreciation" (see Meltzer, 2001). Even industries such as automobiles and electronics that had experienced extraordinary growth in 1980's entered a recessionary phase in the early 1990's. This continued until the zero or negative growth of the real monetary base ended in 1993, suggesting that 1993 serves as a breakpoint for the behavior of the Japanese economy.

We also find that employment growth for Italy is not time-homogeneous. 1993 emerges as a breakpoint in this case as well. Tiraboschi and Del Conte (2004) argue that the 23 July 1993 agreement signed by the socialist parties and the Italian Government was a turning point in Italian industrial relations. This agreement was based on the will to bring pay settlements into line with rigorous incomes policy in order to combat inflation, which was considered as a base step for entry into the EU Economic and Monetary Union (EMU). Following this period, a combination of factors, one being the tax burden on employment, caused the unemployment rate to rise to 11.3% and led to an inflation rate 5%, which was higher than that of Italy's main trading partners. In the middle of 1990's, the unemployment rate started to decrease again due to the 28 November 1996 legislations, which were designed to promote access to employment.

5.2 Developing countries

The developing countries tend to have both different cyclical dynamics relative to the developed economies and also to display much less stability. Furthermore, we show that there are significant differences among these countries, even ones with similar historical or geographical characteristics.

The East Asian countries have been known for their remarkable economic success. Before the 1960's, Korea had been one of the poorest economies. Yet Korea has been one of the world's fastest growing economies since the early 1960's through the late 1990's, and it is 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 or employment performance of Korea.

Before the 1997 Asian financial crisis, Malaysia had been known as a popular investment destination which caused expectations that economic growth would continue. However, in July 1997, the currency of Malaysia - the *ringgit* - suffered a speculative attack. In 1998, real output growth fell and Malaysia entered into its first recession for a long time period. From Table 1, we observe that IP growth in Malaysia does not follow a time-homogeneous over the entire sample beginning in 1985, and that 1998 serves as the breakpoint in the time-homogeneity tests. However, the estimated process for IP growth since 1998 is of order one, as is the case for S. Korea and has similar expected first passage times. By contrast, employment growth since 1997 for Malaysia can be represented as an i.i.d process with very short expected first passage times between the two states.

Unlike many of its neighbors, Philippines had not experienced a long-term rapid growth since the 1970's due to its weak political and institutional foundations. Even in the 1990's corresponding to the peak years of growth for the Asian countries, growth in the Philippines did not exceed 6%. As a consequence, IP growth in the Philippines is generally low and stable, and time-homogeneous first-order Markov processes suffice to capture the behavior of IP and employment growth over the observed sample periods.

In contrast to the East Asian economies, the Latin American countries exhibit far greater heterogeneity. From being a wealthy economy with rich natural resources and an export-oriented agricultural sector with a relatively diversified industrial base, Argentina entered a long period of decline and suffered from a series of economic crises during 1981-2002. Argentina entered 2001 with an economy already mired in a long recession period, partly attributable to the contagion effects of Russia's debt default in August 1998. This caused investors to avoid emerging markets and also raised the cost of Argentina's foreign borrowing. By 2002, the economy suffered its sharpest decline since 1930: Argentina had defaulted on its debt. As a result, we find that both IP and employment growth are time-homogeneous processes over samples that begin in 1997 or 1998. We also find that the process for employment growth in Argentina is highly persistent, reflecting the dynamics of the crises that this country has endured over the sample period.

For the Mexican economy, the signing of the North American Free Trade Agreement (NAFTA) in 1994 between Canada, the US and Mexico constitutes an important turning point. The increase in regional integration among NAFTA partners also affected business cycles in Mexico and led to a significant increase in the co-movement of business cycles within the NAFTA region (Kose, Meredith and Towe, 2004). For this reason, when analyzing the behavior of IP growth, 1994 is considered a breakpoint for the Mexico economy. From Table 1, we observe that IP index growth of Mexico can be represented with a first-order Markov process after 1994. By contrast, we observe that employment growth for Mexico can only be represented with a time-homogeneous process since 2000.

Like most of other countries in Latin America, Chile had experienced economic crisis in the early 1980's which caused sharp decreases in industrial output. On the other hand, unlike Mexico, Chile economy succeeded in recovering rapidly and grew consistently during 1980's. This success may be due to the early reforms undertaken in the 1970's which set the stage for the successful performance of Chile in the 1980's (Bergoeing, Kehoe and Soto, 2001). These facts are mirrored in the behavior of IP growth in Chile, which can be represented as a time-homogeneous Markov process over the available sample period stretching back to 1960. By contrast, we find that employment growth can only be characterized as a time-homogeneous process since 1999.

In the remainder of this section, we consider three other emerging market economies. Following Mao's death, gradual market reforms were initiated and the free-market system began to take hold in China. Today, China is one of the fastest-growing and most important economies in the world, and it has been undergoing a process of very rapid industrialization. In contrast to the process of "de-industrialization" in the US, both IP and employment growth have significant positive trends in China over the respective sample periods.[2] We find that both IP

[2] Bronfenbrenner and Luce (2004) provide evidence regarding the impact of a production shift on jobs from

and employment growth can be represented by homogeneous first-order Markov processes after accounting for the positive trends in both of these series over the relevant sample periods.

The South African economy was able to display average growth rates of 2.1% and 1.4% in the 1980's and 1990's, respectively. However, real GDP growth was more volatile during the 1980's than in the 1990's (Hodge, 2009; Altug and Bildirici, 2010). Our analysis revealed a breakpoint of 1983 for IP growth. One criterion for choosing this year as a breakpoint is that employment growth was 3.7% in 1982, the highest employment growth rate until 2004. However, our analysis revealed no breakpoint for employment growth but this may be due to the shorter sample for this series.[3]

Turkey suffered from two major economic crises in recent years, one of which occurred in 1994 and the other in 2001. We observe a large decline in IP growth in 1994, which is due to the 1994 currency crisis. This crisis caused the highest level of annual output loss in the history of the Turkish Republic. 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 the currency lost 51% of its value against the major foreign monies. The rate of unemployment rose up to 10% and real wages were reduced by 20% upon the impact of 2001 crisis (Yeldan, 2008). For IP growth, the breakpoint occurs in 2002 while for employment growth, it occurs earlier in 2000. Beginning with these years, we observe that the estimated Markov processes for both IP and employment growth are i.i.d processes with very short expected passage times between the two states, reflecting the lack of any major crises in this period except the 2008 financial crisis.[4]

Summarizing, we find that there is greater evidence against time-homogeneity in the estimated Markov processes for the developing countries relative to developed ones. With the exception of the fast-growing East Asian economies, almost all of the developing countries exhibit some form of nonstationarity in the processes describing IP and employment growth. This no doubt reflects the experience of major crises as well as institutional and policy changes that such economies have undergone. This finding is also evident in the nature of the estimated processes over periods for which time-homogeneity can be established.

6 Testing for statistical difference between the cyclical dynamics of two countries

Our analysis in the previous section shows some noteworthy differences in the stochastic processes describing the cyclical dynamics of IP and employment growth for individual countries.

the US and Europe to countries such as China, India, other Asian countries, Mexico and so on.

[3]Our analysis also did not reveal a breakpoint in 1994 associated with the ending of apartheid in 1994. However, the lower and less volatile growth may be attributed partly to this phenomenon as well as the lengthy process of adjustment in employment growth.

