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Business Cycles around the Globe: A Regime Switching Approach

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Abstract

This paper characterizes business cycle phenomena in a sample of 22 developed and developing economies using a univariate Markov regime switching approach. It examines the efficacy of this approach for detecting business cycle turning points and for identifying distinct economic regimes for each country in question. The paper also provides a comparison of the business cycle turning points implied by this study and those derived in other studies and by other methods. Our findings document the importance of heterogeneity of individual countries' experiences. We also argue that consideration of a large and diverse group of countries provides an alternative perspective on the co-movement of aggregate economic activity worldwide.

Keywords: Markov switching approach, business cycles, turning point analysis, non-parametric modelling.
JEL Codes: E32, E37, C32.

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1 Introduction

How do business cycles in developing and emerging market economies differ from those in industrialized countries? In recent years there have been a number of studies that attempt to answer this question. Köse, Otrok and Whiteman (2003) used a dynamic factor model to examine the sources of macroeconomic fluctuations in a sample of 60-odd countries across the world. In a related study, Köse, Terrones, and Prasad (2003) seek to determine whether greater trade and financial integration has led to greater business cycle synchronization for 76 developed and developing countries using annual data between 1960-1996. There are also many studies that seek to determine the existence of an international or euro area business cycle using smaller sets of countries (see, for example, Lumsdaine and Prasad, 2003 or more recently, Canova, Ciccareli and Ortega, 2009.) In a recent study, Benczur and Ratfai (2009) use the Real Business Cycle approach pioneered by Kydland and Prescott (1982) to examine the business cycle characteristics of 62 countries worldwide.[1] As in the study by Benczur and Ratfai (2009), we take as our starting point the experiences of 22 individual countries as a way of uncovering the sources of cyclical fluctuations in industrialized and emerging market economies. While our study is based on a smaller set of countries, we nevertheless consider a representative set of developed and emerging market economies that allows for the heterogeneity of experiences much greater than those based on the OECD or euro area countries. We employ a simple nonlinear regime switching approach to describe the stylized facts of business cycles in these countries. This approach also allows for the dating of business cycles.

There is a large literature that has examined the stylized facts of business cycles. Stock and Watson (2005) provide a comprehensive analysis of the volatility and persistence of business cycles in G7 countries defined to include the U.S., U.K., France, Germany, Italy, Japan and Canada over the period 1960-2002. Artis, Marcellino, and Proietti (2003) discuss parametric and nonparametric approaches to dating euro area business cycles. Another approach to defining a multivariate measure of the business cycle is through the dynamic factor model that was initially proposed by Sargent and Sims (1977). This model seeks to describe the cyclical behavior of a key set of time series in terms of a low-dimensional vector of unobservable factors and a set of idiosyncratic shocks. Altug (1989) estimates a version of the Kydland-Prescott model using maximum likelihood by treating the economy-wide technology shock as an unobserved factor. Diebold and Rudebusch (1996), Chauvet (1998) and others combine the Markov switching model with the dynamic factor framework to account for the changing pattern of economic variables over the business cycle.

An alternative approach to modelling business cycles derives from the work of Neftçi (1982) and Hamilton (1989), who use Markov processes to describe the underlying state of the economy. Neftçi (1982) examines the asymmetries in the U.S. unemployment rate

[1] Specifically, they fit a basic small open economy real business cycle model with permanent and transitory shocks to identify country-specific productivity processes. Their approach is most closely linked to that of Aguiar and Gopinath (2007) and Garcia-Cicco, Pancrazi, and Uribe (2006), who examine versions of a small open economy business cycle model with permanent and transitory shocks to account for developed versus emerging market economy experiences. Likewise, Neumeyer and Perri (2005) examine real business cycle models with shocks to trend productivity and real interest rates as a way of accounting for the observations.

using a second-order Markov process. Hamilton (1989) proposes a Markov switching model with an unobserved state to describe the phases of a business cycle. This class of models has been used extended to a multivariate setting by Krolzig (1997). Applications of this approach include Boldin (1996), who examines the robustness of Hamilton's (1989) two-regime Markov switching specification for capturing business cycles. Krolzig (2001a,b) uses a multivariate version of Hamilton's (1989) univariate Markov switching model to examine changes in the long-run growth rate of real GDP for the US, Japan and developed countries in Europe. Kim and Nelson (1999) implement Bayesian analysis of the Markov switching model with a structural break in the mean growth rates of real GDP and in the variance of the disturbances between the two unobserved regimes. (See also Smith and Summers, 2009.) Taylor, Sheperd and Duncan (2005) estimate an MS-AR model for Australian GDP using Bayesian Markov Chain Monte Carlo simulation methods.

There also exist a few applications of the various approaches to characterizing business cycles in developing or emerging market contexts. Rand and Tarp (2002) ask whether business cycles in developing countries are different by using the non-parametric Bry-Boschan method for dating business cycles. Girardin (2005) examines GDP growth-cycles for 10 East Asian countries including Japan, China, and S. Korea using regime-switching techniques. Taştan and Yıldırım (2008) estimate a Markov switching autoregressive model for industrial production index to identify Turkish business cycles in the post-1987 period. Moolman (2004) estimates a Markov switching model for South African GDP with time-varying transition probabilities.

In a series of papers, Harding and Pagan (2002a,2002b,2005) instigated a lively debate regarding the notion of a "business cycle." In their approach, a business cycle is defined as a pattern in the level of aggregate economic activity, and an algorithm is presented to identify the turning points. This contrasts with much recent work which identifies business cycles in terms of the cyclical time series behavior of the main macroeconomic variables and their co-movement with cyclical output.[2] Instead this approach has much more in common with the work that Burns and Mitchell (1946) instigated at the National Bureau of Research (NBER). As Harding and Pagan (2002b) note, these authors identified a business cycle with the behavior of GDP. However, in the absence of measures of this variable at frequencies lower than a quarter, they chose to find the turning points in a large number of series measured at the monthly frequencies and to aggregate this information in terms of a "reference cycle". This approach continues to guide the business cycle dating methodology at the NBER, which uses data on real output, national income, employment, and trade at the sectoral and aggregate level to identify and date business cycles. Harding and Pagan (2002b) also provide a statistical foundation for the approach in Burns and Mitchell (1946) by linking the moments of the underlying series to characteristics of business cycles such as the probability of a peak or a trough or the duration of the business cycle.

In this paper we seek to analyze business cycles in 22 developed and emerging market

[2]For detailed analyzes of this type, see Backus and Kehoe (1992), who analyze the properties of historical business cycles for ten developed countries using a century-long dataset up to the 1980's or Stock and Watson (2000), who use data on 71 variables to characterize U.S business cycle phenomena over the period 1953-1996.

economies by using a Markov switching autoregressive model for GDP growth. Using this approach, we can ask whether a business cycle as we understand it – a situation where the economy transits from a given regime to another that is specified by the existence of well-defined turning points – can be identified in a meaningful way for a large set of countries. As we indicated above, the experiences of both developed and emerging market economies tend to exhibit considerable diversity. The results in this paper suggest that the Markov switching model provides a simple yet easily interpretable probability model that allows the researcher to examine the cyclical characteristics of the data in terms of the properties of the different regimes. Whether cyclical phenomena exhibit nonlinearities remains a contentious issue.[3] Nevertheless, this approach may lead to richer specifications for examining individual countries' experiences in contrast to much of the recent RBC approach which seeks to match the moments of a linearized version of a fairly standard model with those in the data. Despite some of the criticisms leveled against it, the Markov switching model also allows us to examine the confluence of business cycle turning points and the duration of business cycles, features that are typically recorded by the NBER and the CEPR Business Cycle Dating Committees as well as business cycle dates for individual countries provided by Economic Cycle Research Institute (ECRI). We estimate Markov switching models for each country in our dataset and compare our results with those of other studies as well as the nonparametric Harding-Pagan approach. Our consideration of a sample of both industrialized and emerging market economies allows us to examine the impact of various global and regional shocks, including the financial shock of 2007-2008, on different countries and country groups.

The remainder of this paper is organized as follows. Section 2 provides a literature review. In Section 2, we describe the Markov-switching autoregressive model and its estimation. Section 3 presents our empirical results while Section 4 describes the business cycle dating properties and compares them with the Harding-Pagan approach. Section 5 concludes.

2 A nonlinear univariate model of GDP growth

In a widely known paper, Hamilton (1989) proposed a simple nonlinear framework for modeling economic time series with a stochastic trend and a stationary cyclical component as an alternative to a stationary linear autoregressive model. In this framework, the parameters of the process may change with shifts in an unobserved state. He showed that this model could be used to examine the phases of a business cycle and to obtain business cycle turning points in terms of the regime shifts for the unobserved state. In this paper, we apply this model to describe the evolution of country-specific GDP.

[3]See, for example, Altug, Ashley and Patterson (1999) and Valderrema (2007). For a further discussion, see also Altug (2009), Ch. 6.

2.1 A Markov regime switching model

To describe this model, let $\tilde{y}_t$ denote the level of some series, say log(GDP), and n_t and $\tilde{z}_t$ denote its trend and cyclical components, respectively. Suppose n_t depends on an unobserved Markov state variable denoted s_t as $n_t = \alpha_1 s_t + \alpha_0 + n_{t-1}$:

$$\tilde{y}_t = n_t + \tilde{z}_t, \tag{2.1}$$

where $\tilde{z}_t$ follows an $ARIMA(r, 1, 0)$ process. Differencing yields:

$$y_t = \alpha_0 + \alpha_1 s_t + z_t,$$

where $y_t = \tilde{y}_t - \tilde{y}_{t-1}$ and z_t is a stationary $AR(r)$ process in (log) differences.[4]

In his application, Hamilton (1989) considered a univariate 2-state Markov switching model in the mean with a lag polynomial of order four as:

$$y_t - \mu(s_t) = \sum_{j=1}^{4} \phi_j (y_{t-j} - \mu(s_{t-j})) + \epsilon_t, \tag{2.2}$$

where $\epsilon_t \sim N(0, \sigma^2)$ and $s_t = 1, 2$. In this case, we have the usual classification of the regimes as a "contraction" ($s_t = 1$) or "expansion" ($s_t = 2$).

More generally, suppose $s_t = i, i = 1, \ldots, m$. For example, there may also exist situations where a third regime is appropriate. In this case, we may have "low growth", "normal growth", and "high growth" states. As before, y_t denote the growth rate of real GDP or equivalently, its log differences, and assume that the process for y_t is a univariate autoregression with regime switches such that:

$$y_t = \nu(s_t) + \phi(s_t)\delta(t) + \sum_{j=1}^{p} a_j(s_{t-j}) y_{t-j} + \sigma(s_t)\epsilon_t, \tag{2.3}$$

where $\{\epsilon_t\}_{t=0}^{\infty}$ is an i.i.d. process such that $\epsilon_t | s_t \sim N(0, \sigma(s_t)^2)$. In this expression, $\delta(t)$ denotes a deterministic polynomial in time with a potentially regime-switching coefficient. This specification allows for deterministic trends in the growth rate of an economic time series. The possibly regime-dependent trend coefficients are estimated jointly with the remaining parameters of the Markov switching model. The specification in which the intercept varies with the underlying state s_t is typically used when the mean of the process varies smoothly across regimes. An alternative specification is obtained by allowing the mean to vary with the state.[5] This specification may be useful where a change in regime leads to a one-time change in the mean of the process. Notice that Hamilton's (1989) model just a special case of the model in equation (2.3) where only the mean $\mu(s_t)$ is subject to changes in regime.

[4] One problematic aspect of this derivation is that the cyclical component is assumed to have a unit root. Lam (1990) provides a discussion of relaxing this assumption, and shows it that complicates the implementation of the Markov switching model.

[5] Notice that the mean of the process is related to the intercept and autoregressive parameters as $\mu(s_t) = \nu(s_t)/(1 - \sum_{j=1}^{p} a_j(s_{t-j}))$.

In the business cycle literature, it is customary to distinguish between classical cycles, growth cycles, and growth rate cycles. Returning to (2.3), we note that this representation is consistent with both classical cycles and growth rate cycles.[6] To understand this, suppose that both $\nu(s_t)$ and $\phi(s_t)$ are estimated to be negative in the "low" growth regime. Then on average, we can say that output growth is negative in such a regime, which implies that at any point at which the economy does transit to the "low" growth regime, there will be an absolute decline in output. By contrast, if the intercept and trend terms are above of the opposite signs, we cannot directly conclude that there will be an absolute output decline in the contractionary regime. What we can say by looking at the sign and magnitude of the intercept terms is how much output growth will fall in this regime relative to output growth in the "good" regime.[7]

2.2 Estimation

The dynamics of the $\{y_t\}$ process is completely specified once we specify a probability rule for the evolution of the unobserved state, s_t. A usual assumption is that s_t evolves as a finite first-order Markov process with transition probabilities

$$Pr(s_{t+1} = j | s_t = i, s_{t-1} = k, \ldots) = Pr(s_{t+1} = j | s_t = i) = p_{ij}, \quad i, j = 1, \ldots, m, \quad (2.4)$$

where p_{ij} is the probability that state i will be followed by state j and

$$\sum_{j=1}^{m} p_{ij} = 1, \quad i = 1, \ldots, m \text{ and } 0 \leq p_{ij} \leq 1.$$

The estimation of the model and the determination of the business cycle turning points can be obtained by using the *filtered* and *smoothed* probabilities of the unobserved state. Define $\psi_t = \{y_t, \psi_{t-1}\}$ where ψ_{t-1} contains the past history of y_t. The filtered probability of the unobserved state defined as $Pr(s_t|\psi_t)$ provides an inference about the unknown state conditional on the information up to time t. Given $Pr(s_{t-1}|\psi_{t-1})$, $Pr(s_t|\psi_{t-1})$ can be obtained as

$$Pr(s_t = j|\psi_{t-1}) = \sum_{i=1,\ldots,m} Pr(s_t = j|s_{t-1} = i) \times Pr(s_{t-1} = i|\psi_{t-1}), \quad j = 1, \ldots, m. \quad (2.5)$$

The probability law for y_t conditional on s_t, ψ_{t-1} denoted $f(y_t|s_t, \psi_{t-1})$ can be determined using (2.3). Then the joint density for y_t and s_t is given by

$$f(y_t, s_t = j|\psi_{t-1}) = f(y_t|s_t = j, \psi_{t-1}) \times Pr(s_t = j|\psi_{t-1}), \quad j = 1, \ldots, m. \quad (2.6)$$

The conditional density of the t'th observation can be obtained by summing over all s_t as:

$$f(y_t|\psi_{t-1}) = \sum_{i=1,\ldots,m} f(y_t, s_t = i|\psi_{t-1}). \quad (2.7)$$

[6] See also Goodwin (1993) on this point.

[7] It is important to note that we are not examining the deviations of real activity from some log-linear trend. Rather we are examining how real activity changes after we have controlled for secular changes in growth rate.

As a consequence, the filtered probability of the state at time t conditional on information at that date is given by

$$Pr(s_t = j|\psi_t) = \frac{f(y_t, s_t = j|\psi_{t-1})}{f(y_t|\psi_{t-1})}, \quad j = 1, \dots, m. \tag{2.8}$$

The smoothed probability denoted by $Pr(s_t|\psi_T)$ provides an inference about the unknown state using all the information in the sample where $t = 1, 2, \dots, T$. To derive these probabilities, we run through the basic filter for $t = 1, \dots, T$. The smoothed probabilities are then defined as

$$\begin{aligned} Pr(s_t = j|\psi_T) &= Pr(s_t = j|\psi_t) \times \frac{f(y_{t+1}|s_t = j, \psi_t)}{f(y_{t+1}|\psi_t)} \\ &\quad \times \frac{f(y_{t+2}|s_t = j, \psi_{t+1})}{f(y_{t+2}|\psi_{t+1})} \times \dots \times \frac{f(y_T|s_t = j, \psi_{T-1})}{f(y_T|\psi_{T-1})}. \end{aligned} \tag{2.9}$$

The estimates of the Markov transition probabilities also yield the expected duration of a state. Suppose $m = 1$ and we are interested in the expected duration of a recession. Let D denote the random variable showing the duration of a recession. Then it can be shown that

$$E(D) = \sum_{k=1}^{\infty} kPr(D = k) = \frac{1}{1 - p_{11}}.^{8} \tag{2.10}$$

Hence, these results can be used to determine the duration of a recession based on the value of the estimated transition probability.

As Hamilton (1989) notes, the procedure for obtaining the filtered probability also yields as a by-product the sample log-likelihood function:

$$\ln L = \ln f(y_T, y_{T-1}, \dots, y_0|\psi_{-1}) = \sum_{t=1}^{T} \ln f(y_t|\psi_{t-1}), \tag{2.11}$$

which can be maximized with respect to the unknown parameters $\nu(s_t), \sigma(s_t), a_j(s_t), j = 1, \dots, p, p_{11}, p_{22})'$, $s_t = 1, \dots, m$. In keeping with the notion that state 2 is the expansionary state, we can impose the restriction that $\nu(s_2) > \nu(s_1)$. However, this method may prove infeasible as the number of parameters increases. In this case, the Expectation Maximization (EM) algorithm is used. According to this technique, we start with an initial estimate of the hidden state and iteratively obtain a new joint distribution that increases the probability of the observed data. The estimation of MS-AR (and MS-VAR) models is well-known. For further details, see Hamilton (1989, 1990) and Krolzig (1997).

Following the rule suggested by Hamilton (1989), the peaks (or troughs) of business cycles may be determined as $Pr(s_t = 1|\psi_T) > 0.5$ (or conversely, as $Pr(s_t = 1|\psi_T) < 0.5$),

[8] To derive this result, notice that $D = 1$ if $s_t = 1$ but $s_{t+1} \neq 1$, implying that $Pr(D = 1) = 1 - p_{11}$; $D = 2$ if $s_t = s_{t+1} = 1$ but $s_{t+2} \neq 1$, implying that $Pr(D = 2) = p_{11}(1 - p_{11})$; $D = 3$ if $s_t = s_{t+1} = s_{t+2} = 1$ but $s_{t+3} \neq 1$, implying that $Pr(D = 3) = p_{11}^2(1 - p_{11})$ or, more generally, $Pr(D = k) = p_{11}^{k-1}(1 - p_{11})$. Hence, $E(D) = \sum_{k=1}^{\infty} kPr(D = k) = 1/(1 - p_{11})$.

Country	Data Source	Sample Period	Country	Data Source	Sample Period
Australia	OECD	1960:1-2009:2	Brazil	CB	1991:1-2009:1
Canada	OECD	1961:1-2009:2	Chile	IFS	1980:1-2009:2
France	OECD	1970:1-2009:2	Hong Kong	SO	1973:1-2009:1
Germany	OECD	1960:1-1991:3,1991:1-2009:2	Malaysia	IFS	1991:1-2009:2
Italy	OECD	1960:1-1991:3,1981:1-2009:2	Mexico	OECD	1980:1-2009:2
Japan	OECD	1970:1-2009:2	S. Korea	OECD	1975:2-2009:2
Netherlands	OECD	1960:1-1991:3,1988:1-2009:2	Singapore	IFS	1983:3-2009:2
Spain	OECD	1960:1-1991:3,1980:1-2009:2	S. Africa	CB	1970:1-2009:2
U.K.	OECD	1960:1-2009:1	Taiwan	SO	1981:2-2009:1
U.S.	OECD	1960:1-2009:2	Turkey	CB	1987:1-2009:2
Argentina	SO	1980:1-2009:2	Uruguay	CB	1987:1-2008:4

CB: Central Bank; SO: Statistical Offices

Base years: OECD 2000, IFS 2005, Argentina 1993, Brazil 2007, Hong Kong 2007, S. Africa 2005, Taiwan 2001, Turkey 1998, Uruguay 1983

Table 1: Sample of Countries

where $s_t = 1$ denotes the contractionary regime. If there are m regimes with $m > 2$, the modified rule states that the observation at time t is assigned to regime m with the highest smoothed probability: $m^* = argmax_m Pr(s_t = m|\psi_T)$. As Chauvet and Piger (2003) and others note, this rule can create a problem if the probabilities $Pr(s_t = 1|\psi_T)$ are estimated to be close to 0.5 because in this case, the algorithm will identify a large number of points as corresponding to the peaks or troughs of a business cycle. However, the rule has been known to give satisfactory results in the case of real GDP.

2.3 Data

Table 1 provides the list of countries used in our study as well as the data sources and the sample period associated with them. Our data are quarterly GDP at constant prices measured in units of the national currency.[9] Let $y_{i,t} = \ln(Y_{i,t})$ where $Y_{i,t}$ denotes real GDP 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. Following Stock and Watson (2005), we smoothed out high frequency movements in the different series by taking four-quarter averages of the annual quarter-to-quarter growth rates. Figures 1 and 2 show the smoothed growth rates for the GDP series for the developed and emerging countries in our sample. As Stock and Watson (2005) note, many of the developed countries in our sample have negative trends in their GDP growth rates. For this reason, we include deterministic time trends in our estimated specifications that may also change with the regime as described in equation (2.3).[10]

[9] See Appendix A for a further description of the data sources.

[10] Stock and Watson (2005) use a Kalman filtering approach to remove stochastic trends in GDP growth rates.

We analyze the behavior of the developed countries in two groups, a group of five countries including Australia, Canada, Japan, UK, and the US and a second group consisting of EU countries including France, Germany, Italy, the Netherlands and Spain. In their study, Benczur and Ratfai (2009) include countries such as Hong Kong, Singapore and S. Korea among the developed countries. Many studies have also emphasized geographical groupings such as those pertaining to the Latin American countries or the East Asian countries. In this vein we consider a group of developed East Asian economies consisting of Hong Kong, Singapore, S. Korea and Taiwan plus three emerging market economies including Malaysia, South Africa and Turkey. We also separately consider a group of five Latin American countries including Argentina, Brazil, Chile, Mexico and Uruguay.

3 Results

In this section we present estimation results for the regime switching autoregressive model in equation (2.3) for a sample of 22 industrial and emerging market economies. Our analysis is based on univariate models because our goal is to uncover the so-called stylized facts of business cycles using this approach. In many recent studies of cyclical phenomena, the convention has been to consider the G7 countries consisting of the Canada, France, Germany, Italy, Japan, UK, and the US. Our study differs from previous studies in terms of considering a much longer sample for the developed countries and also for the mix of emerging market economies that are included. We discuss the efficacy of the estimated models in identifying distinct economic regimes and in capturing business cycle turning points for each country in question.

3.1 Empirical business cycles

Tables 2 through 5 present our results for the different country groups.[11] We begin by making some general observations about our conclusions. On the whole we find that the business cycle characteristics of the developed countries are similar in terms of the expected growth rates of real output in the different phases and the durations of these phases. However, excluding Spain, there is some evidence that recessions are milder in the EU. In terms of business cycle synchronization, we also find some evidence that the business cycle in Europe tends to lag the business cycle in the U.S.

