Business Cycles around the Globe: A Regime-switching Approach

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Abstract

This paper characterizes business cycle phenomena in a sample of 27 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. 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, nonparametric modeling.
JEL Codes: E32, E37, C32.

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1 Introduction

There have been different approaches proposed for analyzing business cycle phenomena. Perhaps the earliest and best known approach is due to Burns and Mitchell (1946) and the National Bureau of Research (NBER). 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. An alternative approach is due to Sargent and Sims (1977), who formulated the dynamic factor model as a way of defining a multivariate measure of the business cycle. 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. In their pioneering work, Kydland and Prescott (1982) identified business cycles in terms of the cyclical time series behavior of the main macroeconomic variables and their co-movement with cyclical output. They proposed a canonical Real Business Cycle (RBC) model with productivity shocks and intertemporal substitution motives as a way of explaining the cyclical behavior of the main economic aggregates. A final approach to modeling 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 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).[1]

In a recent application, Benczur and Ratfai (2009) use the Real Business Cycle framework pioneered by Kydland and Prescott (1982) to examine the business cycle characteristics of 62 countries worldwide. Specifically, they fit a basic small open economy real business cycle model with permanent and transitory shocks along the lines in Aguiar and Gopinath (2007) and Garcia-Cicco, Pancrazi and Uribe (2006) to identify country-specific productivity processes and to generate the stylized facts of business cycles.[2] As in the study by Benczur and Ratfai (2009), we take as our starting point the experiences of 27 individual countries as a way of uncovering the sources of cyclical fluctuations in industrialized and emerging market economies. We use a simple Markov switching approach for each country in our dataset. 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.

[1] Other applications include Altug (1989), who 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) and Chauvet (1998) combine the Markov switching model with the dynamic factor framework to account for the changing pattern of economic variables over the business cycle. Kim and Nelson (1999b) 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.)

[2] Other papers that seek to understand how cyclical fluctuations in developing and emerging market economies differ from those in industrialized countries include Köse, Otrok and Whiteman (2003) and Köse, Otrok, and Prasad (2008). These papers examine the sources of macroeconomic fluctuations based on a dynamic factor framework that seeks to identify global, regional and national factors driving cyclical fluctuations.

There is a large literature that has examined the stylized facts of business cycles. Backus and Kehoe (1992) analyze the properties of historical business cycles for 10 developed countries using a century-long dataset up to the 1980's whereas Stock and Watson (2000) use data on 71 variables to characterize U.S business cycle phenomena over the period 1953-1996. 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). 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. over the period 1960-2002. Canova, Ciccarelli, and Ortega (2007) use a panel VAR setting to uncover the factors underlying cyclical fluctuations in the G-7 countries. Artis, Marcellino, and Proietti (2003) discuss alternative approaches to dating euro area business cycles.

There also exist a few applications of the various approaches to characterizing business cycles in various developed and emerging market contexts. Taylor, Sheperd and Duncan (2005) estimate an MS-AR model for Australian GDP using Bayesian Markov Chain Monte Carlo simulation methods. Girardin (2005) examines GDP growth-cycles for 10 East Asian countries including Japan, China, and S. Korea using regime-switching techniques. 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. 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. Unlike much of the recent literature on business cycles, this approach has much more in common with the work of Burns and Mitchell at the NBER. Harding and Pagan (2002b) adapt the nonparametric Bry-Boschan model for determining business cycle turning pints to a quarterly level. They 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 27 developed and emerging market 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

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

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).

The remainder of this paper is organized as follows. 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

Hamilton (1989) proposed a simple nonlinear framework for modeling economic time series with a permanent component and a cyclical component as an alternative to a stationary linear autoregressive model. In his framework, recessions are due to permanent negative shocks. Another type of business cycle asymmetry is due to Kim and Nelson (1999a). This is known as the "plucking model" of business cycles. Here recessions occur as temporary deviations from the long-run level of GDP as occasional "plucks" whereas expansions reflect permanent shocks.[4] In this paper, we consider the approach followed by Hamilton (1989) for describing the evolution of country-specific GDP. While the plucking model of cyclical fluctuations may have some relevance for developed countries which experience deviations from a long-run trend, the crises and sharp recessions experienced by the emerging market economies suggest that negative shocks may have a permanent effect on the level of real output. We leave for future research models which allow for both permanent and transitory asymmetric effects.

2.1 A Markov regime switching model

To describe the Hamilton (1989) model, let $\tilde{y}_t$ denote the level of some series, say log(GDP), and n_t and $\tilde{z}_t$ denote its permanent or 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

$$y_t = \alpha_0 + \alpha_1 s_t + z_t = \mu(s_t) + z_t, \tag{2.2}$$

where $y_t = \tilde{y}_t - \tilde{y}_{t-1}$ and z_t is a stationary $AR(p)$ process in (log) differences. As Lam (1990) has shown, relaxing the assumption that the cyclical component has a unit root significantly complicates the implementation of the Markov switching model. In particular, it implies that

[4] The evidence in favor of either forms of asymmetry is mixed. For example, Koop and Potter (1999) find evidence in favor of the Hamilton (1989) model using Bayesian methods while Sichel (1993, 1994) and Beaudry and Koop (1999) provide support for the peak-reverting model. Kim and Piger (2002) propose a framework which allows for infrequent asymmetric transitory shocks which come from a Markov process as well as continuous transitory symmetric shocks.

the past history of the Markov switching variable must be incorporated in the calculation of the log-likelihood function.

Assuming that $A(L)z_t = \epsilon_t$ where $\{\epsilon_t\}$ is an i.i.d $N(0, \sigma^2)$ process and applying $A(L)$ to both sides of (2.2) yields:

$$y_t - \mu(s_t) = \sum_{j=1}^{p} a_j(y_{t-j} - \mu(s_{t-j})) + \epsilon_t. \tag{2.3}$$

In his application, Hamilton (1989) considered a univariate 2-state Markov switching model in the mean with a lag polynomial order four. In this case, the unobserved state is defined as $s_t = 1, 2$, where $s_t = 1$ denotes a "contraction" and $s_t = 2$ an "expansion".

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:

$$y_t = \nu(s_t) + \phi(s_t)\delta(t) + \sum_{j=1}^{p} a_j(s_{t-j})y_{t-j} + \sigma(s_t)\epsilon_t, \tag{2.4}$$

where $\{\epsilon_t\}_{t=0}^{\infty}$ is an i.i.d. process such that $\epsilon_t | s_t \sim N(0, \sigma(s_t)^2)$. 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.[5] Hamilton's (1989) model is just a special case of the model in equation (2.4) where only the mean $\mu(s_t)$ is subject to changes in regime. This specification may be useful where a change in regime leads to a one-time change in the mean of the process.

In this expression, $\delta(t)$ denotes a deterministic polynomial in time with a potentially regime-switching coefficient. In their peak-reverting model of GDP growth, Kim and Nelson (1999a) assume that both the trend component of real GDP and its growth rate follow a random walk. As in Kim and Nelson (1999a), this implies that GDP is an I(2) rather than I(1) process but they find that the estimated variance of the growth rate process is small. This is similar to the approach in Stock and Watson (2005), who control for secular changes in the growth rates of GDP of the G-7 countries for the post-war period by allowing for stochastic growth in the average growth rates. Kim and Piger (2002) allow for a break in the average growth rate of the common stochastic trend in their model to capture the productivity slowdown that has been known to occur sometime in the 1970's. In our case, we allow the permanent component to vary with the Markov switching process as we simultaneously allow for secular changes in the average growth rates of GDP according to a deterministic polynomial in time.

The dynamics of the $\{y_t\}$ process is completely determined 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

$$Pr(s_{t+1} = j | s_t = i, s_{t-1} = k, \ldots) = Pr(s_{t+1} = j | s_t = i) = p_{ij}, \quad i, j = 1, \ldots, m, \tag{2.5}$$

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

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

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

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. 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 $t = 1, 2, \ldots, T$. The estimation of the Markov switching model follows Hamilton (1989, 1990). Krolzig (1997) provides an extension to the multivariate case.

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

$$E(D) = \sum_{k=1}^{\infty} kPr(D = k) = \frac{1}{1 - p_{11}}. \tag{2.6}$$ [6]

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

The peaks (or troughs) of business cycles may be determined as $Pr(s_t = 1|\psi_T) > 0.5$ (or conversely, as $Pr(s_t = 1|\psi_T) < 0.5$), 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: $m^* = argmax_m Pr(s_t = m|\psi_T)$.[7]

2.2 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.[8] 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 1-3 show the smoothed growth rates for the GDP series for the developed and emerging countries in our sample.

[6] 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, $E(D) = \sum_{k=1}^{\infty} kPr(D = k) = 1/(1 - p_{11})$.

[7] 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.

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

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

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

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 Austria, France, Germany, Italy, the Netherlands, Finland, Greece, Spain, and Sweden. 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 East Asian economies consisting of Hong Kong, Malaysia, Singapore, S. Korea and Taiwan plus three emerging market economies - Israel, 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 (2.4) for a sample of 27 industrial and emerging market economies. 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.

