Cyclical Dynamics of Industrial Production and Employment:

Markov Chain-based Estimates and Tests

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Abstract

The purpose of this paper is to understand differences in cyclical phenomena across a broad range of developed and emerging countries based on the behavior of two key economic times series - industrial production and employment. The paper characterizes the series in question as a recurring Markov chain. Univariate processes are estimated for each series individually, and a composite indicator is constructed by using information on both series. Based on tests of equality of the estimated Markov chains across countries as well as the expected times to switch between different states, we find evidence that (i) the developed and emerging economies are “de-coupled” from each other in terms of their cyclical dynamics, and (ii) the behavior of industrial production and employment growth are “de-coupled” for the emerging economies. Our results suggest new directions for the analysis of emerging economy cyclical fluctuations.

Keywords: Markov chain, tests of time homogeneity and time dependence, composite indicator

JEL Codes: C14, E32

1 Introduction

Understanding the differences in cyclical phenomena for developed and emerging economies has been gaining importance in recent years. The growing role of many emerging economies in the global economy as well as their strong growth performance during the financial crisis of 2007-2008 has been generating much interest in their cyclical dynamics. One of the aims of the recent research has been to determine the impact of increasing trade and financial integration on business synchronization across countries. Yet there are still relatively few studies that have studied these questions in a comprehensive manner.

Some of the most prominent studies in this regard include Kose, Otrok and Whiteman (2003), who investigated the issue of a world business cycle, and Kose, Otrok and Prasad (2010), who examine the impact of greater trade and financial integration on business cycle synchronization for a large set of industrialized, emerging and developing economies.¹ Somewhat surprisingly, Kose, Otrok and Prasad (2010) find that national business cycles have not become more synchronized at the global level in the post-1985 period. Instead, they provide evidence that convergence of cyclical phenomena has occurred within but not across the industrial and emerging economies, suggesting a form of “de-coupling” of business cycles during the era of globalization. Similar to these studies, the objective of this paper is to examine the differences and similarities in cyclical phenomena for a set of developed and emerging economies.

In this study, we analyze the behavior of industrial production and employment growth as economic indicators of cyclical activity. 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

¹Earlier studies such as Lumsdaine and Prasad (2003) and Canova, Ciccarelli and Ortega (2007) seek to identify a world business cycle using data only on developed economies. Stock and Watson (2005) study the evolution of business cycle synchronization for the G-7 economies over the period 1960-2002.

(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 to real economic decisions. Likewise, the NBER uses information on indicators such as real GDP, real income, industrial production, employment, and trade at the sectoral level to classify the different phases of economic activity in terms of recessions and expansions.

We model the cyclical behavior of the economic indicators as a recurring Markov chain, which allows for asymmetries in the underlying time series. The importance of accounting for asymmetries in economic time series has been noted by Neftci (1984), Hamilton (1989), and Kim and Nelson (1999), amongst others. Neftci (1984) argued that the behavior of the unemployment rate in the US is characterized by sudden jumps and slower drops. Likewise, in Hamilton’s (1989) framework, recessions are due to permanent negative shocks. As in their analyses, we seek to capture potential nonlinearities in the behavior of the time series using a Markov chain approach. This is in contrast to analyses based on auto- or cross-correlations, which cannot account for nonlinearities in the underlying series. Unlike many other parametric approaches, the Markov chain approach is also a parsimonious approach that does not require an extensive set of assumptions regarding the distribution, homoscedasticity, or serial correlation properties of the time series under consideration.

Our main findings are summarized as follows. We document the existence of significant breaks in the time series behavior for both industrial production and employment growth for the emerging economies. We also find evidence for greater heterogeneity in the estimated processes for employment growth compared to industrial production growth across the different countries. More importantly, however, we find that cyclical phenomena are “de-coupled” for the developed countries and a set of emerging economies which include Chile, China, Malaysia, Mexico, the Philippines, and Turkey based on the behavior of both industrial production and employment growth. Interestingly, we find that industrial production and employment growth are also “de-coupled” from each other for many emerging countries. This finding is based on the behavior of a composite indicator that uses information on both industrial production and employment growth. We conclude by noting that our results suggest some new directions for the study of emerging economy business cycles.

The rest of this paper is organized as follows. Section 2 describes the methodology while Section 3 describes the data. Section 4 presents the results of implementing the Markov chain approach for the understanding the cyclical behavior of industrial production and employment growth. Section 5 concludes.

2 Methodology

In this study, we propose and use a Markov chain-based methodology for investigating the cyclical behavior of key economic aggregates. Our discussion follows Anderson and Goodman (1957), Kemeny and Snell (1976), and Tan and Yilmaz (2002) directly.

Our results are based on Markov chain processes estimated individually for industrial production and employment growth for each country as well as a composite indicator that combines information on both indicators. Section 2.1 describes the discrete Markov chain representation for continuous economic time series and Section 2.5 discusses the derivation of a composite indicator that combines information on the individual indicators.