[4]As a point of comparison, we can also examine the behavior of the estimated Markov process for IP growth in the period between 1980-2001 for Turkey. This is a first-order Markov process with the following transition probability matrix:

$$P = \begin{bmatrix} 0.6957 & 0.3034 \\ 0.3514 & 0.6486 \end{bmatrix} \quad \text{with} \quad E(T_{U,D}) = 3.28 \quad \text{and} \quad E(T_{D,U}) = 2.84.$$

These are similar to the properties of the estimated Markov chains for countries such as China or S. Korea. Hence, we find that the cyclical properties of IP are not out of line with experience of other developing economies.

These differences are reflected in the persistence properties of the estimated Markov chains. We now test formally to determine whether such differences are statistically significant. This test involves testing whether the estimated transition probabilities of each country are statistically different from the transition probabilities estimated by combining the time series. That is, if the cyclical dynamics of two countries cannot be distinguished from each other statistically, then the transition probabilities of these two countries are estimated by using the combined time series of both countries.

We assume that the estimated order of time dependency for both countries is the same and denoted by u. Note that if these countries have different order of time dependency, we can state automatically that their cyclical dynamics are statistically different.

We would like to test the null hypothesis that the transition probabilities for countries A and B, $P(A) = \{p_{i,j}(A)\}$ and $P(B) = \{p_{i,j}(B)\}$ are not statistically different from the transition probabilities determined for both countries $P = \{p_{i,j}\}$ versus the alternative hypothesis that they are different. By following the approach for the time-homogeneity test, an asymptotically equivalent test statistic for the likelihood ratio test statistic can be given as

$$-2\ln(\Lambda) = 2\sum_{c}\sum_{i,j} n_{i,j}(c)\left[\ln(p_{i,j})(c) - \ln(p_{i,j})\right], \quad i \in S^u, j \in S, c \in \{A, B\}. \tag{6}$$

where $n_{i,j}(c)$ is the number of observed transitions from state i to state j for country c. This test statistic has a ξ^2 asymptotic distribution with 2 degrees of freedom.

In case the null hypothesis is not rejected, one can state that the transition probabilities of these two countries are not statistically different. Otherwise, the transition probabilities, and therefore the cyclical behavior, of these two countries can be considered statistically different. Tables 3 and 4 report the p-values, or the probability that the value of likelihood ratio statistic is less than its sample counterpart, for IP and employment growth, respectively.

6.1 Test results for IP and employment growth

From Table 1, we observe that the estimated Markov chain for Turkey is i.i.d and those for the Netherlands and the UK are of order two. *A priori* this is evidence indicating differences in the cyclical dynamics of IP growth for Turkey *vis a vis* all of the other countries in Table 2 as well as those for the Netherlands and the UK *vis a vis* the remaining countries. Table 1 shows that the process for IP growth estimated over the period since 2002 for Turkey has very short expected first passage times. While the second-order processes for IP growth for the Netherlands and the UK differs from those for the remaining countries, the p-value for their equivalence is 0.1616, indicating that these processes cannot be differentiated from each other. In Table 3, we report the p-values pertaining to those countries whose IP growth follows a first-order process. Here we observe that among the developed countries Spain stands out in terms of the properties of its IP growth process. We can reject at the 10% level that IP growth in Spain follows the same process as those for other developed countries such as Australia, Japan, Finland, and France as well as for Chile, S. Korea, the Philippines, and China. Table 1 shows that the reason for this finding lies in the sluggish behavior of Spanish IP growth, especially in the "Down" state. We argue below that this finding may be related to the behavior of employment growth in Spain.

We do observe a group of East Asian countries for which the cyclical dynamics of IP growth appears to differ from other developed and developing countries - namely, China, the

Philippines and S. Korea - at the same time that it exhibits similar behavior across these countries. Table 3 shows that the process for IP growth for S. Korea differs significantly from that for Canada, the US, Germany, Spain, Argentina, Chile, and S. Africa, the process for China differs from that for Canada, the US, Spain, Chile, and Argentina, and the process for the Philippines differs from that for Canada, the US, Spain and Chile. From Table 1, we observe that IP growth for China, S. Korea and the Philippines appears to spend relatively short periods either above or below expected IP growth. This contrasts with a country such as the US whose expected first passage time from above trend to below trend IP growth is among the longest in the sample or with countries such as Spain or Argentina which exhibit highly persistent IP growth. Conversely, we cannot reject the hypothesis that the processes describing IP growth for many of the EU countries do not differ from each other or from other developed and developing countries.

Next, we turn to tests of the equivalence of the processes for employment growth across the different countries. First, from Table 2, we observe that the expected first passage times for the employment processes tend to be longer than those for IP growth for most of the countries in our sample. Second, we find greater heterogeneity in the estimated Markov processes for employment growth. For one, Malaysia, Mexico and Turkey possess i.i.d. processes for employment growth, reflecting the experience of crises and hence, the shorter horizon over which stationary employment processes can be estimated. Second, while the process for employment growth for Finland is stationary over the available sample periods, its behavior can be represented by a second-order process for this country. This finding constitutes evidence for significant differences in employment growth for countries with estimated processes following i.i.d or order two processes relative to those following order one processes. As before, we can test for the equivalence of the processes among the first country group. The results of the tests of the equivalence of the employment processes for Malaysia, Mexico, and Turkey do not indicate any evidence of significant differences.[5]

Table 4 reports the test results for the remaining countries whose employment processes are of order one. Here we observe that the employment growth processes for Spain and the UK are estimated to be significantly different from most of the other developed and developing countries for which a relevant comparison can be made. Specifically, out of the 15 countries reported in Table 4 with first-order employment growth processes, the process for Spanish employment growth differs significantly from 11 of these processes while UK employment differs from 8 of them. The reason for these differences stems from the highly persistent nature of both Spanish and UK employment growth. The persistence of the UK unemployment rate is well noted.[6] To understand the reasons for this phenomenon, we observe that the annual growth rate for the UK economy in the 1960-1973 period was far below the rates of other European countries like France, West Germany and Italy and remained low after the 1973 oil shock. The election of Margaret Thatcher in 1979 ushered in a new period of neo-liberal economic policies, which initially led to mass unemployment. Unemployment rose again as a result of the ERM crisis of 1992. However, during the ten years of Tony Blair's rule since 1997, inflation, interest rates and unemployment all remained relatively low until the 2008-2009 recession due to the global financial crisis (see Tang, 2008).

[5] The p-values for the test between the employment processes for Malaysia and Mexico is 0.495, for Malaysia and Turkey is 0.8851, and for Mexico and Turkey is 0.8090.

[6] See, for example, Arulampalam, Booth, and Taylor (1998), who study this phenomenon using individual-specific data.

The experience of Spain also reflects some idiosyncratic features. Perhaps Spain is the only country in our sample that can be considered in the EU "periphery" (see, for example, Giannone, Lenza and Reichlin, 2008). Despite showing impressive gains during the process of European Union integration, the Spanish economy has also had the highest unemployment rates in the EU (see Blanchard and Jimeno, 1995). The persistence of Spanish unemployment has been an oft-mentioned phenomenon.Alana and del Bario (2006) corroborate this finding using regional unemployment data and find that persistence of unemployment is greater in the most industrialized regions in Spain.[7] They conjecture that the low rate of interregional migration may be as important in explaining such persistence as the institutional features of Spanish labor markets.[8]

The results of Table 4 also provide some noteworthy conclusions regarding the processes for employment growth in developing countries. Here we find that the employment growth processes for the Philippines, Chile and China are significantly different from those of developed or other developing economies. Countries such as Chile and the Philippines display short expected first passage times, in contrast to other developed or developing economies. By contrast, employment growth in China tends to remain below trend longer than for many other economies.