What is striking from Tables 2 through 5 is just how different the emerging economies are from the developed countries. Köse, Otrok and Prasad (2008) find that during the period of globalization (1985-2005), there is evidence of business cycle convergence within the group of industrial economies and within the group of emerging market economies but divergence (or decoupling) between them. Our findings go further and show that not only are the business cycle characteristics of different groups of emerging economies quite distinct from each other but that even among well defined country groupings, individual countries appear to display highly heterogeneous responses to similar international and regional conditions. We discuss these observations in more detail below and relate them to findings in the literature.

[11] Appendix A provides a detailed description of our model selection procedure.

3.1.1 The Anglophone countries plus Japan

Beginning with Hamilton (1989), the business cycle characteristics for the US and other developed countries have been studied extensively using a Markov regime switching approach. In many early applications of the Markov switching model, researchers adopted the 2-regime model with a fourth-order autoregressive lag structure that Hamilton (1989) had initially used. Goodwin (1993) uses this specification for dating business cycles based on the behavior of GDP growth in eight developed economies, including the US, the UK, Germany, Japan, Canada, Switzerland, France and Italy in the postwar era. Likewise, Bodman and Crosby (2000) adopt the fourth-order autoregressive structure in both their 2- and 3-regime models of the Canadian business cycle. However, both of these studies only test the fourth-order MS model against a linear specification. Many subsequent studies also considered the implications of a 3-regime model. Following Sichel (1994), Layton and Smith (2000) argue that the 3-regime specification allows for richer business cycle dynamics in which a contraction is followed by a rapid recovery phase, to be succeeded by a normal growth phase. As Hamilton and Susmel (1994) suggest, the 3-regime specification may also be useful for capturing outliers or unusual growth episodes in GDP growth in developed countries. Bodman and Crosby (2000) consider a 3-regime model for the Canadian business cycle which allows for such dynamics. Likewise, Girardin (2005) chooses 3-regime models for many fast-growing East Asian economies, including Japan.

Table 2 shows the estimated regime-specific intercepts $\nu(s_t)$, standard deviations $\sigma(s_t)$, autoregressive coefficients $\alpha_i(s_t)$, $i = 1, \ldots, p$, and the durations of regime D_i for each chosen specification for the first group of developed countries. It also provides values of the log-likelihood function, the Akaike information criterion (AIC), and the Likelihood Ratio statistics for the test against a linear specification. The LR test is implemented with modified critical values that account for the presence of nuisance parameters under the null.[12] With these values, Table 2 shows that the linear specifications are rejected for all the countries in the first grouping. Turning to the choice of regime, a consideration of all the model features suggests that 3-regime models fit best for Australia, Canada and Japan. By the same token, 2-regime models appear to capture the cyclical dynamics for the UK and US economies.[13]

The models for Japan, the U.K., and the U.S feature longer lag lengths. This is similar to Hamilton's (1989) study and studies such as Krolzig and Toro (2005). Table 2 can be also used to examine the expected output loss for the countries in question. In unreported results, we estimated the trends for all the counties to be negative. However, the trends in the growth rate of real GDP are estimated to be significantly negative only for Japan and the US. The magnitude of the de-trended expected growth change during a contraction varies across the different countries. While Australia and Canada display expected output declines that are negative during a recession, this effect is significantly different from zero only for Canada. By contrast, controlling for any secular declines in expected growth rates, Japan tends to grow less during a contraction. Second, with the exception of the U.K.,

[12]See Appendix B.

[13]See Appendix B.

the expected growth rates of output during an expansion tend to be fairly similar across the different countries. A mature economy such as the UK does not display episodes of high growth and hence, grows at a modest rate during expansions. The expected growth rates of output during "normal" times are lower for Australia and Canada because we allow for a third regime. By contrast, Japan experiences higher growth in both the 'normal" and "high" regimes that any of the other countries. The high rate of output growth for Australia is somewhat misleading because the "high" growth regime for Australia appears to pick a few unusual growth episodes in the data. Finally we note the standard deviations of the shocks in the "low" growth and "high" growth phases are larger than the standard deviation of the shocks in the "normal" growth state for Canada and Japan, suggesting greater volatility during recessions and "high" growth episodes.

The filtered and smoothed probabilities of the different regimes for the countries in Table 2 are provided in Figure 3. The chosen models are typically successful in identifying the major recessions that the developed countries experienced in 1973-1975, 1980-1982, 1990-1991, 2001 as well as the 2008 financial crisis. The model predicts accurately the double-dipped shape of the recession over the 1980-1982 period for the US. Nevertheless, there is significant heterogeneity in the experiences of the individual countries. The 1990 recession in Canada is observed to be more severe than the recessions at this time for the remaining countries.[14] September 11, 2001 and its aftermath register formally as a recession for Japan and the US, but not Australia, Canada or the UK, although there are real output declines for all the industrialized countries listed in Table 2.

Table 2 shows that the duration of recessions for countries such as Australia and the US range are around three quarters. By contrast Canada, Japan, and the UK experience longer recessions. The duration of recessions for Canada and Japan can be attributed to the experience of a severe and lengthy recession in 1990 for Canada and to an extended period of low growth and stagnation in the 1990's for Japan. There is more variability in the duration of expansions. The expected duration of expansions is estimated to be slightly under twenty quarters. The shortest expansion is for the US, its length being equal to fifteen quarters. It is worthwhile noting that the durations of the different regimes and the episodes observed in the actual data need not coincide. To understand this result, we note that Table 2 reports the *expected duration* of the regimes in the model whereas Figure 3 provides the regime classifications based on a rule such as $Pr(s_t = 1|y_T)$. Nevertheless, there is some correspondence between the two approaches. It is well known that according to the NBER business cycle dating methodology the US experienced one of the longest expansions in post-WWII history between March 1991 to November 2001 of 120 months. Another long expansion occurred between November 1982 to July 1990 of 92 months. We observe that expansions recorded by official business cycle dating methods are captured by the implied sequence of probabilities of the "normal" growth regime for the US in Figure 3. Finally, we note that countries such as Australia, Canada and Japan experienced episodes

[14]Part of the reason for the severity of the recession in Canada during this period is that interest rates in Canada rose dramatically relative to those in the US. This occurred partly as a result of the Bank of Canada's concern about preventing the Canada−US exchange rate from slipping, and partly (from 1991 on) to the radical inflation reduction strategy that it adopted.

of "high" growth in the early 1960's and 1970's. Such an episode also re-appears in Japan during the late 1980's and early 1990's as part of the asset market bubble. (See Girardin, 2005.) We can also compare our results regarding business cycle durations with those of other studies. For example Girardin (2005) estimates the duration of recessions for Japan to be fourteen quarters. This is partly due to the fact that he identifies the entire period 1995-2000 as a recession. The severity of the 1990 recession for Canada is also noted by Bodman and Crosby (2000).

The findings for Australia deserve some special mention. Taylor *et al.* (2005) argue that there is "no business cycle" in Australia in the sense that a 2-state Markov switching model in the variance is sufficient to describe the data. Our results indicate that the best-fitting model for Australia is a Markov switching model in which the dynamics of GDP growth are best described by switching means and variances. Taylor *et al.* (2005) note that from a Bayesian point of view, the preponderant feature of the Australian experience is a switch from a high variance to a low variance state sometime in the mid-1980's. Quoting from Taylor *et al.*:

> "Having said [that there are no business cycle features in the Australian growth process], it should be emphasized that our failure to identify a business cycle feature does not of course mean that the Australian economy has never experienced periods of recession and recovery. What it suggests, rather, is that any such recession and recovery phases are best regarded as random events contained within the white noise component of the model and not part of any identified regularity in the series."

In our case, the statistical model that is chosen for Australia tends to display the episodes that are normally associated with business cycles. Nevertheless, these comments raise important issues regarding the nature of a business cycle itself. As we discussed in the Introduction, if we take the view propounded by Harding and Pagan (2002a,b,2005), the business cycle <u>is</u> the phases of recession and recovery that ought to be identified solely based on data-driven methods. By contrast, the MS model also delivers a statistical representation of the data that associates different regimes characterized by different moments to such phases as recession, recovery and expansion.

3.1.2 The EU countries

The existence of a European business cycle has been an important topic in the recent business cycle literature (see, for example, Artis and Zhang, 1997 or Artis, Kontolemis, and Osborn, 1997). Canova, Ciccarelli, and Ortega (2007) use a panel VAR setting with a time-varying index structure on the underlying VAR coefficients to uncover the factors underlying cyclical fluctuations in the G-7 countries. In contrast to other work, they find <u>no</u> evidence for the independent effect of a European cycle driving the behavior of a key set of aggregate variables for France, Germany and Italy.

Table 3 shows that the linear specifications are rejected for all the countries in question, strongly so in the case of France, Italy and Spain. Based on the modified likelihood ratio criterion, a 2-regime model is selected for Germany and a 3-regime model for Spain.

Furthermore, based on the discussion in Appendix B, 2-regime models are selected for the remaining EU countries. We find that the models that are used to describe the cyclical dynamics of the EU countries typically feature regime-dependent intercepts, variances, and/or autoregressive coefficients. All the models for the EU countries indicate the existence of significant persistence in their autoregressive structure. We estimate negative trends in the GDP growth rates for all the countries except Spain but such trends are only significant for the case of Germany in the contractionary regime and for Italy in the "normal" regime. By contrast, the trend in GDP growth for Spain is positive but insignificant. Table 3 also shows that Italy, the Netherlands, and Spain have negative intercepts in the contractionary regime. However, aside from Germany none of the intercepts for the EU countries is estimated to be significantly different from zero during recessions. The case of Germany is slightly anomalous in that the expected growth rate of output is greater in the contractionary regime than during expansions. However, this is before controlling for the significant negative trend in GDP growth for the contractionary regime. Excluding Spain, we can say that there is less evidence for real output declines during a contraction for EU countries. Second, the duration of recessions for the EU countries does not differ significantly from that for the Anglophone countries plus Japan. The exception is the Netherlands, which has the shortest duration of recessions. Germany and Italy experience the longest expansions, and Spain experiences a regime of "high" growth. This is evidently the result of Italy's and Spain's strong growth performance following entry in the European Union.

Comparing our results with those of others, Krolzig and Toro (2005) use quarterly GDP data to estimate univariate and multivariate MS models for Germany, UK, France, Italy, Austria, and Spain. However, their sample comprises the years 1970-1996, and is significantly shorter than ours. These authors argue that a 3-regime model is appropriate for countries such as Italy and Spain which have been subject to the process of European Union membership. This is similar to our results for Spain. In terms of business cycle characteristics, we also find that contractions tend to be milder in the EU countries. However, unlike the results of Krolzig and Toro (2005), we cannot find any significant differences in the duration of recessions.

The lower part of Figure 3 shows the regime classification for the five countries under consideration based on the filtered and smoothed probabilities. The worldwide recessions associated with the oil shocks of 1973-1975 and 1980-1982 and the 1992 recession register for the EU countries as does the effects of the financial crisis of 2007-2008. The recently established CEPR Business Cycle Dating Committee has identified three recessions for the euro area countries – 1974:3-1975:1, 1980:1-1982:3, and 1992:1-1993:3. These recessions are captured, on the whole, by our chronology. However, we observe from Figure 3 that the countries are not uniform in their response to such events as oil shocks. According to our classification, France experiences a double-dipped recession during the 1980-1982 period as in the US whereas the recessions in Italy and the Netherlands are spread out over the entire 1980-1983 or 1984 period. Unlike ECRI, we do not identify a recession for Spain in the early 1980's. The main recession in the 1990's for the EU countries is the one associated with the ERM crisis of 1992. From Figure 3 we observe that France, Germany, Italy, and Spain as well as the UK suffer recessions during the period 1991-1993.[15] We can also discuss the experience of the EU countries since 2001. We can identify a recession for France during 2002-2003 but none for Germany, Italy, the Netherlands and Spain.

We note that our results are in line with the business cycle chronology in Artis, Kontolemis and Osborne (1997) for Germany, Italy, the Netherlands, and Spain. These authors use monthly data on industrial production for the period 1961:1-1993:12 and argue that with respect to the 1980-1982 recession "Germany, Italy, and the Netherlands experienced a single prolonged recession, while Spain escaped any recession." Turning to the 1992 recession, Artis, Kontolemis and Osborne (1997) indicate a recession for the Netherlands as of 1991:3 whereas we do not. In reviewing the evidence since 2001, the CEPR Business Cycle Dating Committee argued that the euro area experienced a prolonged pause in the growth of economic activity rather than a full-fledged recession in 2003:1-2003:2.[16] Elaborating further on the differences between the US and Europe, the Committee concluded: "Thus, the euro-area has essentially stagnated since 2001:1, and we have observed neither the sharp (though short) decline in GDP that the US experienced nor the US recovery. This appears to repeat the pattern seen in the 1980's: euro-area GDP is less volatile than that of the US."[17] This assessment seems to be born out by the experience of the EU countries that we have described above and also captured in our estimated models.

It is worth noting that the model that we estimate for Germany performs worst in terms of business cycle dating. No recession is identified for Germany during 2001-2003 and the recessions of 1980 and 1991 are estimated to be both later and shorter compared to the ECRI dates. Authors such as Harding and Pagan (2002a,b,2005) have typically attributed such poor results to the properties of the Markov switching model.[18] In our mind, the problems occur due to the enormous structural changes that have been occurring in the European economies during the period 1960-2009. No doubt one of these changes has to do with German re-unification and the events in its aftermath. From Figure 1, we observe that there is a long episode of low growth and stagnation for the German economy lasting until 2005.[19] Such changes appear to be creating uncertainty about what counts as a recession during some key periods for the EU countries according to formal business cycle dating organizations as well as the results of different studies. This uncertainty appears to stem from the cyclical properties of real activity in the EU countries, and it is reflected in our estimates as well.

[15] As is well known, the Exchange Rate Mechanism (or ERM) was a precursor to the current monetary union in the EU. It broke down in the wake of German re-unification in 1990. Many of the countries in the Exchange Rate Mechanism agreement experienced financial disturbances and speculative attacks on their currencies. Italy and the UK were forced to exit from the ERM while Spain suffered a large devaluation. Buiter, Corsetti and Pesenti (1998) examine the issue of contagion and structural policy spillovers for the ERM crisis.

[16] See http://www.cepr.org/data/dating/.

[17] See http://www.cepr.org/press/Dating-Committee-Findings-22-September-2003.pdf.

[18] See our discussion in Section 3.3.

[19] This event has also affected the construction of German GDP data directly, as GDP data is for West Germany before 1991 and for unified Germany thereafter. See Stock and Watson (2005).

3.1.3 The developed East Asian countries and other emerging economies

The East Asian countries have been the topic of much attention due to their postwar growth experience. Table 4 shows the estimated models for four relatively more developed East Asian countries, Hong Kong, Singapore, S. Korea, and Taiwan. First, we select 3-regime models Hong Kong and Singapore but in contrast to studies such as Girardin (2005) we find that 2-regime models are adequate to describe the business cycle dynamics of de-trended real output growth for S. Korea and Taiwan. All East Asian countries except Singapore display positive growth in the "low" growth state as noted by Girardin (2005). Average expected growth across the four developed East Asian countries is 3.56 percent in the contractionary regime and it is 8.46 percent in the "normal" growth regime.[20] The average duration of recessions for the developed East Asian countries is 3.74 quarters, which is significantly shorter than that for the developed economies. Furthermore, not only is the average duration of the "normal" growth regime around eighteen quarters, the East Asian economies display episodes of "high" growth averaging six and a half quarters.

Figure 3 displays the filtered and smoothed probabilities of the different regimes for the developed East Asian countries. The 1997 East Asian crisis registers as a major event for all the East Asian countries. Hong Kong, Singapore and Taiwan, three small open economies with strong trade and financial linkages to the rest of the world, also show recessions and output declines corresponding to the 2000-2001 recession in the US. Finally, all of the East Asian countries are affected by the 2007-2008 financial crisis that erupted in the US. Thus, we observe that openness and financial linkages are important channels for the transmission of the international business cycles in recent decades. Whereas earlier studies on East Asian countries were concerned with the presence of the high growth regime, our study also sheds light on the more recent events involving the role of financial disturbances. Despite important similarities, however, there are also significant differences among the experiences of the individual countries. In this vein, S. Korea suffers only three recessions over the sample period of 1976:4-2009:2 and undergoes very long periods of expansion and strong growth between 1981 and 1997 as well as in the aftermath of the 1997 East Asian crisis. Excluding the 2008 financial crisis, the Taiwanese economy is characterized by high growth rates and a single short recession in 2001-2002.

Table 4 also presents results for three countries that are typically counted among the emerging market economies - Malaysia, S. Africa, and Turkey. First, we note that we can select 2-regime model for Turkey based on the modified likelihood criterion; for Malaysia and S. Africa, we present further arguments in Appendix B to show that a 2-regime model is sufficient to describe their cyclical dynamics. This is in line with evidence obtained by Girardin (2005) for Malaysia, by Moolman (2004) for South Africa, and by Taştan and Yıldırım (2008) for Turkey. Moolman (2004) uses data on South Africa between 1978-2001 to estimate a Markov switching model with time-varying transition probabilities. Taştan and Yıldırım (2008) use monthly observations on the industrial production index between 1985-2005 to estimate a MSIH-AR model for Turkey. Second, Table 4 shows that reces-

[20]However, all of the developed East Asian countries display significant negative trends in GDP growth, which implies that the magnitude of the expected output growth in each regime is slightly overstated.

sions lead to output declines in Malaysia and Turkey. However, output growth during the contractionary regime is not significantly different from zero for S. Africa, a country which has also features low growth during expansions.[21] By contrast, Malaysia enjoys a very high rate of growth during expansions. As a consequence, the volatility of real output is also higher in Malaysia than for S. Africa or Turkey. Third, Table 4 shows that contractions are the longest in S. Africa and expansions the longest in Malaysia. By contrast, Turkey experiences short-lived recessions amid relatively short expansions. While the sample period for Turkey is shorter, we note the significant differences between its cyclical characteristics and those of countries such as Spain or S. Korea. These countries have succeeded in converging to the per capita income levels of the US and Western Europe in the postwar era whereas Turkey, which shared similar initial conditions with them in the 1960's, has not.[22] Figure 3 shows that the most important recessions for Malaysia are those associated with the East Asian crisis and the financial crisis of 2007-2008. The model tracks fairly well the recessions of 1982, 1984-1986, 1990-1992 and 2008 for South Africa. Likewise, we can distinctly identify the recessions associated with the severe financial and banking crises that Turkey suffered during 1994-1995, 1999-2000 and 2001-2002. The global financial crisis also leads to a recession in Turkey as of the last quarter of 2008.

3.1.4 The Latin American countries

Data series for the Latin American countries are typically available from the 1980's onwards, and less for the case of Brazil. Nevertheless, we believe that the existing data allow us to make some useful observations about business cycles in Latin America.

Table 5 presents the results for the Latin American countries. First, we find that 3-regime models can be selected for Chile, and Uruguay whereas 2-regime models are appropriate for Argentina, Brazil, and Mexico.[23] The expected growth rates of output in the "bad" regime are estimated to be significantly negative for all of the Latin American countries. Recessions in Latin American countries are associated with output declines ranging from around two percent for Mexico to close to seven percent for Argentina.[24] The duration of recessions averages nearly eight quarters for all the Latin American countries and the duration of expansions only eleven quarters. However, we observe that Chile and Uruguay tend to display short episodes of "high" growth as well. The experience of Brazil is slightly anomalous as it is predicted to display sharp declines in output during recessions and high rates of growth during expansions. This is most likely due to the small sample size and the highly volatile performance of the Brazilian economy over the sample period.

The Latin American countries have been the topic of much study. Issues such as the

[21] We find that the trend in output growth is negative but insignificantly different from zero for all of these countries. Hence, there is some evidence of negative output growth during contractions for S. Africa as well.

[22] For a further discussion and a comparative analysis of Turkey's long-term growth experience, see Altug, Filiztekin and Pamuk (2008).

[23] See Appendix B.

[24] However, this is before controlling for the trends in output growth, which were estimated to be negative for Argentina and significantly negative for Brazil in the "normal" and "high" growth regimes, and positive for Chile, Mexico, and Uruguay, significantly so for the first and third countries.

debt crises of the 1980's and the reversal of capital flows known as the "Sudden Stops" phenomenon as described, for example, by Arellano and Mendoza (2003) have dominated the policy discussion regarding many of the Latin American countries. The results in Table 5 lend some support to these observations. Argentina is an obvious example in this regard: the duration of its recessions or crises is nearly as long as the duration of its expansions and even during expansions it experiences only one percent of output growth. Yet it would be wrong to conclude that all the Latin American countries are characterized by recurring crises. For one, Chile experiences long expansions and even longer periods of 'high" output growth. Expected output growth is over three percent in the expansionary regime for Mexico, which also enjoys long expansions. Even Uruguay displays expected output growth of two percent in the "high" growth regime. As we discuss below, this corresponds to the period after 2002 and its recovery following the recession of 1998-2002.

A visual examination of the recession probabilities for each country provides more evidence regarding their similarities and differences. There is evidence that Argentina, Chile and Mexico were adversely affected by the 1980's debt crisis. However, while Argentina and Mexico experienced recessions all the way into 1985, Chile's negative experiences are confined to the period of 1982-1983. Second, based on the estimated probabilities of being in each regime, we note that the Tequila crisis which originated in Mexico in 1994-1995 is associated with recessions in Argentina, Brazil and Uruguay but in not Chile.[25] There are also recessions in all Latin American countries beginning in 1998. Argentina undergoes a prolonged recession and crisis between 1998-2002 as a result of the collapse of its currency board system. (See Bleaney, 2004.) Uruguay, a country which is highly economically interlinked with Argentina, also undergoes an extended period of output declines during 1998-2002. According to our chronology Brazil and Chile experience recessions during 1998 and also over the 2000-2003 period. However, Brazil's 1999 recession is due to the eventual failure of the Real Plan adopted in 1994 and the ensuing devaluation of its currency. As Gruben and Welch (2001) observe, this was a short-lived crisis relative to the other exchange-rate crises experienced by Mexico in 1994 as well by S. Korea and Thailand in 1997, partly because it was anticipated by market participants and also because it did not feature a banking crisis simultaneously. As a consequence, the real output effects are also small.[26] Finally, we observe the impact of the global financial crisis of 2008 on all of the Latin American countries.

We also find it instructive to compare the business cycle characteristics of two countries such as Mexico and Turkey which, at first glance, display little in terms of a common geography or history. Yet such a cursory viewpoint may be deceptive. For one, Mexico and Turkey are among the larger emerging market economies and they both have memberships in trade arrangements involving their region. Mexico is a member of the North American

[25] The contagious effects of this crisis have been studied by Kaminsky and Rheinhart (2000).

[26] Aolfi, Catao, and Timmerman (2010) provide a historical account of cyclical phenomena for four Latin American countries – Argentina, Brazil, Chile, and Mexico – over the period 1870-2004. They examine business cycle synchronization using newly constructed measures of real GDP and argue that the major turning points in each of the countries' history have been associated with well-known global shocks. As our own discussion above highlights, they find that another set of turning points have been associated with country-specific shocks that have propagated to other countries through primarily financial contagion.