The Markov chain approach allows for simple tests of time-homogeneity and time-dependence to establish stationarity and persistence properties of each series. These tests are given in Sections 2.2 and 2.3. The time-homogeneity tests help to determine if the transition probabilities between the states of the Markov model are invariant over time or not.² Similarly, tests of the equality for different Markov chains given in Section 2.4 and an examination of the expected times to switch between alternating states (referred to as the expected *first passage time*) discussed in Section 2.6 enable us to identify similarities and differences in the cyclical dynamics of the relevant series across countries.

2.1 Markov chain representation of economic time series

In order to analyze cyclical dynamics of economic time series as a Markov chain, we focus on the direction of movements of the time series which indicate whether the consecutive states show an increase or decrease over time. It is possible to include more information on a continuous time series to study not only the direction of change but also the magnitude of change by

²As 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 a standard linear time series model.

increasing the number of states. However, the size of the probability transition matrix to be estimated increases exponentially with the number of states. As a result, when the number of observations is limited, the power of the tests decreases. 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 our approach, the continuous state space of a stationary economic time series $y(t)$ 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 $[0, T]$, i.e.,

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

where $\bar{y} = 1/(T+1) \sum_{t=0}^T y(t)$. In economic time series which exhibit a trend over the sample period, the movements in the series are defined relative to this trend. The seasonality effects are also eliminated by taking the annual quarter-to-quarter growth rates. In our study, we analyze the annual quarter-to-quarter growth rate for country i : $\Delta y_{i,t} = \ln(Y_{i,t}) - \ln(Y_{i,t-4})$ where $Y_{i,t}$ denotes the industrial production index (or total employment) of country i in quarter t and $y_{i,t} = \ln(Y_{i,t})$. For seasonally unadjusted data, this transformation eliminates any seasonal effects that might exist at the quarterly frequency.

For a u^{th} -order Markov chain, the probability that the process will be at a particular state only depends on the states at u previous time periods:

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

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 $j \in \{U, D\}$.

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

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

When the transition probabilities between states do not vary over time, i.e. when $p_{i,j}(t) = p_{i,j}$ and therefore $P(t) = P$, the underlying Markov chain is *time homogeneous*.

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

$$\hat{p}_{i,j} = \frac{n_{i,j}}{\sum_j n_{i,j}}, \quad i \in S^u, j \in S, \quad (2)$$

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).

2.2 Testing for time dependence

Tests of time dependence provide information about the order of the Markov chain describing the cyclical dynamics of the underlying series and its persistence properties. 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

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

with $\tilde{Q} = \{\tilde{q}_{i,j}\} = \underbrace{[P^T, P^T, \dots, P^T]^T}_{2^{v-u}}$ 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 is repeated until the null hypothesis is not rejected. Since it is assumed that the Markov chain is time homogeneous to perform this test, this assumption must be tested to finalize the time-dependency test.

2.3 Testing for time homogeneity

In order to test a time series for time homogeneity, we divide observations on $\{X_t, t = 0, 1, 2, \dots\}$ 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 $k, k = 1, 2, \dots, K$ is given by

$$p_{i,j}(k) = P(X_t = j | X_{t-1} = i_1, \dots, X_{t-u} = i_u),$$

$$i = (i_1, \dots, i_u) \in S^u, j \in S, t \in [(k-1)\Delta, k\Delta], \quad (4)$$

where $\Delta = \lfloor (T+1)/K \rfloor$. We 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:

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

$$i \in S^u, j \in S, k = 1, 2, \dots, K \quad (5)$$

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 χ^2 asymptotic distribution with $2(K-1)$ degrees of freedom.

In case the null hypothesis is not rejected, one can state that 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.

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

The Markov chain approach also allows us to test for the equivalence of the Markov processes describing the cyclical dynamics of each indicator across countries. This test involves testing whether the transition probabilities of each country are statistically different from the transition probabilities estimated by combining the time series from two different countries.

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

We 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 is given as

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

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 χ^2 asymptotic distribution with 2 degrees of freedom.

In case the null hypothesis is not rejected, one states 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 are considered statistically different.

2.5 Markov chain representation of the composite index

In this study, in addition to analyzing the time series of industrial production (IP) and employment growth, we create an index comprised of IP and employment growth using the methodology of finite Markov chains described in the preceding sections. An index comprised of several economic indicators may provide a healthier indication of the state of economic activity.

The composite indicator is constructed by taking into account the time-homogeneity of the estimated Markov chains. First, the minimum of the two dates for which time homogeneity of the Markov chains for IP and employment growth holds is identified. Second, the fact that there may be second-order dependence in the composite indicator depending on the order of the underlying univariate Markov chains is considered. If the underlying Markov processes are i.i.d. or of orders one, the composite indicator is constructed by identifying a pair of states H (High) and L (Low) for IP index growth and another pair of states U and D for employment growth. In this framework, there exist four states for which the composite indicator is 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 is of order two, then the composite indicator is constructed to take into account this second-order dependence. We discuss the results of constructing the composite estimator in Section 3.4.

2.6 First passage time analysis

The final topic of this section is the derivation of the expected first passage time from one state to another. The time to switch from one state to another yields valuable information to study cyclical behavior of economic time series with possible asymmetries.