7 Expected first passage times and their variability

The first passage time to switch form from up states to down states and from down states to up states gives information related to the cyclical dynamics of economic time series. By using the first passage analysis presented in Appendix A, Figures 1 and 2 display the expected value of the first passage times between the different states and their coefficient of variation (CV) for IP and employment growth of each country analyzed in this study, respectively. One way to interpret such patterns is to use notions of proximity. Geographical proximity suggests that 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). Organizational proximity denotes the interaction ability among members of an organization (Torre and Rallet, 2004). Technological proximity and global networks, on the other hand, refer to the shared technological experiences and knowledge bases (Oerlemans and Knoben, 2006).

Figures 1 and show that observations on expected passage times for the different countries generally cluster together. However, this clustering is more dense for IP growth than employment growth. For European countries such as France, Germany and Italy, we see the expected passage times between the different states of IP growth are very close. Employment growth

[7] As we noted above, this finding may also explain the persistence of IP growth in Spain.

[8] The greater persistence or *hysteresis* in employment patterns that many EU economies have displayed especially since the oil shocks of 1970's and 1980's was noted Blanchard and Summers (1989), who define this situation as one in which the equilibrium unemployment rate depends on the history of the actual unemployment rate or equivalently, that there is path-dependence in the underlying equilibrium of the economy. The explanations that have typically been given for this phenomenon focus on alternative labor market institutions and practices. Ball (2009) re-visits the hysteresis hypotheses and presents evidence for it using data on twenty OECD countries since the 1980's. He argues that the evidence regarding changes in the natural rate of unemployment are inconsistent with theories in which the natural rate is independent of aggregate demand. Regardless of the explanation that is put forward, however, our results provide additional evidence on the persistent nature of employment that reflect other findings in the literature.

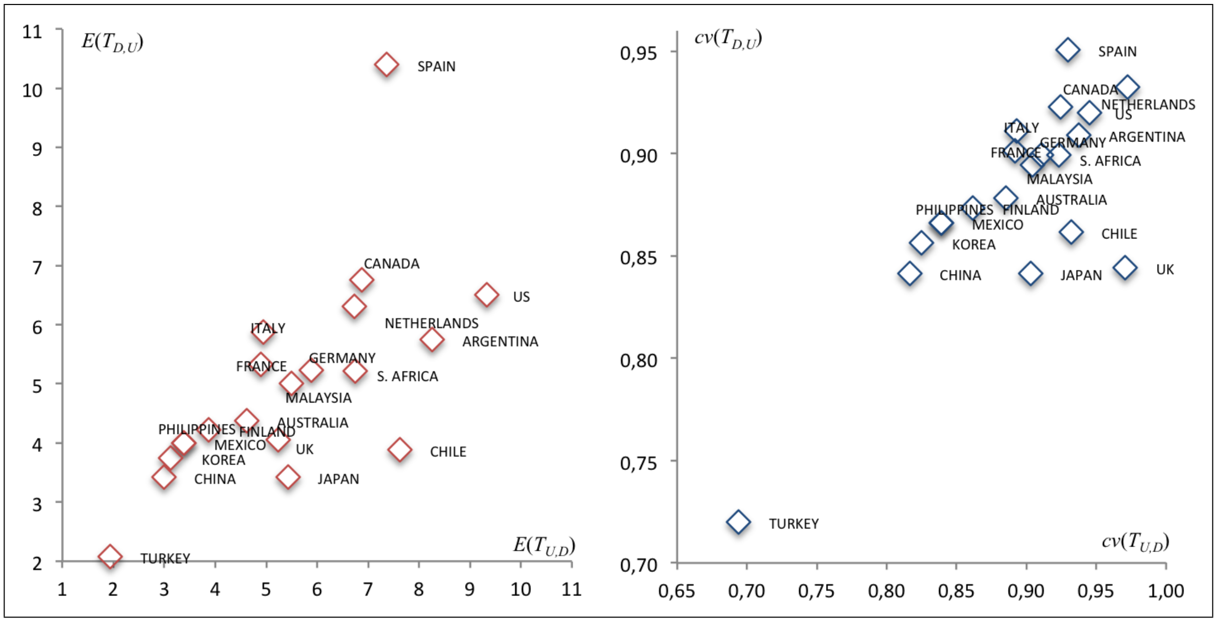

Figure 1: Expectation and Coefficient of Variation of the First Passage Times between U and D States based on IP Growth

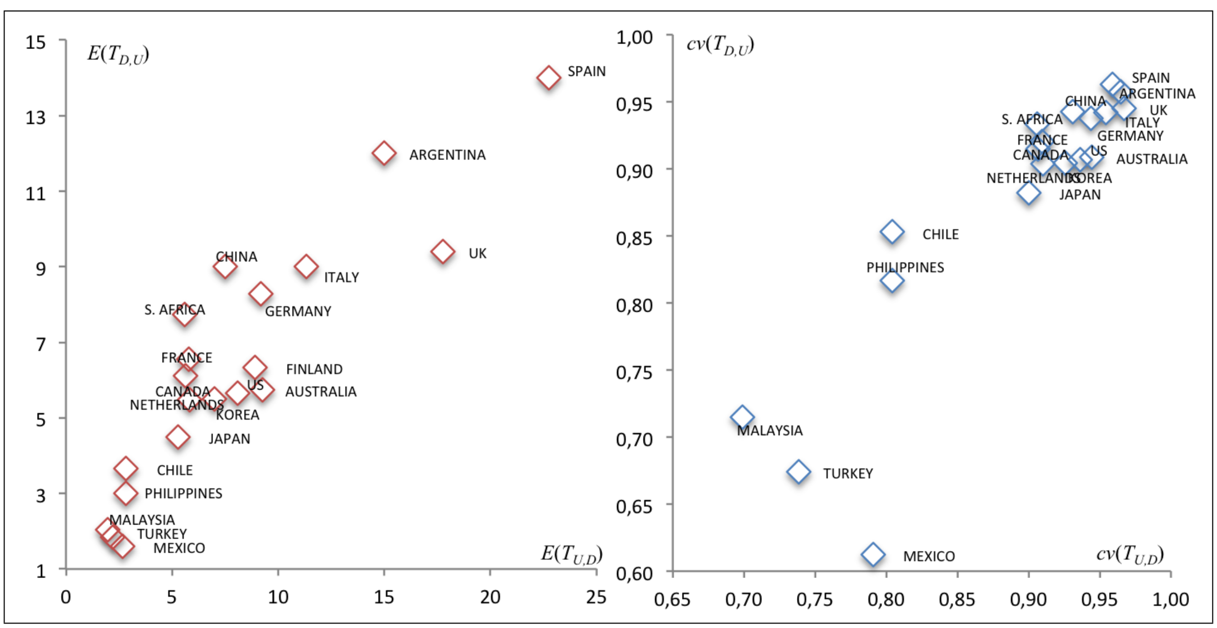

Figure 2: Expectation and Coefficient of Variation of the First Passage Times between U and D States based on Employment Growth

passage times also show such similarity. Typically these countries benefit from geographical proximity and their participation in the European Union provides an organizational proximity. As we already noted, the exceptions include Spain and the UK. For Spain, the expected passage time for both IP and employment growth tend to be longer than most of the countries in our sample. For the UK, it is the behavior of employment growth that differentiates it from the remaining developed countries.

For Asian countries, we cannot talk about a systematically organized political, economic and monetary union like the one that exists in Europe. However, the 21^{st} century has brought rapid integration of Asian economy and the emergence of what can be termed an informal "Asian Union" (see Gresser, 2004). These observations justify the similarities that we observe in the estimated processes for IP growth for Asian countries such as China, Japan, South Korea, Philippines, and Malaysia. Finally, we observe similarities in employment growth for emerging economies such as China, the Philippines, Turkey, Malaysia, and Mexico. The short expected passage expected passage times in employment growth for countries such as Malaysia, Mexico and Turkey reflect the existence of crises and institutional and policy changes that limit the sample period over which stationary processes for employment growth can be fitted.