Free Trade Agreement (NAFTA) while Turkey entered into a customs union agreement with the European Union in 1995 and possesses candidate status for full EU membership as of 1999. Both countries have been the subject of much volatility and crises in the 1980's, 1990's and 2000's and subsequent stabilization and reform. Tables 4 and 5 show that their business cycle characteristics share some similarities and differences. First, we find that their experience since the 1980's can be best described by a 2-regime model. Turkey suffers shorter recessions whereas Mexico experiences longer expansions but its rate of output growth in such expansions is also lower. By contrast, expansions in Turkey are characterized by output growth of over six percent. Second, the recessions and crises that they suffer – in the 1980's and 1990's for Mexico and in the 1990's and 2000's for Turkey – are domestic crises that erupted in an environment of increasing trade and financial openness and capital mobility. The macroeconomic policy mistakes that lay at the root of the 1994 crisis in Turkey triggered a run on the Turkish lira and an ensuing depreciation that was accompanied by a 6 percent decline in real output. Likewise, an increase in US interest rates led to massive capital outflows from Mexico in 1994 when it had already experienced a large domestic credit expansion and incidents of political risk.[27]

3.2 A comparison with the Harding-Pagan approach

As we discussed in the Introduction, Harding and Pagan (2002a,b) have advocated an alternative approach to characterizing business cycles that has closer parallels with the Burns-Mitchell methodology. They have also argued that the approach based on the Markov switching model, which they term a parametric approach in that it specifies a statistical model for the series in question, 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. As an alternative approach, Harding and Pagan (2002b) have proposed a modification to the Bry-Boschan algorithm – the so-called BBQ algorithm – that can be used to identify the peaks and troughs of the classical cycle at a quarterly frequency. We now briefly describe this approach and compare the results with those we discussed above.[28]

First, let y_t denote the (logarithm) of real GDP at time t. The BBQ algorithm identifies a trough at time t if $\{\Delta_2 y_t < 0, \Delta y_t < 0, \Delta y_{t+1} > 0, \Delta_2 y_{t+2} > 0\}$ where $\Delta_2 y_t = y_t - y_{t-2}$ and a peak if $\{\Delta_2 y_t > 0, \Delta y_t > 0, \Delta y_{t+1} < 0, \Delta_2 y_{t+2} < 0\}$. A natural requirement that is imposed is that peaks and troughs alternate. In the event that this condition fails, the least pronounced of the adjacent turning points is deleted.[29] Using the BBQ algorithm, we obtained the business cycle peaks and troughs for all the countries in our sample and

[27]For a further comparison of cyclical phenomena in Mexico and Turkey over the period that also encompasses the financial crises of 1994-1995, see Altug and Yilmaz (1998). See also Canova (2005) regarding the role of US interest rate shocks on Latin American business cycles.

[28]Since the BBQ algorithm makes use of quarterly growth rates, we used the level data and removed seasonal effects by taking four-quarter rolling averages of the levels.

[29]Harding and Pagan (2002a) relate the data-based procedures for finding turning points to those in the Markov switching approach. They use an approximation to the dating rule for a peak (trough) $Pr(s_t = 1|\psi_T) > 0.5$ ($Pr(s_t = 1|\psi_T) < 0.5$) for this purpose.

calculated these measures as a further way of characterizing business cycles.

Harding and Pagan (2002b) also proposed a variety of measures to examine the characteristics of the phases of a business cycle. These include the duration, amplitude, asymmetry and cumulative movements of the phases of the cycle as well as a concordance index to determine to measure conformity. Once the turning points have been determined according to this data-based approach, the different measures of business cycle activity can be computed. To describe these measures, let D_i be the duration of a business cycle phase, say a recession or an expansion, and let A_i denote its amplitude. If the consecutive turning points fall on the dates t and $t+d$, then $D_i = d$ and $A_i = y_{t+d} - y_t = \Delta_d y_t$. If the duration and amplitude are thought to form a triangle, then the area of the triangle measures the welfare loss (gain) of a recession (expansion). Let $C_{Ti} = 0.5D_i \times A_i$ denote the triangle approximation to the cumulated movements of the series over a business cycle phase, C_i be the actual movement defined as $C_i = 0.5A_i + \sum_{s=1}^{d-1} \Delta_s y_{t+s}$, and $E_i = 100 \times (C_{Ti} - C_i)/C_i$ be the measure of excess cumulated movement as a percentage of the actual cumulated movements.

Table 6 presents these measures for all the countries in our sample. First, we note that the results obtained using the BBQ method are broadly consistent with results reported in Tables 2-5. As in the Markov switching approach, the BBQ algorithm predicts notable disparities between the developed and emerging economies as well as the heterogeneity within the different groups themselves. For the Anglophone countries plus Japan, the BBQ algorithm estimates the average duration of recessions to be 4.25 quarters whereas we estimate them to be 5.65 quarters. The BBQ dating underestimates the duration of recessions for Japan because it underestimates the recession that occurred in the early 2000's for this country. Likewise, our estimate of the average duration of expansions is 19 quarters versus 30 quarters according to the BBQ algorithm. According to the BBQ algorithm, the percentage decline in output during recessions ranges between 1% for the US to close to 3% for Canada.

Turning to the EU countries, the BBQ algorithm predicts shorter recessions and somewhat longer expansions than the MS-AR approach. While we predict the average duration of recessions and expansions to be 4.4 and 15 quarters for the EU countries, the BBQ algorithm estimates these magnitudes to be 3.66 and 40.5 quarters, respectively. However, this finding is due to the fact that the BBQ algorithm cannot identify the double-dipped recession for France corresponding to the effects of the second oil shock whereas we do. It also does not account for the high growth episodes in Spain. However, both approaches tend to agree on the point that recessions tend to be milder in the euro area countries. Comparing the magnitude of the expansions, we note that among the developed countries, the UK and Japan experience the weakest expansions with amplitudes of 13.41% and 18.75% while France and Canada experience the strongest expansions with amplitudes of 37.37% and 38.64%, respectively. This result is consistent with the result that we found for the U.K. in Table 2. The amplitude of expansions for the remaining developed countries ranges from 20.79% for Germany on the low end to 29.08% for Spain on the high end, with the US somewhere in the middle.

The results for the emerging economies are also in agreement with the results that we described earlier for these countries. The average duration of recessions for the Latin

American economies is estimated to be 6 quarters according to the BBQ algorithm and 8 quarters according to the Markov switching model. The corresponding average durations for expansions are 20.5 and 11, respectively. However, the BBQ algorithm does not account for episodes of "high" growth. Countries such as Argentina undergo lengthy and frequent recessions and experience sharp declines in output when they do so. Uruguay's economy which is highly interlinked with that of Argentina shares these characteristics. By contrast, Chile experiences a significant decline in output during a recession but it is also characterized by long expansions with an amplitude of 48.96%. Both the Markov switching model and the BBQ algorithm estimate the average duration of contractions for the developed East Asian economies to be around 3 quarters, and the duration of expansions to be significantly higher than those of the remaining emerging economies. The developed East Asian countries of Hong Kong, Singapore, and S. Korea not only experience relatively long expansions but the amplitude of these expansions typically exceeds 50%. By contrast, the duration of expansions is only twelve quarters for Turkey, a finding that is also reflected in Table 4, and the amplitude of the expansion is 20.35%, far less than that of the East Asian economies or even Chile.

We end this section by examining the measures of excess cumulation, which capture the shape of the business cycle phase. Considering first the developed countries, we note that there is considerable variability across both contractions and expansions. Countries such as the UK and the US experience declines in output during a contraction that are greater than the triangle area. By contrast, all of the EU economies plus Australia, Canada, and Japan experience less declines relative to the triangle area. During expansions, only Japan, the UK, Germany and Spain exhibit growth that is *less* than the triangle area. Among the emerging economies, it is Singapore, Taiwan, Malaysia, Turkey, Brazil, and Chile that exhibit negative excess cumulation measures during a contraction, indicating a more rapid subsequent decline in growth over this phase of the business cycle. A similar group of countries, namely, Singapore, Taiwan, Malaysia, S. Africa, Turkey, Chile, and Mexico, also exhibit positive excess cumulation measures during an expansion, implying that they experience rapid recovery coming out of an expansion that tends to levels off around the amplitude A_i. Taken together, these findings for countries such as Singapore, Taiwan, Malaysia and Turkey imply the sharp and deep recessionary experiences that we documented earlier.

4 Business cycle dating

In the Introduction, we discussed the findings of several papers about the usefulness of the Markov switching model for identifying business cycle turning points. In particular, Harding and Pagan (2002a,b, 2005) have argued that the Markov switching model is best viewed as a model that allowed for a simple way of introducing some nonlinearity. By contrast, Artis, Krolzig, and Toro (2004) and Krolzig and Toro (2005) have argued that the Markov switching model is capable to identifying business cycle turning points. In this section, we examine the business cycle dating properties based on both approaches and also provide a further characterization of business cycles for developed and emerging market economies.

4.1 Business cycle chronologies

In Table 7, we provide a list of business cycle turning point dates obtained by the NBER for the US economy, by the CEPR for the euro area, and by ECRI for a selected set of countries. The business cycle dating approach by all three groups is based on the methodology developed Burns and Mitchell at the NBER. Typically, these groups will examine the behavior of seasonally adjusted real GDP, employment, sales, and industrial production when deciding on the state of the economy. However, while the NBER and ECRI use monthly data and examine the behavior of such indicators for the US or each country individually, the CEPR Dating Committee uses quarterly data and examines euro area aggregates as well as country-specific data. As a way of examining our results, we note that our chosen specifications track the NBER and ECRI dates fairly well. Using a measure of coincidence suggested by Canova, Ciccarelli, and Ortega (2009), we can calculate the number of instances in which our peak or trough dates are plus or minus one (two) quarters away from the ECRI dates denoted Coin$\pm$1 and Coin$\pm$2. In Table 7, we calculated Coin$\pm$1 and Coin$\pm$2 for the developed and emerging economies. Thus, allowing for one (two) quarter of maximum discrepancy, the average coincidence between our dating and ECRI dating for the developed economies is 53% (69%). As a comparison, Canova, Ciccarelli, and Ortega (2009) date growth rate cycles and obtain an average coincidence of 58% (63%) for one (two) quarters maximum discrepancy with ECRI dates. Considering the emerging economies, here we do less well for more volatile countries such as Brazil. However, given our success in identifying the turning points for more stable economies such as S. Korea or Taiwan, the average coincidence given one (two) quarter discrepancy is calculated as 42% (68.4%).

The Markov switching model shows that a recession occurred in almost all the major industrialized economies in the period between the end of 1973 and the end of 1975. For developing countries for which there exist data that cover this period such as Hong Kong and S. Africa, we also observe evidence of a recession. However, not all countries in our sample experience recessions in this period. Canada and Spain do not suffer absolute output declines during this period. Hence, no recessions are identified for them by ECRI or our estimated Markov switching model. As a way of providing further evidence on the global nature of cyclical fluctuations, we examine the average value of pairwise correlations of the "low growth" regime probabilities across all countries at a set of dates which have featured economic downturns in a large number of countries. Considering first the period of the first oil shocks of 1974-1975, we estimate the average value of the pairwise correlations to be 0.763 during this episode using information on all countries that have the required data.

We can also examine the response to the oil shocks of 1980-1982. For the US, there is a double-dip recession that is identified by both the NBER and ECRI. Australia's recession occurs in 1982-1983 and Canada experiences a shorter recession in 1981-1982. There is some disagreement regarding the existence of a recession for Spain during the early 1980's. Figure 1 shows that Spain lived through a prolonged growth slowdown during this period but did not experience any substantial absolute output decline. By contrast, the CEPR identifies a single recession for the euro area between 1980:1-1982:3. The recessions identified by our estimated models coincide on the whole with those determined by ECRI for the individual countries. Table 7 also shows that there are recessions (or growth slowdowns) in Hong Kong, S. Korea and S. Africa in the 1980-1982 period as well as in the Latin American countries. (Recall that our data for Brazil and Uruguay only begin in the late 1980's and 1990's.) However, we also observe recessions in countries such as Argentina and Mexico that last into the mid-1980's. Such behavior corresponds to the effects of the Latin American debt crisis, which came on the wake of the oil shocks of the 1970's and 1980's and which was triggered partly by the increase in interest rates in the US and in Europe in 1979. Examining the average value of the pairwise correlations of the estimated probabilities for the recessionary or "low growth" regime across all countries in our sample for the period 1979-1980, we find this to be 0.772. However, this magnitude increases to 0.811 when we consider the period 1983. Hence our findings are in line with those of Köse, Otrok, and Whiteman (2003). These authors consider the issue of a *world* business cycle and use data on 60-odd countries covering seven regions of the world to determine common factors underlying the cyclical fluctuations. In contrast to recent studies of international business cycles that focus on a subset of countries, they find that the world factor based on a large set of developed and developing countries implies that the recession of the 1980's was, if anything, as severe as the recession of the mid 1970's.

The synchronization of business cycles has been the focus of much study in the business cycle literature. Stock and Watson (2005) provide evidence on the synchronization of international business cycles based on various measures of correlation of GDP growth across countries for the G7 countries over the period 1960-2002. They find no evidence for closer international synchronization over their period of study (see also Köse, Prasad, and Terrones, 2003). However, they do find evidence on the emergence of two cyclically coherent groups, the eurozone countries and English-speaking countries, including Canada, the U.K., and the U.S., respectively. When we examine the period beginning with the 1990's, we begin to observe a divergence of performance for the Anglophone countries and the EU countries as well as differences in business cycles timing and characteristics for industrialized and emerging market economies.[30] Beginning with the first set of groups of countries, we observe that the next major recession in industrialized countries after the 1980's occurs at the beginning of the 1990's. For Anglophone countries such as the US, Australia, Canada, and the UK, the recession typically takes place in the period 1990-1992. For the EU countries, however, we observe that the recessionary episode sets in later, reflecting the effect of the 1992 ERM crisis. This divergence is reflected in the NBER versus CEPR timing of the 1990 recession. Whereas the NBER dates the recession in the US from the third quarter of 1990 to the first quarter of 1991, the CEPR Business Cycle Dating Committee dates the recession in the euro area to be from the first quarter of 1992 to the first quarter of 1993. Similarly, ECRI dates the recessions in France, Italy, and Spain beginning from 1992, which are also captured by our chronologies.

The lagged response of the business cycle in the euro area is also noted by Giannone, Lenza, and Reichlin (2008), who review the findings on euro area business cycles and also provide new evidence regarding the characteristics of aggregate and national cycles in a

[30]See also Artis (2003).

forty-year time period that also includes the EMU. They examine the behavior of per capita GDP for the US and the euro area over the period 1970-2006 and conclude that both have moved along the same trend with a gap that is stationary around a constant. They measure this gap to around 30% and argue that fluctuations in this gap reflect the duration and amplitude of the cycles in the two areas. An examination of their results shows that the gap narrows during recessionary periods - the mid 1970's, the beginning of the 1980's and 1990's as well as from 2001 or 2002. Estimating a bivariate VAR for the euro area and the US using data up to 1998 that excludes the formation of EMU in 1999, they conduct a forecasting exercise whereby they predict future per capita GDP for the euro area in the post-EMU period using current, past, and future realizations of US growth. They find that they can account for some but not all of the growth slowdown in the euro area using this structure, suggesting some divergence between US and euro area performance especially since the 1990's.

The case of Japan also deserves special mention. As Stock and Watson (2005) argue, cyclical fluctuations in Japan during the 1980's and 1990's become "almost detached from the other G7 countries", both because of its increasing trade with the East Asian countries and also because of the nature of its domestic difficulties.[31] In particular, Japan undergoes recessions at the beginning of the 1990's, between 1997-1999 and between 2000-2003. Our business cycle dating captures the essentially stagnant nature of Japanese growth since the 1990's and the lack of any apparent synchronization with other developed countries.

Turning to the developing economies, we note that Malaysia, Singapore, S. Korea and Taiwan do not experience a recession in the 1990 period. Hong Kong suffers a slowdown in growth that ends in the second quarter of 1990 whereas S. Africa and Turkey undergo recessions beginning in 1989 and ending around 1991 or 1992.[32] The short recession in Turkey between the first quarter of 1991 to the third quarter of the same year corresponds to the effects of the first Gulf War. We also observe recessions in Latin American countries such as Argentina, Chile and Mexico in the period leading up and including 1990-1992 that reflect both global and local factors. Examining the pairwise correlations of the recession probabilities in 1991 across all countries in our sample, we find that it is 0.703 on average, suggesting the global impact of the recession. However, we observe greater heterogeneity during the remainder of the 1990's. The Tequila crisis of 1994-1995 has strong effects on countries such as Mexico, Argentina, and Brazil but no significant effects elsewhere. Turkey's 1994-1995 crisis is close in timing to the Tequila crisis but otherwise related to domestic factors as explained above. The 1997 East Asian crisis is more global in impact, affecting Japan and all the East Asian countries. The pairwise correlations of the recession probabilities across all countries in our sample for 1997 is calculated to be 0.5357 on average, indicating a significant but weaker effect relative to earlier recessions. Evidently the 1990's

[31] This pattern may also be changing over time, however. In his analysis of the East Asian countries, Girardin (2005) considers the correlations of the smoothed probabilities of the smaller East Asian countries with those of Japan and China. He concludes that the correlations of the East Asian countries with China increased at the expense of those with Japan.

[32] The dating of S. African recessions is very similar to the recession dates announced by the South African Reserve Bank. See Moolman (2004).

are a period of regional and local crises that occur in an increasingly globalized environment.

Indeed, while commenting on the financial crisis in Uruguay in 2002, John Taylor (2007), then Under Secretary for the US Treasury for International Affairs, asks whether the period beginning with the Tequila crisis in Mexico and ending with the Uruguayan crisis of 2002 should be viewed as "8 years of crises or one 8-year crisis". His comments are directed in particular at the issue of contagion of emerging market crises. As discussed earlier, these are evident in the Tequila crisis of 1994 and the East Asian crisis of 1997. As Taylor (2007) notes, the Russian crisis of 1998 also affected a number of emerging market economies, including Brazil in 1998 and ultimately, Argentina beginning in 1999. By contrast, no significant contagious effects were witnessed during the Argentinian crisis and sovereign debt default of 2001-2002.[33] These comments show that while the emerging market crises of this time had some global or regional repercussions, they were not necessarily uniform in their effects on countries of close geographical proximity or similar characteristics.

The 2001 recession in the US that follows on the back of the September 11 terrorist attacks is associated with recessions in many industrialized and emerging market economies worldwide. The average value of the pairwise correlations of the recession probabilities across all countries in our sample for 2001 is 0.412. We already discussed the CEPR Business Cycle Dating Committee's assessment that the euro area experienced a prolonged slowdown in growth but not a recession during 2003. Nevertheless, according to the ECRI business cycle dates, there are recessions in the US, Japan, Germany, Mexico and Brazil as of 2000 or 2001, and countries such as France and S. Korea are indicated to be in a recession by 2002. Our business cycle chronology is not far off in terms of the duration and timing of the recessions in Japan at this time. Our chosen models are also successful in capturing the recessions that occurred in Hong Kong, Malaysia, Turkey, Brazil, and Mexico beginning in 2000. No doubt some of these recessions are due directly to the effects of the September 11, 2001 terrorist shocks whereas others, such as the twin crises in Turkey of 1999 and 2001 or the prolonged crisis and recession in Argentina between 2001-2003, reflect domestic and policy factors as well.

It is the recession that is associated with the US sub-prime crisis and its aftermath of 2007-2008 that best qualifies as a global recession since the recessions associated with the oil shocks of the 1970's and 1980's. The average value of the pairwise correlations of the recession probabilities across all the countries in our sample is calculated to be 0.935 during 2007-2008. From Table 7, we observe almost all the countries in our sample are indicated to be in a recession by 2008, with the exact timing varying from the fourth quarter of 2007 to sometime in 2008.

4.2 A world business cycle?

Many recent studies have sought to uncover a so-called "world business cycle". In Köse, Otrok, and Whiteman (2003) an unobservable index or dynamic factor model is used to

[33] See also Boschi (2005), who examines correlation coefficients corrected for heteroscedasticity to measure increases in cross-market linkages in financial markets. She shows that there were no effects of the Argentinian crisis on countries such as Brazil, Mexico, Russia, Turkey, Uruguay and Venezuela.

identify a world factor as well as regional and country-specific factors. The importance of the different factors are typically examined in terms of the percentage of variance that they explain in the variance of the individual variables under consideration, be these output, consumption or investment growth. In a different application, Lumsdaine and Prasad (2003) consider 17 OECD countries including the US, Japan, Canada and a group of EU countries, and construct a measure of the common component of international business cycles by weighing output growth in each country using estimates of time-varying conditional volatility obtained from univariate models. In their approach, the importance of the common component is measured using correlations of this component with individual countries' output growth. In a recent application, Canova, Ciccarelli, and Ortega (2009) examine a sample of 10 European countries to investigate the sources of changing business cycle characteristics using a panel VAR that incorporates an index or factor structure on the underlying time-varying VAR coefficients. This model allows them to construct European and national cyclical indicators and to examine the impact of institutional factors such as the Maastricht treaty, the creation of the ECB and the Euro changeover on such cycles.

Yet as we discussed earlier, a business cycle is defined as much by the recurring ups and downs of economic activity as it is by the correlation structure of different economic variables and their volatility and persistence. Our detailed narrative in Section 4.2 suggests that the synchronization of economic activity across different countries and country groupings in terms of the timing and characteristics of recessions and expansions may be an equivalent way of examining the nature of a "world business cycle". Canova, Ciccarelli, and Ortega (2007) show that business cycles tend to become more synchronized during recessions than expansions. According to their results, expansions tend to have large idiosyncratic components whereas declines in economic activity have common timing and dynamics, both within and across countries. In studies that have employed the Markov switching methodology for dating and characterizing business cycles, a popular approach has been to examine the cross-correlations of the recession probabilities over the sample period to determine the synchronization of economic activity for different groups of countries.[34]

In Table 8, we present similar results for the developed and emerging economies over the periods 1970-2009 and 1990-2009, respectively. For the emerging economies, we also present the cross-correlations of the recession probabilities of the emerging economies with the US. Some striking observations are immediately evident from the top panel of Table 8. For one, Australia's cyclical responses are not correlated with any of the developed economies except Canada. Likewise, the largest cross-correlations for Canada are those with the US, followed by smaller but positive cross-correlations with France and Germany. Over the long time period 1970-2009 Japanese recessions show the strongest synchronization with the U.S., France, Germany, and the U.K. as well as with the remaining European countries except Spain. The U.K. economy shows a smaller correlation with Germany than it does with the U.S. Furthermore, the European economies tend to show strong cross-correlations amongst each other, and little or no correlation with Australia, Canada and in some cases, Japan. Some have taken these findings as signifying the existence of a "European" business

[34]See, for example, Krolzig and Toro (2005) or Girardin (2005).

cycle (see, for example, Artis, Krolzig and Toro, 2005.) Nevertheless, the German economy shows the strongest cross-correlations with the U.S. economy and European countries such as Italy, the Netherlands, and Spain tend to display strong cross-correlations with the U.K. In their study of G-7 business cycles, Canova, Ciccarelli, and Ortega (2007) find no evidence for the existence of a unique European factor driving business cycles for the largest European economies. Instead, they argue that while European economies may display common fluctuations, their source is not distinctly European. Instead European and Anglo-Saxon fluctuations tend to be similar in timing, size, and amplitude because they are driven by the same source of disturbances. These findings are not inconsistent with those that we reported above. While we found some evidence for differences in the severity and duration of Anglophone versus European cycles, our results indicate that such cycles tend to be similar on the whole. Furthermore, while some of the smaller Anglophone economies such as Australia and Canada tend to exhibit behavior that is more detached from the European economies, there are strong cross-correlations across the major G-7 economies such as the U.S, Germany, and France.