Let $T_{i,j}$ be the first passage time from state i to state j . The matrix of expected first passage times, $M = \{E[T_{i,j}]\}$ is written as

$$M = (I - Z + EZ_{diag})D \quad (7)$$

where I is the identity matrix, $Z = (I - (P - \Pi))^{-1}$, Π is a matrix constructed by the row vector of steady-state probabilities π in its each row, Z_{diag} is a diagonal matrix that contains the diagonal elements of Z , E is a matrix of ones, and D is a diagonal matrix with $1/\pi_i$ as its $D_{i,i}$ th element (Kemeny and Snell, 1976). The first passage time analysis for the first- and second-order Markov chains are given as special cases next.

2.6.1 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 from state U to state D occurs in period t 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 and the expected first passage time from state D to state U are $E[T_{U,D}] = \frac{1}{1-p_{U,U}}$ and $E[T_{D,U}] = \frac{1}{p_{D,U}}$.

2.6.2 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:

$$P = \begin{bmatrix} p_{UU,UU} & 0 & p_{UU,UD} & 0 \\ p_{DU,UU} & 0 & p_{DU,UD} & 0 \\ 0 & p_{UD,DU} & 0 & p_{UD,DD} \\ 0 & p_{DD,DU} & 0 & p_{DD,DD} \end{bmatrix}. \quad (8)$$

Using the above transition matrix, we define the following submatrices:

$$Q_U = \begin{bmatrix} p_{UU,UU} & 0 \\ p_{DU,UU} & 0 \end{bmatrix} \quad \text{and} \quad Q_D = \begin{bmatrix} p_{DD,DU} & 0 \\ p_{UD,DU} & 0 \end{bmatrix}, \quad (9)$$

$$R_U = \begin{bmatrix} p_{UU,UD} & 0 \\ p_{DU,UD} & 0 \end{bmatrix} \quad \text{and} \quad R_D = \begin{bmatrix} p_{DD,DD} & 0 \\ p_{UD,DD} & 0 \end{bmatrix}. \quad (10)$$

In this case, the up states include two different states UU and DU and the down states include UD and DD . By using the weighted sum of the first passage times with respect to the likelihood of being in each of these states, the expected first passage time is written as

$$E[T_{U,D}] = \pi_U(I - Q_U)^{-2}R_U u \quad (11)$$

where $u = [1, 1]^T$ and $\pi_U = \left[\frac{\pi_{UU}}{\pi_{UU} + \pi_{DU}}, \frac{\pi_{DU}}{\pi_{UU} + \pi_{DU}} \right]$ is the steady-state probability vector for the up states. Similarly,

$$E[T_{D,U}] = \pi_D(I - Q_D)^{-2}R_D u \quad (12)$$

where $\pi_D = \left[\frac{\pi_{DD}}{\pi_{UD} + \pi_{DD}}, \frac{\pi_{UD}}{\pi_{UD} + \pi_{DD}} \right]$ is the steady-state probability vector for the down states.

3 Data

In this study, we analyze the behavior of industrial production and employment growth as economic indicators which provide information about the underlying state of the economy. Economic indicators are typically 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 recurring fluctuations in a broad set of economic time series. Such series not only

underlie the generation of business cycles but also constitute the most useful data to forecast the turning points of economic activity.

Changes in industrial production play a key role in defining turning points of a business cycle, as 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. The unemployment rate is generally considered as a lagging indicator, as it tends 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.

The sample of countries considered in this study includes twenty developed and emerging economies playing key roles in the global economy. Table A.1 in the Appendix provides the list of countries as well as the data sources and the relevant sample periods over which data on industrial production and employment are available for each country.

4 Results

This section presents the results of applying the Markov chain methodology to analyze the cyclical dynamics of industrial production (IP) and employment growth. Section 4.1 presents the estimated Markov chains for industrial production and employment growth for the entire sample of countries while Section 4.2 discusses the results of the time-homogeneity and time-dependence tests. Section 4.3 presents the expected first times analysis for the different indicators while Section 4.4 is devoted to a discussion of the results for the composite indicator.

4.1 Estimated Markov processes for IP and employment growth

Tables 1 and 2 provide the estimated Markov chains and the results of implementing the tests of dependence and time homogeneity for the IP and employment growth series. Column 1 in Tables 1 and 2 shows the beginning year for which time homogeneity of the series is established while Column 2 shows the order of the estimated Markov chain. These tables report the time series properties of the economic indicators in the period after a break is detected, if such a break exists.

Tables 1 and 2 show that IP and employment growth are represented by time-homogeneous Markov chains over the sample period of 1960-2008 for most of the developed countries. However, there are also a set of developed countries for which the Markov chain-based time homogeneity tests are rejected over the relevant sample periods. For these countries, a breakpoint that ensures the time-homogeneity of a shorter period is determined. These include the Netherlands, which has a breakpoint in IP growth in 1963, and the UK and Italy, which have breakpoints in employment growth 1975 and 1993, respectively.³ The case of Japan deserves special mention. Tables 1 and 2 show that both IP and employment growth for Japan follow non-homogeneous processes over the sample period. 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, suggesting that 1993 serves as a breakpoint after which time-homogeneity of both IP and employment growth is established.