Figures 1 and 2 also allow us to examine the variability of the first passage times from the different states using their CV. Typically countries such as China, Korea, Mexico have less variability in their first passage times from the different states. Turkey stands out as an outlier in terms of its CV for the first passage times, no doubt reflecting the short sample over which this measure is computed both for IP and employment growth.

8 Composite indicators

Up to this point, we examined the time-homogeneity and time-dependence properties of important leading economic indicators such as IP and employment growth of various countries. On the other hand, an index composed of more than one leading economic indicator may provide a healthier indication of future economic activity. In this section, an index comprised of IP and employment growth is created using the methodology of finite Markov chains described above.

Recall that the estimated Markov chains were not necessarily time-homogeneous for all the countries in our sample. To construct the composite indicators, we first identify the minimum of the two dates for which time homogeneity of the Markov chains for IP and employment growth can be established. Second, we allow for the fact that there may be second-order dependence in the composite indicator depending on the order of the underlying univariate Markov chains. If the underlying Markov processes are i.i.d. or of orders one, we construct the composite indicator as follows: we identify a pair of states H (High) and L (Low) for IP index growth, and U and D for employment growth. In this framework, there exist four states for which the composite indicator can be observed: HU, LU, HD and LD. As an example, if the process is in state LU, this means that IP growth is below average but employment growth above average. On the other hand, if either one of the univariate processes for IP or employment growth are of order two, then the composite indicator is constructed to take into account this second-order dependence. For example, suppose that IP growth follows a second-order process while employment growth follows a first-order process. In this case, the relevant states for the composite indicator are given by UUH, UUL, UDH, UDL, DUH, DUL, DDH, and DDL. Thus, UUL denotes the state in which IP growth has been above average for the last two periods in a row while employment growth has been below average last

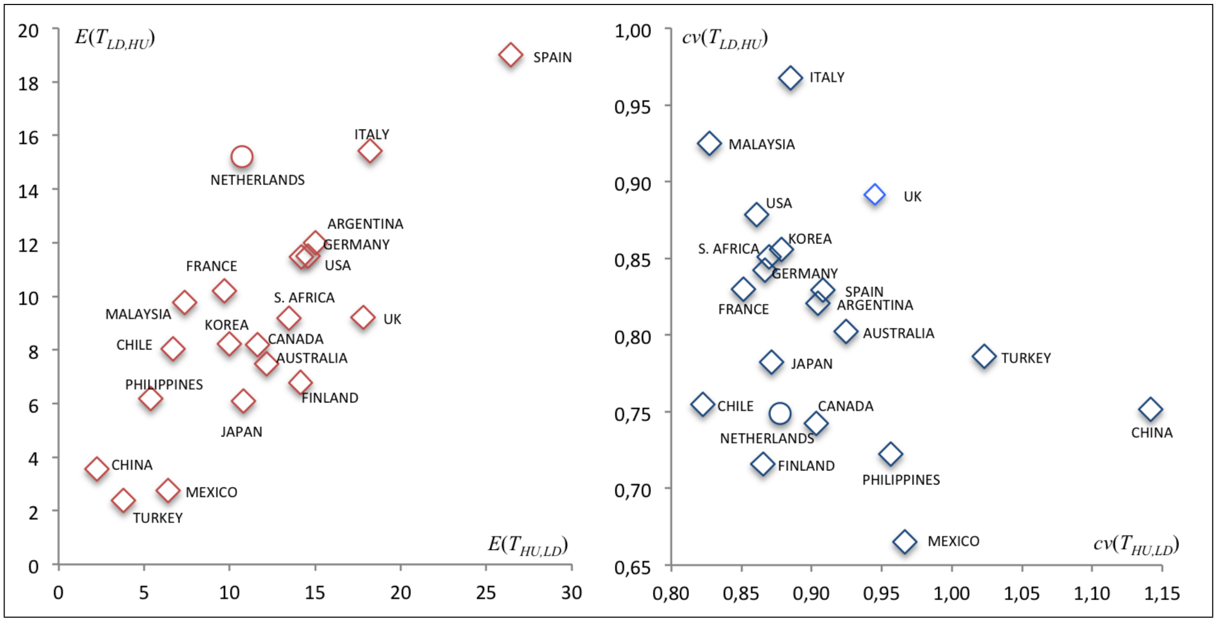

Figure 3: Expectation of the First Passage Times between UP-High and Down-Low States based on the Employment Growth-Industrial Production Index Growth Time Series

period. The process can then transit to one of four possible states today, UUH, UUL, DUL, and DUH. There were only three countries for which we estimated second-order processes for either IP or employment growth, Finland, the Netherlands, and the UK. Let (p, q) denote the orders of IP and employment growth in the composite indicator. As before, we conducted a test of the time dependence of the composite process by testing for the equality of the $(2, 1)$ or $(1, 2)$ processes against a $(1, 1)$ process. We were unable to reject the null hypothesis that the composite processes for Finland and the UK are of order $(1, 1)$. By contrast, we could reject the $(1, 1)$ process for the Netherlands against a $(2, 1)$ process.

Tables 7 and 8 show the transition probabilities between the possible states for all $(1, 1)$ processes. These tables show that most developed countries as well as developing countries such as S. Korea or S. Africa the estimated probabilities that the composite process will remain in the states HU or LD, conditional on starting out in these states, respectively, are higher compared to the probabilities of transiting to the other states. These probabilities are also typically higher than the probabilities of remaining in the states HD and LU, conditional on starting out these states, respectively. When the composite indicator is in state HU, the economy is in a period when activity is unambiguously high. Similarly, when the indicator is in state LD, economic activity is unambiguously low. Thus, we find that for many economies, IP growth and employment growth tend to move together, lending credence to the idea of considering their behavior in terms of a composite index. For other countries such as China, Malaysia, Mexico, the Philippines, or Turkey, there is a weaker relationship between IP and employment growth. For example, for Turkey the probabilities of remaining in the HD or LU states are higher than remaining in the HU or LD states. This implies that the behavior of IP growth and employment growth are "de-coupled" from each other, at least over the sample period in question. Furthermore, the probabilities of transiting to the HU state conditional on being in the HD or LD states are higher than the probability of remaining in the HU state. This results suggest that the economy exhibits very little persistence. Similar findings occur for other developing economies such as Chile, China, Malaysia, Mexico and the Philippines. In the case of Turkey, this may have to do with the shortness of the sample. However, the presence of similar behavior for other developing economies suggests that there are some fundamental differences in the cyclical dynamics of these countries relative to developed ones.

Table 9 presents the p-values for the test of the equality of the composite processes across different countries. The findings that we observed in Tables 7 and 8 emerge much more clearly here. For countries such as Chile, Mexico, China, Malaysia, the Philippines and Turkey, we can reject at significance levels of 10% or less the hypothesis that these countries have probability transition matrices that are identical to those of others in our sample. These rejections occur especially relative to the developed countries. Considering the case of China, we can reject the equality of probability transition matrices for all countries in Table 9 except Japan, Chile, Mexico, Malaysia, the Philippines and Turkey. For Mexico, there is slightly less evidence of such differences in the cyclical dynamics of the composite indicator. Here we can reject the null hypothesis of equality against Canada, the UK, the US, France, Germany, Italy, Spain as well as S. Africa. Indeed Chile, Mexico, China, Malaysia, the Philippines and Turkey appear to comprise one distinct group and the remaining developed countries plus S. Korea and S. Africa comprise another group in terms of their cyclical dynamics. There is some evidence that the UK composite indicator has different properties than those of some other developed countries such as the US and France but this is most likely due to the persistent nature of its employment process.