Tables 2 through 5 present our estimates of the MS-AR model for the countries in the different groups while Table 6 provides a summary description of the properties of the solutions. On the whole we find that the business cycle characteristics of the Anglophone countries and a core set of EU countries comprising Austria, France, Germany, Italy, and the Netherlands are similar in terms of the expected growth rates of real output in the different phases and the durations of these phases. However, the remaining EU countries tend to display more idiosyncracies in their cyclical responses. Considering the emerging market economies, the business cycle characteristics of a group of developed East Asian countries have more in common with those of developed countries than other emerging economies. Furthermore, even among well defined country groupings such as the Latin American countries, individual countries appear to display highly heterogeneous responses to similar international and regional conditions. Third, perhaps not surprisingly, we also find that institutional, historical and political factors often tend to be a key determinant of business cycles in emerging market economies.

3.1 The Anglophone countries plus Japan

Table 2 shows the estimated regime-specific intercepts $\nu(s_t)$, standard deviations $\sigma(s_t)$, and autoregressive coefficients $\alpha_i(s_t)$, $i = 1, \ldots, p$ 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.[9] 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. The models for Japan, the U.K., and the U.S feature longer lag lengths.

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. Our results are, on the whole, consistent with the earlier evidence provided for countries such as Canada, the UK, and the US. As in Girardin (2005), we choose a 3-regime model for Japan.

Table 6 uses the results in Table 2 to estimate expected output growth in recessions and expansions and to derive the durations of the different phases of the business cycle. Table 6 shows that the growth rates for all the counties in question display negative trends over the sample period. The largest (in absolute value) and significant trends occur for Japan and the US. After accounting for such trends, our results suggest that Australia, Canada, the UK and the US all tend to suffer output declines during a recession. This effect is the largest for Canada. However, even after accounting for the secular decline in expected growth, Japan displays positive growth during a contraction.[10] Second, the expected growth rates of output during an expansion tend to be fairly similar across countries such as Australia, Canada, Japan

[9] See Appendix B.

[10] In the parlance of business cycle analysis, we can say that Australia, Canada, the UK and the US are predicted to experience classical cycles during which there is an absolute decline in real output. By contrast, Japan experiences growth cycles, as noted by Girardin (2005), in that the “low” growth regime does not entail an expected output loss. The Markov switching model is thus able to capture both types of contractions depending on the sign of expected output growth in the “low” growth regime. This point is also noted by Goodwin (1993).

and the US. By contrast, a mature economy such as the UK tends to grow at a modest rate during expansions. These growth rates are also consistent with the earlier evidence.[11] The expected rate of output growth during the "high" growth regime for Australia shows that the third regime appears to pick up a few unusual growth episodes in the data. Finally we note the volatility of the shocks in the "low" growth and "high" growth phases are larger than those in the "normal" growth state for Canada and Japan whereas for Australia, the volatility of the shocks in the "low" growth regime tends to be larger than that in the "normal" and "high" growth regimes.

Table 6 shows that the duration of recessions for countries such as Australia and the US range around three quarters. By contrast, Canada, Japan, and the UK experience longer recessions. The duration of recessions for Canada can be attributed to the experience of a severe and lengthy recession in 1990, a fact which has also noted by Bodman and Crosby (2000). In the case of Japan, this finding reflects the extended period of low growth and stagnation in the 1990's. The filtered and smoothed probabilities of the different regimes are provided in Figure 4. 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. We can identify accurately the double-dipped shape of the recession over the 1980-1982 period for the US. Nevertheless, there are some differences in the experiences of the individual countries. For one, Japan's recession in the 1990's comes later than the other countries in this group. In addition to the recession that follows the bursting of the asset market bubble in the early 1990's, Japan also experiences recessions in the latter part of the 1990's and also in the early 2000's. In his study, Girardin (2005) identifies the entire period 1995-2000 as a recession whereas our dating identifies two recessions separated by around a year between 1997-2003. September 11, 2001 and its aftermath lead to real output declines for all the industrialized countries listed in Table 2. However, the filtered and smoothed probabilities reported in Figure 4 are not estimated to be greater than 0.5 for Australia, Canada, the UK, or the US for this period, although the evidence for a recession in 2001 is greater for the US than the other three countries.[12]

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. To understand this result, we note that Table 2 reports the *expected duration* of the regimes in the model. By contrast, Figure 4 provides the regime classifications based on a rule such as $Pr(s_t = 1|\psi_T) > 0.5$ for a recession (or $Pr(s_t = 1|\psi_T) < 0.5$ for an expansion). As Harding and Pagan (2002a) note, the dating rule implicitly defines a new random variable, say ξ_t, that takes on value of one when $Pr(s_t = 1|y_T) > 0.5$ and zero otherwise.[13] Nevertheless, we note that the implied sequence

[11]To illustrate this fact, consider the expected growth of output for the US during expansions. This is estimated to be 5.83% before controlling for trends. If we consider the expected growth rate of output 80 quarters into the sample (which corresponds to the early 1980's), then we find that US GDP grows about 4.38% during expansions. This is comparable to the findings of Layton and Smith (2000) for their 2-regime model of GDP, for which they report an annualized growth rate of 4.7% during expansions.

[12]This is in contrast for the NBER chronology for the US, as we show in Table 7 below. The discrepancy arises because the NBER business cycle dating makes use of employment and other sources of data in addition to GDP data.

[13]Harding and Pagan (2002a) make use of an approximation to the original probability model for real output growth to compute the filtered and smoothed probabilities defined as $Pr(s_t = 1|\psi_t)$ and $Pr(s_t = 1|\psi_T)$. They

of probabilities for the US capture the long expansion that occurred between the end of 1982 to the middle of 1990 as well as the expansion between the beginning of 1991 and the end of 2001. Finally, Figure 4 shows that countries such as Canada and Japan experienced episodes 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). Canada also experiences "high" growth episodes in the late 1980's and early 1990's as well as during the early 2000's.

3.2 The EU countries

In this grouping, we allow for countries that are typically viewed as "core" EU countries such as Austria, France, Germany, Italy and the Netherlands as well as countries in the "periphery" such as Greece and Spain. We also allow for countries such as Finland and Sweden that display more heterogeneity in their country-specific characteristics. In this regard, our sample constitutes more diverse sample than is typically considered.

Table 3 shows that 2-regime models are selected for all EU countries except Italy and Spain.[14] The linear specifications are all strongly rejected. Table 6 shows that the estimate trends in GDP growth rates are negative for all the countries except Greece, Spain and Sweden. Furthermore, aside from France, these negative trends are estimated to be significantly different from zero. The positive trend in GDP growth for Greece is also estimated to be significantly different from zero but it is useful to view this result with some care in light of the fact that Greece implemented a 26% increase in its GDP in 2006 to account for the effects of the informal economy. Table 3 shows that Finland, Greece, Italy, the Netherlands, Spain, and Sweden have negative intercepts in the contractionary regime. However, such negative intercepts are estimated to be significantly different from zero only for Finland, Greece and Sweden. Considering jointly the effects of the trends and expected output growth rates reported in Table 6, we conclude that there is less evidence for real output declines during a contraction for most of the core EU countries such as Austria, France, Germany, Italy and the Netherlands compared to the Anglophone countries.[15] The magnitude of the expected declines in output during recessions are the greatest for Italy and Spain but these effects are not estimated to be significantly different from zero over the sample period. By contrast, Finland, Greece and Sweden experience significant absolute output declines during recessions. Second, if we restrict our attention to countries such as Austria, France, Germany, Italy, and the Netherlands, the duration of recessions and expansions are similar to those for the Anglophone countries plus Japan. By contrast, the duration of recessions for the remaining EU countries is typically longer. Greece also displays long expansions, and Italy and Spain experience regimes of "high" growth. However, the longest expansions occur for Finland and Sweden. Finally, we observe that the greatest volatility in output growth occurs for Italy and Spain during their "low" regime.

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use a Kalman Filter algorithm to compute these quantities and compare the Hamilton-type dating rule to the NBER dating rule discussed in Section 3.5. They find that the Hamilton-type rule tracks fairly well the NBER turning points but typically involves a wider window.

[14]For a discussion of the selection procedure, see Appendix B.

[15]The estimates for Germany are slightly anomalous in that the expected growth rates of output are 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.

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 in line with our findings. They also argue that contractions tend to be milder in the EU countries. Their results are comparable to ours if we limit our sample to such core countries as Austria, France, Germany, Italy and the Netherlands. However, this conclusion changes if we include countries from the periphery such as Greece and Spain or with more heterogeneous characteristics such as Finland and Sweden. Clearly, how one views the EU countries has an effect on the conclusions regarding their common characteristics. As we discussed above, the duration of contractions and expansions also shows variability depending on the set of EU countries that are considered.

Figure 4 shows the regime classification for the EU countries 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 that have the requisite data 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 Figures 1 and 2 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 2 we observe that Austria, France, Germany, Italy, and Spain as well as the UK suffer declines in growth during the period 1991-1993.[16] We can also discuss the experience of the EU countries since 2001. We can identify recession for Austria during 2001-2002 and 2003 and for France during 2002-2003 but none for the remaining EU countries. We also note the idiosyncracies in the experiences of the different countries. Both Italy and Spain experience episodes of "high" growth in the late 1960's, the late 1980's and also in the period between 1995-2000 and even later for Italy. Clearly the dynamics of growth for these countries is quite different relative to that for France or Germany. In the case of Greece, we observe recurrent recessions and volatility in the pre-1995 period, and relative quietude thereafter. As the recent Greek debt crisis has shown, however, the latter period may just have been a figment of the data. For Finland and Sweden, we observe a deep recession that is associated with the Nordic banking crisis of 1990's but stable growth thereafter.