The bottom panel of Table 8 shows the cross-correlations among the emerging economies plus the U.S. Some striking conclusions again emerge from this table. First, we find that we can identify at least two distinct groups within the emerging economies. The East Asian economies of Hong Kong, Malaysia, Singapore, and S. Korea tend to display strong cross-correlations amongst each other and relatively weak ones with most of the other emerging market economies. Taiwan appears to be a special case as it displays a recession only during 2000-2001. Likewise, we observe large pairwise correlations among Argentina, Mexico, and Turkey, countries which have experienced much volatility and crises during the 1990's and 2000's. Yet it would be wrong to conclude that the emerging economies are driven solely by national cycles. Indeed countries such as Chile, Mexico, and Singapore show at least as strong if not stronger cross-correlations with the U.S., as do Argentina, Brazil, and Malaysia.

How can we interpret these findings? First, it appears that there is an important world factor that is driving cyclical fluctuations in both developed and emerging economies. Here we can capture the impact of this world factor through the correlations with the U.S. Perhaps what does drive the "world business cycle" are those periods that feature large common disturbances. In the debate regarding the factors behind the decline in output volatility observed for the G7 countries or the "Great Moderation", Stock and Watson (2002) argue that it is "good luck" rather than "good policy": international business cycles have moderated because of the apparent lack of large international shocks during the 1980's and 1990's. They also argue that in a "mechanical" sense, the absence of such large common shocks may also explain the apparent failure of business cycles to become more synchronous even in the presence of increasing international trade over the period in question. However, there also appear to exist a whole host of idiosyncratic factor that affect national cycles. Aolfi, Catao, and Timmerman (2010) argue that historically, business cycle synchronization is far from perfect even among a geographically coherent group of countries such as Argentina, Brazil, Chile and Mexico. They attribute such lack of synchronization to differences in terms of trade shocks to the countries due to national differences in the commodity composition of exports. A second factor that they identify is the role of national policy, including differences in policy management and political upheavals and disruptions in the political regime. Many studies have documented significant heterogeneity even among the European countries. Giannone, Lenza and Reichlin (2008) examine twelve "core" and "non-core" eurozone countries over the period 1970-2009.[35] They show that the former have highly synchronized growth rates whereas the growth rates in the periphery are very heterogeneous and the linkages between each of the countries and the rest of the euro area are relatively weak. They also find that EMU has not affected the business cycles and their cross-correlations in either group. Somewhat surprisingly, after examining a set of institutional factors that are hypothesized to affect European business cycles, Canova, Ciccarelli, and Ortega (2009) conclude that a process of cyclical convergence has been taking place in Europe since the 1980's but this process appears to precede the institutional changes that are discussed and may well be consistent with a greater conformity of the shocks affecting the various economies.

To us, these findings suggest that the cyclical movement of macroeconomic variables in different country groupings depend on a host of factors, including global shocks, the nature of trade links and endowments, policy choices as well as historical, institutional, political, and political economy considerations. Furthermore, such country-specific and idiosyncratic may tend to persist over long periods and even across alternative institutional arrangements. They also imply that documenting the commonalities and idiosyncrasies based on the experience of individual economies, as we have done in this study, may constitute an alternative if not equally important way of understanding the factors that are thought to drive fluctuations in economic activity worldwide.

5 Conclusion

How do business cycles in developing and emerging market economies differ from those in industrial countries? Our analysis was primarily motivated by this question. In their study of business cycles around the globe, Benczur and Ratfai (2009) conclude that not only do developing economies differ in significant ways from developed economies but they also exhibit wide heterogeneity relative to each other. As in the study by Benczur and Ratfai (2009), we have documented significant differences in the business cycle behavior for individual countries. We find that not only are the characteristics of developing economies significantly different form those of the developed ones, they also tend to exhibit quite disparate behavior relative to each other. Yet our study also documents episodes when business cycle activity appears highly synchronized. In this regard, our analysis shows the importance of the large global shocks in inducing major recessions - the oil shocks of the 1970's and 1980's as well as the financial shock of 2008. Yet we have also documented many more individualized crises - the 1992 ERM crisis in Europe, the Tequila crisis of 1995, or the East Asian crisis of 1997. In contrast to much earlier work where oil shocks were the

[35] The former include Italy, Germany, France, Belgium, Austria, the Netherlands and Finland whereas the periphery includes Portugal, Luxembourg, Greece, Ireland, and Spain.

focus of business cycle studies, our analysis has revealed that financial disturbances and the contagious effects of different types of crises are much more important in the period following the 1980's and especially since the 1990's. Even in countries such as Mexico and Turkey where recurring crises seem to arise more from country-specific factors, we could argue that such crises were exacerbated by financial linkages in an increasingly globalized economy.

Our study also has implications for the debate regarding the appropriate method for dating business cycles as it does for the uncovering business cycle facts. Clearly both data-based methods that seek to formalize the judgmental approach of the NBER (or ECRI) and the business cycle dating obtained from estimates of Markov switching models can lead to differing results. Yet our study has shown that even in short samples, the Markov switching model is capable of differentiating among the heterogeneous business cycle experiences of developed and developing economies rather accurately. The fact that the two approaches are essentially in agreement regarding business cycle dating suggests both have their uses in business cycle analysis. Additionally, we argue that deriving the so-called facts of business cycles based on the approach of identifying and tracking a business cycle in the manner of Burns and Mitchell may yield as much information as analyses based on uncovering the correlation structure of variables driving this activity. While some have advocated the use of purely data-based approaches for examining cyclical fluctuations, we believe that the Markov switching model is also a valuable tool that complements these methods.

A Data

The data for the industrialized countries, Mexico and S. Korea are obtained from the OECD Quarterly National Accounts database. For a subset of the OECD countries, we extended the sample back to 1960 using the growth rates of GDP volume indices. These include France, Germany, the Netherlands, Italy, and Spain. The data from the OECD are seasonally adjusted, in constant 2000 prices, and in units of the national currency. The data from the OECD are seasonally adjusted, in constant 2000 prices and in units of the national currency. The data for Chile, Malaysia, and Singapore are from the International Financial Statistics (IFS) of the IMF. These data are in constant 2005 prices and in units of the national currency. The data for Brazil, S. Africa, Turkey and Uruguay are from the relevant central banks while data on GDP for Argentina, Hong Kong, and Taiwan are obtained from the national statistical offices. Other studies that have made use of data sets with a larger number of countries typically consider shorter sample periods or use frequencies greater than a quarter. For example, the study by Benczur and Ratfai (2009) uses quarterly data on 62 countries, including information on eleven Central European (CE) countries and seven CIS countries but the data for the CE or CIS countries coincide with the establishment of national income accounts for these countries in 1995. Likewise, Köse, Prasad and Terrones (2003) consider annual data for 76 countries over the period 1960-1999.

Many studies that have made use of these data have followed the approach of eliminating outliers (see Stock and Watson, 2005.) We identified outliers as values that were 3.5 standard deviations away from the mean growth rate across the sample and replaced them with the average of the adjacent values. We identified almost no outliers for the emerging economies in this way. Instead most of the outliers were for the developed countries in the part of the sample corresponding to the early 1960's, where the OECD data are likely to be less reliable. Hence, our estimated models typically start in 1963 to eliminate such outliers.

B Model selection procedure

There is a large literature that has discussed estimation and valid asymptotic inference in the Markov switching model. It is beyond the scope of this paper to fully summarize these results. In this appendix, we describe some of the issues and also illustrate our model selection procedure in more detail.

The MS-AR model requires that the researcher choose (i) the number of regimes, (ii) the model specification (changing intercepts versus means, regime-dependent AR coefficients, and heteroscedasticity), and (iii) the order of the lag polynomial in a specification such as (2.3). The choice of the regime can be accomplished using a variety of approaches, including visual inspection of the data, the use of the Likelihood Ratio (LR) test, and penalized likelihood criteria such as the Akaike Information criterion (AIC), Hannan-Quinn criterion (HQC), and the Schwarz criterion (SIC). As noted by Hansen (1992) and Garcia (1998), the use of the LR test can be problematic because there exist nuisance parameters such as the transition probabilities that are unidentified under the null hypothesis of linearity. Garcia and Perron (1996) provide an upper bound, the Davies upper bound, for the correct

p-value based on an adjustment of the LR test statistic. Likewise, based on Monte Carlo experiments, Ang and Bekaert (2002) suggest that the true underlying distribution of the LR Statistic in an MS framework may be $\chi^2(n)$, where n equals the number of linear restrictions and nuisance parameters. Another approach is due to Krolzig (1997, p. 132-134) and Zhang and Stine (2001), who have shown that the autocovariance structure of Markov switching models can be represented by ARMA(p,q) models. Furthermore, the orders p and q are shown to be less that the number of regimes for MS models with changing means and variances. Hence, the number of regimes can be determined using the autocovariance structure of the data. Alternatively, the various model selection criteria can be used determine the number of regimes for a fixed lag length p.Given the number of regimes m, a variety of model selection criteria can be applied to choose the lag length p for each model. These include the Akaike Information for choosing the lag length. According to Kapetanios (2001), the AIC tends to choose longer lag lengths in MS-AR models whereas the SIC tends to select more parsimonious models. See also Ivanov and Killian (2005), who suggest that the HQC is the most accurate criterion for selecting lag lengths in a quarterly VAR situation. Their metric is mean squared error (MSE) of the impulse response estimates normalized by their MSE relative to knowing the true lag order.

Before we describe our model selection procedure in more detail, we provide some initial observations on the type of models that were successful in capturing the cyclical behavior of a diverse set of countries. In the literature on Markov switching models, 3-regime models have been used to model periods of high growth together with normal expansionary and contractionary phases. An inspection of Figures 1 and 2 shows that both developed and emerging economies such as the East Asian economies tend to exhibit periods of high growth in the early 1960's and 1970's. By contrast there is a subsequent slowdown of growth and of volatility in the post 1980's period for many developed economies. We initially tried to fit 3-regime Markov switching models without trends to account for the experiences of the developed and a subset of the emerging countries. Our results which are available upon request show that such 3-regime models cannot capture the dynamics of recessions across the entire sample period, especially for the developed economies. In particular, their implied solution typically attributes the 1960's and early 1970's to the "high" growth regime, captures some of the recessions in the earlier part of the sample, and attributes a regime of "normal" growth to the 1990's and 2000's. These arguments suggest that models with trends in GDP growth that are simultaneously estimated with the remaining parameters of the Markov switching model may be more appropriate for capturing the cyclical behavior for many of the developed countries across the sample. However, after allowing for trends, we found that 2-regime models were adequate for capturing the experience of economies such as S. Korea and Taiwan that have witnessed very strong performance with only few recessions during the sample period. Likewise, 2-regime models were adequate to account for the experience of emerging economies that have typically experienced boom-and-bust episodes. For a subset of the developed and emerging economies, we found that 3-regime models were better able to account for their cyclical dynamics. We elaborate on these points further below and also in the text.

In our application, we considered specifications which allowed for jointly estimated trends in GDP growth rates as described by equation (2.3).[36] We found that specifications with changing means (MSM-AR) only or changing means, variances, and autoregressive coefficients (MSMH-AR or MSMAH-AR) fared poorly in terms of the stability of the parameter estimates or model selection criteria such as AIC, HQC or SIC. Hence, the reported models typically involve specifications with changing intercepts only (MSI), changing intercepts and variances (MSIH), changing intercepts and autoregressive coefficients (MSIA), or changing intercepts, variances, and autoregressive coefficients (MSIAH). We allowed for the possibility of two or more regimes so that $m = 1, 2, 3$, and with quarterly data, we considered the lag lengths $p = 0, 1, \ldots, 4$. This gives up a total of 36 models per country, excluding the linear specification. We used the likelihood ratio (LR) test to test for the 2- versus 3-regimes and also to test against a linear specification. Given the number of regimes, we chose models on the basis of model selection criteria such as AIC, HQC, and SIC.[37] We examined the properties of the standardized residuals, the general fit of the model, and how well the models performed in regime classification. All models were chosen to perform as well as possible based on the results of the diagnostic tests. We also checked their forecasting performance and examined their business cycle dating properties.

Tables 2 through 5 show that the chosen specifications feature coefficients that have been estimated significantly and also imply plausible magnitudes for such quantities as the underlying mean growth rates of each series. We also note that the linear specifications are strongly rejected for many of the economies in our sample even when one considers modified critical values such as the Davies upper bound or the simple adjustment proposed by Ang and Bekaert (2002).[38] In the results reported in Tables 2 through 5, many of the linear specifications are rejected – strongly so for a subset – based on the values of the LR statistics regardless of the approach that is taken. However, there are some interesting exceptions. The linear specification is rejected for S. Africa only with a probability level of 0.032, suggesting that the deviation from nonlinearity is not overwhelming.

We also used the modified likelihood ratio criterion together with the properties of the implied solutions to distinguish between 2- and 3-regime models. The simple modification proposed by Ang and Bekaert (2002) implies that the corrected degrees of freedom for the LR test is equal to the number of restrictions obtained from constraining the model to two regimes, $p_{11} + p_{12} = 1$ and $p_{21} + p_{22} = 1$, plus the nuisance parameters in each model that are unidentified under the null hypothesis. These include the transition probabilities p_{31}, p_{32} plus the regime-dependent parameters in regime 3. The above table shows the LR test statistics and the associated degrees of freedom for the countries in our study. Hence, we fail to reject the 2-regime model for Canada, Japan, Germany, S. Korea, Hong Kong, Turkey, and Argentina based on the modified LR critical values while there exists evidence against the 2-regime model for the remaining countries. However, we note that the evidence

[36] We used OX package 3.1 in our calculations.

[37] See also Krolzig and Toro (2005) and Artis, Krolzig and Toro (2005).

[38] It is easy to illustrate this latter adjustment. For example, when testing an MSIH(2)-AR(1) specification against a linear specification, the null hypothesis is given by $p_{11} = 1$, which implies that the parameters $\nu(s_2), \sigma(s_2), p_{22}$ which are unidentified under the null. These are denoted the nuisance parameters, and the degrees of freedom the chi-square statistic must be adjusted to incorporate their impact.

	LR Tests of 2 versus 3 Regimes					
	Australia	Canada	Japan	UK	US	France
LR	27.5886	10.5202	6.4508	47.9452	34.7586	54.7856
df	6	8	6	5	5	10
	Germany	Italy	Netherlands	Spain	Hong Kong	Singapore
LR	7.877	49.111	50.8332	38.5696	11.5094	24.8478
df	9	6	5	6	6	6
	S. Korea	Taiwan	Malaysia	S. Africa	Turkey	Argentina
LR	3.3146	14.5032	18.0316	37.3834	4.1976	14.9978
df	5	6	9	5	5	10
	Brazil,	Chile	Mexico	Uruguay		
LR	34.4256	58.252	13.3044	58.2292		
df	7	6	6	6		

LR denotes the Likelihood Ratio statistic; df denotes degrees of freeedom.

against the 2-regime model is not overwhelmingly strong for the case of Taiwan, Malaysia or Mexico. Furthermore, in the case of Taiwan, the coefficients for the third regime are not estimated to be significantly different from those for the second regime. The 3-regime models for Malaysia is characterized by extreme parameter instability, perhaps due to the small sample size and highly volatile performance of this economy. Even though the 2-regime specification is rejected for Brazil based on the modified LR test, a similar finding occurs for this country. Based on this evidence, we selected 2-regime models for Germany, S. Korea, Malaysia, Turkey, Taiwan, Argentina, Brazil and Mexico. The table above shows that the 2-regime specification is rejected for Spain, Singapore and Uruguay. Hence, we selected 3-regime models for these countries. While the test results are consistent with a 2-regime specification for countries such as Canada, Japan, and Hong Kong, we selected 3-regime models for these countries after a consideration of the implied solutions under the 2- and 3-regime specifications. We discuss the case of Japan in more detail below.

For the remaining countries, the LR test tends to indicate rejection of the 3-regime models but the solutions to such models are characterized by parameter instability or implausible values for the underlying moments. We can illustrate this situation on a country-by-country basis. Consider first the UK. The LR statistic for the test of a 2- versus 3-regime indicates rejection of the 2-regime model. However, the 3-regime model implies that the transition probability of remaining in the third regime, conditional on being there, p_{33} is estimated to be nearly zero. Equivalently, the probability p_{32} is estimated to be nearly unity. This suggests that the higher likelihood value of the 3-regime model is occurring due to some outliers that have very little significance on the overall results. Indeed as Table 9 shows, the 2-regime model for the UK is one of the most successful in terms of its diagnostic tests. Second, we found some *a priori* evidence against the 2-regime model for the US based on the LR test. However, as we discussed in the text, 2-regime models with a fourth-order autoregressive terms have been used in the literature to characterize US business cycles. Moreover, examining the corresponding 3-regime models with AR(4) lag polynomials, we found evidence for lack of convergence of the EM algorithm as well as problems of instability in the parameter estimates and very poor regime classification. For a subset of the European

	Model Selection for Japan				
Specification	AIC	HQC	SIC	LL	LR
MSIH(2)-AR(3)	-7.2487	-7.1672	-7.0480	553.6544	-
MSIH(2)-AR(4)	-7.2395	-7.1498	-7.0187	553.9632	-
MSIH(3)-AR(3)	-7.2021	-7.0716	-6.8809	556.1560	5.0032
MSIH(3)-AR(4)	-7.2025	-7.0639	-6.8613	557.1886	6.4508

economies, we also found some *a priori* evidence against the 2-regime model based on the modified likelihood criterion. These include France, Italy, and the Netherlands. However, an examination of the 3-regime models do not indicate an improved performance for these countries in terms of the diagnostic tests or the plausibility of the estimated parameters. Finally, the 3-regime version of the 2-regime specification reported in Table 4 for S. Africa would not converge and other 3-regime alternatives had much worse diagnostics.

Up to this point, we have not dwelt on problems associated with the selection of the lag lengths. In some cases, the selection of the regime and the selection of the lag lengths must be considered jointly. We can illustrate this situation for the case of Japan. A general specification search showed that all the model selection criteria favored the MSIH(m)-AR(k) model with longer lags for Japan. As the table shows, however, the estimated specifications with 2 or 3 regimes and 3 or 4 lags for each regime have criterion values that are typically close. These results suggest that according to the penalized likelihood criteria we should select the 2-regime model with 3 lags. If we consider only the 3-regime model, then both the HQC and SIC which favor more parsimonious models suggest that we should select the specification with 3 lags. Now consider implementing a likelihood ratio test of the 2- versus 3-regime specifications using the modified critical values. In this case, we fail to find any difference between the 2- versus 3-regime models! We chose the 3-regime model with 3 lags that is reported in the text because all of the other specifications have nearly the same performance on the diagnostic tests but imply poor business cycle dating and implausibly high values for expected output growth in the contractionary regime.

We can also discuss the implications of lag length choice for regime classification and model fit using the case of Malaysia. We initially estimated a model with four lags for this country, which tended to have better criterion values than other specifications. However, this specification identified a spurious recession during 2005:4-2006:4 as well as a single-quarter recession between 2007:4-2007:4. Furthermore, it failed to identify the recession between 2000-2001 when the economy experiences negative GDP growth. In some cases, models with longer lags lead to spurious business cycle dating. Layton and Smith (2000) have noted that while a longer AR lag structure can aid in the general fit of the model, the greater persistence that it implies in the series also increases the estimated probability that the series will continue to remain in the current regime. As a consequence, this feature may lead the model to fail to predict that a turning point has occurred. For this reason, we chose a model with a single lag for Malaysia that performs equally well on the diagnostic tests.

Table 9 show the values of the BDS test statistic, the Ljung-Box statistics for lags 2, 4 and 12, and the Jacques-Bera test statistic for tests.[39] These are implemented using the standardized residuals from the selected specifications in Tables 2 through 5. The BDS test is a nonparametric method for testing for serial dependence and non-linear structure in a given time series. The Ljung-Box test is a test of the significance of the sum of autocorrelations up to lag k for $k = 1, 2, \ldots$. Finally, the Jacques-Bera test is a test of normality. We notice almost all the countries in our sample the standardized residuals from the reported specifications pass the BDS test for linearity and serial independence as well as the Jacques-Bera test for normality. The Ljung-Box statistics show some evidence of serial correlation in the standardized residuals from the estimated Markov switching specifications. However, a closer look reveals that the significant coefficients typically occur at lag four, suggesting that there are some moving average terms that have not been completely eliminated by the estimated models through the autoregressive lag structure. It is clear that such moving average terms (and their corresponding impact on the autocorrelation function of the standardized residuals) arise from the smoothing method that we have employed for eliminating high frequency movements in the data. However, this practice of smoothing the underlying series in business cycle analysis is not confined to our paper. For example, Artis, Kontolemis and Osborne (1997) also derive turning points using a data-based approach after using a seven-month moving average window on monthly industrial production data. Likewise, Canova, Ciccareli and Ortega (2009) state that their panel VAR with a time-varying index structure allows for an averaging of the underlying data, which tends to eliminate high frequency movements in the series. Despite the existence of such moving average terms, we find that at least a half of our estimated specifications display no or little evidence of serial correlation based on the Ljung-Box statistics.

In Figure 4, we also present the fitted and the one-step ahead predicted values implied by the different models as a way of examining their adequacy. We note that most of the models that we have chosen are capable of capturing the magnitude and direction of the fluctuations in each of the variables under study. Among the developed economies, the models for almost all of the countries track very closely the behavior of the underlying growth process in these countries. Our chosen models are able to detect the magnitudes of the declines and increases in GDP growth. Moreover, our models perform quite well in identifying the timing of the shifts between contractionary and expansionary regimes, an issue that we discuss in the text. Finally, we find that the chosen models are capable of tracking the observed GDP fluctuations even for the developing economies. For countries such as Hong Kong, Singapore, Malaysia, and Brazil, there is some misalignment of the predicted and fitted values with the underlying GDP growth series but even in these cases, the models track well the highly volatile GDP series of emerging market economies.

We discuss the business cycle dating properties of the Markov switching model in Section 4.1 and we provide a further comparison with the nonparametric Harding-Pagan approach in Section 4.2. In the Markov switching model, there is a possibility that the algorithm will identify a large number of points as corresponding to the peaks or troughs of a business cycle. This occurs if the probabilities $Pr(s_t = 1|\psi_T)$ are estimated to be close to 0.5. The

[39] The issue of specification testing of the Markov switching model is discussed further by Brenuig, Najarian, and Pagan (2003). They argue for the use of parametric and nonparametric encompassing tests.

algorithm may also identify single periods as corresponding to a separate regime. We did not constrain the algorithm to avoid this situation and encountered several occasions of its occurring. These are reported in Table 7. However, in most of the chosen specifications, the estimates of the smoothed probabilities were also close to unity, indicating a clear delineation of the different regimes.