In Figure 3, we examine the relation between the estimated passage times between the states HU and LD for each country. We observe that the estimated passage times between different phases of economic activity exhibit symmetric behavior for most of the countries in question, that is, $E(T_{HU,LD})$ and $E(T_{LD,HU})$ are similar. What is more, we see that the expected passage times between the different phases of industrialized economies like Germany, Japan and United States are typically longer than they are for less industrialized countries such as Turkey, China and Mexico. However, the expected passage times for the composite indicator tend to more dispersed than those for the individual indicators, suggesting more variation across countries in factors that affect IP and employment growth jointly. We observe that Spain continues to exhibit highly persistent behavior in that it has very high expected passage times from HU to LD, and vice versa. However, based on the behavior of the composite index, the UK economy tends to resemble other developed economies such as Japan, suggesting that the composite index provides a better summary of cyclical dynamics than the behavior of individual components separately.

9 Conclusion

In this study, we have used a simple but effective nonparametric testing procedure which estimates the transition probability distribution of economic time series directly. This testing procedure does not require any distributional assumptions which are generally involved in the application of parametric tests. By following a systematic Markov based testing procedure, we revealed the time-dependence and time-homogeneity properties of industrial production and employment growth of a key set of developed and developing countries.

Our results yield some interesting conclusions. First, we find that the processes for both industrial and employment growth tend to be more stable for developed countries such as the Anglophone and EU countries as well as some newly industrialized countries in East Asia. By contrast, the processes for various developing and emerging economies tend to exhibit more instability. An important exception to this finding is Japan, which appears to have undergone important changes as a result of the factors that led to the "lost decade" of the 1990's. Second, we find that the processes for employment growth tend to exhibit greater heterogeneity than those for industrial production growth across different countries. This result holds whether we consider the developed or the developing countries. In the former, we find evidence for oft-mentioned persistence of employment (or unemployment) growth in countries such as the UK and Spain. More generally, we compare the expected passage times between the high and low economic activity periods for the economic times series in hand to identify common patterns across countries. Our analysis shows that the estimated durations of the alternative states for industrial production and employment growth are very close in European countries like Germany, Italy and France. This finding reflects their geographical and organizational proximity in the European Union, and forms the basis for the notion of a Euro area business cycle. Similar behavior is also observed in Asian countries like Japan, China, Philippines, Malaysia and South Korea. This is the result not only of their geographical proximity but also their strengthened international economic relationships. Next, we find that a disparate set of emerging market economies such as China, Mexico, and Turkey share similar characteristics in terms of the cyclical dynamics of their industrial production and employment series, suggesting the importance of underlying institutional and policy factors that transcend simple geographical considerations or trade linkages. Finally, we construct a composite indicator of economic activity using information on both IP and employment growth. Here we find that the behavior of IP and employment growth tend to behave similarly for many developed countries. By contrast, we find that the behavior of IP growth and employment growth are "de-coupled" from each other for developing countries such as Chile, China, Malaysia, Mexico, the Philippines and Turkey, at least over the sample period in question. This finding is suggestive of a more complex set of factors that determine the IP and employment series jointly. Such factors may be related to the phenomenon of "jobless growth" and the process of structural transformation that such economies have been undergoing.

A First Passage Time Analysis

Once a time series is represented as a time-homogeneous Markov chain with a determined order of u, various measures can be calculated by using a finite state Markov chain analysis, e.g. see (Kemeny and Snell, 1976) or (Ross, 2003). The steady state probabilities π_i satisfy

$$\begin{aligned}\sum_j \pi_j &= 1, \\ \pi_j &= \sum_i \pi_i p_{ij}, \\ \pi_j &\geq 0, j \in S^u. \end{aligned} \tag{7}$$

The row vector of steady-state probabilities is π. The time to switch from state U to state D and from state D to state U can be determined by using a first passage analysis.

Let $T_{i,j}$ be the first passage time from state i to state j. Let $M = \{E(T_{i,j})\}$ be the matrix of expected first passage times and $M_2 = \{Var(T_{i,j})\}$ be the matrix of the variance of the first passage times. Kemeny and Snell (1976) give M and M_2 in closed form by using the fundamental matrix Z given as

$$Z = (I - (P - \Pi))^{-1} \tag{8}$$

where Π is a matrix constructed by π in its each row.

Then the expected first passage time matrix is

$$M = (I - Z + EZ_{diag})D \tag{9}$$

where I is the identity matrix, E is a matrix of ones, D is a diagonal matrix with $1/\pi_i$ as its $D_{i,i}$th element, Z is the fundamental matrix, and Z_{diag} is a diagonal matrix that contains the diagonal elements of Z.

The matrix of the variance of the first passage time is given as

$$M_2 = M(2Z_{diag}D - I) + 2(ZM - E(ZM)_{diag}) - M^2. \tag{10}$$

The first passage time analysis for the first- and second-order Markov chains are given as special cases next.

A.1 First-order Markov chain

Let the probability transition matrix for a stochastic process following a first-order Markov chain with the state space $S = \{U, D\}$ is given as:

$$P = \begin{bmatrix} p_{U,U} & 1 - p_{U,U} \\ p_{D,U} & 1 - p_{D,U} \end{bmatrix}.$$

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

$$P(T_{U,D} = t) = {p_{U,U}}^{t-1}(1 - p_{U,U}).$$

The expected first passage time from state U to state D is thus as follows:

$$E(T_{U,D}) = \frac{1}{1 - p_{U,U}}.$$

Similarly the variance of the expected first passage time from state U to state D is

$$Var(T_{U,D}) = \frac{p_{U,U}}{(1 - p_{U,U})^2}.$$

Consequently, the coefficient of variation of the first passage time from state D to state U is

$$cv(T_{U,D}) = \sqrt{p_{U,U}}.$$

Similarly, the expectation, variance and the coefficient of variation of the first passage time from state D to state U are as follows:

$$E(T_{D,U}) = \frac{1}{p_{D,U}},$$

$$Var(T_{D,U}) = \frac{(1 - p_{D,U})}{p_{D,U}^2},$$

$$cv(T_{D,U}) = \sqrt{1 - p_{D,U}}.$$

A.2 Second-order Markov chain:

The transition probability matrix for a stochastic process following a second-order Markov chain with the state space $\{UU, DU, UD, DD\}$ is given as:

$$P = \begin{bmatrix} p_{UU,UU} & 0 & p_{UU,UD} & 0 \\ p_{DU,UU} & 0 & p_{DU,UD} & 0 \\ 0 & p_{UD,DU} & 0 & p_{UD,DD} \\ 0 & p_{DD,DU} & 0 & p_{DD,DD} \end{bmatrix}. \tag{11}$$

Using the above transition matrix, let the matrix Q_U stand for the transient matrix for transition between the up states, i.e., UU and DU. Similarly, let matrix Q_D represent the transient matrix for transitions between the down states, i.e., UD and DD. Similarly, let the matrix R_U stand for the transient matrix for transition from the up states to the down states, and similarly, let matrix Q_D represent the transient matrix for transitions from the down states to the up states:

$$Q_U = \begin{bmatrix} p_{UU,UU} & 0 \\ p_{DU,UU} & 0 \end{bmatrix} \quad \text{and} \quad Q_D = \begin{bmatrix} p_{DD,DU} & 0 \\ p_{UD,DU} & 0 \end{bmatrix}, \tag{12}$$

$$R_U = \begin{bmatrix} p_{UU,UD} & 0 \\ p_{DU,UD} & 0 \end{bmatrix} \quad \text{and} \quad R_D = \begin{bmatrix} p_{DD,DU} & 0 \\ p_{UD,DU} & 0 \end{bmatrix}. \tag{13}$$