There is evidence for greater heterogeneity in the behavior of the economic indicators for the emerging economies. For the East Asian countries, we find no evidence of breakpoints in IP or employment growth for either S. Korea or the Philippines over the observed sample periods. There is a breakpoint in IP growth for Malaysia in 1997, which corresponds to the date of the East Asian crisis. Since data on total employment are available since 1997, both IP and employment growth follow time-homogeneous processes for Malaysia as of this date. Considering the Latin American countries, IP growth for Argentina follows a time homogeneous process over the entire sample period for which data are available but the time homogeneity of employment growth is established only after 2002, which represents the date of the Argentinian debt default. Furthermore, the process for employment growth in Argentina is highly persistent.⁴ For Mexico, IP growth follows a time homogeneous process since 1995, corresponding to the date of the Tequila crisis which also affected Argentina and Brazil. There are no breakpoints in employment growth for Mexico over the relevant sample period beginning in 2000.⁵ IP growth in Chile follows a time-homogeneous Markov process over the available

³The breakpoint for Italy corresponds to the date of an agreement signed by the socialist parties and the Italian government to bring pay settlements into line with rigorous incomes policy and to combat inflation, considered as a base step for entry into the European Monetary Union (see Tiraboschi and Del Conte, 2004).

⁴Alvarez, 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.

⁵The signing of the North American Free Trade Agreement (NAFTA) in 1994 between Canada, the US and

sample period stretching back to 1960. By contrast, there is a breakpoint in employment growth in 1999, after which this indicator follows a time-homogeneous process.⁶

The cyclical experiences of the three remaining emerging market economies reflect the impact of alternative institutional and policy changes. Following pro-market reforms undertaken in the 1980's, the Chinese economy embarked on a process of rapid industrialization.⁷ Consistent with this experience, there are significant positive trends in IP and employment growth in China over the respective sample periods but after accounting for these trends, both IP and employment growth follow time-homogeneous Markov processes. For S. Africa., there is a breakpoint of 1983 for IP growth but no breakpoint for employment growth.⁸ There is a breakpoint in 2002 for IP growth in Turkey, reflecting the impact of the 2000-2001 crisis.⁹ Since data for total employment in Turkey are available as of 2000, there is no breakpoint in this series.

4.2 Test results for IP and employment growth

In this section, we determine the differences in the cyclical dynamics across the different countries using the tests described in Section 2.4. Tables 3 and 4 show the p -values of the tests pertaining to the countries for which IP and employment growth follow first-order processes.

First, Table 1 shows that the estimated Markov chain for IP growth 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 1 as well as those for the Netherlands and the UK *vis a vis* the remaining countries. Second, Table 3 shows that the hypothesis of the equality of the processes for IP growth for many of the developed economies is not rejected.¹⁰ By contrast, the hypothesis that IP growth in Spain follows the same process as those for other developed countries such as Australia,

Mexico is also an important turning point for the Mexican economy (see Kose, Meredith and Towe, 2004). However, the breakpoint for IP growth comes later than this date.

⁶For the impact of reforms undertaken in Chile in the 1970's on its relative growth performance, see Bergoeing, Kehoe and Soto (2002)

⁷See Xu (2011) for a discussion of the impact of China's institutional structure and reforms on its growth performance.

⁸This last finding may be due to the shorter sample for this series. There are no breakpoints associated with the ending of apartheid in 1994 for S. Africa but the lower and more volatile real GDP growth in the 1990's may be attributed to this event (see Hodge, 2009; Altug and Bildirici, 2010).

⁹For a discussion of this crisis and its aftermath, see Yeldan (2008).

¹⁰In unreported results, we also find that the hypothesis for the equality of the processes for IP growth for the Netherlands and the UK is not rejected, with the p -value for their equivalence being equal to 0.1616.

Japan, Finland, and France as well as for Chile, S. Korea, China, and the Philippines is rejected at the 10% level. As Table 1 shows, 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.

Third, there exists a group of East Asian countries for which the cyclical dynamics of IP growth differs from other developed and emerging countries - namely, China, the Philippines and S. Korea. Table 1 shows that IP growth for China, S. Korea and the Philippines appears to spend relatively short periods either above or below expected IP growth. Hence, we reject the equality of the estimated Markov processes for IP growth for China, the Philippines, and S. Korea with those of countries which tend to have more persistent processes for this indicator.¹¹ By contrast, we cannot reject the hypothesis that the IP growth processes for these countries are similar to each other. We note this finding as one piece of evidence in favor of a form of a “de-coupling” of cyclical phenomena between developed and emerging economies that we discuss further below.