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	Australia	**Canada**	**Japan**	**UK**	**US**
Regime-specific intercepts					
$\nu(s_1)$	-0.55	-0.34	0.50	-0.22	0.11
	(-1.92)	(-4.05)	(3.17)	(-1.27)	(2.00)
$\nu(s_2)$	0.89	0.88	0.87	1.04	0.74
	(5.38)	(15.05)	(19.24)	(8.10)	(10.92)
$\nu(s_3)$	2.41	1.44	1.31	-	-
	(10.81)	(13.86)	(6.00)		
Regime-specific standard deviations					
$\sigma(s_1)$	0.69	0.23	0.96	0.57	0.28
$\sigma(s_2)$	0.50	0.23	0.33	-	-
$\sigma(s_3)$	0.46	0.39	0.56	-	-
Regime-specific autoregressive coefficients					
Regime 1					
α_1	0.82	1.68	1.36	0.36	1.63
	(21.65)	(17.28)	(16.15)	(5.51)	(22.47)
α_2	-	-0.91	-0.46	0.13	-0.73
		(-10.45)	(-3.52)	(1.86)	(-5.00)
α_3	-	-	-0.08	0.22	-0.15
			(-0.93)	(3.09)	(-1.08)
α_4	-	-		-0.45	0.13
				(-6.20)	(1.87)
Regime 2					
α_1	-	1.59	-	-	-
		(38.74)			
α_2	-	-0.80	-	-	-
		(-20.68)			
Regime 3					
α_1	-	1.47	-	-	-
		(12.08)			
α_2	-	-0.66	-	-	-
		(-5.89)			
Regime-specific expected output growth rates					
$\mu(s_1)$	-2.96	-1.48	3.36	-0.30	0.87
$\mu(s_2)$	4.80	4.18	5.85	1.40	5.83
$\mu(s_3)$	12.99	5.83	8.81	-	-
Durations of the regimes					
D_1	3.15	6.56	8.38	6.42	3.74
D_2	23.06	14.86	13.31	28.65	15.95
D_3	3.40	9.76	10.80	-	-
Log-likelihood	685.1175	796.5790	556.1560	664.3680	784.5314
AIC	-7.1777	-8.4302	-7.2021	-7.1127	-8.4648
LR statistic†	68.9497	57.3053	40.2360	19.7870	15.1335

Australia 1962:4-2009:2; Canada 1963:3-2009:2; Japan 1972:1-2009:2; UK 1963:3-2009:2; US 1963:4-2009:2.

Regime-specific intercepts and variances are measured in percent terms. Asymptotic t-statistics in parentheses.

Test of the linear versus the Markov switching model.

Table 2: Anglophone Countries and Japan

	France	**Germany**	**Italy**	**Netherlands**	**Spain**
Regime-specific intercepts					
$\nu(s_1)$	0.41	0.53	-0.26	-0.02	-0.21
	(0.48)	(3.05)	(-0.27)	(-0.11)	(-0.53)
$\nu(s_2)$	0.53	0.58	1.04	1.36	0.11
	(8.17)	(8.81)	(16.25)	(12.22)	(2.30)
$\nu(s_3)$	-	-	-	-	0.17
					(1.67)
Regime-specific standard deviations					
$\sigma(s_1)$	1.30	0.40	3.64	0.50	0.45
$\sigma(s_2)$	0.23	-	0.42	-	-
Regime-specific autoregressive coefficients					
Regime 1					
α_1	0.39	1.93	1.20	0.99	1.31
	(2.14)	(6.04)	(24.77)	(17.12)	(21.31)
α_2	0.07	-1.71	-0.30	0.03	-0.25
	(0.40)	(-2.46)	(-5.55)	(0.34)	(-2.90)
α_3	-0.04	0.82	-0.06	-0.03	-0.04
	(-0.22)	(1.19)	(1.44)	(-0.30)	(-0.55)
α_4	-0.05	-0.25	0.018	-0.22	-0.06
	(-0.36)	(-0.91)	(0.65)	(-3.18)	(-1.83)
Regime 2					
α_1	1.48	0.74	-	-	-
	(17.02)	(9.76)			
α_2	-0.36	0.20	-	-	-
	(-1.87)	(2.03)			
α_3	-0.53	-0.02	-	-	-
	(-2.24)	(-0.20)			
α_4	0.31	-0.22	-	-	-
	(2.73)	(-3.05)			
Regime-specific expected output growth rates					
$\mu(s_1)$	0.65	2.68	-1.86	-0.13	-4.94
$\mu(s_2)$	5.50	1.96	7.45	5.89	2.59
$\mu(s_3)$	-	-	-	-	4.00
Durations of the regimes					
D_1	5.62	4.04	3.26	2.92	6.31
D_2	14.07	23.66	15.77	15.13	7.19
D_3	-	-	-	-	9.86
Log-likelihood	590.4634	723.4166	641.5994	673.7418	719.6142
AIC	-7.7109	-7.7848	-6.8543	-7.2146	-7.6788
LR statistic†	203.3562	24.9777	265.2419	30.7508	152.0584

France 1972:2-2009:2; Germany 1964:1-2009:2; Italy 1963:3-2009:2, Netherlands 1963:3-2009:2; Spain 1963:4-2009:2

Regime-specific intercepts and variances are measured in percent terms. Asymptotic t-statistics in parentheses.

† Test of the linear versus the Markov switching model.

Table 3: The EU Countries

	Hong Kong	**Singapore**	**S. Korea**	**Taiwan**	**Malaysia**	**S. Africa**	**Turkey**
Regime-specific intercepts							
$\nu(s_1)$	1.94	-0.49	0.73	2.29	1.75	0.01	-0.99
	(1.40)	(-2.53)	(8.88)	(9.63)	(0.09)	(0.07)	(-3.51)
$\nu(s_2)$	2.88	0.52	1.75	3.48	2.48	0.99	2.48
	(17.88)	(3.80)	(23.66)	(26.86)	(0.40)	(6.02)	(6.03)
$\nu(s_3)$	3.70	1.16	-	-	-	-	-
	(3.28)	(10.90)					
Regime-specific standard deviations							
$\sigma(s_1)$	0.93	0.62	0.25	0.83	1.18	0.49	1.00
$\sigma(s_2)$	0.36	0.24	-	0.47	-	0.42	-
$\sigma(s_3)$	0.91	0.30	-	-	-	-	-
Regime-specific autoregressive coefficients							
Regime 1							
α_1	1.36	0.86	1.22	1.47	1.29	0.52	0.94
	(11.28)	(22.42)	(17.04)	(42.48)	(1.18)	(5.74)	(8.54)
α_2	-0.54	-	-0.19	-0.76	-	0.25	-0.16
	(-3.42)		(-1.57)	(-20.62)		(2.62)	(-1.11)
α_3	0.02	-	-0.40	-	-	-0.05	-0.14
	(0.16)		(-3.31)			(-0.55)	(-1.07)
α_4	-0.11	-	0.07	-	-	-0.20	-0.13
	(-1.44)		(1.14)			(-2.53)	(-0.17)
Regime 2							
α_1	-	-	-	-	0.83		-
					(2.24)		
Regime-specific expected output growth rates							
$\mu(s_1)$	7.12	-3.94	2.54	8.54	-6.03	0.02	-2.64
$\mu(s_2)$	10.58	4.18	6.09	13.00	14.08	2.06	6.61
$\mu(s_3)$	13.60	9.32	-	-	-	-	-
Durations of the regimes							
D_1	2.74	4.77	3.29	4.16	5.74	5.16	4.12
D_2	18.18	5.66	22.39	26.65	12.17	10.45	11.52
D_3	9.20	3.73	-	-	-	-	-
Log-likelihood	455.4175	385.4914	562.0746	399.8304	188.1739	540.8202	231.7237
AIC	-6.4951	-7.6596	-8.4935	-7.3052	-5.4295	-7.1251	-5.4747
LR statistic†	49.1968	69.0343	42.3220	26.6566	37.1839	8.3570	17.5413

Hong Kong 1975:4-2009:2; Singapore 1985:2-2009:2; S. Korea 1977:1-2008:4; Taiwan 1982:3-2009:1; Malaysia 1993:1-2008:4;

S. Africa 1972:1-2009:1; Turkey 1989:2-2009:2

Regime-specific intercepts and variances are measured in percent terms. Asymptotic t-statistics in parentheses.

† Test of the linear versus Markov switching model.

Table 4: East Asian Countries and Other Emerging Market Economies

	Argentina	**Brazil**	**Chile**	**Mexico**	**Uruguay**
Regime-specific intercepts					
$\nu(s_1)$	-0.82	-2.19	-0.59	-0.55	-1.57
	(-6.90)	(-6.92)	(-4.20)	(-2.73)	(-7.80)
$\nu(s_2)$	0.15	2.13	-0.20	0.89	0.27
	(0.11)	(8.24)	(-3.00)	(5.81)	(2.54)
$\nu(s_3)$	-	-	0.21	-	0.95
			(1.95)		(11.03)
Regime-specific standard deviations					
$\sigma(s_1)$	1.28	0.60	0.57	1.38	1.00
$\sigma(s_2)$	0.37	0.58	0.22	0.58	0.35
$\sigma(s_3)$	-	-	0.32	-	0.19
Regime-specific autoregressive coefficients					
Regime 1					
α_1	1.34	0.71	1.53	1.24	0.71
	(9.14)	(9.94)	(18.81)	(15.36)	(9.84)
α_2	-0.59	-	-0.73	-0.51	-0.05
	(-2.09)		(-11.50)	(-7.50)	(-0.43)
α_3	-0.03	-	-	-	0.02
	(-0.13))				(0.16)
α_4	0.05	-	-	-	-0.19
	(0.65)				(-2.91)
Regime 2					
α_1	1.86	0.82	-	-	-
	(11.32)	(16.30)			
α_2	-1.17	-	-	-	-
	(-3.92)				
α_3	0.30	-	-	-	-
	(1.00				
α_4	-0.10	-	-	-	-
	(-0.64)				
Regime-specific expected output growth rates					
$\mu(s_1)$	-6.73	-7.53	-2.91	-2.04	-3.14
$\mu(s_2)$	1.23	11.50	-0.98	3.30	0.54
$\mu(s_3)$	-	-	1.04	-	2.00
Durations of the regimes					
D_1	6.31	5.32	7.56	9.99	10.68
D_2	8.82	5.70	18.86	17.54	4.37
D_3	-	-	24.41	-	4.98
Log-likelihood	347.9245	211.6164	470.9887	353.3478	291.8711
AIC	-6.2042	-6.4005	-8.2160	-6.3768	-7.0480
LR statistic†	40.4078	27.0939	37.3590	36.9668	67.3376

Argentina 1982:4-2009:2; Brazil 1993:4-2009:2; Chile 1981:4-2009:2; Mexico 1982:3-2009:2; Uruguay 1990:1-2009:2

Regime-specific intercepts and variances are measured in percent terms. Asymptotic t-statistics in parentheses.

† Test of the linear versus Markov switching model.

Table 5: Latin American Countries

		Australia	Canada	Japan	UK	US
Duration (quarters)	PT	4.000	5.500	4.000	4.500	3.750
Duration (quarters)	TP	28.500	48.000	23.600	18.667	30.750
Amplitude (%)	PT	-1.500	-2.840	-1.530	-2.210	-1.170
Amplitude (%)	TP	25.640	38.640	18.750	13.410	25.860
Excess (%)	PT	6.284	2.867	10.073	-15.554	-0.791
Excess (%)	TP	-4.915	-6.305	11.023	13.0957	-5.490
		France	**Germany**	**Italy**	**Netherlands**	**Spain**
Duration (quarters)	PT	3.500	3.800	3.000	4.000	4.000
Duration (quarters)	TP	64.000	29.600	31.800	41.000	36.000
Amplitude (%)	PT	-1.100	-0.860	-0.790	-1.370	-1.880
Amplitude (%)	TP	37.370	20.790	24.300	28.400	29.080
Excess (%)	PT	2.620	2.063	0.796	6.979	8.774
Excess (%)	TP	-5.574	0.314	-5.423	-6.730	14.273
		Hong Kong	**Singapore**	**S. Korea**	**Taiwan**	**Malaysia**
Duration (quarters)	PT	3.000	2.500	4.000	3.000	3.500
Duration (quarters)	TP	31.000	28.333	39.000	26.000	18.500
Amplitude (%)	PT	-2.760	-1.650	-7.100	-2.360	-4.160
Amplitude (%)	TP	51.380	52.00	52.290	30.68	30.920
Excess (%)	PT	5.635	-12.068	5.376	-8.481	-2.792
Excess (%)	TP	-3.951	0.444	-11.131	4.421	0.138
		S. Africa	**Turkey**	**Argentina**	**Brazil**	**Chile**
Duration (quarters)	PT	7.667	3.600	8.500	2.667	5.500
Duration (quarters)	TP	28.000	12.400	11.750	9.667	46.500
Amplitude (%)	PT	-3.160	-4.430	-11.330	-0.63	-5.570
Amplitude (%)	TP	22.830	20.35	16.640	9.56	48.96
Excess (%)	PT	20.136	-0.127	17.556	-7.60	-2.21
Excess (%)	TP	6.632	6.157	-9.3885	-8.68	26.56
		Mexico	**Uruguay**			
Duration (quarters)	PT	4.500	9.500			
Duration (quarters)	TP	21.750	13.000			
Amplitude (%)	PT	-4.000	-12.540			
Amplitude (%)	TP	19.660	14.890			
Excess (%)	PT	7.493	14.402			
Excess (%)	TP	0.377	-6.827			

Table 6: Business Cycle Characteristics: The Harding-Pagan Approach

	NBER	**CEPR**	**ECRI**	**US†**	**ECRI**	**Australia**	**ECRI**	**Canada**
	69:4-70:4		69:4-70:4	69:2-70:4				
	73:4-75:1	74:3-75:1	73:4-75:1	74:1-75:2	74:2-75:1	74:3-74.4		
	80:1-80:3		80:1-80:3	79:2-80:4				
	81:3-82:4	80:1-82:3	81:3-82:4	81:4-82:3	82:2-83:2	82:2-83:3	81:2-82:4	82:1-82:4
	90:3-91:1	92:1-1993:3	90:3-91:1	90:3-91:2	90:2-91:4	90:3-91:4	90:1-92:1	90:3-93:1
	01:1-01:4		01:1-01:4	01:2-02:1				
	08:1-09:1		07:4-	08:3-09:1		08:4-09:2	08:1-	08:2-09:1
Coin±1				8/13 = 62%		6/6 = 100%		3/5=60%
Coin±2				11/13 = 85%		6/6 = 100%		4/5 = 80%
	ECRI	**Japan**	**ECRI**	**UK**	**ECRI**	**France†**	**ECRI**	**Germany**
							66:1-67:2	67:1-68:2
				73:4-74:1				
	73:4-75:1	73:4-75:2	74:3-75:2	75:1-75:4	74:3-75:2	74:2-75:1	73:3-75:3	72:4-75:4
		80:1-82:1	79:3-81:2	80:2-82:3	79:3-80:2	79:4-80:4	80:1-82:4	82:1-82:3
					82:2-84:4	82:2-84:2		
	92:2-94:1	90:4-92:1	90:2-92:1	90:2-92:4	92:1-93:3	92:2-93:4	91:1-94:2	92:4-93:1
	97:1-99:3	97:4-99:4						
	00:3-03:2	01:1-03:3			02:3-03:2	02:2-03:4	01:1-03:3	
	08:2-	08:4-09:2	08:2-	08:4-09:2	08:1-	08:1-09:2	08:4-	08:4-09:1
Coin±1		4/9 = 44%		1/6 = 17%		8/11 = 73%		3/11=27%
Coin±2		5/9 = 56%		3/6 = 50%		11/11 = 100%		3/11 =27%
	ECRI	**Italy**	**Netherlands†**	**ECRI**	**Spain**	**Hong Kong**	**Malaysia**	**Singapore**
	64:1-65:1	64:2-65:2						
			66:1-66:1					
	70:4-71:3	70:4-71:4						
	74:2-75:2	73:4-74:2	74:4-75:3					
		77:3-77:4	76:4-77:3			77:1-77:1		
	80:2-83:2	80:4-81:1	80:2-81:1	80:1-84:2		82:1-83:1		
			82:1-83:1			84:4-86:1		85:3-86:2
	92:1-93:4	92:2-92:3	84:2-85:1	91:3-93:4	92:1-94:1	89:3-90:1		
		93:4-94:1				97:4-99:1	97:2-98:4	98:2-99:1
						03:2-03:3	00:4-01:4	01:3-02:1
	07:3-	08:1-09:2	08:4-09:2	08:1-	08:2-09:2	08:4-09:1	08:4-09:2	08:2-09:2
Coin±1		6/11 = 54%			2/5 = 40%			
Coin±2		7/11 = 64%			3/5 = 60%			
	ECRI	**S. Korea**	**ECRI**	**S. Africa**	**ECRI**	**Taiwan**	**Turkey**	
				72:1-72:2				
				74:4-75:1				
			76:2-77:4	76:2-77:1				
		77:4-78:1		77:3-77:4				
	79:1-80:4	79:2-80:4	77:1-81:4	82:1-83:3	82:1-83:3			
		81:2-81:3	84:2-86:2	84:3-86:4				
			89:1-92:3	89:3-93:1			89:2-89:3	
							91:1-91:3	
							94:2-95:1	
	97:3-98:3	97:2-98:1	97:2-98:4	98:2-98:3			98:4-99:4	
	02:4-03:3				00:3-01:3	00:1-02:3	01:1-02:1	
	08:3-	08:4-09:1	08:2-	08:4-09:2	08:1-	07:4-08:2	08:4-09:2	
Coin±1		4/7=57%		5/11 = 45%		1/3 = 33%		
Coin±2		5/7 =71%		10/11 = 91%		2/3 = 66%		
	Argentina	**ECRI**	**Brazil**	**Chile**	**ECRI**	**Mexico**	**Uruguay**	
	82:4-83:2			81:4 -83:1	82:1-83:3	82:3-86:4		
	84:4-86:3				85:4-86:4			
	87:3-90:1				92:4-93:4			
	90:4-92:3							
	95:1-96:1	95:1-95:3	95:4-96:2		94:4-95:3	94:3-95:3	94:4-95:2	
	98:3-02:4	97:4-99:2	97:3-99:3	98:3-99:4	98:1-98:4		98:4-02:4	
		01:1-01:4	01:2-02:3		00:3-03:3	00:4-03:1		
		02:4-03:2	03:2-03:4					
			05:3-06:2					
	08:3-09:2	08:3-09:1	08:4-09:2	08:3-09:2	08:2-	08:2-09:2	09:1-09:2	
Coin±1			4/10 = 40%			5/13 = 38%		
Coin±2			6/10 = 60%			7/13 = 54%		

Coin$\pm k$ denotes the fraction of times the estimated business cycle dates are $\pm k$ quarters away from the ECRI dates.
Single quarter recessions: US 72:1-72:1, 77:1-77:1; France 91:1-91:1; Netherlands 63:3-63:3, 66:1-66:1, 79:1-79:1, 03:1-03:1.

Table 7: Business Cycle Dating

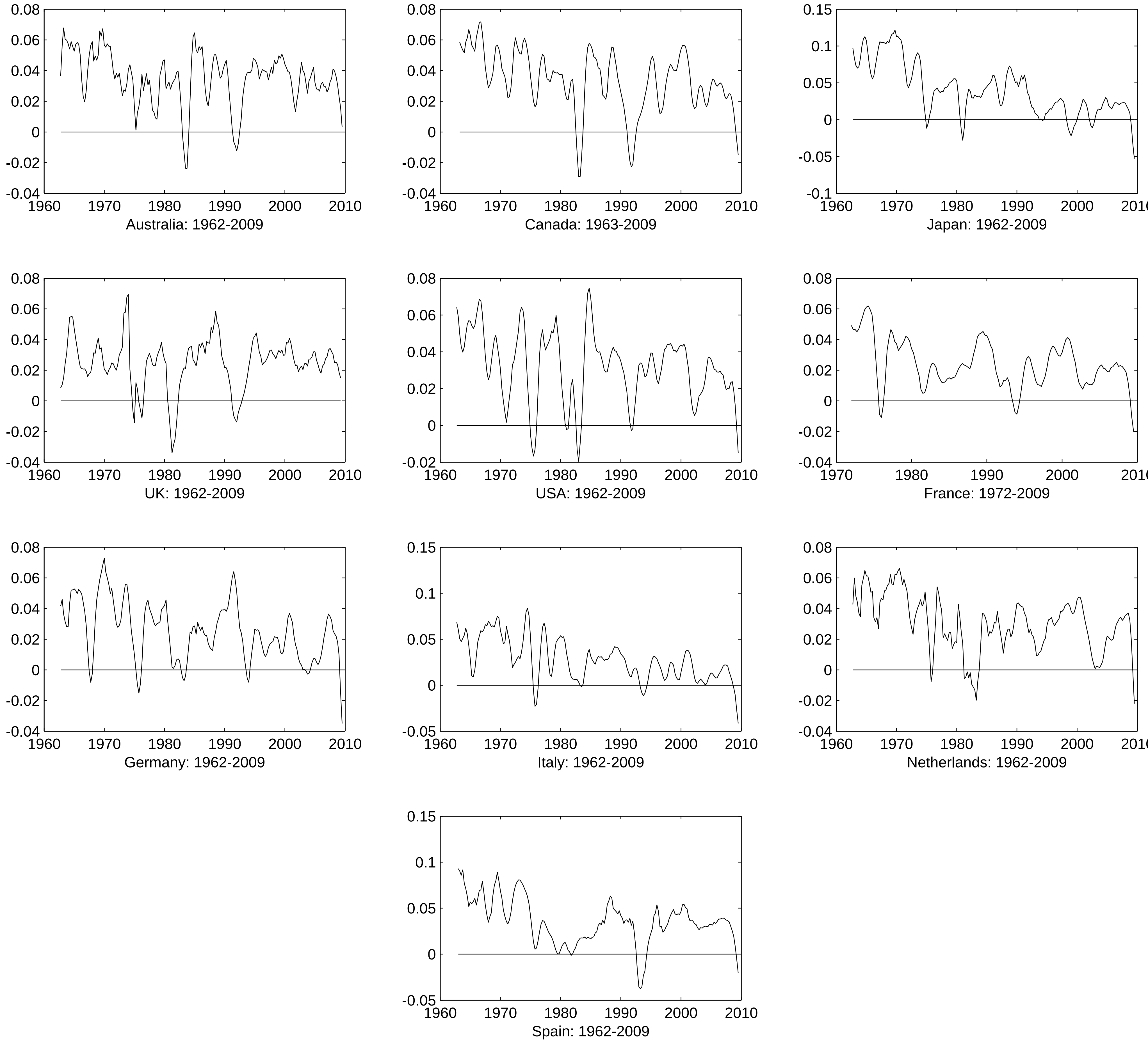
	Contemporaneous Correlations of the Recession Probabilities for Developed Countries, 1970-2009									
	Australia	Canada	Japan	UK	US	France	Germany	Italy	Nether.	Spain
Australia	1.0000									
Canada	0.2114	1.0000								
Japan	-0.0880	0.0326	1.0000							
UK	-0.2687	0.0028	0.3442	1.0000						
US	-0.3917	0.4115	0.4809	0.4191	1.0000					
France	-0.2523	0.1721	0.4207	0.4036	0.4799	1.0000				
Germany	-0.2533	0.1833	0.3300	0.2763	0.4975	0.4178	1.0000			
Italy	-0.1637	0.0324	0.2373	0.5058	0.3841	0.5810	0.4903	1.0000		
Nether.	-0.3047	-0.0150	0.2463	0.4045	0.3320	0.4106	0.3136	0.3199	1.0000	
Spain	0.0094	0.0569	-0.0733	0.4196	0.4028	0.3553	0.2807	0.4788	0.532171	1.0000
	Contemporaneous Correlations of the Recession Probabilities for Emerging Economies and the U.S., 1990-2009									
	Hong Kong	Singapore	S. Korea	Taiwan	Malaysia	S. Africa	Turkey	Argentina	Brazil	Chile
Hong Kong	1.0000									
Singapore	0.5065	1.0000								
S. Korea	0.4598	0.4574	1.0000							
Taiwan	-0.2418	0.1471	-0.1779	1.0000						
Malaysia	0.3049	0.5670	0.4506	0.5495	1.0000					
S. Africa	0.6736	0.5878	0.3565	-0.2193	0.3356	1.0000				
Turkey	0.0355	0.4024	-0.1693	0.2077	-0.2160	0.1347	1.0000			
Argentina	0.0883	0.4137	-0.2341	0.4237	-0.3399	0.1368	0.4801	1.0000		
Brazil	0.3996	0.3274	0.1750	-0.0792	-0.1893	0.2025	0.3050	0.3455	1.0000	
Chile	0.0737	0.2602	-0.0718	0.3068	0.5970	0.2568	-0.0328	-0.0825	-0.2310	1.0000
Mexico	-0.1064	0.3264	-0.2217	0.4607	-0.1106	0.0454	0.3793	0.5238	0.0512	0.2584
Uruguay	-0.1545	0.0620	-0.2268	0.5239	-0.4305	-0.2361	0.2289	0.7825	0.1877	-0.2405
	Mexico	Uruguay		Correlations with US						
Hong Kong				0.2022						
Singapore				0.4646						
S. Korea				-0.0645						
Taiwan				0.3491						
Malaysia				0.3374						
S. Africa				0.5117						
Turkey				0.1897						
Argentina				0.3796						
Brazil				0.3235						
Chile				0.6385						
Mexico	1.0000			0.4015						
Uruguay	0.4015	1.0000		-0.0732						