In this case, the up states include two different states UU and DU and the down states include DU and DD. By using the weighted sum of the first passage times with respect to the likelihood of being in each of these states, Equations (9) and (10) can be written in a simpler way to express the expected first passage times and the variance of the first passage times as

$$E(T_{U,D}) = \pi_U (I - Q_U)^{-2} R_U u \tag{14}$$

$$Var(T_{U,D}) = 2\pi_U (I - Q_U)^{-3} Q R_U u + E(T_{U,D}) - E^2(T_{U,D}) \tag{15}$$

where $u = [1, 1]^T$ and π_U is the initial probability vector for the up states. By calculating the conditional probabilities in each of the up states UU and DU, π_U can be written as

$$\pi_U = \left[\frac{\pi_{UU}}{\pi_{UU} + \pi_{DU}}, \frac{\pi_{DU}}{\pi_{UU} + \pi_{DU}} \right].$$

Similarly,

$$E(T_{D,U}) = \pi_D (I - Q_D)^{-2} R_D u \tag{16}$$

$$Var(T_{D,U}) = 2\pi_D (I - Q_D)^{-3} Q R_D u + E(T_{D,U}) - E^2(T_{D,U}) \tag{17}$$

where π_D is the initial probability vector for the down states. By calculating the conditional probabilities in each of the down states UD and DD, π_D can be written as

$$\pi_D = \left[\frac{\pi_{DD}}{\pi_{UD} + \pi_{DD}}, \frac{\pi_{UD}}{\pi_{UD} + \pi_{DD}} \right].$$

B Data

The data sources and sample periods for the countries in the full sample are as follows:

Industrial production:

- Australia, Chile, Finland, France, Germany, Italy, Japan, Mexico, the Netherlands, UK, US 1960:1-2008:2 (IFS)
- Canada, S. Korea, Turkey 1980:1-2008:3 (IFS)
- China 1992:1-2008:2 (IFS)
- Malaysia 1985:1-2008:2 (IFS)
- Philippines 1986:1-2006:1
- S. Africa, Spain 1961:1-2008:1 (IFS)
- Argentina 1994:1-2009:1 (SO)

Total employment

- Australia 1978:1-2009:1 (ILO)
- Canada 1961:1-2009:1 (ILO)
- Japan (ILO), UK (OECD), US 1960:1-2009:1

- Germany 1962:1-2008:4 (ILO)
- France, Spain 1980:1-2008:4 (Eurostat); Italy 1980:1-2008:4 (ILO)
- Netherlands 1984:1-2008:3 (ILO)
- Finland 1992:1-2009:1 (ILO)
- Malaysia 1997:1-2009:1 (BIS); S. Korea 1983:1-2009:1 (ILO)
- China 1999:3-2008:3; Philippines 1990:3-2009:1 (ILO);
- S. Africa 1970:1-2p;009:1 (BIS)
- Turkey 2000:1-2009:1 (CB)
- Argentina 1998:3-2009:1 (IFS)
- Chile 1986:1-2009:1; Mexico 2002:2-2009:1 (ILO)

References

Alana, L. and P. del-Barrio (2006). "New Revelations about Unemployment Persistence in Spain," Universidad de Navarra Working Paper no. 10/06.

Altug, S. and M. Bildirici (2010). "Business Cycles around the Globe: A Regime-switching Approach," No. 7968 CEPR/EABCN No. 53/2010.

Alvarez, E., F. Ciocchini and K. Konwar (2008). "A Locally Stationary Markov Chain Model for Labor Dynamics," *Journal of Data Science* 7, 27-42.

Arulampalam, W., A. Booth and M. Taylor (1998). "Unemployment Persistence," Paper presented at the CEPR conference on Unemployment Persistence and the Long Run: Evaluating the Natural Rate, Vigo, Spain, November 1997.

Anderson, T. and L. Goodman (1957). "Statistical Inference using Markov Chains," *Annals of Mathematical Studies* 28, 12-40.

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

Artis, M., Z. Kontolemis, and D. Osborn (1997). " Business Cycles for G7 and European Countries," *Journal of Business* 70, 249-279.

Artis, M., H.-M. Krolzig nd J. Toro (2004). "The European Business Cycle," *Oxford Economic Papers*, 46, 1-44.

Ball, L. (2009). "Hysteresis in Unemployment: Old and New Evidence," NBER Working Paper 14818.

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

Blanchard, O. and J. Jimeno (1995). "Structural Unemployment: Spain versus Portugal," *The American Economic Review* 85 (2), pp. 212-218.

Blanchard, O. and L. Summers (1986) "Hysteresis and the European Unemployment Problem," In *NBER Macroeconomics Annual*, Vol 1, Stanley Fischer (ed.), MIT Press, September.

Bronfenbrenner, K. and S. Luce (2004). "The Changing Nature of Corporate Global Restructuring: The Impact of Production Shifts on Jobs in the US, China, and around the Globe," US-China Economic and Security Review Commission.

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

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

Canova, F., M. Ciccarelli, and E. Ortega (2009). "Do Institutional Changes Affect the Business Cycle? Evidence from Europe," Bank of Spain.

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.

De Pace, Pierangelo (2010). "Currency Union, Free-Trade Areas, and Business Cycle Synchronization," manuscript, Pomona College.

Eckstein, Z. and van den Berg, G. (2007). "Empirical Labor Search: A Survey," *Journal of Econometrics* 136, 531-564.

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

Flinn, C. and Heckman, J. (1982). "New Methods for Analyzing Structural Models of Labor Force Dynamics," *Journal of Econometrics*, 18, 115-168.

Gali, J. (1999). "Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?," *American Economic Review* 89, pp. 249-271.

Giannone, D., M. Lenza, and L. Reichlin (2008). "Business Cycles in the Euro Area," In A. Alesina and F. Giavazzi (eds.), *Europe and the EMU*, NBER, forthcoming.

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 (2002a). "A Comparison of Two Business Cycle Dating Methods," *Journal of Economic Dynamics and Control* 27, 1681-1690.

Harding, D. and A. Pagan (2002b). "Dissecting the Cycle: A Methodological Investigation," *Journal of Monetary Economics* 49, 365-381.

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

Hodrick, R. and E. Prescott (1997). "Postwar US Business Cycles: An Empirical Investigation," *Journal of Money, Credit and Banking* 29, 1-16.

Kemeny, J. G. and J. L. Snell (1976). *Finite Markov Chain*, Springer-Verlag, New York.

Kim, C. and C. Nelson (1999). "Friedman's Plucking Model of Business Fluctuations: Tests and Estimates of Permanent and Transitory Components," *Journal of Money, Credit and Banking*, 31(3), Part 1, 317-334.

Kim, C. and C. Piger (2002). "Common Stochastic Trends, Common Cycles, and Asymmetry in Economic Fluctuations," *Journal of Monetary Economics* 49, 1189-1211.

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

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

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

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

Neftci, S. (1984). “Are Economic Time Series Asymmetric Over the Business Cycle?,” *Journal of Political Economy* 92, 307-328.

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

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. (2008). “Twin Global Shocks Dent United Kingdom Outlook,” *IMF Survey* 37(9).

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

Tiraboschi, M. and M. Del Conte (2004). “Recent Changes in the Italian Labor Law,” Paper presented in JILPT Comparative Labor Law Seminar, Tokyo, Japan.