Table 2 shows that the expected first passage times for the employment processes tend to be longer than those for IP growth, especially for the developed economies. Second, there is greater heterogeneity in the estimated Markov processes for employment growth. For one, Malaysia, Mexico and Turkey possess i.i.d. processes for employment growth while the process for Finland is of second-order. These findings constitute *a priori* evidence for significant differences relative to countries with order one Markov processes for employment growth. However, for countries with i.i.d. processes such as Malaysia, Mexico, and Turkey, the test results do not indicate any evidence of significant differences between their employment growth processes.¹²

Table 4 shows that the hypothesis of the equality of the employment growth processes is not rejected for many of the developed economies. However, there is evidence for significant differences between the employment growth processes for Spain and the UK relative to the remaining countries.¹³ The reason for these differences stems from the highly persistent nature

¹¹Specifically, we reject the equality of the estimated Markov processes for IP growth for China, S. Korea and Philippines with those for Canada, the US, Spain, and Chile as well as the equality of the processes for China and S. Korea with that for Argentina and S. Korea with that for Germany.

¹²In unreported results, we find that the p -values for the test between Malaysia and Mexico is 0.495, between Malaysia and Turkey 0.8851, and between Mexico and Turkey 0.8090.

¹³Specifically, the process for Spanish employment growth differs significantly from ten of these processes while UK employment differs from eight of them.

of both Spanish and UK employment growth. The persistence of the UK unemployment rate is well noted (see, for example, Arulampalam, Booth, and Taylor, 2000). The persistence of Spanish unemployment is also an oft-mentioned phenomenon (see Blanchard and Jimeno, 1995).¹⁴

Finally, Table 4 shows that the employment growth processes for Chile, China, and the Philippines are significantly different from those of developed or other emerging 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. Combined with the evidence for i.i.d. employment growth for Malaysia, Mexico and Turkey, we note this as another piece of evidence with regards to “de-coupling” of cyclical phenomena for the developed and emerging economies.

4.3 Expected first passage times

Figures 1 and 2 display the expected value of the first passage times between from the up state to the down state ($E[T_{U,D}]$) and from the down state to the up state ($E[T_{D,U}]$) for IP and employment growth of each country analyzed in this study, respectively. In these figures, we have drawn the line $E[T_{U,D}] = E[T_{D,U}]$ to delineate the location of the observations for the expected first passage times.

One way to examine the information in Figures 1 and 2 is in terms of the asymmetry in the behavior of the underlying economic indicators.¹⁵ In this study, our objective is to examine the differences in the cyclical dynamics of the different economic indicators for the developed and emerging economies. Figures 1 and 2 show that there are a significant number of developed and emerging countries for which the values of $E[T_{U,D}]$ and $E[T_{D,U}]$ lie in a relatively tight band around the equal expected first passage time line, suggesting that such an asymmetry

¹⁴Alana and del Barrio (2006) corroborate this finding using regional unemployment data and find that the persistence of unemployment is greater in the most industrialized regions in Spain. As we noted above, this finding may also explain the persistence of IP growth in Spain. 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.

¹⁵This is the issue that had motivated Neftci’s (1984) study for the US unemployment rate. Neftci (1984) implemented a formal test of asymmetry by testing for the equality of the transition probabilities $p_{U,U}$ and $p_{D,D}$. Notice that for first-order Markov chains, this test is equivalent to testing for the equality of the expected first passage times $E[T_{U,D}]$ and $E[T_{D,U}]$. Recall from Section 2.6 that $E[T_{U,D}] = 1/(1-p_{U,U})$ and $E[T_{D,U}] = 1/p_{D,U}$. Since $p_{D,U} = 1 - p_{D,D}$, the result follows.

Figure 1: Expected First Passage Times for IP Growth

Figure 2: Expected First Passage Times for Employment Growth

test would not yield much information about the differences of the developed versus emerging economies. There are countries which do display significant differences in expected first passage times across the alternative states but these include both developed and emerging economies

such as Argentina, Spain or the UK.

In this paper, we pursue the approach of testing for the equality of the Markov chains characterizing the entire cyclical dynamics for each indicator individually as well as those for the composite indicator constructed below. These tests were described in Section 2.4, and they provide information about the *synchronization* of business cycles across developed versus emerging economies.¹⁶ Viewed from this perspective, Figures 1 and 2 show that there appears to be two separate clusterings for the developed versus the emerging economies. Specifically, the expected first passage times of IP growth for Chile, China, the Philippines, S. Korea, and Turkey and those of employment growth for Chile, Malaysia, Mexico, the Philippines, and Turkey tend to cluster together. Furthermore, these expected first passage times tend to be relatively short. By contrast, the developed economies tend to have longer expected first passage times for both IP and employment growth. These findings point to a form of “de-coupling” of the different economies that we already noted above.

4.4 The composite indicator

In this section, we create an index comprised of IP and employment growth using the methodology of finite Markov chains described in Section 2. Let (p, q) denote the orders of IP and employment growth in the composite indicator described in Section 2.5. 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. There were only three countries for which we estimated second-order processes for either IP or employment growth – Finland, the Netherlands, and the UK.¹⁷ 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.

¹⁶The potential determinants business cycle synchronization have been discussed extensively in the literature. These include gravity or economic geography arguments – see Masahisa, Krugman, and Venables (1999 or Combes, Mayer and Thisse (2008). The establishment of trade pacts, common currency areas, economic and political unions, and institutional proximity as well as the role of trade and financial integration have also been put forth as factors enhancing similarity in the cyclical dynamics of countries – see Baxter and Kouparitsas (2005); Canova, Ciccarelli, and Ortega (2009); Kose, Otrok and Prasad (2010); De Pace (2010); Altug, Emin and Neyapti (2012), amongst others.