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

[16] 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.

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. As in Artis, Krolzig, and Toro (2004), the 3-regime model for Italy nearly misses recession of 1992. Table 8 below shows that we identify only a single-year recession for Italy in 1992.

Perhaps that model that performs least well in terms of business cycle dating is the one that is estimated for Germany. 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. 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 2, we observe that there is a long episode of low growth and stagnation for the German economy lasting until 2005.[17] 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.

3.3 The 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 the relatively more developed East Asian countries, Hong Kong, Malaysia, 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, Malaysia, and Taiwan.[18] All of the developed East Asian countries display significant negative trends in GDP growth. However, even after controlling for the decline in expected growth rates over time, Table 6 shows that Hong Kong, S. Korea and Taiwan display positive expected growth in the "low" growth state, as noted by Girardin (2005). Likewise, they display high rates of growth in the "normal" growth regime. The average duration of recessions for the developed East Asian countries is 3.74 quarters while the average duration of the "normal" growth regime around eighteen quarters, which are comparable to those for the developed countries. The East Asian economies also display episodes of "high" growth averaging six and a half quarters. The estimated model for Malaysia differs from the models for the remaining East Asian countries in terms of the sharp differences in expected rates of output growth and trends across recessions and expansions. However, this is most likely due to the short length of the sample which includes the 1997 East Asian crisis and 2007-2008 financial crisis. Finally, all four developed East Asian countries tend to display greater volatility during the "low" growth regime.

Figure 4 displays the filtered and smoothed probabilities of the different regimes for the

[17] 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).

[18] As we discuss in the Appendix, we cannot reject a 2-regime model based on the LR test for Hong Kong but choose the 3-regime model because it is better able to capture the business cycle dynamics in Hong Kong.

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 experience recessions and output declines during 2000-2001 due to slowdown in US and regional economic growth. As various commentators have argued, declining exports that affected their manufacturing sectors lay at the root of such recessions. Finally, all of the East Asian countries are affected by the financial crisis that erupted in the US in 2007-2008. Thus, we observe that openness in trade and financial linkages are important channels for the transmission of the international business cycles in recent decades. However, even among the East Asian economies, there are differences in cyclical dynamics depending on the degree and nature of openness. S. Korea and Taiwan display more stable growth interrupted by some major recessions over the sample period whereas Hong Kong and Singapore experience growth slowdowns and episodes of "high" growth that oftentimes alternate with each other.

Table 4 also presents results for three countries that are typically counted among the emerging market economies, but with varying degrees of development - Israel, S. Africa, and Turkey. First, we note that we can select 2-regime models for S. Africa and Turkey. This is in line with evidence obtained by Moolman (2004) for South Africa, and by Taştan and Yıldırım (2008) for Turkey.[19] However, we find that a 3-regime model fits best for Israel over the sample period. The chosen models for these countries clearly reflect their idiosyncratic experiences. S. Africa suffers a small decline in output during recessions but it also features low growth during expansions. This is no doubt due to the regime of trade sanctions against the S. African state until the dismantling of apartheid in 1994. After that period, Figure 3 shows that S. Africa experiences more stable growth. Figure 4 also shows that the estimated model for S. Africa tracks fairly well the recessions of 1982, 1984-1986, 1990-1992 and 2008. Turkey experiences short-lived recessions amid relatively short expansions. It tends to suffer sharp declines in output during recessions but also experiences strong subsequent recoveries. These characteristics are no doubt due to the severe financial and banking crises that Turkey suffered during 1994-1995, 1999-2000 and 2001-2002 as well as reflecting the effects of the First Gulf War in 1991 and the Marmara earthquake in 1999. By contrast, the cyclical behavior of the Israeli economy is characterized by three different regimes. Even after controlling for the positive trend in output growth, we note that the Israeli economy tends to suffer absolute output declines during the "recessionary" regime. This is most likely due to the effect of the demand-driven recession in Israel during 2000-2001, which arose from a worsening security situation due to the *intifada* and reflected the impact of global economic conditions. More interestingly, Israel experiences a "high growth" regime which is also characterized by high volatility. From Figure 4, we observe that this regime corresponds to the period following the end of Israel's hyperinflationary episode in the mid 1980's to the end of the 1990's when Israel experienced growth in its high-tech sector and an influx of skilled immigrants from Eastern Europe. Since 2003, we observe a regime of "normal" growth in Israel that is characterized by positive growth and low volatility.

[19] 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.

3.4 The Latin American countries

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. The trends in expected output are estimated to be positive for Chile, Mexico, and Uruguay. For Argentina and Brazil, the trends are positive in the "low" growth regime and negative in the "normal" growth regimes. However, even after controlling for such trends, recessions in Latin American countries are associated with significant output declines, with the largest declines occurring for Argentina and Brazil. 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.[20] Aside from Brazil, all of the Latin American countries experience the greatest volatility in output growth during the recessionary regime.[21]

The Latin American countries have been the topic of much study. Issues such as the 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. 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 cyclical dynamics. 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.[22] 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. 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. Brazil's 1999 recession is due to the eventual failure of the Real Plan adopted in 1994 and the ensuing devaluation of its currency.[23]

[20] 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.

[21] The volatility of output growth in Brazil in the recessionary and expansionary states are equal but this is most likely due to the small sample size.

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

[23] 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

Finally, we observe the impact of the global financial crisis of 2007-2008 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 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. 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.[24]

3.5 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 directly 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.[25]

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 $\{\Delta_2 y_t > 0, \Delta y_t > 0, \Delta y_{t+1} < 0, \Delta_2 y_{t+2} < 0\}$. These conditions yield the turning points for classical cycles, as defined by the NBER methodology. 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. Using the BBQ algorithm, we obtained

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.

[24] 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.

[25] 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.

the business cycle peaks and troughs for all the countries in our sample and 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 loss (gain) of a recession (expansion). Let $C_{Ti} = 0.5 D_i \times A_i$ denote the triangle approximation to the cumulated movements of the series over a business cycle phase, C_i be the actual movement defined as $C_i = 0.5 A_i + \sum_{s=1}^{d-1} \Delta_s y_{t+s}$, 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 7 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 18 quarters versus nearly 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 4.04 and 13 quarters for the core EU countries, the BBQ algorithm estimates these magnitudes to be 3.38 and 39 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 Italy. 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%. If we exclude Malaysia, 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 18 quarters. The amplitude of expansions for the developed East Asian countries of Hong Kong, Singapore, and S. Korea 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 developed 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 sharp and deep recessionary experiences that we documented earlier.

4 Business cycle dating

In this section, we examine the business cycle dating properties based on the Markov switching approach. In studies that have employed the Markov switching methodology, 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.[26] We use this approach as a way of further characterization of business cycle behavior for developed and emerging market economies.

4.1 Business cycle chronologies

In Table 8, 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

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

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±1 and Coin±2. In Table 8, we calculated Coin±1 and Coin±2 for the developed and emerging economies.[27] Thus, allowing for one (two) quarter of maximum discrepancy, the average coincidence between our dating and ECRI dating for the developed economies is 54% (71%). 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%).

We can use the results in Table 8 to gain further understanding about the nature of recessions worldwide. The first global recession for the countries in our sample corresponds to the effects of the oil shock of 1973-1975. However, not all countries are affected in the same way. Figure 1 shows that Canada and Spain do not experience absolute declines in output during this period. Hence, no recessions are identified for them by ECRI or our estimated Markov switching model. Furthermore, an oil exporter such as Australia experiences a recession during this period due to factors other than oil prices increases, such as a decline in its trade with the US and Europe. As a way of providing further evidence on the global nature of cyclical fluctuations, we examine the average value of the pairwise correlations of the "low growth" regime probabilities across all countries for the period of the first oil shocks. This is estimated to be 0.7993 during 1974-1975 using information on all countries that have the required data.[28]

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 2 shows that Spain lived through a prolonged growth slowdown during this period but did not experience any substantial absolute output decline. 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 8 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. 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

[27] In this table, we also report the incidence of single years being identified as "low" growth regimes or recessions. The BBQ algorithm rules this out by construction. In the MS model, this may occur because there are some remaining outliers in the data.

[28] An alternative way to examine the presence of worldwide recessions is to compute the fraction of countries that are known to be in a recession over a time period. This approach is followed by the IMF *World Economic Outlook*.

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 1980, we find this to be 0.7859. However, this magnitude increases to 0.8311 when we consider the period 1983. Hence our findings are in line with those of Köse, Otrok, and Whiteman (2003), who find the recession of the 1980's was, if anything, as severe as the recession of the mid 1970's when a larger sample countries that includes the developing countries is considered.

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. 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. 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.[29]

Turning to the developing economies, we note that 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.[30] 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 0.7579 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 0.5513 on average, indicating a significant but weaker effect relative to earlier recessions. Evidently the 1990's are a period of regional and local crises that

[29]The lagged response of the business cycle in the euro area is also noted by Giannone, Lenza, and Reichlin (2008), who provide new evidence regarding the characteristics of aggregate and national cycles in a forty-year time period that also includes the EMU.