Yeldan, E. (2008). “Turkey and the Long Decade with The IMF: 1998-2008,” http://www.networkideas.org/news/jun2008/Turkey-IMF.pdf

Country	Beginning Year	Order	Transition Probabilities				Expected Passage Times (Quarters)	
			$p_{U,U}$	$p_{U,D}$	$p_{D,U}$	$p_{D,D}$	$E(T_{U,D})$	$E(T_{D,U})$
Australia	1960	1	0.784	0.216	0.228	0.772	4.62	4.38
Canada	1980	1	0.855	0.145	0.148	0.852	6.87	6.75
Japan	$1993^\dagger$	1	0.816	0.184	0.292	0.708	5.43	3.43
UK	1974	2	See (1) below				5.24	4.06
USA	1960	1	0.893	0.107	0.154	0.846	9.34	6.50
Finland	1960	1	0.742	0.258	0.237	0.763	3.87	4.22
France	1960	1	0.796	0.204	0.187	0.813	4.90	5.33
Germany	1960	1	0.830	0.170	0.191	0.809	5.88	5.24
Italy	1960	1	0.798	0.202	0.170	0.830	4.95	5.88
Netherlands	$1963^\dagger$	2	See (2) below				6.73	6.32
Spain	1960	1	0.864	0.136	0.096	0.904	7.36	10.40
Argentina	1997	1	0.879	0.121	0.174	0.826	8.25	5.75
Chile	1960	1	0.869	0.131	0.258	0.742	2.83	3.67
Mexico	$1995^\dagger$	1	0.839	0.161	0.227	0.773	6.20	4.40
Malaysia	$1997^\dagger$	1	0.818	0.182	0.200	0.800	5.50	5.00
S.Korea	1980	1	0.680	0.320	0.267	0.733	3.13	3.75
China	1992	1	0.667	0.333	0.292	0.708	3.00	3.43
Philippines	1981	1	0.704	0.296	0.250	0.750	3.38	4.00
S.Africa	1983	1	0.852	0.148	0.192	0.808	6.75	5.33
Turkey	$2002^\dagger$	0	0.482	0.518	0.482	0.518	1.93	2.08

† Denotes break year

Table 1: Transition Probabilities and Expected Passage Times: IP Growth

where

$$(1) \qquad P = \begin{bmatrix} 0.823 & 0 & 0.177 & 0 \\ 0.522 & 0 & 0.478 & 0 \\ 0 & 0.130 & 0 & 0.870 \\ 0 & 0.253 & 0 & 0.747 \end{bmatrix}$$

and

$$(2) \qquad P = \begin{bmatrix} 0.859 & & 0.141 & \\ 0.588 & & 0.412 & \\ & 0.250 & & 0.750 \\ & 0.156 & & 0.844 \end{bmatrix}$$

Country	Beginning Year	Order	Transition Probabilities				Expected Passage Times (Quarters)	
			$p_{U,U}$	$p_{U,D}$	$p_{D,U}$	$p_{D,D}$	$E(T_{U,D})$	$E(T_{D,U})$
Australia	1978	1	0.892	0.108	0.174	0.826	9.25	5.75
Canada	1960	1	0.828	0.172	0.183	0.817	5.82	5.47
Japan	1993†	1	0.811	0.189	0.222	0.778	5.29	4.50
UK	1975	1	0.944	0.056	0.106	0.894	17.79	9.40
USA	1960	1	0.876	0.124	0.177	0.823	8.07	5.64
Finland	1992	2	See (3) below				9.39	6.33
France	1980	1	0.827	0.173	0.152	0.848	5.78	6.56
Germany	1962	1	0.891	0.109	0.121	0.879	9.20	8.27
Italy	1993†	1	0.912	0.088	0.111	0.889	11.34	9.00
Netherlands	1984	1	0.822	0.178	0.163	0.837	5.62	6.12
Spain	1980	1	0.957	0.043	0.071	0.929	22.99	14.01
Argentina	2002†	1	0.933	0.067	0.083	0.917	14.99	12.01
Chile	1999†	1	0.647	0.353	0.273	0.727	2.83	3.67
Mexico	2000	0	0.625	0.375	0.625	0.375	2.67	1.60
Malaysia	1997†	0	0.489	0.511	0.489	0.511	1.96	2.05
S.Korea	1983	1	0.857	0.143	0.182	0.818	7.00	5.50
China	1999	1	0.867	0.133	0.111	0.889	7.50	9.00
Philippines	1990	1	0.647	0.353	0.333	0.667	2.83	3.00
S. Africa	1970	1	0.821	0.179	0.129	0.871	5.58	7.73
Turkey	2000†	0	0.546	0.455	0.545	0.455	2.20	1.83

† Denotes break year

Table 2: Transition Probabilities and Expected Passage Times: Employment Growth

where

$$(3) \qquad P = \begin{bmatrix} 0.895 & 0 & 0.105 & 0 \\ 0.8 & 0 & 0.2 & 0 \\ 0 & 0.75 & 0 & 0.25 \\ 0 & 0.125 & 0 & 0.875 \end{bmatrix}.$$

	Canada	US	Japan	Finland	France	Germ.	Italy	Spain	Argen.	Chile	Mexico	Malay.	S. Kor.	China	Philip.	S. Afr.
Austr.	0.27	0.045	0.75	0.79	0.77	0.60	0.58	0.015	0.39	0.23	0.80	0.93	0.35	0.41	0.58	0.51
Canada		0.78	0.11	0.11	0.55	0.73	0.64	0.62	0.91	0.32	0.71	0.78	0.03	0.06	0.08	0.85
US			0.17	0.007	0.13	0.33	0.17	0.42	0.95	0.26	0.53	0.53	0.002	0.01	0.009	0.65
Japan				0.57	0.53	0.57	0.42	0.05	0.48	0.69	0.86	0.78	0.34	0.42	0.46	0.58
Finland					0.48	0.26	0.34	0.003	0.19	0.06	0.52	0.75	0.68	0.66	0.89	0.23
France						0.85	0.95	0.09	0.54	0.21	0.80	0.98	0.16	0.24	0.35	0.69
Germ.							0.81	0.13	0.77	0.43	0.92	0.98	0.07	0.14	0.19	0.93
Italy								0.15	0.56	0.15	0.73	0.94	0.11	0.18	0.25	0.68
Spain									0.58	0.02	0.26	0.38	0.001	0.007	0.005	0.28
Argen.										0.70	0.81	0.77	0.07	0.097	0.13	0.92
Chile											0.88	0.68	0.02	0.073	0.06	0.68
Mexico												0.25	0.39	0.93	0.94	0.98
Malay.													0.44	0.43	0.59	0.90
S. Kor.														0.97	0.95	0.07
China															0.88	0.12
Philip.																0.16

Table 3: p-values for Industrial Production Growth

	Canada	UK	US	Japan	France	Germany	Italy	Nether.	Spain	Argen.	Chile	S. Korea	China	Philip.	S. Africa
Austra.	0.49	0.31	0.95	0.45	0.56	0.71	0.72	0.56	0.11	0.63	0.05	0.83	0.78	0.003	0.38
Canada		0.02	0.62	0.88	0.89	0.23	0.31	0.96	0.006	0.34	0.17	0.89	0.13	0.02	0.61
UK			0.13	0.04	0.07	0.42	0.82	0.07	0.79	0.96	0.002	0.13	0.0005	0.000	0.05
US				0.55	0.66	0.55	0.60	0.67	0.04	0.54	0.06	0.94	0.03	0.002	0.42
Japan					0.73	0.22	0.25	0.81	0.012	0.27	0.41	0.77	0.38	0.18	0.52
France						0.48	0.46	0.99	0.03	0.44	0.16	0.84	0.12	0.02	0.92
Germany							0.93	0.43	0.20	0.81	0.015	0.53	0.007	0.0003	0.45
Italy								0.42	0.58	0.93	0.026	0.53	0.02	0.003	0.44
Nether.									0.03	0.41	0.21	0.87	0.16	0.04	0.87
Spain										0.93	0.0004	0.04	0.0001	0.0000	0.02
Argen.											0.05	0.48	0.04	0.014	0.45
Chile												0.13	0.98	0.89	0.098
S.Korea													0.09	0.02	0.63
China														0.93	0.06
Philip.															0.007