¹⁷The composite indicator must be constructed to take into the account this second-order dependence. 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 period. The process can then transit to one of four possible states today, UUH , UUL , DUL , and DUH .

Figure 3: Expected First Passage Times for the Composite Indicator

Tables 5 and 6 show the transition probabilities between the possible states for all $(1, 1)$ processes. We observe that most developed countries as well as emerging economies 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, 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. 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, 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 many emerging economies, 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. Similar findings occur for other developing economies such as Chile, China, Malaysia, Mexico, and the Philippines. These results imply that the behavior of IP growth and employment growth are “de-coupled” from each other, at

least over the sample period in question.

Table 7 presents the p -values for the test of the equality of the composite processes across different countries. First, we observe that there is evidence for heterogeneity even among the developed economies.¹⁸ Second, the hypothesis that emerging economies such as Chile, China, Malaysia, Mexico, the Philippines and Turkey have probability transition matrices that are identical to those of others in our sample is rejected at significance levels of 10% or less. These rejections occur especially relative to the developed countries.¹⁹ Indeed Chile, China, Malaysia, Mexico, the Philippines, and Turkey appear to comprise one distinct group and the developed countries comprise another group in terms of their cyclical dynamics.

Figure 3 shows the relation between the estimated passage times between the HU and LD states for each country. The expected first passage times between the different states are typically longer for industrialized economies. Among the developed economies, Spain continues to exhibit highly persistent behavior. Surprisingly, a similar finding occurs for Italy, suggesting that the composite indicator provides additional information relative to that contained in the individual indicators. More importantly, we continue to observe the existence of two separate country groupings, those corresponding to the developed and emerging economies, respectively.

5 Discussion and Concluding Remarks

In this study, a simple but effective testing procedure has been used 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 methods. By following a systematic Markov based testing procedure, we revealed the time-dependence and time-homogeneity properties of industrial production and employment growth for a key set of developed and emerging countries.

It is worthwhile relating these results to those in the literature. Many studies have examined the behavior of individual countries or country groupings based on the behavior of a

¹⁸The null hypothesis that the UK composite indicator is the same as those of the US and France is rejected at significance levels of less than 5%. Likewise, the results indicate that the composite indicator for Italy differs significantly from those of Canada, Japan, or France while the Spanish composite indicator differs from that of France, providing additional evidence about differences among the EU countries that have emerged more fully during the recent EU debt crisis.

¹⁹Considering the case of China, the equality of the probability transition matrices is rejected for all countries in Table 7 except Japan, Chile, Mexico, Malaysia, the Philippines and Turkey. For Mexico, the null hypothesis of equality is rejected against Canada, the UK, the US, France, Germany, Italy, Spain as well as S. Africa.

single indicator such as real GDP or industrial production. There are other studies that have considered the joint behavior of the main macroeconomic aggregates such as consumption, investment, and real output at the same time as they have considered the synchronization of real activity across different sets of countries. As we discussed in the Introduction, these studies include Kose, Otrok and Whiteman (2003), Canova, Ciccarelli, and Ortega (2007), and Kose, Otrok and Prasad (2010), amongst others.

The interest in relating our results to the findings in these papers arises from the issue of considering multiple indicators to determine business cycle characteristics. As a case in point, Kose, Otrok and Prasad (2010) find that one of the distinguishing factors between business cycles for industrialized and emerging economies concerns the behavior of consumption. They find that group-specific factors have had a greater role in accounting for the consumption aggregate in industrialized economies, suggesting that such economies have been able to improve consumption risk sharing by making use of greater financial integration in the era of globalisation. By contrast, consumption behavior in emerging economies reflects an increased role for country-specific factors since 1985. This finding constitutes one of the factors behind their conclusions regarding the “de-coupling” of business cycles in industrialized and emerging economies, and points to the role that multiple indicators can play in identifying patterns of economic activity worldwide.

An important contribution of our study also pertains to the use of a composite indicator of economic activity, which is constructed based on information for IP and employment growth. As we discussed above, the composite indicator implies that IP and employment growth tend to behave similarly for many developed countries. By contrast, the behavior of IP growth and employment growth are “de-coupled” from each other for emerging countries such as Chile, China, Malaysia, Mexico, the Philippines and Turkey. 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 many emerging economies have been undergoing, with substantial sectoral shifts out of agriculture and into industry that is characteristic of their growth processes.²⁰

²⁰See Lin (2011) for discussion about the process of structural transformation that has been occurring in the large middle-income countries such as China, India and Brazil, and its relation to employment growth in developing economies.

The structure of labor markets has been studied very extensively and linked to the nature of shocks, incentive schemes and other institutional arrangements for the developed economies. Our analysis has revealed one of the most studied aspects of European labor markets, namely, the persistence or “hysteresis” of employment (see Blanchard and Summers, 1989). Yet there is much less known about the structure of emerging economy labor markets. An important phenomenon that governs the behavior of labor markets for such economies is the existence of a large informal sector.²¹ The apparent lack of synchronization between IP and employment growth for the emerging countries together with the lack of synchronization of cyclical dynamics between developed and emerging economies suggests that one potential reason for such differences may lie in the presence of a large informal sector. It also suggests that much further work is needed to understand the drivers of economic activity for emerging economies.