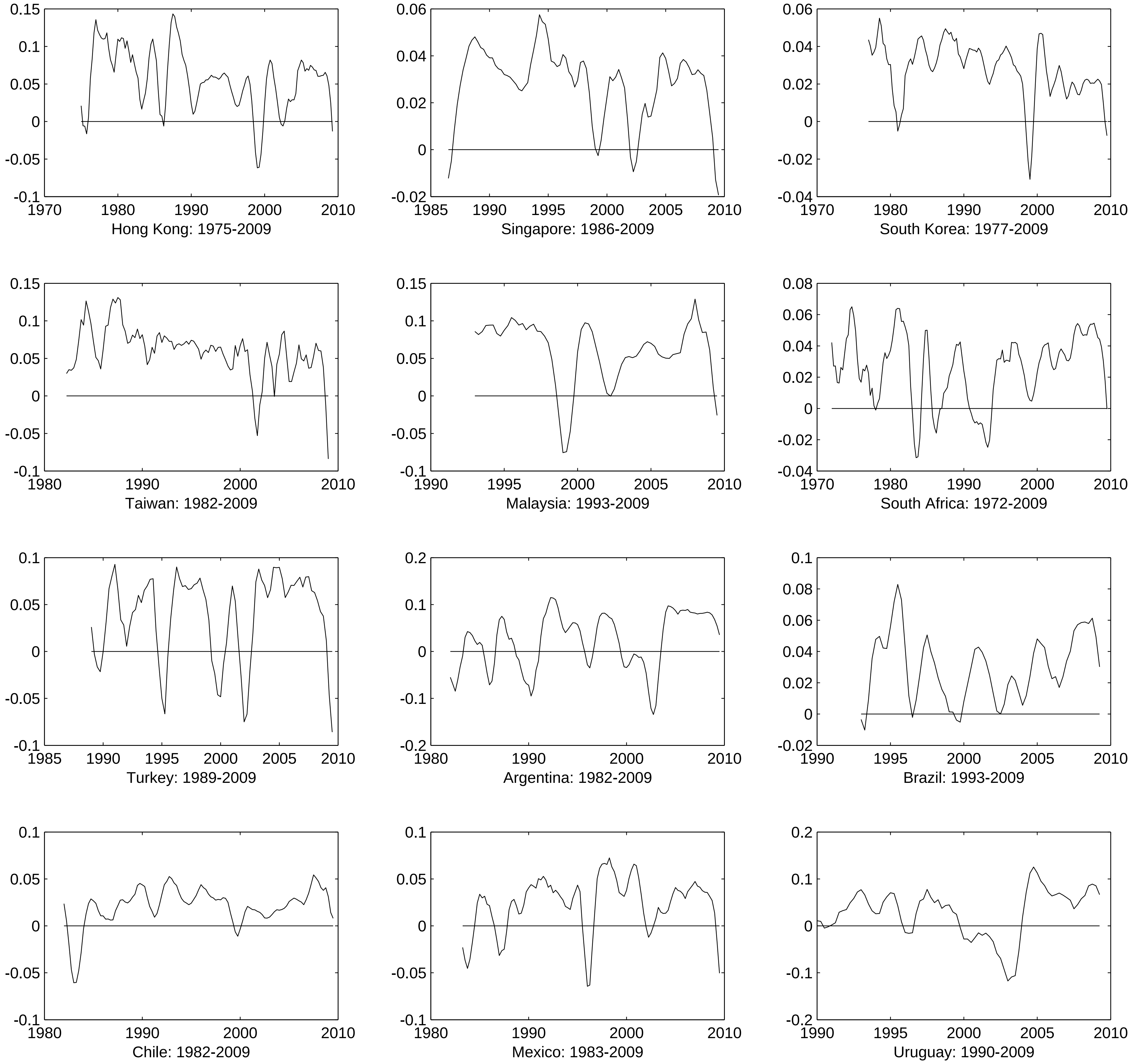
Table 8: Contemporaneous Correlations of the Recession Probabilities

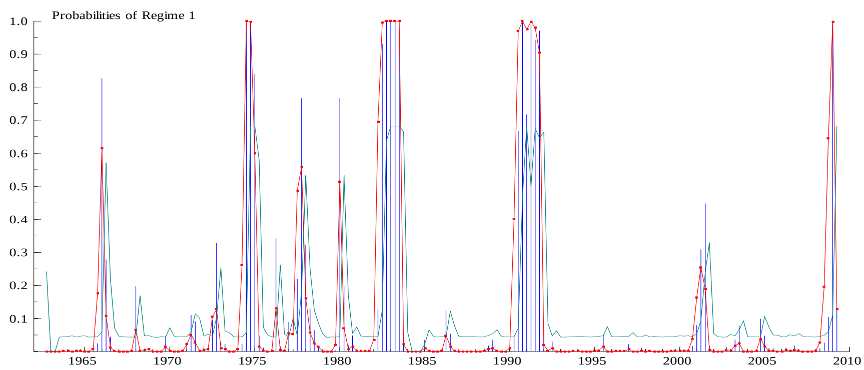
	Australia	Canada	Japan	UK	US	France	Germany	Italy	Netherlands	Spain
BDS Test	0.0025	0.0019	0.0009	0.0044	0.0110	0.0086	-0.0035	0.0014	0.0065	0.0031
	[0.621]	[0.704]	[0.830]	[0.496]	[0.043]	[0.181]	[0.598]	[0.791]	[0.882]	[0.659]
LB(2)	3.1454	0.8507	0.8812	0.3271	2.3626	5.1462	0.8146	3.3534	0.1981	1.0222
	[0.207]	[0.654]	[0.644]	[0.849]	[0.307]	[0.076]	[0.665]	[0.187]	[0.592]	[0.600]
LB(4)	29.968	33.321	20.988	6.3692	58.459	11.365	4.0395	5.5207	11.041	4.8856
	[0.000]	[0.000]	[0.000]	[0.173]	[0.000]	[0.023]	[0.401]	[0.238]	[0.026]	[0.299]
LB(12)	37.697	47.482	26.793	12.754	83.064	16.672	13.537	13.884	16.189	19.232
	[0.000]	[0.000]	[0.002]	[0.387]	[0.000]	[0.162]	[0.331]	[0.308]	[0.040]	[0.083]
Normality	2.195	0.563	3.606	1.2250	3.063	11.648	12.364	1.8329	3.5797	1.0944
	[0.333]	[0.755]	[0.165]	[0.5420]	[0.216]	[0.003]	[0.002]	[0.400]	[0.167]	[0.579]
	Hong Kong	Singapore	S. Korea	Taiwan	Malaysia	S. Africa	Turkey	Argentina	Brazil	Chile
BDS Test	0.0019	0.00004	0.0061	0.0120	0.0063	0.0060	0.0095	0.0014	0.0246	0.0005
	[0.723]	[0.995]	[0.248]	[0.247]	[0.513]	[0.411]	[0.227]	[0.841]	[0.013]	[0.946]
LB(2)	0.3252	3.3077	0.5753	0.2703	13.123	1.1161	3.5803	0.9506	10.683	4.7868
	[0.850]	[0.191]	[0.750]	[0.874]	[0.001]	[0.572]	[0.167]	[0.622]	[0.005]	[0.091]
LB(4)	33.988	15.652	11.043	9.8685	18.471	4.8421	33.664	15.926	26.894	23.563
	[0.000]	[0.004]	[0.026]	[0.043]	[0.001]	[0.304]	[0.000]	[0.003]	[0.000]	[0.000]
LB(12)	44.467	29.595	16.028	18.730	26.227	29.059	49.003	28.805	30.009	32.146
	[0.000]	[0.003]	[0.190]	[0.095]	[0.010]	[0.004]	[0.000]	[0.004]	[0.000]	[0.001]
Normality	0.323	0.801	0.7434	0.7815	1.8788	9.519	0.585	5.042	1.3164	1.6564
	[0.851]	[0.670]	[0.689]	[0.677]	[0.390]	[0.009]	[0.746]	[0.080]	[0.518]	[0.437]
	Mexico	Uruguay								
BDS Test	0.0039	0.0030								
	[0.476]	[0.690]								
LB(2)	1.8256	0.6779								
	[0.401]	[0.713]								
LB(4)	15.518	2.4820								
	[0.004]	[0.648]								
LB(12)	26.361	8.3510								
	[0.014]	[0.757]								
Normality	0.300	2.8005								
	[0.862]	[0.247]								

p-values shown in brackets. The BDS test is implemented for $\epsilon = 0.7$.
LB(k) denotes the Ljung-Box autocorrelation test at lag k.

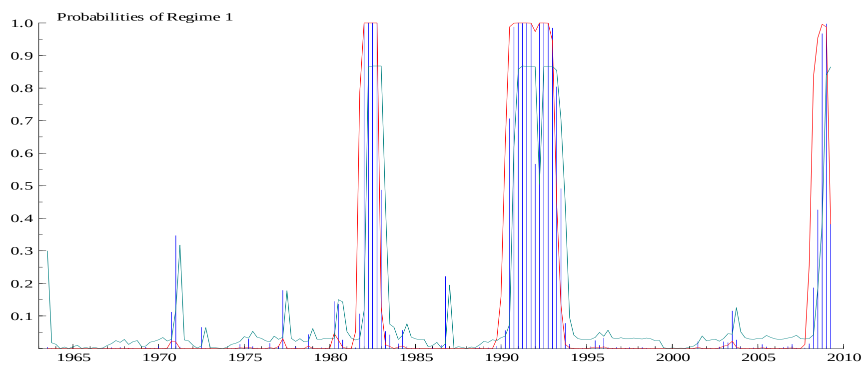
Table 9: Test Statistics


Australia: 1962-2009
Canada: 1963-2009
Japan: 1962-2009
UK: 1962-2009
USA: 1962-2009
France: 1972-2009
Germany: 1962-2009
Italy: 1962-2009
Netherlands: 1962-2009
Spain: 1962-2009

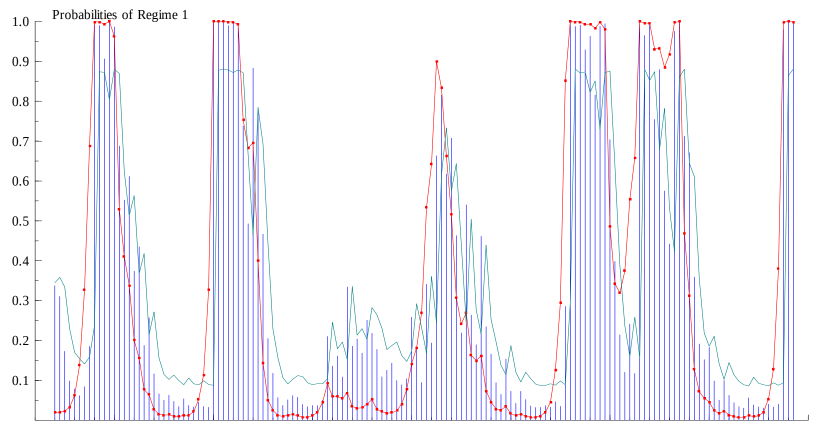

Hong Kong: 1975-2009
Singapore: 1986-2009
South Korea: 1977-2009
Taiwan: 1982-2009
Malaysia: 1993-2009
South Africa: 1972-2009
Turkey: 1989-2009
Argentina: 1982-2009
Brazil: 1993-2009
Chile: 1982-2009
Mexico: 1983-2009
Uruguay: 1990-2009



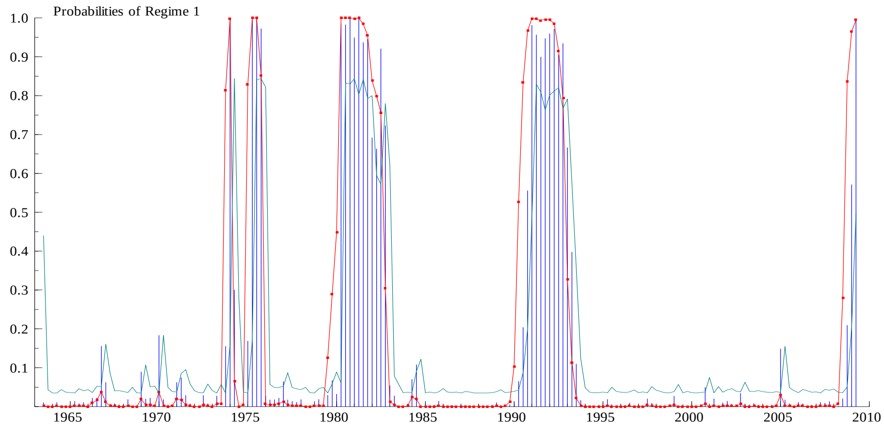
Australia



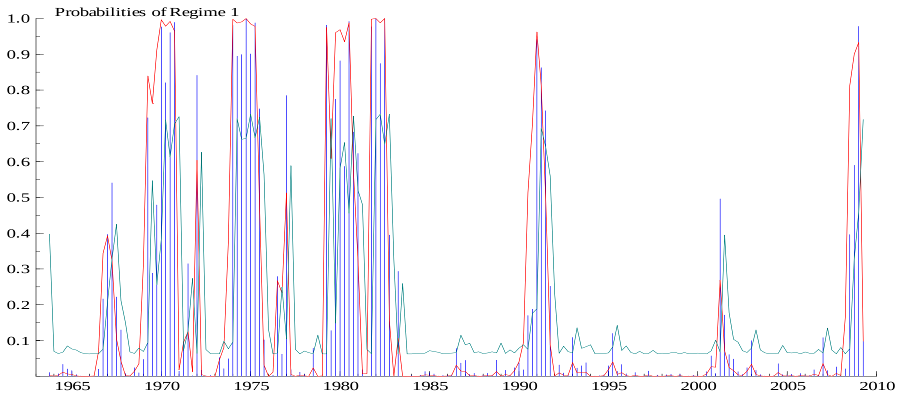
Canada



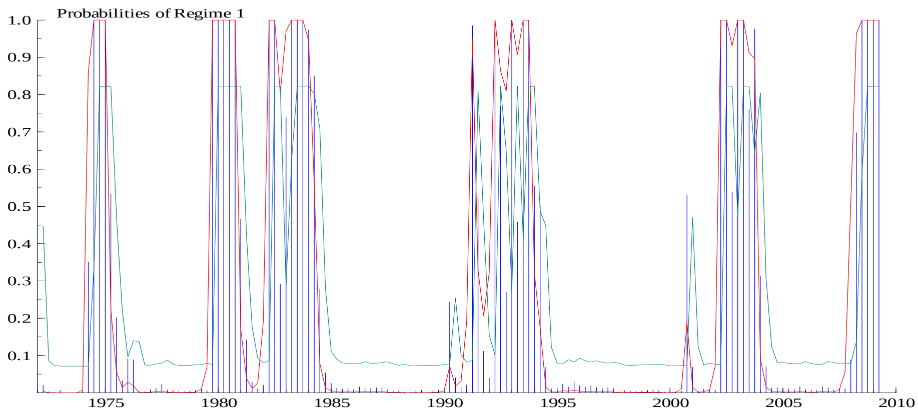
Japan


Probabilities of Regime 1
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010

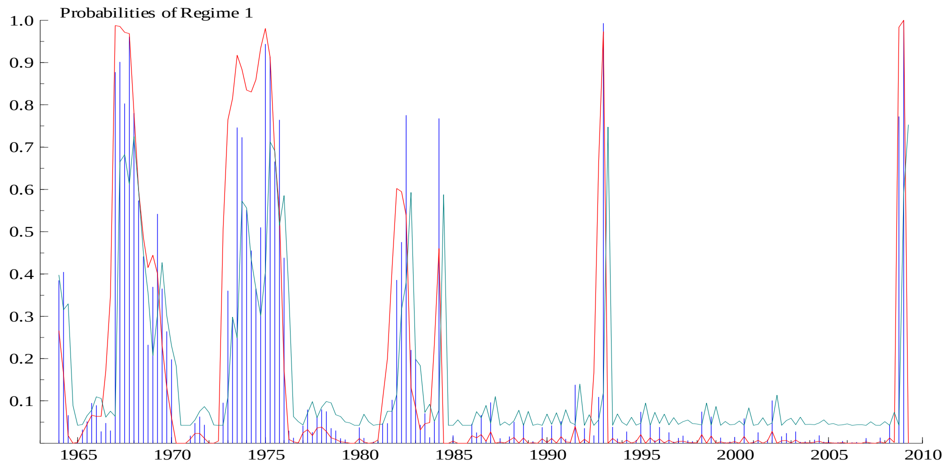
UK


Probabilities of Regime 1
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010

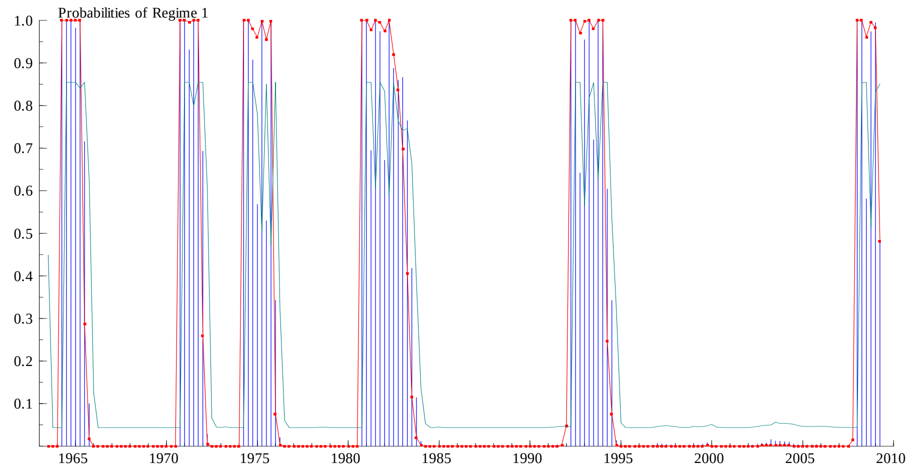
US


Probabilities of Regime 1
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
1975
1980
1985
1990
1995
2000
2005
2010