Table 4: p-values for Employment Growth

	Beginning Year		Transition Probabilities				Expected Passage Times (Quarter)	
			HU	HD	LU	LD	$E(T_{HU,LD})$	$E(T_{LD,HU})$
Australia	1978	HU	0.739	0	0.196	0.065	12.18	7.47
		HD	0.333	0.5	0	0.167		
		LU	0.259	0.037	0.593	0.111		
		LD	0.0625	0.125	0.0625	0.75		
Canada	1980	HU	0.818	0	0.114	0.068	11.64	8.18
		HD	0.364	0.636	0	0		
		LU	0.125	0	0.75	0.125		
		LD	0.033	0.133	0.033	0.8		
Japan	1992	HU	0.72	0.08	0.16	0.04	10.81	6.11
		HD	0.308	0.538	0.077	0.077		
		LU	0.167	0.083	0.5	0.25		
		LD	0.083	0.25	0	0.667		
UK	1974	HU	0.083	0.25	0	0.667	17.80	9.22
		HD	0.15	0.65	0	0.2		
		LU	0.282	0	0.641	0.077		
		LD	0.08	0.24	0	0.68		
US	1960	HU	0.831	0.052	0.104	0.013	14.57	11.51
		HD	0.2	0.65	0	0.15		
		LU	0.194	0	0.548	0.258		
		LD	0.048	0.048	0.097	0.807		
Finland	1992	HU	0.636	0.046	0.318	0	14.13	6.79
		HD	0.636	0.046	0.318	0		
		LU	0.375	0.5	0	0.125		
		LD	0.263	0	0.600	0.157		
France	1980	HU	0.714	0.114	0.143	0.029	9.68	10.21
		HD	0.333	0.278	0	0.389		
		LU	0.267	0	0.533	0.2		
		LD	0	0.220	0.073	0.707		
Germany	1962	HU	0.824	0.029	0.132	0.015	14.20	11.49
		HD	0.214	0.643	0	0.143		
		LU	0.208	0.042	0.5	0.25		
		LD	0.032	0.115	0.05	0.803		
Italy	1992	HU	0.727	0.091	0.182	0	18.20	15.43
		HD	0	0.786	0	0.214		
		LU	0.091	0	0.864	0.045		
		LD	0.083	0.167	0.167	0.583		
Spain	1980	HU	0.805	0	0.195	0	26.42	19.00
		HD	0.077	0.692	0.077	0.154		
		LU	0.25	0	0.643	0.107		
		LD	0	0.148	0.037	0.815		

Table 5: Transition Probabilities and Expected Passage Times for the Composite Indicators: Developed Countries

	Beginning Year		Transition Probabilities				Expected Passage Times (Quarter)	
			HU	HD	LU	LD	$E(T_{HU,LD})$	$E(T_{LD,HU})$
Malaysia	1997	HU	0.667	0.25	0	0.083	7.39	9.7
		HD	0.3	0.4	0.1	0.2		
		LU	0	0.111	0.444	0.445		
		LD	0.090	0.182	0.364	0.364		
Korea	1983	HU	0.677	0.065	0.193	0.065	9.96	8.21
		HD	0.25	0.375	0.0625	0.3125		
		LU	0.167	0.125	0.625	0.083		
		LD	0.074	0.148	0.074	0.704		
Argentina	2001	HU	0.846	0	0.154	0	15.00	12.00
		HD	0.2	0.6	0	0.2		
		LU	0.5	0	0	0.5		
		LD	0	0.286	0	0.714		
Chile	1998	HU	0.5	0.125	0.375	0	6.69	8.05
		HD	0.333	0.445	0.222	0		
		LU	0.2	0.2	0	0.6		
		LD	0	0.25	0.083	0.667		
Mexico	2000	HU	0.455	0.090	0.273	0.182	6.42	2.76
		HD	0.6	0.4	0	0		
		LU	0.4	0.2	0.2	0.2		
		LD	0.285	0.143	0.143	0.49		
China	1999	HU	0.25	0.125	0.125	0.5	2.26	3.57
		HD	0.4	0.6	0	0		
		LU	0.5	0	0	0.5		
		LD	0.222	0.111	0.111	0.556		
Philippines	1990	HU	0.308	0.154	0.308	0.230	5.41	6.20
		HD	0.353	0.471	0	0.176		
		LU	0.1875	0.125	0.5625	0.125		
		LD	0	0.333	0.25	0.417		
S.Africa	1982	HU	0.771	0.114	0.086	0.029	13.47	9.17
		HD	0.263	0.526	0.053	0.158		
		LU	0.154	0	0.692	0.154		
		LD	0.059	0.147	0	0.794		
Turkey	2001	HU	0.25	0	0.375	0.375	3.78	2.40
		HD	0.4	0.6	0	0		
		LU	0.166	0	0.667	0.167		
		LD	0.428	0.286	0	0.286		

Table 6: Transition Probabilities and Expected Passage Times for the Composite Indicators: Developing Countries

	Can.	Japan	UK	US	Fin.	France	Germ.	Italy	Spain	Argen.	Chile	Mexico	S. Kor.	China	Malay.	Philip.	S. Afr.	Turk.
Austra.	0.81	0.60	0.77	0.27	0.61	0.21	0.78	0.11	0.44	0.75	0.016	0.26	0.79	0.044	0.002	0.055	0.26	0.10
Can.		0.36	0.27	0.24	0.23	0.04	0.46	0.08	0.32	0.53	0.007	0.05	0.11	0.03	0.0005	0.003	0.35	0.07
Japan			0.24	0.35	0.55	0.35	0.77	0.08	0.17	0.78	0.39	0.53	0.87	0.14	0.20	0.18	0.97	0.20
UK				0.01	0.41	0.03	0.11	0.16	0.51	0.80	0.0007	0.023	0.104	0.006	0.0000	0.003	0.17	0.14
US					0.39	0.12	0.95	0.22	0.18	0.62	0.006	0.022	0.106	0.007	0.008	0.0006	0.43	0.0009
Fin.						0.86	0.56	0.32	0.65	0.79	0.19	0.19	0.43	0.03	0.02	0.34	0.24	0.05
France							0.23	0.04	0.09	0.70	0.03	0.04	0.46	0.009	0.02	0.13	0.32	0.002
Germ.								0.12	0.42	0.90	0.03	0.06	0.37	0.006	0.005	0.005	0.55	0.002
Italy									0.29	0.25	0.0007	0.01	0.17	0.016	0.01	0.02	0.17	0.03
Spain										0.89	0.01	0.001	0.08	0.0002	0.0001	0.0005	0.19	0.001
Argen.											0.61	0.19	0.44	0.09	0.04	0.08	0.64	0.06
Chile												0.42	0.06	0.28	0.05	0.07	0.02	0.02
Mexico													0.41	0.96	0.16	0.63	0.05	0.74
S.Kor.														0.08	0.09	0.29	0.58	0.06
China															0.11	0.36	0.02	0.70
Malay.																0.13	0.02	0.01
Philip.																	0.007	0.27
S. Afr.																		0.02

Table 7: p-values for the Composite Index