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

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, partly due to policy measures to overcome such contagion.[31]

The 2001 recession in the US that follows on the back of the September 11 terrorist attacks is associated with growth slowdowns or 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 0.4501. However, 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 0.9548 during 2007-2008.[32] From Table 8, 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".[33] Our detailed narrative in the previous section suggests that examining the confluence of economic activity 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 the previous section, we sought to identify the incidence of worldwide recessions using the behavior of the estimated recession probabilities. In this section, we further examine the behavior of the pairwise correlations of the recession probabilities over longer periods.

In Table 9, we present results of this analysis for the developed countries over the periods 1970-2009 and 1990-2009 and for the emerging economies over the period 1990-2009, respec-

[31] 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.

[32] The IMF *World Economic Outlook* (2009) suggests that highly synchronized recessions tend to be longer and deeper than other recessions and further, that"developments in the United States often play a pivotal role both in the severity and duration of these recessions"

[33] As an example, Lumsdaine and Prasad (2003) construct a measure of the common component of international business cycles by considering 17 OECD countries including the US, Japan, Canada and a group of EU countries 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..

tively. We also consider the correlations between the developed and emerging economies over the period 1990-2009. Some noteworthy observations are evident from Panel I of Table 9. For one, Australia's cyclical responses are not correlated with any of the developed economies except Canada over the longer sample. 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. 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, with Japan. Panel II of Table 9 shows that there have been some interesting changes in these relations over time. For one, the correlations of Australia have tended to decrease with all of the developed countries included in our study. In the case of Canada, the correlations with the US have tended to increase during the 1990-2009 period, no doubt as a result of the impact of NAFTA. There is also a slight increase in synchronization with the UK economy. The case of Japan also deserves special mention. The correlations in Panel II of Table 8 capture the lack of any apparent synchronization of the Japanese economy with other developed countries. 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. Fourth, we observe that the UK economy has become more synchronized with an economy such as Spain during the 1990-2009. This is mostly likely due to the more robust growth that countries such as the UK and Spain experienced over this period.

Our last finding from Panel II of Table 9 shows that the core EU economies including France, Germany, Italy, the Netherlands and also Spain have become more synchronized with each other in the 1990-2009 period. Some have taken these last findings as signifying the existence of a "European" business cycle (see, for example, Artis, Krolzig and Toro, 2005.) However, we also observe the correlations of all of the core EU economies with the US have tended to stay constant and in some cases, increase during the 1990-2009 period. 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. Second, we find that the EU countries also display significant differences in their interlinkages. The Nordic economies such as Finland and Sweden do not appear to be synchronized with the core EU countries. Nor do they show any significant cyclical pattern with the remaining developed countries such as Japan, the UK or the US.

Panel III of Table 9 shows the cross-correlations among the emerging economies plus the U.S. First, 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. 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. Furthermore, we observe large cross-correlations between countries such as Brazil, on the one hand, and Hong Kong, Singapore, and Turkey, on the other, suggesting that the contagionary effects of crises during the 1990's may also figure as an important source of fluctuations in the emerging economies. Finally, in Panel IV of Table 9, we examine the cross-correlations of the emerging economies with the remaining developed economies. First, with the exception of Japan, it is difficult to talk about any discernible pattern of cross-correlation of the developed economies with the emerging economies. For the case of Japan, we observe some large cross-correlations with the East Asian economies such as Hong Kong, Singapore and Taiwan, reflecting the trade and financial interlinkages among these economies.

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. Perhaps what does drive the "world business cycle" are those periods that feature large common disturbances that are associated with worldwide recessions. These typically correspond to the oil shocks of the 1970's and 1980's and other global factors surrounding them as well as the financial crisis of 2007-2008. Our discussion suggests, however, that there may also exist a whole host of idiosyncratic factors 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, as we have.[34] For example, the Nordic countries have more in common with each other than they do with the remaining EU countries. 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 differences 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.

[34] See, for example, Giannone, Lenza and Reichlin (2008).

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 our study, we have documented significant differences in the business cycle behavior for individual countries. 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 2007-2008. 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 focus of business cycle studies, our analysis has revealed that the transmission of financial disturbances are more important in the period following the 1980's and especially since the 1990's. Our study also illustrates how recurring recessions and crises experienced during one period determines policy responses in later periods. In this regard, Diamond and Rajan (2009) have commented that the lessons learned by emerging market economies in previous crises were instrumental in their avoiding some of the worst effects of the 2007-2008 financial crisis.

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.

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 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, Israel, 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.

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 (2.4). 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. 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.[35]

[35]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 1-3 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 ("the Great Moderation") 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 as well as emerging economies across the sample.

In our application, we considered specifications which allowed for jointly estimated trends in GDP growth rates as described by equation (2.4).[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. 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 based on the likelihood ratio (LR) even when one considers modified critical values such as the Davies upper bound or the simple adjustment proposed by Ang and Bekaert (2002).[37]

The specifications reported in the text were chosen on the basis of model selection criteria such as AIC, HQC, and SIC.[38] As a further check on the choice of regime, we also considered the results of a modified LR test. The above table shows the LR test statistics and the associated degrees of freedom for the countries in our study.[39] We also examined the properties of the

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

[37] It is easy to illustrate this 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 $\nu(s_2), \sigma(s_2), p_{22}$ 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.

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

[39] To implement this test, we need to adjust the degrees of freedom as proposed by Ang and Bekaert (2002). Thus, the corrected degrees of freedom is equal to the number of restrictions obtained from constraining the

	LR Tests of 2 versus 3 Regimes						
	Australia	Canada	Japan	UK	US	Austria	France
LR	27.5886	10.5202	6.4508	47.9452	34.7586	15.7644	54.7856
df	6	8	6	5	5	5	10
	Germany	Italy	Netherlands	Finland	Greece	Spain	Sweden
LR	7.877	49.111	50.8332	20.008	3.0732	38.5696	15.6094
df	9	6	5	6	5	6	6
	Hong Kong	Singapore	S. Korea	Taiwan	Malaysia	Israel	S. Africa
LR	11.5094	24.8478	3.3146	14.5032	18.0316	41.2194	37.3834
df	6	6	5	6	6	6	5
	Turkey	Argentina	Brazil	Chile	Mexico	Uruguay	
LR	4.1976	14.9978	34.4256	58.252	13.3044	58.2292	
df	5	10	7	6	6	6	

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

standardized residuals, the general fit of the model, and how well the models performed in regime classification.

Results:

- The Anglophone countries plus Japan: The table shows that we fail to reject the 2-regime model for Canada and Japan while the LR test tends to indicate rejection of the 2-regime models for the remaining countries. Based on the LR test results and other model selection criteria, we chose the 3-regime model for Australia. Despite our failure to reject a 2-regime model, we also chose the 3-regime model for Canada because the 2-regime model failed to capture the cyclical behavior of the Canadian economy over the sample period. In particular, it attributed the entire 1990's to a recessionary state and estimated an implausibly large output drop during recessions. We discuss the case of Japan further below.

  For the UK and the US, the LR test results indicate a rejection of the 2-regime model. However, the 3-regime model for the UK 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 little significance on the overall results. Second, we found some *a priori* evidence against the 2-regime model for the US based on the LR test. However, the 3-regime model with AR(4) lag polynomial tend to display lack of convergence of the EM algorithm as well as problems of instability in the parameter estimates and very poor regime classification.

- EU countries: We fail to reject the 2-regime model Germany and Greece based on the LR test and other model selection criteria. We also selected a 3-regime model for Italy and Spain based on the LR test. For another group of the European economies, we find some *a priori* evidence against the 2-regime model based on the modified likelihood ratio criterion. These include Austria, Finland, France, the Netherlands, and Sweden. However, based on the Schwarz criterion (SC) which favors more parsimonious specifications,

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.

	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

the 2-regime model was selected for Austria, France, Finland and Sweden. We also chose a 2-regime model for the Netherlands based on the performance of the diagnostic tests and business cycle dating properties.

- East Asia plus other emerging economies: We fail to reject the 2-regime models for S. Korea, Hong Kong and Turkey based on the LR test and other model selection criteria. Likewise, the LR test selects a 3-regime model for Israel. However, we selected a 3-regime model for Hong Kong since the 2-regime specification estimates attribute long durations for recessions. There is evidence against the 2-regime models for Malaysia, Taiwan and S. Africa based on the LR test. However, the evidence against the 2-regime model is not overwhelmingly strong for the case of Taiwan or Malaysia. In the case of Taiwan, the coefficients for the third regime are not estimated to be significantly different from those for the second regime while there is parameter instability in the 3-regime model for Malaysia. Finally, an MSIH(3)-ARX(4) specification for S. Africa would not converge and other 3-regime alternatives had much worse diagnostics.

- Latin American countries: The 2-regime models are rejected for Chile and Uruguay but not for Argentina based on the modified LR critical values. There exists some evidence against the 2-regime model for the remaining countries. However, the evidence is not overwhelmingly strong in the case of Mexico whereas for Brazil the 3-regime specification displays parameter instability. Hence, we chose 2-regime models for Mexico and Brazil as well.

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.

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.[40] 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. Despite the existence of such moving average terms, we find that more than half of our estimated specifications display no or little evidence of serial correlation based on the Ljung-Box statistics.