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²¹See Tansel and Kan (2012) for an examination of individual-level transitions in and out of different employment states, including those that involve work in informal sector jobs, using a Markov chain approach for the Turkish economy.

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Industrial Production					
Country	Data Source	Sample Period	Country	Data Source	Sample Period
Australia	IFS	1960:1-2008:2	Argentina	SO	1994:1-2009:1
Canada	IFS	1980:1-2008:2	Chile	IFS	1960:1-2008:1
U.K.	IFS	1960:1-2008:2	Mexico	IFS	1960:1-2008:2
U.S.	IFS	1960:1-2008:2	Malaysia	IFS	1985:1-2008:3
Japan	IFS	1960:1-2008:2	Philippines	IFS	1981:1-2006:1
Finland	IFS	1960:1-2008:2	S. Korea	IFS	1980:1-2008:3
France	IFS	1960:1-2008:2	China	IFS	1992:2-2008:3
Germany	IFS	1960:1-2008:2	S. Africa	IFS	1961:1-2008:2
Italy	IFS	1960:1-2008:2	Turkey	IFS	1980:1-2008:3
Netherlands	IFS	1960:1-2008:2			
Spain	IFS	1961:1-2008:2			
Employment					
Australia	ILO	1978:1-2009:1	Argentina	SO	1998:4-2009:1
Canada	ILO	1960:1-2009:1	Chile	ILO	1986:1-2009:1
U.K.	OECD	1960:1-2009:1	Mexico	ILO	2002:1-2009:1
U.S.	OECD	1960:1-2009:1	Malaysia	BIS	1997:1-2009:1
Japan	ILO	1960:1-2009:1	Philippines	ILO	1990:3-2009:1
Finland	ILO	1992:1-2009:1	S. Korea	ILO	1983:1-2009:1
France	Eurostat	1980:1-2008:4	China	ILO	1999:3-2008:4
Germany	ILO	1962:1-2008:4	S. Africa	BIS	1970:1-2009:1
Italy	ILO	1980:1-2008:4	Turkey	CB	2000:1-2009:1
Netherlands	ILO	1984:1-2008:3			
Spain	Eurostat	1980:1-2009:1			

IFS: International Financial Statistics database of the IMF.

ILO: International Labor Office. BIS: Bank of International Settlements

CB: Central Bank; SO: Statistical Offices

Table A.1: Sample of Countries

A Data

This section presents the sample periods and sources for the data on industrial production and employment.²² Data on the industrial production index are typically available from the International Financial Statistics (IFS) database of the IMF. Data on aggregate employment are obtained from the International Labor Office (ILO), Eurostat or Bank of International Settlements (BIS).

²²We 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”.

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 [†]	1	0.816	0.184	0.292	0.708	5.43	3.43
UK	1974	2	See (1) below				5.23	4.11
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 [†]	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 [†]	1	0.839	0.161	0.227	0.773	6.20	4.40
Malaysia	1997 [†]	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
Philippines	1981	1	0.704	0.296	0.250	0.750	3.38	4.00
China	1992	1	0.667	0.333	0.292	0.708	3.00	3.43
S.Africa	1983 [†]	1	0.852	0.148	0.192	0.808	6.75	5.33
Turkey	2002 [†]	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

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

and

$$(2) \quad P_{Nether.} = \begin{bmatrix} 0.859 & 0.141 \\ 0.588 & 0.412 \\ 0.250 & 0.750 \\ 0.156 & 0.844 \end{bmatrix}$$

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	1961	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
Philippines	1990	1	0.647	0.353	0.333	0.667	2.83	3.00
China	1999	1	0.867	0.133	0.111	0.889	7.50	9.00
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

$$(3) \quad P_{\text{Finland}} = \begin{bmatrix} 0.895 & 0 & 0.105 & 0 \\ 0.8 & 0 & 0.2 & 0 \\ 0 & 0.75 & 0 & 0.25 \\ 0 & 0.125 & 0 & 0.875 \end{bmatrix}.$$