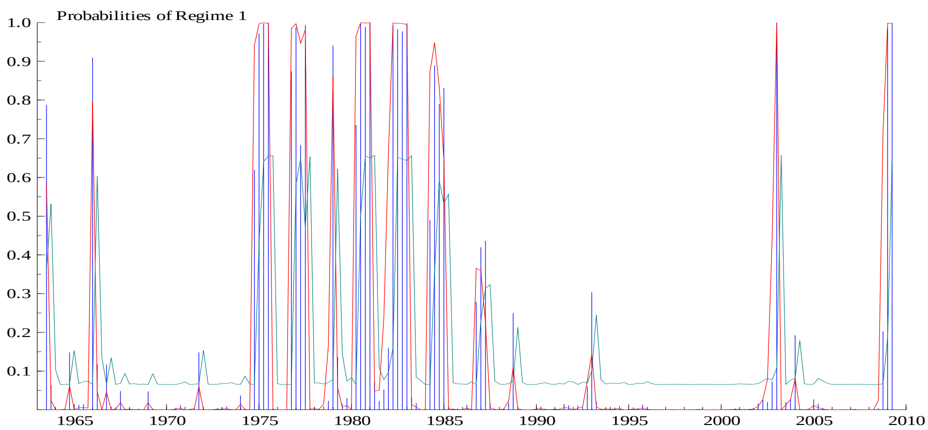
France



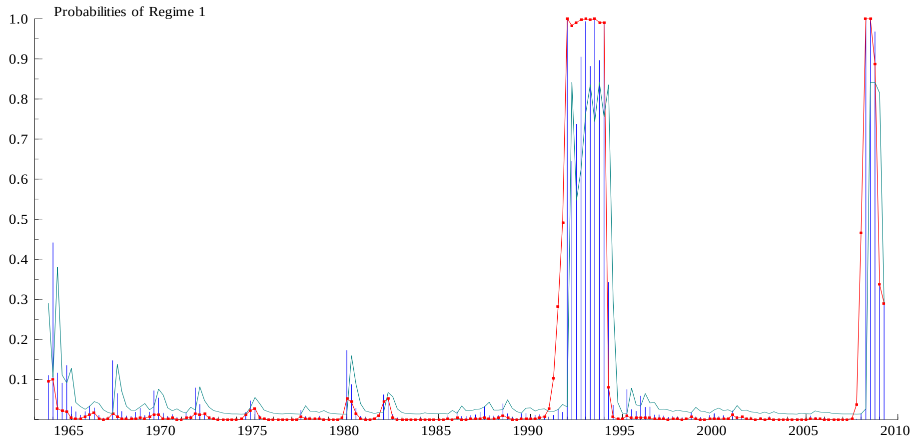
Germany



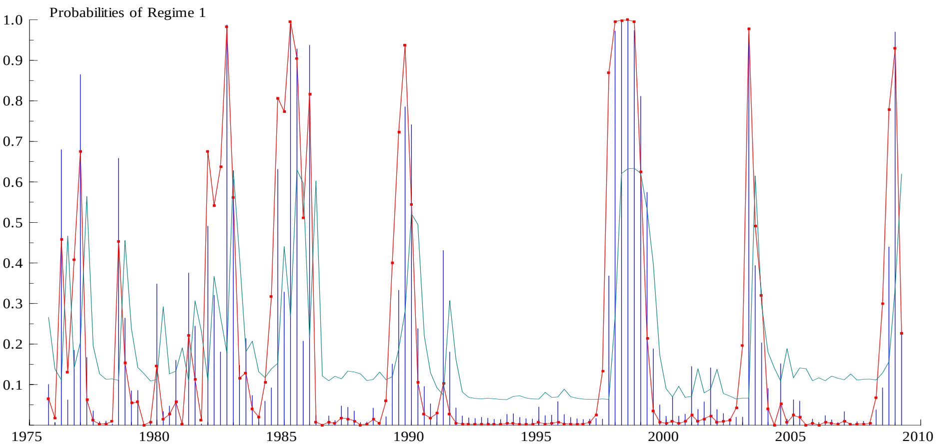
Italy



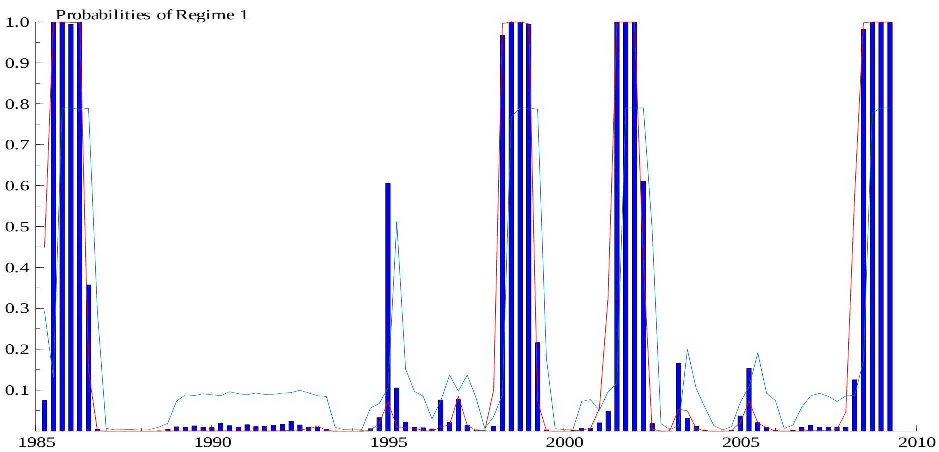
Netherlands



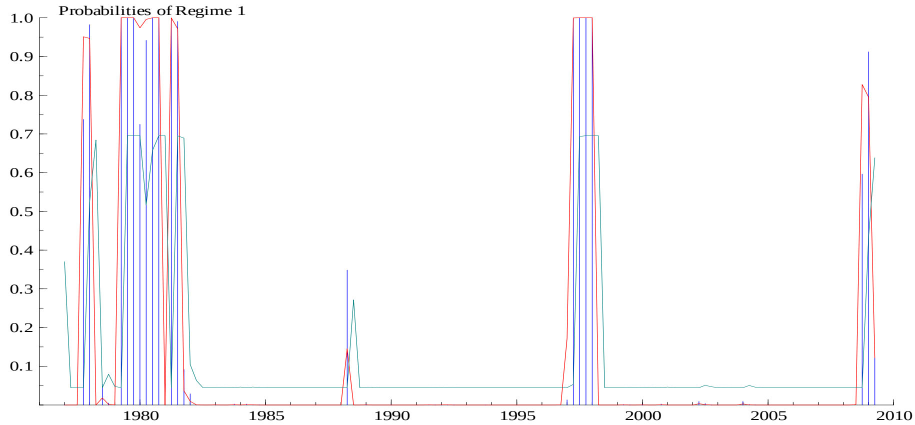
Spain



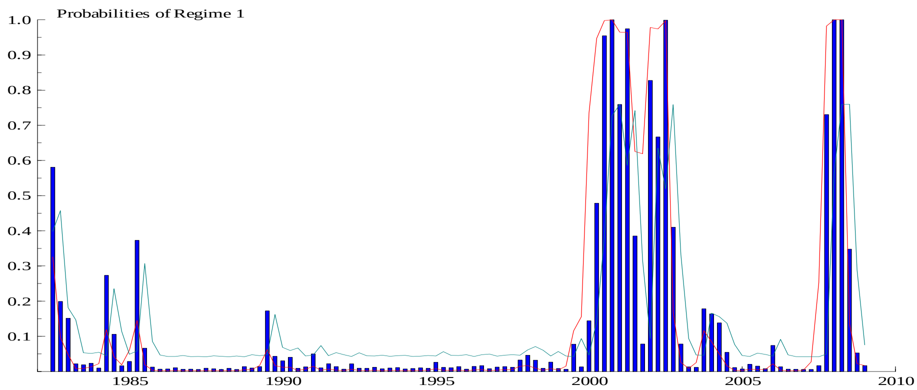
Hong Kong



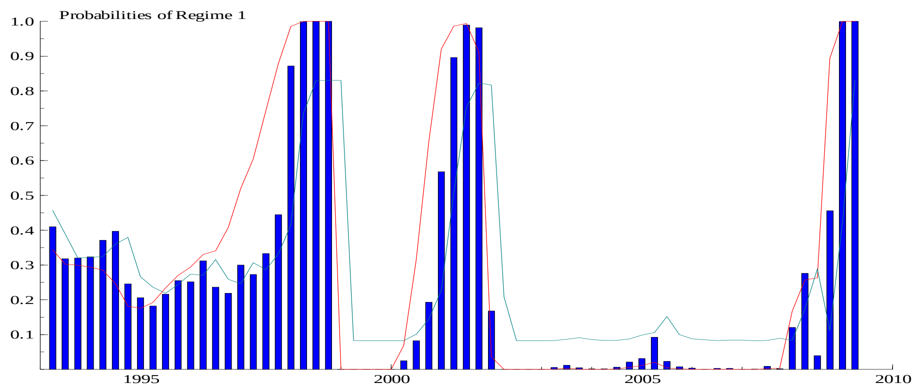
Singapore



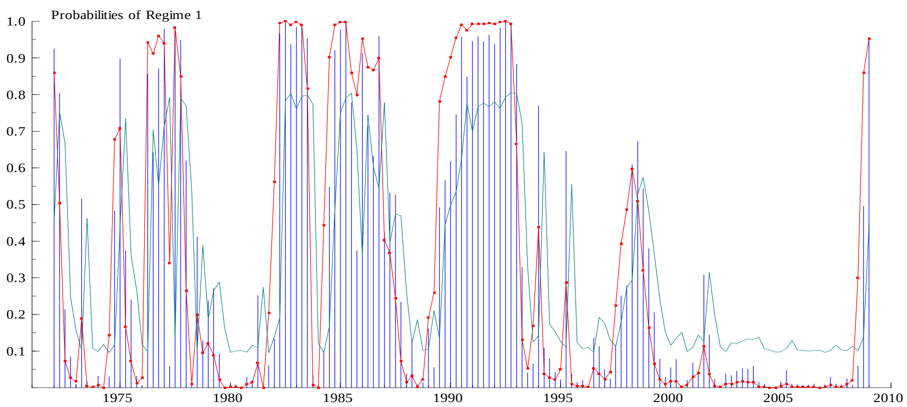
S. Korea



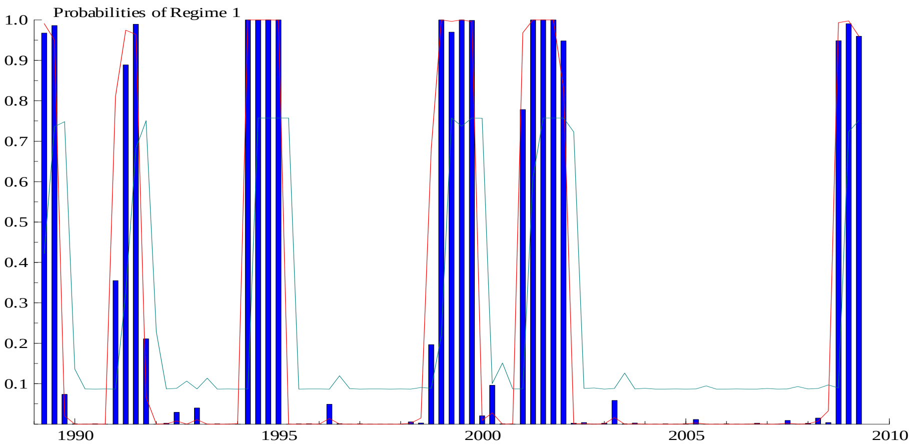
Taiwan



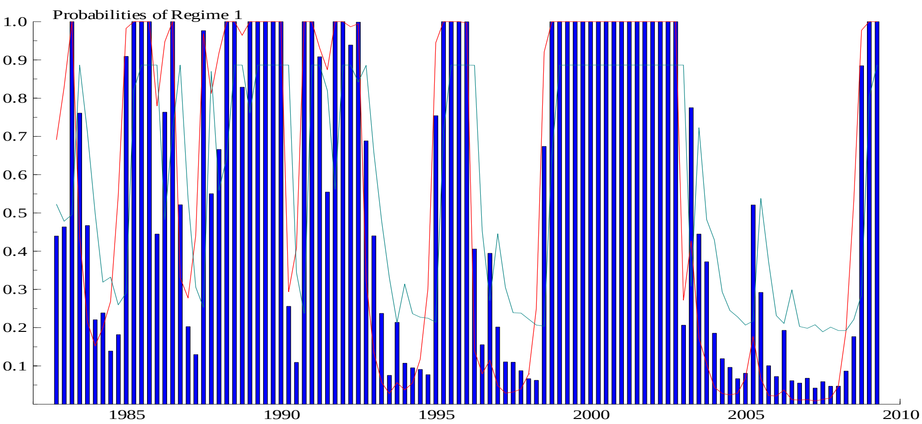
Malaysia



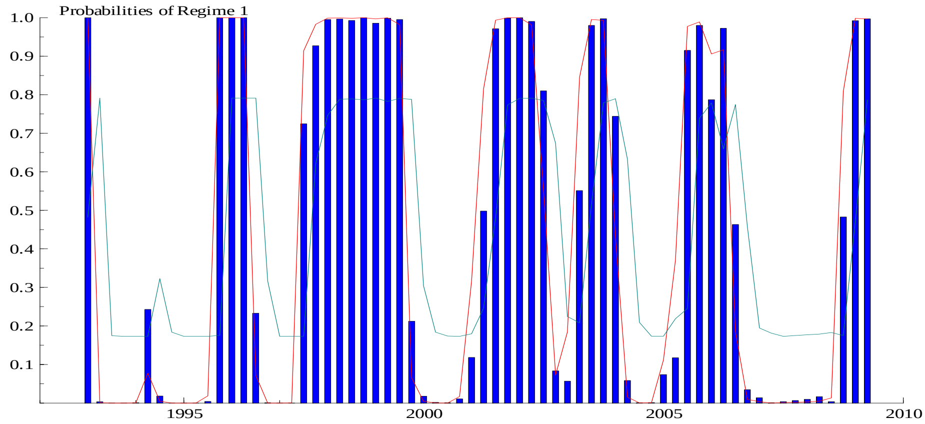
S. Africa



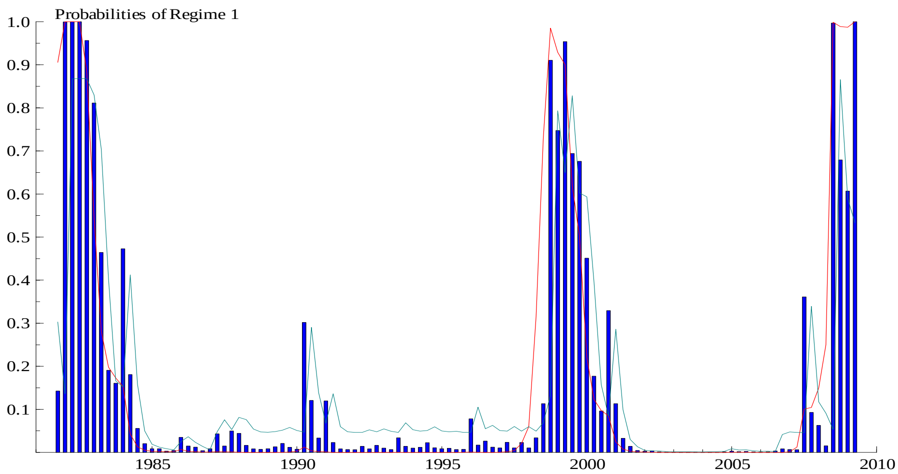
Turkey



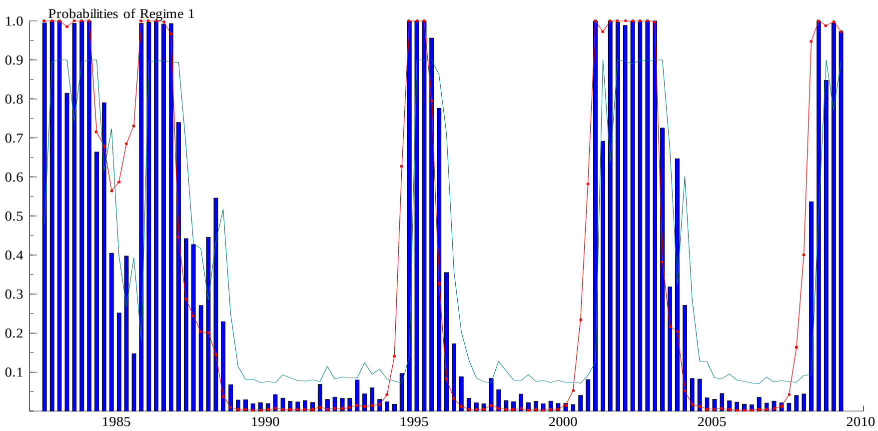
Argentina



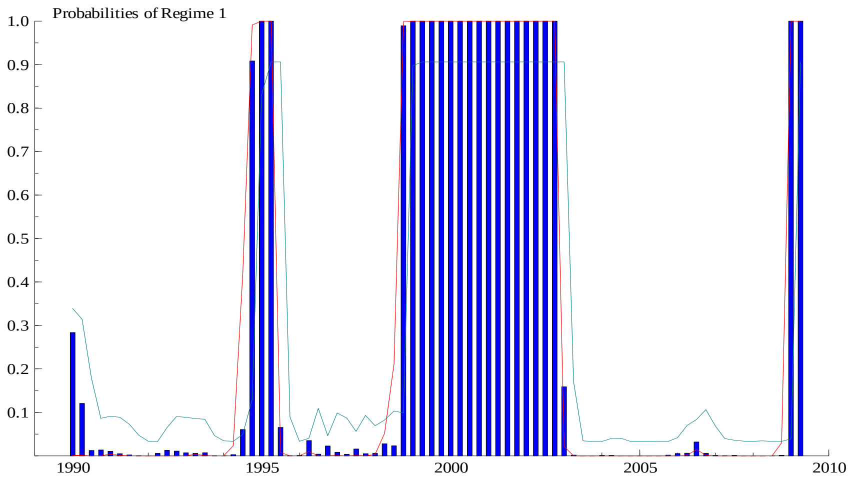
Brazil



Chile

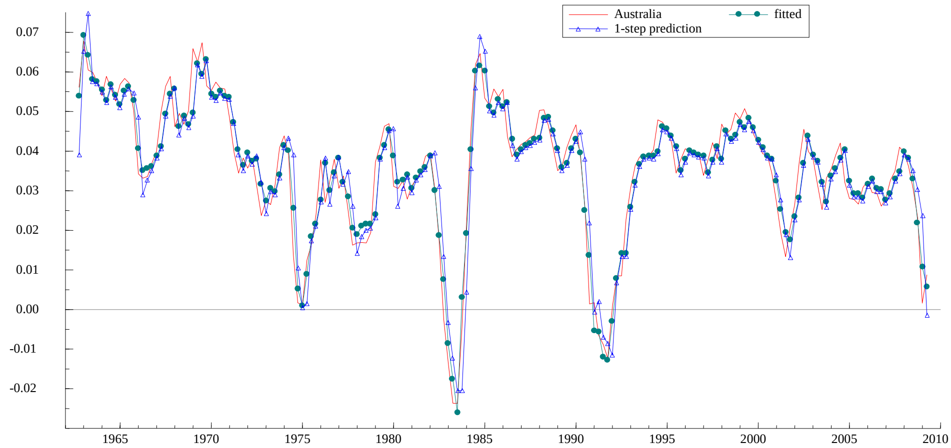


Mexico

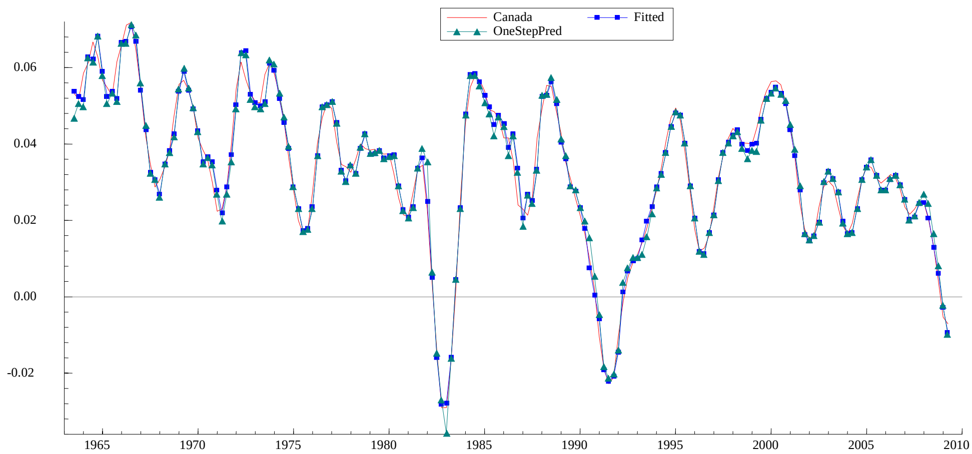


Uruguay

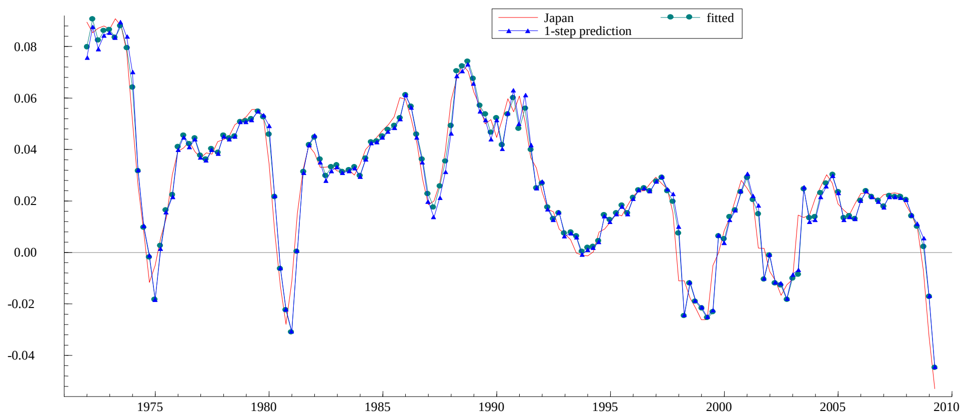
Figure 3: Smoothed and Filtered Probabilities of a Recession



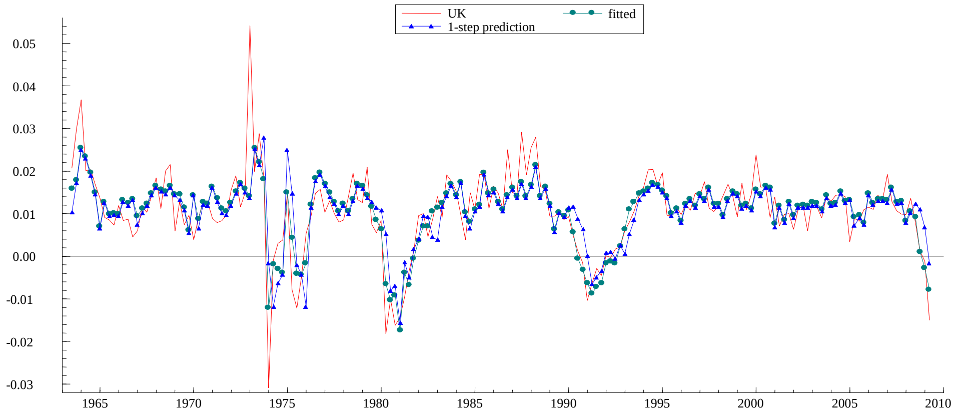
Australia



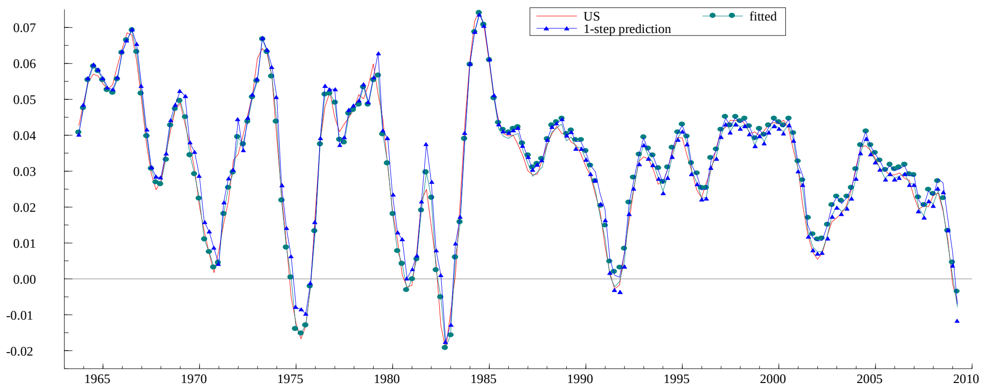
Canada



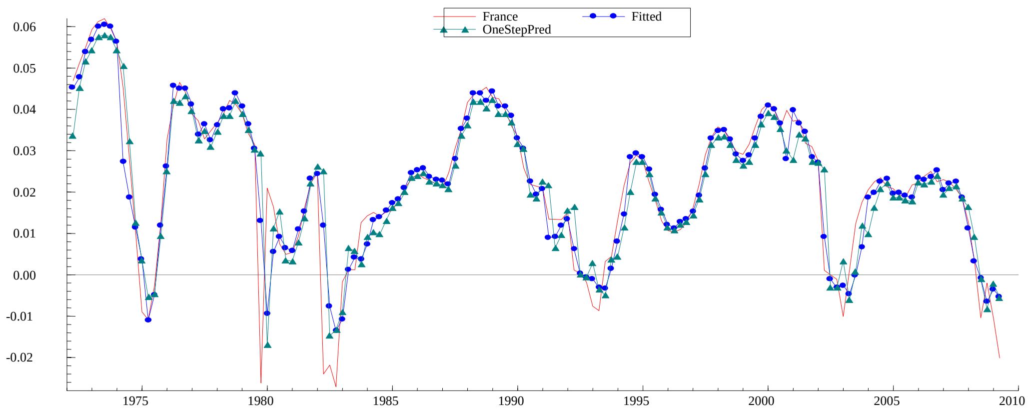
Japan


UK
1-step prediction
fitted
0.05
0.04
0.03
0.02
0.01
0.00
-0.01
-0.02
-0.03
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010