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

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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	1.14	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	1.39	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)			
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

	Austria	**France**	**Germany**	**Italy**	**Nether.**	**Finland**	**Greece**	**Spain**	**Sweden**
Regime-specific intercepts									
$\nu(s_1)$	0.41	0.41	0.53	-0.45	-0.02	-0.61	-1.27	-0.21	-0.68
	(4.05)	(0.48)	(3.05)	(-0.42)	(-0.11)	(-3.61)	(-13.0)	(-0.53)	(-2.40)
$\nu(s_2)$	1.26	0.53	0.58	1.09	1.36	0.30	0.02	0.11	0.20
	(9.11)	(8.17)	(8.81)	(7.94)	(12.22)	(4.28)	(0.22)	(2.30)	(2.47)
$\nu(s_3)$	-	-	-	1.50	-	-	-	0.17	-
				(27.98)				(1.67)	
Regime-specific standard deviations									
$\sigma(s_1)$	0.30	1.30	0.40	4.55	0.50	0.59	0.42	2.05	0.97
$\sigma(s_2)$	-	0.23	-	0.80	-	0.33	-	0.15	0.35
$\sigma(s_3)$	-	-	-	0.32	-	-	-	0.58	-
Regime-specific autoregressive coefficients									
Regime 1									
α_1	0.80	0.39	1.93	1.26	0.99	0.53	-0.04	1.31	0.52
	(17.40)	(2.14)	(6.04)	(19.42)	(17.12)	(6.58)	(-0.42)	(21.31)	(6.55)
α_2	-	0.07	-1.71	-0.40	0.03	0.25	0.21	-0.25	0.33
		(0.40)	(-2.46)	(-4.64)	(0.34)	(3.12)	(2.69)	(-2.90)	(3.89)
α_3	-	-0.04	0.82	-0.08	-0.03	0.58	0.44	-0.04	0.44
		(-0.22)	(1.19)	(1.27)	(-0.30)	(7.28)	(5.84)	(-0.55)	(5.14)
α_4	-	-0.05	-0.25	0.01	-0.22	-0.51	-0.21	-0.06	-0.56
		(-0.36)	(-0.91)	(0.27)	(-3.18)	(-6.70)	(-2.75)	(-1.83)	(-7.33)
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)						
Log-likelihood	315.5247	590.4634	723.4166	666.1549	673.7418	444.7505	415.0447	719.6142	439.8913
AIC	-8.0136	-7.7109	-7.7848	-7.0560	-7.2146	-8.0324	-7.5008	-7.6788	-7.9424
LR statistic†	22.9161	203.3562	24.9777	314.3530	30.7508	20.4394	20.9241	152.0584	29.0854

Austria 1990:1-2009:2; France 1972:2-2009:2; Germany 1964:1-2009:2; Italy 1963:3-2009:2, Netherlands 1963:3-2009:2; Finland 1981:2-2009:2;

Greece 1982:1-2009:2; Spain 1963:4-2009:2; Sweden 1982:1-2009:2.

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	**Malaysia**	**Singapore**	**S. Korea**	**Taiwan**	**Israel**	**S. Africa**	**Turkey**
Regime-specific intercepts								
$\nu(s_1)$	1.94	1.75	-0.49	0.73	2.29	-3.14	0.01	-0.99
	(1.40)	(0.09)	(-2.53)	(8.88)	(9.63)	(-2.66)	(0.07)	(-3.51)
$\nu(s_2)$	2.88	2.48	0.52	1.75	3.48	-0.10	0.99	2.48
	(17.88)	(0.40)	(3.80)	(23.66)	(26.86)	(-0.08)	(6.02)	(6.03)
$\nu(s_3)$	3.70	-	1.16	-	-	1.41	-	-
	(3.28)		(10.90)			(1.38)		
Regime-specific standard deviations								
$\sigma(s_1)$	0.93	1.18	0.62	0.25	0.83	0.17	0.53	1.00
$\sigma(s_2)$	0.36	-	0.24	-	0.47	0.18	-	-
$\sigma(s_3)$	0.91	-	0.30	-	-	0.65	-	-
Regime-specific autoregressive coefficients								
Regime 1								
α_1	1.36	1.29	0.86	1.22	1.50	0.42	0.52	0.94
	(11.28)	(1.18)	(22.42)	(17.04)	(29.86)	(4.39)	(5.74)	(8.54)
α_2	-0.54	-	-	-0.19	-0.77	0.11	0.25	-0.16
	(-3.42)			(-1.57)	(-14.47)	(1.04)	(2.62)	(-1.11)
α_3	0.02	-	-	-0.40	-	0.02	-0.05	-0.14
	(0.16)			(-3.31)		(0.18)	(-0.55)	(-1.07)
α_4	-0.11	-	-	0.07	-	-0.31	-0.20	-0.13
	(-1.44)			(1.14)		(-4.05)	(-2.53)	(-0.17)
Regime 2								
α_1	-	0.83	-	-	-		-	-
		(2.24)						
Log-likelihood	455.4175	188.1739	385.4914	562.0746	399.8304	-75.9183	540.8202	231.7237
AIC	-6.4951	-5.4295	-7.6596	-8.4935	-7.3052	1.6742	-7.1251	-5.4747
LR statistic[†]	49.1968	37.1839	69.0343	42.3220	26.6566	52.5057	8.3570	17.5413

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

Israel ; 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)				
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	Austria	France	Germany
$\mu(s_1)$	-2.96	**-1.48**	3.36	-0.30	0.87	**2.09**	0.65	**2.68**
$\mu(s_2)$	**4.80**	**4.18**	**5.85**	**1.40**	**5.83**	**6.36**	**5.50**	**1.96**
$\mu(s_3)$	**12.99**	**5.83**	**8.81**	-	-	-	-	-
$\mu_\tau(s_1)$	-0.0076	0.0104	**-0.0262**	-0.0008	**-0.0181**	**-0.0195**	-0.0044	**-0.0414**
$\mu_\tau(s_2)$	-	**-0.0105**	-	-	-	-	**-0.0197**	**-0.0116**
$\mu_\tau(s_3)$	-	**-0.0373**	-	-	-	-	-	-
D_1	3.15	6.56	8.38	6.42	3.74	4.35	5.62	4.04
D_2	23.06	14.86	13.31	28.65	15.95	9.45	14.07	23.66
D_3	3.40	9.76	10.80	-	-	-	-	-

	Italy	Nether.	Finland	Greece	Spain	Sweden
$\mu(s_1)$	-2.15	-0.13	**-4.07**	**-2.12**	-4.94	**-2.52**
$\mu(s_2)$	**5.21**	**5.89**	**2.00**	0.03	**2.59**	**0.70**
$\mu(s_3)$	7.18	-	-	-	4.00	-
$\mu_\tau(s_1)$	**-0.0401**	**-0.0208**	**-0.0007**	**0.0002**	0.0024	0.0029
$\mu_\tau(s_2)$	-	-	-	-	-	-
D_1	2.94	2.92	8.88	5.27	6.31	5.66
D_2	8.62	15.13	41.49	19.20	7.19	43.23
D_3	21.58	-	-	-	9.86	-

	Hong Kong	Malaysia	Singapore	S. Korea	Taiwan	Israel	S. Africa	Turkey
$\mu(s_1)$	7.12	-6.03	**-3.94**	**2.54**	**8.54**	**-4.088**	0.02	**-2.64**
$\mu(s_2)$	**10.58**	14.08	**4.18**	**6.09**	**13.00**	-0.132	**2.06**	**6.61**
$\mu(s_3)$	**13.60**	-	**9.32**	-	-	1.84	-	-
$\mu_\tau(s_1)$	-0.0447	**0.1294**	-0.1029	**-0.0240**	**-0.0482**	**0.0068**	-0.0230	-0.0013
$\mu_\tau(s_2)$	-	**-0.0317**	-	-	-		-	-
$\mu_\tau(s_3)$	-	-	-	-	-		-	-
D_1	2.74	5.74	4.77	3.29	4.16	5.02	5.16	4.12
D_2	18.18	12.17	5.66	22.39	26.65	9.45	10.45	11.52
D_3	9.20	-	3.73	-	-	26.79	-	-

	Argentina	Brazil	Chile	Mexico	Uruguay
$\mu(s_1)$	**-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**
$\mu_\tau(s_1)$	**0.0682**	0.0457	**0.0168**	0.0041	**0.0078**
$\mu_\tau(s_2)$	-0.0066	-0.0281	-	-	-
$\mu_\tau(s_3)$	-	-	-	-	-
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

"Bold" denotes significant at the 5% level or less.