	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)	
			<i>HU</i>	<i>HD</i>	<i>LU</i>	<i>LD</i>	$E(T_{HU,LD})$	$E(T_{LD,HU})$
Australia	1978	<i>HU</i>	0.739	0	0.196	0.065	12.18	7.47
		<i>HD</i>	0.333	0.5	0	0.167		
		<i>LU</i>	0.259	0.037	0.593	0.111		
		<i>LD</i>	0.0625	0.125	0.0625	0.75		
Canada	1980	<i>HU</i>	0.818	0	0.114	0.068	11.64	8.18
		<i>HD</i>	0.364	0.636	0	0		
		<i>LU</i>	0.125	0	0.75	0.125		
		<i>LD</i>	0.033	0.133	0.033	0.8		
Japan	1992	<i>HU</i>	0.72	0.08	0.16	0.04	10.81	6.11
		<i>HD</i>	0.308	0.538	0.077	0.077		
		<i>LU</i>	0.167	0.083	0.5	0.25		
		<i>LD</i>	0.083	0.25	0	0.667		
UK	1974	<i>HU</i>	0.68	0	0.28	0.04	17.80	9.22
		<i>HD</i>	0.15	0.65	0	0.2		
		<i>LU</i>	0.282	0	0.641	0.077		
		<i>LD</i>	0.08	0.24	0	0.68		
US	1960	<i>HU</i>	0.831	0.052	0.104	0.013	14.57	11.51
		<i>HD</i>	0.2	0.65	0	0.15		
		<i>LU</i>	0.194	0	0.548	0.258		
		<i>LD</i>	0.048	0.048	0.097	0.807		
Finland	1992	<i>HU</i>	0.636	0.046	0.318	0	14.13	6.79
		<i>HD</i>	0.375	0.5	0	0.125		
		<i>LU</i>	0.263	0	0.600	0.157		
		<i>LD</i>	0	0.231	0.154	0.615		
France	1980	<i>HU</i>	0.714	0.114	0.143	0.029	9.68	10.21
		<i>HD</i>	0.333	0.278	0	0.389		
		<i>LU</i>	0.267	0	0.533	0.2		
		<i>LD</i>	0	0.220	0.073	0.707		
Germany	1962	<i>HU</i>	0.824	0.029	0.132	0.015	14.20	11.49
		<i>HD</i>	0.214	0.643	0	0.143		
		<i>LU</i>	0.208	0.042	0.5	0.25		
		<i>LD</i>	0.032	0.115	0.05	0.803		
Italy	1992	<i>HU</i>	0.727	0.091	0.182	0	18.20	15.43
		<i>HD</i>	0	0.786	0	0.214		
		<i>LU</i>	0.091	0	0.864	0.045		
		<i>LD</i>	0.083	0.167	0.167	0.583		
Spain	1980	<i>HU</i>	0.805	0	0.195	0	26.42	19.00
		<i>HD</i>	0.077	0.692	0.077	0.154		
		<i>LU</i>	0.25	0	0.643	0.107		
		<i>LD</i>	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)	
			<i>HU</i>	<i>HD</i>	<i>LU</i>	<i>LD</i>	$E(T_{HU,LD})$	$E(T_{LD,HU})$
Malaysia	1997	<i>HU</i>	0.667	0.25	0	0.083	7.39	9.7
		<i>HD</i>	0.3	0.4	0.1	0.2		
		<i>LU</i>	0	0.111	0.444	0.445		
		<i>LD</i>	0.090	0.182	0.364	0.364		
S. Korea	1983	<i>HU</i>	0.677	0.065	0.193	0.065	9.96	8.21
		<i>HD</i>	0.25	0.375	0.0625	0.3125		
		<i>LU</i>	0.167	0.125	0.625	0.083		
		<i>LD</i>	0.074	0.148	0.074	0.704		
Argentina	2001	<i>HU</i>	0.846	0	0.154	0	15.00	12.00
		<i>HD</i>	0.2	0.6	0	0.2		
		<i>LU</i>	0.5	0	0	0.5		
		<i>LD</i>	0	0.286	0	0.714		
Chile	1998	<i>HU</i>	0.5	0.125	0.375	0	6.69	8.05
		<i>HD</i>	0.333	0.445	0.222	0		
		<i>LU</i>	0.2	0.2	0	0.6		
		<i>LD</i>	0	0.25	0.083	0.667		
Mexico	2000	<i>HU</i>	0.455	0.090	0.273	0.182	6.42	2.76
		<i>HD</i>	0.6	0.4	0	0		
		<i>LU</i>	0.4	0.2	0.2	0.2		
		<i>LD</i>	0.285	0.143	0.143	0.428		
Philippines	1990	<i>HU</i>	0.308	0.154	0.308	0.230	5.41	6.20
		<i>HD</i>	0.353	0.471	0	0.176		
		<i>LU</i>	0.1875	0.125	0.5625	0.125		
		<i>LD</i>	0	0.333	0.25	0.417		
China	1999	<i>HU</i>	0.25	0.125	0.125	0.5	2.26	3.57
		<i>HD</i>	0.4	0.6	0	0		
		<i>LU</i>	0.5	0	0	0.5		
		<i>LD</i>	0.222	0.111	0.111	0.556		
S.Africa	1982	<i>HU</i>	0.771	0.114	0.086	0.029	13.47	9.17
		<i>HD</i>	0.263	0.526	0.053	0.158		
		<i>LU</i>	0.154	0	0.692	0.154		
		<i>LD</i>	0.059	0.147	0	0.794		
Turkey	2001	<i>HU</i>	0.25	0	0.375	0.375	3.78	2.40
		<i>HD</i>	0.4	0.6	0	0		
		<i>LU</i>	0.166	0	0.667	0.167		
		<i>LD</i>	0.428	0.286	0	0.286		

Table 6: Transition Probabilities and Expected Passage Times for the Composite Indicators: Emerging Economies

	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