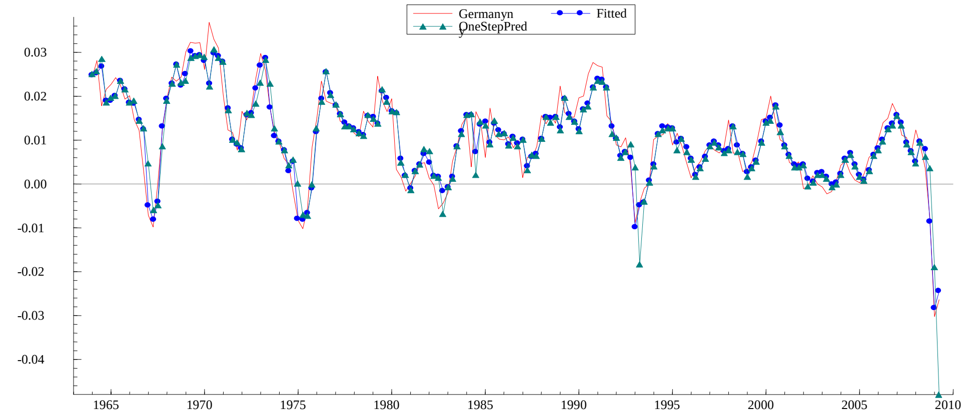
UK


US
1-step prediction
fitted
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
-0.01
-0.02
1965
1970
1975
1980
1985
1990
1995
2000
2005
2010

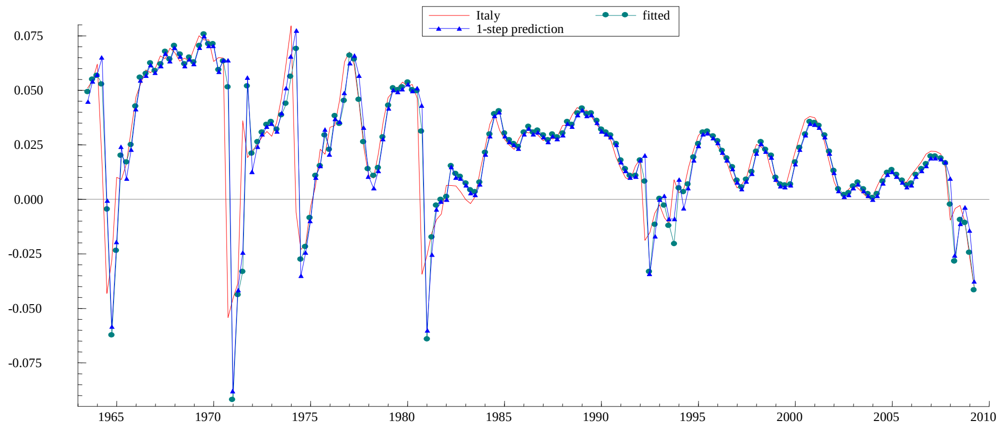
US


France
OneStepPred
Fitted
0.06
0.05
0.04
0.03
0.02
0.01
0.00
-0.01
-0.02
1975
1980
1985
1990
1995
2000
2005
2010

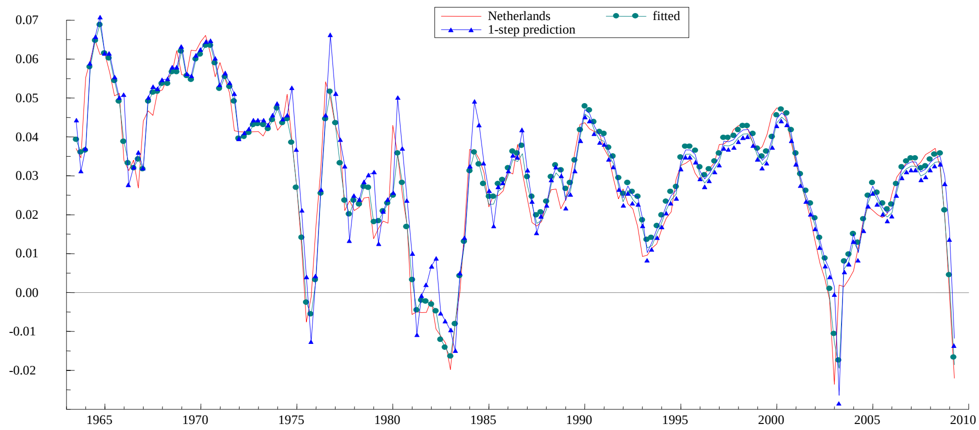
France



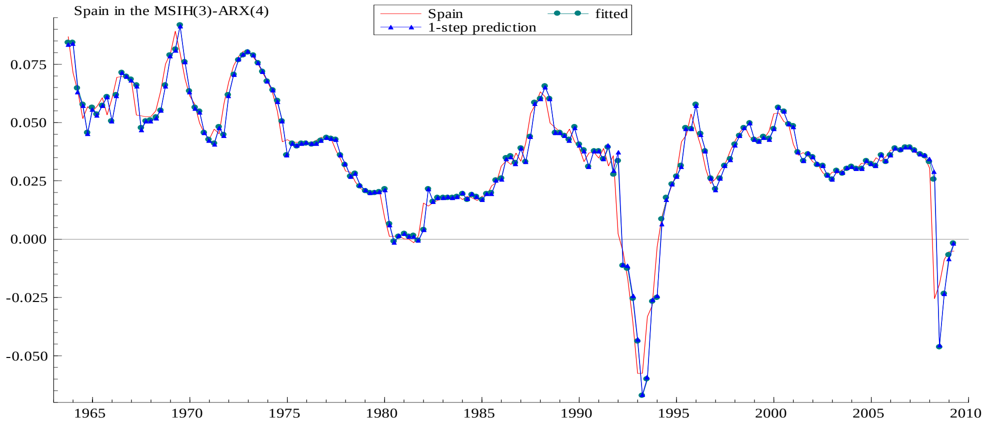
Germany



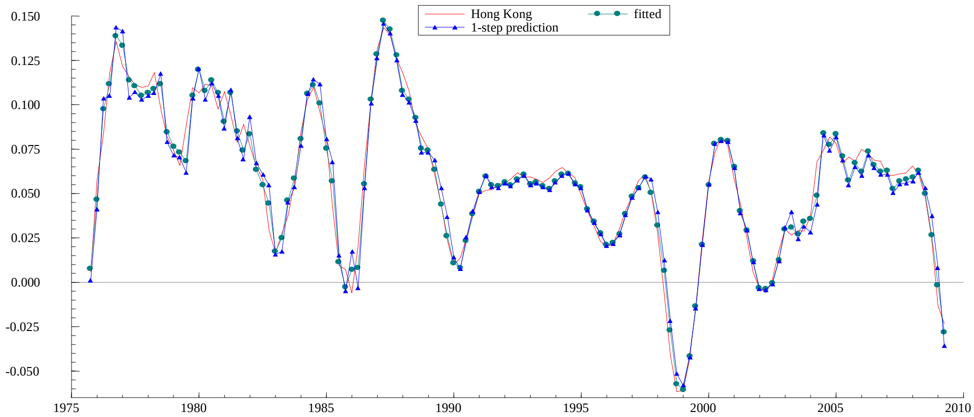
Italy



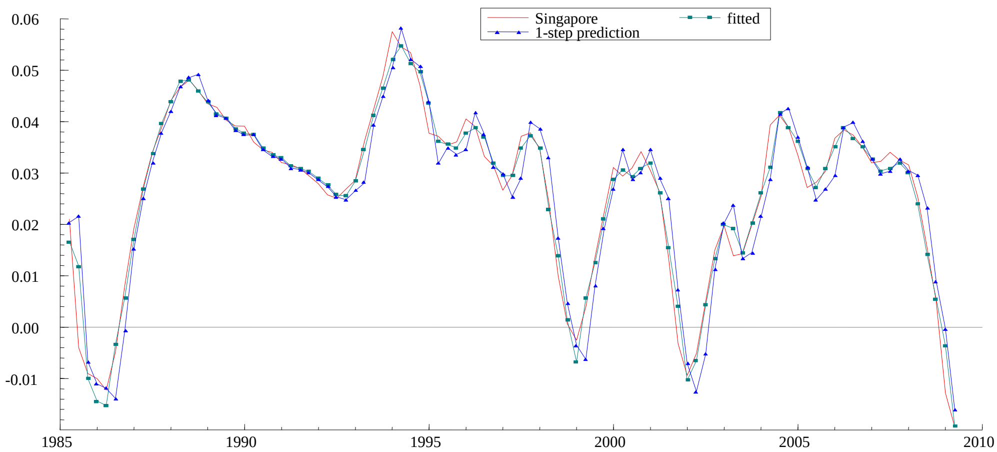
Netherlands



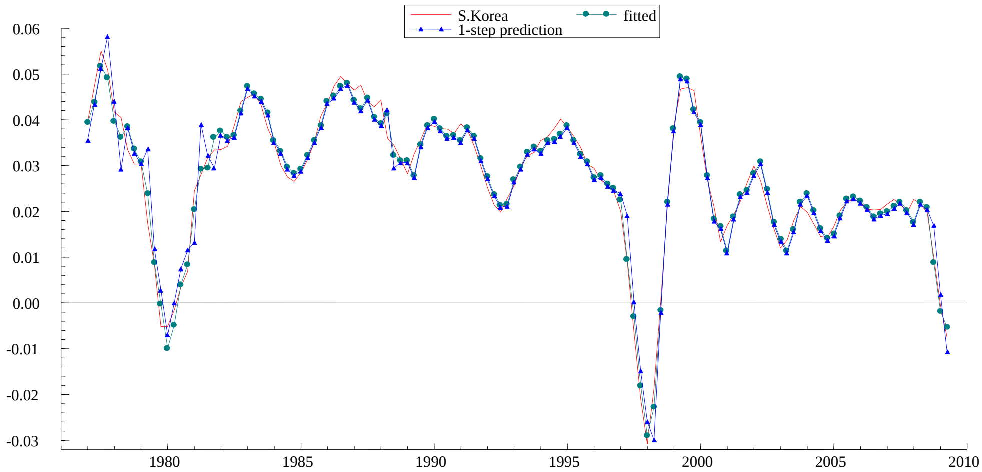
Spain



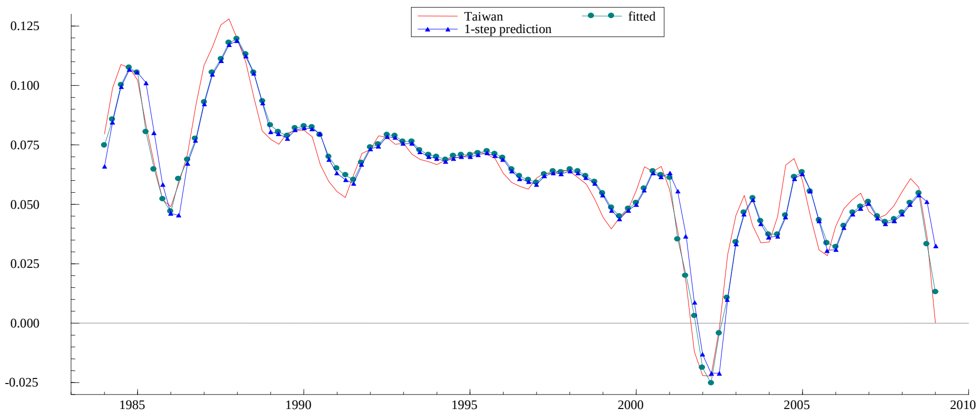
Hong Kong



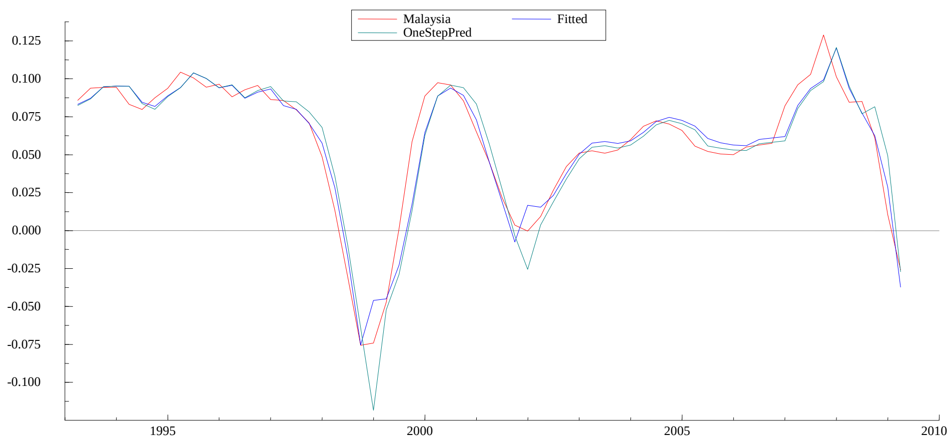
Singapore



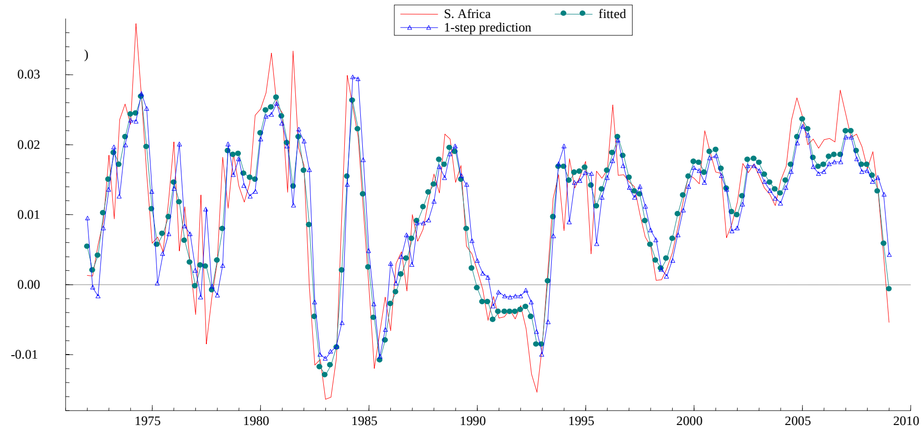
S. Korea



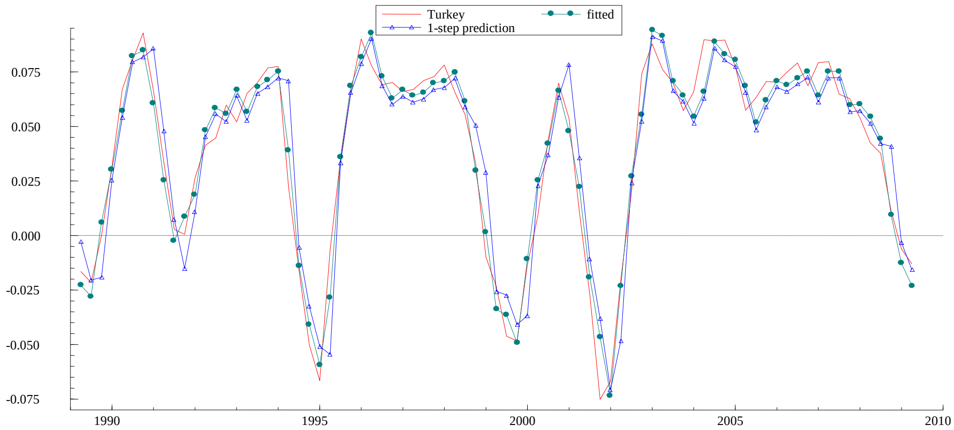
Taiwan



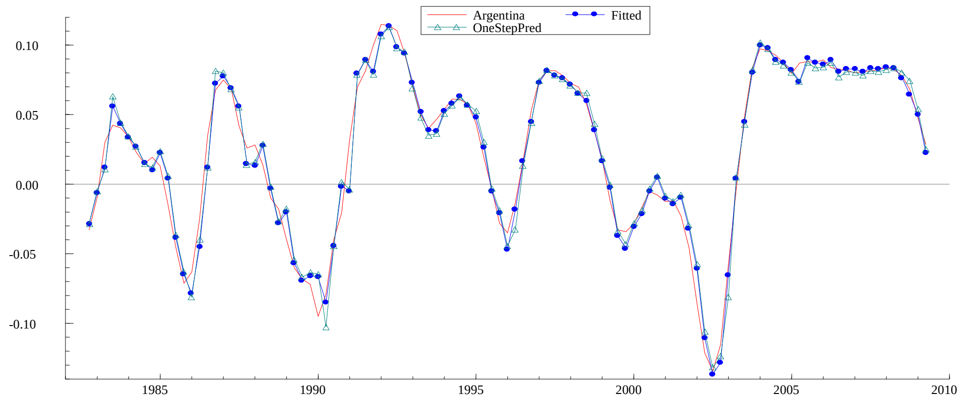
Malaysia



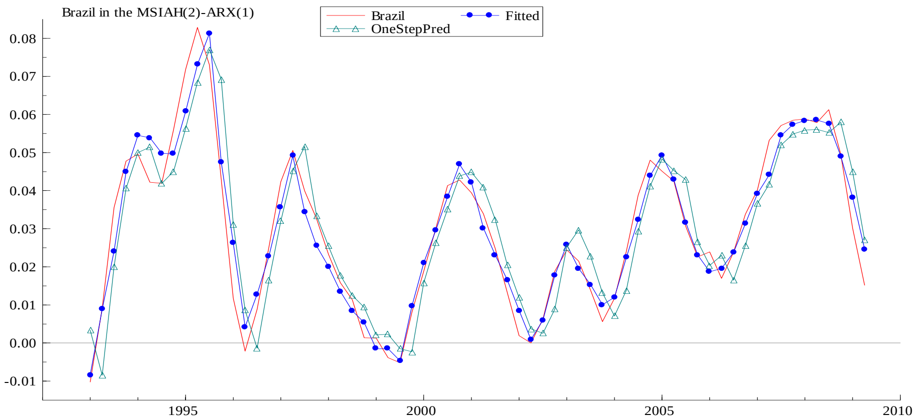
S. Africa



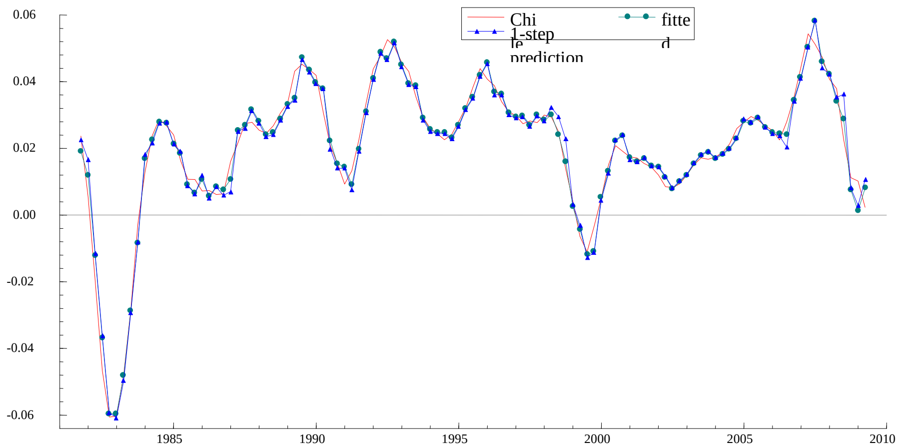
Turkey



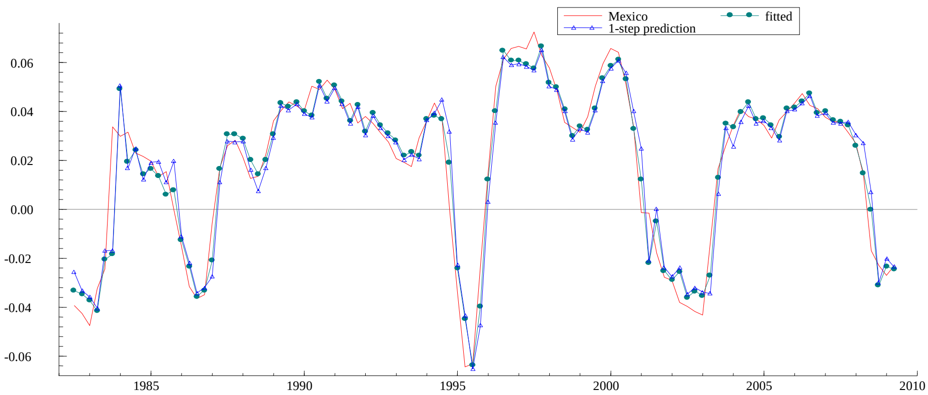
Argentina



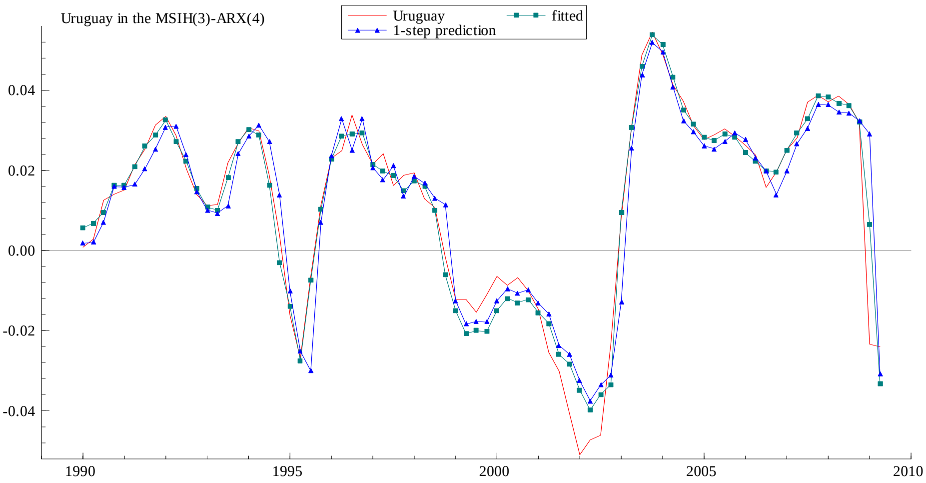
Brazil



Chile



Mexico



Uruguay

Figure 4: Fitted and One-step Ahead Predicted Values of Each Series