Table 6: Business Cycle Characteristics: The Markov Switching Approach

		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
		Austria	**France**	**Germany**	**Italy**	**Netherlands**
Duration (quarters)	PT	2.000	3.500	3.800	3.000	4.000
Duration (quarters)	TP	32.000	64.000	29.600	31.800	41.000
Amplitude (%)	PT	-0.19	-1.100	-0.860	-0.790	-1.370
Amplitude (%)	TP	18.850	37.370	20.790	24.300	28.400
Excess (%)	PT	-1.3417	2.620	2.063	0.796	6.979
Excess (%)	TP	13.2396	-5.574	0.314	-5.423	-6.730
		Finland	**Greece**	**Spain**	**Sweden**	
Duration (quarters)	PT	8.500	4.000	4.000	6.000	
Duration (quarters)	TP	58.000	14.750	36.000	43.667	
Amplitude (%)	PT	-7.480	-3.720	-1.880	-2.350	
Amplitude (%)	TP	50.100	11.730	29.080	29.040	
Excess (%)	PT	12.2134	1.5172	8.774	29.9408	
Excess (%)	TP	2.0661	-4.5105	14.273	-2.8035	
		Hong Kong	**Malaysia**	**Singapore**	**S. Korea**	**Taiwan**
Duration (quarters)	PT	3.000	3.500	2.500	4.000	3.000
Duration (quarters)	TP	31.000	18.500	28.333	39.000	26.000
Amplitude (%)	PT	-2.760	-4.160	-1.650	-7.100	-2.360
Amplitude (%)	TP	51.380	30.920	52.00	52.290	30.68
Excess (%)	PT	5.635	-2.792	-12.068	5.376	-8.481
Excess (%)	TP	-3.951	0.138	0.444	-11.131	4.421
		Israel	**S. Africa**	**Turkey**	**Argentina**	**Brazil**
Duration (quarters)	PT	2.667	7.667	3.600	8.500	2.667
Duration (quarters)	TP	50.500	28.000	12.400	11.750	9.667
Amplitude (%)	PT	-0.72	-3.160	-4.430	-11.330	-0.63
Amplitude (%)	TP	37.600	22.830	20.35	16.640	9.56
Excess (%)	PT	-0.0167	20.136	-0.127	17.556	-7.60
Excess (%)	TP	12.7978	6.632	6.157	-9.3885	-8.68
		Chile	**Mexico**	**Uruguay**		
Duration (quarters)	PT	5.500	4.500	9.500		
Duration (quarters)	TP	46.500	21.750	13.000		
Amplitude (%)	PT	-5.570	-4.000	-12.540		
Amplitude (%)	TP	48.96	19.660	14.890		
Excess (%)	PT	-2.21	7.493	14.402		
Excess (%)	TP	26.56	0.377	-6.827		

Table 7: Business Cycle Characteristics: The Harding-Pagan Approach

NBER	**CEPR**	**ECRI**	**US†**	**ECRI**	**Australia**	**ECRI**	**Canada**	**ECRI**	**Japan**
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			73:4-75:1	73:4-75:2
80:1-80:3		80:1-80:3	79:2-80:4						80:1-82:1
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	92:1-93:3	90:3-91:1	90:3-91:2	90:2-91:4	90:3-91:4	90:1-92:1	90:3-93:1	92:2-94:1	90:4-92:1
								97:1-99:3	97:4-99:4
01:1-01:4		01:1-01:4						00:3-03:2	01:1-03:3
08:1-09:1		07:4-	08:3-09:1		08:4-09:2	08:1-	08:2-09:1	08:2-	08:4-09:2
			8/13 = 73%		6/6 = 100%		3/5=60%		4/9 = 44%
			9/13 = 82%		6/6 = 100%		4/5 = 80%		5/9 = 56%
ECRI	**UK**	**ECRI**	**Austria**	**ECRI**	**France†**	**ECRI**	**Germany**	**ECRI**	**Italy†**
						66:1-67:2	67:1-68:2	64:1-65:1	64:2-65:2
								70:4-71:3	70:4-71:4
	73:4-74:1							74:2-75:2	74:1-74:2
74:3-75:2	75:1-75:4			74:3-75:2	74:2-75:1	73:3-75:3	72:4-75:4		
79:3-81:2	80:2-82:3			79:3-80:2	79:4-80:4	80:1-82:4	82:1-82:3	80:2-83:2	80:4-81:1
				82:2-84:4	82:2-84:2				
90:2-92:1	90:2-92:4	92:2-93:2	92:3-93:4	92:1-93:3	92:2-93:4	91:1-94:2	92:4-93:1	92:1-93:4	
		95:2-96:1	95:4-96:4						
		01:1-01:4	01:1-02:1	02:3-03:2	02:2-03:4	01:1-03:3			
			03:2-03:4						
08:2-	08:4-09:2		08:4-09:1	08:1-	08:1-09:2	08:4-	08:4-09:1	07:3-	08:1-09:2
	1/6 = 17%	3/6=50%	3/6= 50%		8/11 = 73%		3/11=27%		6/11 = 54%
	3/6 = 50%	5/6=83%	5/6= 83%		11/11 = 100%		3/11 =27%		8/11 = 72%
Nether.†	**Finland**	**Greece**	**ECRI**	**Spain**	**Sweden**	**Hong Kong†**	**Malaysia**	**Singapore**	
			66:1-66:1						
74:4-75:3									
76:4-77:3									
80:2-81:1			80:1-84:2			82:1-83:1			
82:1-83:1		82:1-82:3							
84:2-85:1		85:4-86:3				84:4-86:1		85:3-86:2	
	89:3 - 91:1	91:4-93:1	91:3-93:4	92:1-94:1	91:4-92:1	89:3-90:1			
						97:4-99:1	97:2-98:4	98:2-99:1	
						03:2-03:3	00:4-01:4	01:3-02:1	
08:4-09:2	07:4-09:2	08:4-09:2	08:1-	08:2-09:2	07:4-09:2	08:4-09:1	08:4-09:2	08:2-09:2	
				2/5 = 40%					
				3/5 = 60%					
ECRI	**S. Korea**	**ECRI**	**Taiwan**	**Israel**	**ECRI**	**S. Africa**	**Turkey**		
						72:1-72:2			
						74:4-75:1			
					76:2-77:4	76:2-77:1			
	77:4-78:1				77:1-81:4	77:3-77:4			
79:1-80:4	79:2-80:4			82:3-82:4	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	01:3-03:3			01:1-02:1		
08:3-	08:4-09:1	08:1-	07:4-08:2	09:1-09:2	08:2-	08:4-09:2	08:4-09:2		
	4/7=57%		5/11 = 45%			1/3 = 33%			
	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			
		4/10 = 40%			5/13 = 38%				
		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; Austria 95:1-95:1; France 91:1-91:1; Italy 92:2-92:2; Netherlands 63:3-63:3, 66:1-66:1, 79:1-79:1, 03:1-03:1; Greece 89:3-89:3, 90:2-90:2;Hong Kong 77:1-77:1; Israel 99:2-99:2.

Table 8: Business Cycle Dating

I. 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	-0.2329	0.1773	0.3300	0.2695	0.4888	0.4208	1.0000			
Italy	-0.1637	0.0023	0.1373	0.5100	0.3889	0.5900	0.4990	1.0000		
Nether.	-0.3047	-0.0150	0.2463	0.4045	0.3320	0.4106	0.3200	0.4000	1.0000	
Spain	0.0094	0.0569	-0.0733	0.4196	0.4028	0.3553	0.2800	0.4890	0.5321	1.0000

II. Contemporaneous Correlations of the Recession Probabilities for Developed Countries, 1990-2009

	Australia	Canada	Japan	UK	US	Austria	France	Germany	Italy	Nether.	Finland	Greece	Spain
Australia	1.0000												
Canada	0.0949	1.0000											
Japan	-0.2809	-0.1622	1.0000										
UK	-0.0090	0.1131	-0.1194	1.0000									
US	-0.8544	0.4428	0.1785	0.0153	1.0000								
Austria	-0.1741	-0.1261	0.4344	-0.0977	-0.1667	1.0000							
France	-0.3160	0.0226	0.2749	0.2203	0.4637	0.1970	1.0000						
Germany	-0.8446	-0.1297	0.2009	0.0466	0.4870	-0.2060	0.5115	1.0000					
Italy	-0.3200	-0.1000	-0.1500	0.4500	0.5008	-0.0801	0.5001	0.5569	1.0000				
Nether.	-0.4339	0.0444	0.2546	0.2783	0.3904	-0.0733	0.5275	0.5335	0.1181	1.0000			
Finland	0.1899	0.2113	-0.0523	0.2901	0.2159	-0.0737	-0.0300	-0.0042	-0.0280	-0.0517	1.0000		
Greece	-0.1613	-0.1391	0.6824	-0.1004	-0.1428	0.2839	-0.0355	-0.6338	-0.0123	-0.0882	-0.0331	1.0000	
Spain	-0.2428	0.6818	-0.1415	0.5767	0.4249	-0.0745	0.5219	0.4072	0.7770	0.1583	0.0751	-0.1484	1.0000
Sweden	-0.2748	-0.2826	0.8960	-0.1585	-0.2816	0.4806	-0.0622	-0.5390	-0.1004	-0.1538	-0.0628	0.6202	-0.1423

III. Contemporaneous Correlations of the Recession Probabilities for Emerging Economies, 1990-2009

	Hong Kong	Malaysia	Singapore	S. Korea	Taiwan	Israel	S. Africa	Turkey	Argentina	Brazil	Chile	Mexico	US
Hong Kong	1.0000												0.2022
Malaysia	0.3049	1.0000											0.3374
Singapore	0.5065	0.5670	1.0000										0.4646
S. Korea	0.4598	0.4506	0.4574	1.0000									-0.0645
Taiwan	-0.2418	0.5495	0.1471	-0.1780	1.0000								0.0349
Israel	0.7332	0.2739	-0.1728	-0.1500	0.1497	1.0000							-0.0949
S. Africa	0.6736	0.3355	0.5878	0.3565	-0.2193	-0.1728	1.0000						0.5117
Turkey	0.0355	-0.2160	0.4024	-0.1693	0.2077	0.0405	0.1347	1.0000					0.1897
Argentina	0.0883	-0.3399	0.4137	-0.2341	0.4237	0.2401	0.1368	0.4801	1.0000				0.1796
Brazil	0.3996	-0.1893	0.3274	0.1750	-0.0792	0.1988	0.2025	0.3050	0.3455	1.0000			0.0024
Chile	0.0737	0.5970	0.2602	-0.0718	0.3068	-0.0929	0.2568	-0.0328	-0.0825	-0.2310	1.0000		0.6385
Mexico	-0.1064	-0.1107	0.3264	-0.2217	0.4607	0.4579	0.0454	0.3793	0.5238	0.0512	0.2584	1.0000	0.4015
Uruguay	-0.1545	-0.4305	0.0620	-0.2268	0.5240	0.1530	-0.2361	0.2289	0.7825	0.1877	-0.2405	0.4857	-0.0732

IV. Contemporaneous Correlations of the Recession Probabilities for Emerging Economies and Developed Countries, 1990-2009

	Australia	Canada	Japan	UK	Austria	France	Germany	Italy	Nether.	Finland	Greece	Spain	Sweden
Hong Kong	-0.2003	-0.5071	0.6148	-0.0673	-0.2186	0.1824	0.2691	-0.0113	0.1395	-0.0517	-0.0886	-0.0026	-0.1538
Malaysia	-0.2050	-0.8408	-0.0539	-0.0795	-0.1299	0.0957	0.3198	0.2111	0.0298	0.3479	-0.0856	-0.0771	-0.1446
Singapore	-0.4276	-0.3599	0.5825	-0.0623	-0.0161	0.1536	0.3231	0.1909	0.1026	0.3528	-0.0812	0.1121	-0.1423
S. Korea	0.0676	-0.4913	0.1845	-0.0568	0.2263	-0.1510	-0.0137	-0.1611	-0.0635	-0.0603	-0.0595	0.0373	-0.0823
Taiwan	-0.1184	0.1156	0.3650	-0.1089	0.0060	0.1717	-0.0603	0.0221	-0.0814	0.1839	-0.1062	-0.0298	-0.1952
Israel	0.2401	0.5014	-0.1180	0.0405	0.2263	-0.0929	-0.0838	0.4441	0.1056	-0.0702	-0.0727	0.1342	-0.1510
S. Africa	-0.5198	-0.4317	0.3877	0.3627	-0.0402	0.1895	0.5901	0.3008	0.2576	0.0700	0.2942	0.4350	0.2488
Turkey	-0.3612	0.0781	0.4145	-0.0833	-0.0977	-0.1492	0.2441	-0.1009	0.0381	0.2901	-0.1005	-0.0845	-0.1585
Argentina	-0.2693	0.1632	0.6002	-0.1441	-0.1741	0.0760	0.1674	-0.1112	0.1076	0.1899	-0.1613	-0.1696	-0.2748
Brazil	-0.1693	0.0873	0.4131	-0.1857	-0.0635	-0.0717	0.1255	-0.1995	-0.0319	0.1274	-0.2211	-0.1965	-0.2110
Chile	-0.4604	-0.4057	-0.0519	-0.0253	-0.1286	0.4489	0.4300	0.5667	0.1934	-0.0300	-0.0355	0.4662	-0.0622
Mexico	-0.4148	0.2333	0.2677	-0.1112	0.0282	0.4825	0.2200	0.1000	0.3695	0.2823	-0.1196	0.2479	-0.1962
Uruguay	-0.0548	0.4139	0.4897	-0.1376	-0.1667	0.1503	-0.0870	-0.2009	0.1647	0.2158	-0.1428	-0.2618	-0.2816

Table 9: Contemporaneous Correlations of the Recession Probabilities

	Australia	Canada	Japan	UK	US	Austria	France	Germany	Italy
BDS Test	0.0025	0.0019	0.0009	0.0044	0.0110	0.0016	0.0086	-0.0035	0.0014
	[0.621]	[0.704]	[0.830]	[0.496]	[0.043]	[0.806]	[0.181]	[0.598]	[0.791]
LB(2)	3.1454	0.8507	0.8812	0.3271	2.3626	2.1331	5.1462	0.8146	3.3534
	[0.207]	[0.654]	[0.644]	[0.849]	[0.307]	[0.344]	[0.076]	[0.665]	[0.187]
LB(4)	29.968	33.321	20.988	6.3692	58.459	4.3274	11.365	4.0395	5.5207
	[0.000]	[0.000]	[0.000]	[0.173]	[0.000]	[0.364]	[0.023]	[0.401]	[0.238]
LB(12)	37.697	47.482	26.793	12.754	83.064	16.281	16.672	13.537	13.884
	[0.000]	[0.000]	[0.002]	[0.387]	[0.000]	[0.179]	[0.162]	[0.331]	[0.308]
Normality	2.195	0.563	3.606	1.2250	3.063	0.9914	11.648	12.364	1.8329
	[0.333]	[0.755]	[0.165]	[0.5420]	[0.216]	[0.6091]	[0.003]	[0.002]	[0.400]
	Netherlands	Finland	Greece	Spain	Sweden	Hong Kong	Singapore	S. Korea	Taiwan
BDS Test	0.0065	0.0026	-0.0014	0.0031	0.0013	0.0019	0.00004	0.0061	0.0120
	[0.882]	[0.650]	[0.801]	[0.659]	[0.838]	[0.723]	[0.995]	[0.248]	[0.247]
LB(2)	0.1981	4.5958	0.3620	1.0222	0.0820	0.3252	3.3077	0.5753	0.2703
	[0.906]	[0.100]	[0.834]	[0.600]	[0.960]	[0.850]	[0.191]	[0.750]	[0.874]
LB(4)	11.041	7.4693	4.7823	4.8856	2.2128	33.988	15.652	11.043	9.8685
	[0.026]	[0.113]	[0.310]	[0.299]	[0.697]	[0.000]	[0.004]	[0.026]	[0.043]
LB(12)	19.962	14.492	16.087	19.232	7.4580	44.467	29.595	16.028	18.730
	[0.068]	[0.270]	[0.187]	[0.083]	[0.826]	[0.000]	[0.003]	[0.190]	[0.095]
Normality	3.5797	1.8425	1.9879	1.0944	1.5158	0.323	0.801	0.7434	0.7815
	[0.167]	[0.398]	[0.370]	[0.579]	[0.469]	[0.851]	[0.670]	[0.689]	[0.677]
	Malaysia	Israel	S. Africa	Turkey	Argentina	Brazil	Chile	Mexico	Uruguay
BDS Test	0.0063	-0.0017	0.0060	0.0095	0.0014	0.0246	0.0005	0.0039	0.0030
	[0.513]	[0.772]	[0.411]	[0.227]	[0.841]	[0.013]	[0.946]	[0.476]	[0.690]
LB(2)	13.123	0.5054	1.1161	3.5803	0.9506	10.683	4.7868	1.8256	0.6779
	[0.001]	[0.777]	[0.572]	[0.167]	[0.622]	[0.005]	[0.091]	[0.401]	[0.713]
LB(4)	18.471	17.084	4.8421	33.664	15.926	26.894	23.563	15.518	2.4820
	[0.001]	[0.002]	[0.304]	[0.000]	[0.003]	[0.000]	[0.000]	[0.004]	[0.648]
LB(12)	26.227	32.672	29.059	49.003	28.805	30.009	32.146	26.361	8.3510
	[0.010]	[0.001]	[0.004]	[0.000]	[0.004]	[0.000]	[0.001]	[0.014]	[0.757]
Normality	1.8788	0.5183	9.519	0.585	5.042	1.3164	1.6564	0.300	2.8005
	[0.390]	[0.772]	[0.009]	[0.746]	[0.080]	[0.518]	[0.437]	[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 10: Test Statistics

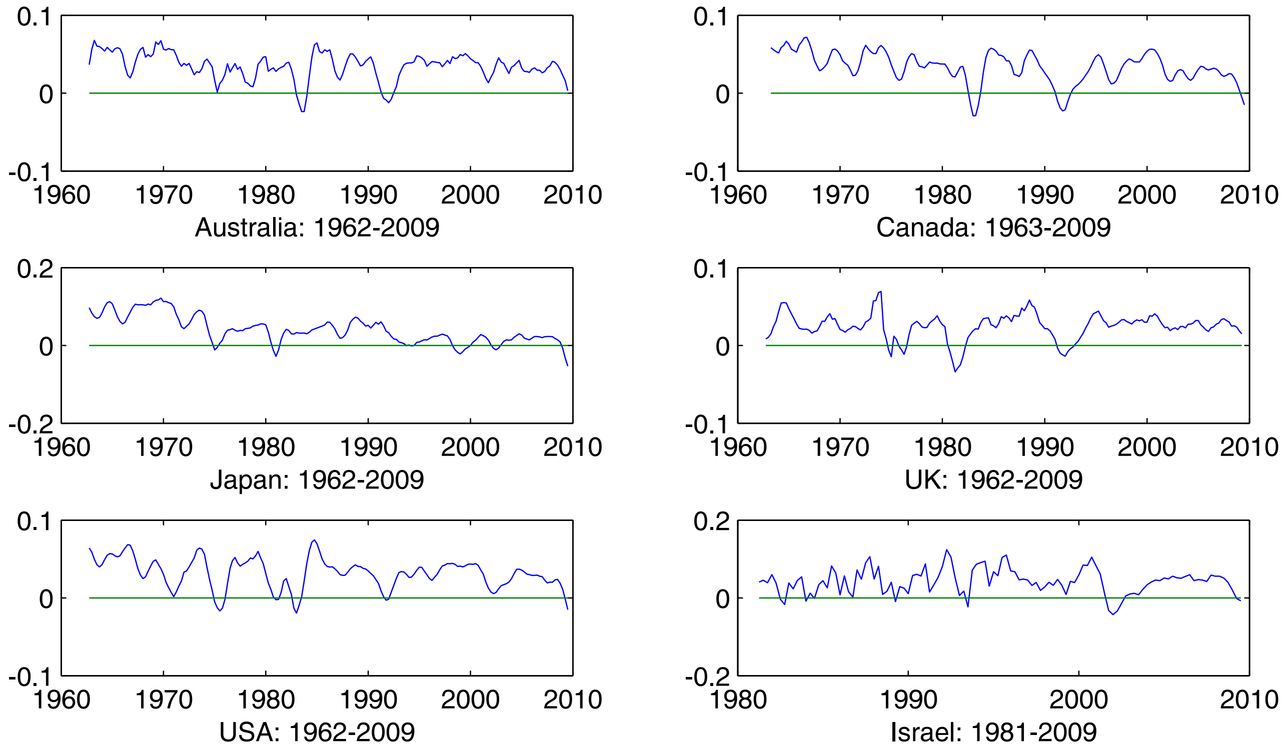

0.1
0
-0.1
1960
1970
1980
1990
2000
2010
Australia: 1962-2009
Canada: 1963-2009
0.2
-0.2
Japan: 1962-2009
UK: 1962-2009
USA: 1962-2009
Israel: 1981-2009

Figure 1

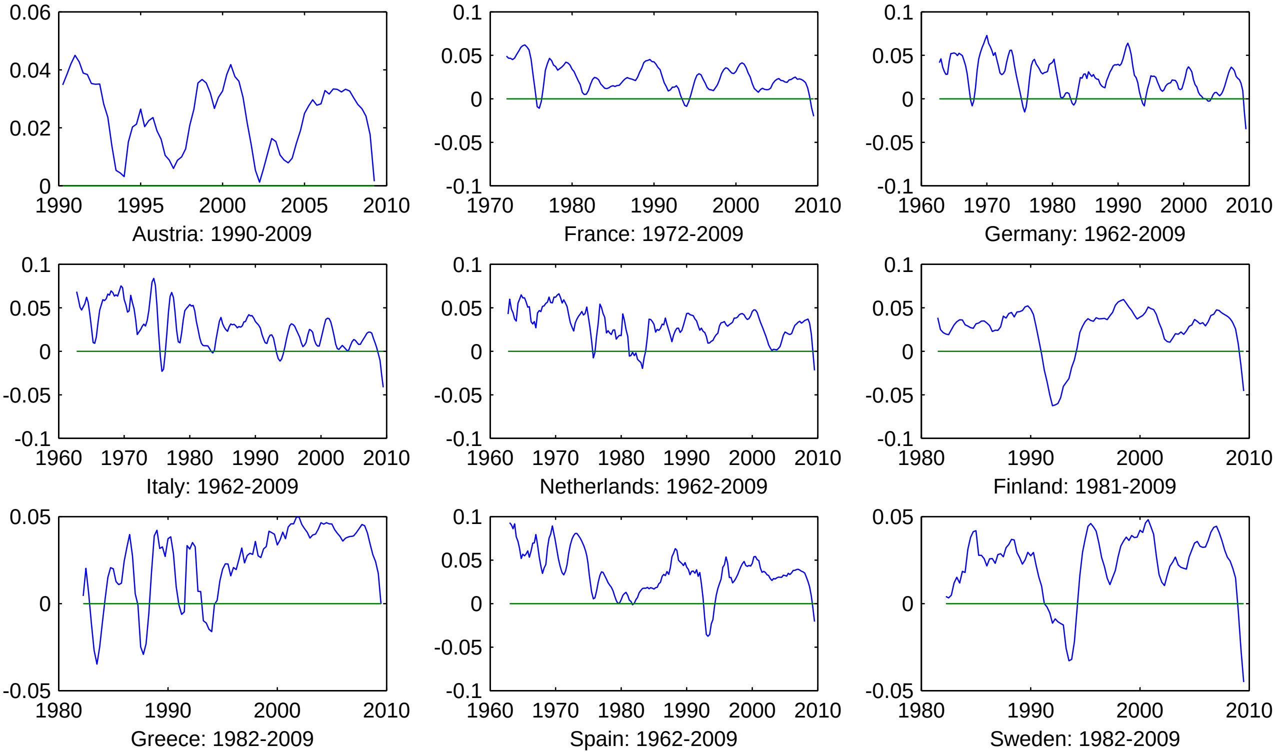

Austria: 1990-2009
France: 1972-2009
Germany: 1962-2009
Italy: 1962-2009
Netherlands: 1962-2009
Finland: 1981-2009
Greece: 1982-2009
Spain: 1962-2009
Sweden: 1982-2009

Figure 2

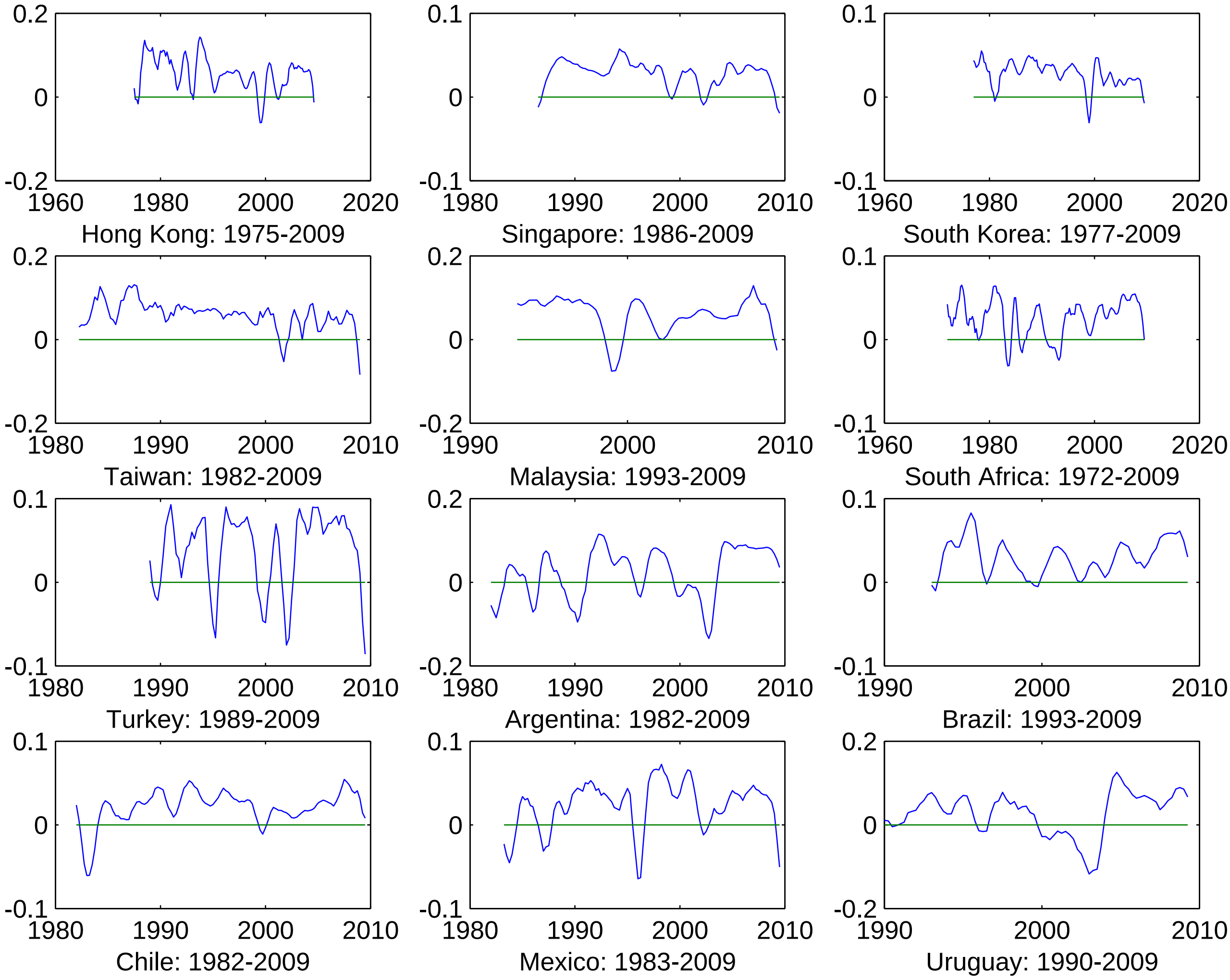
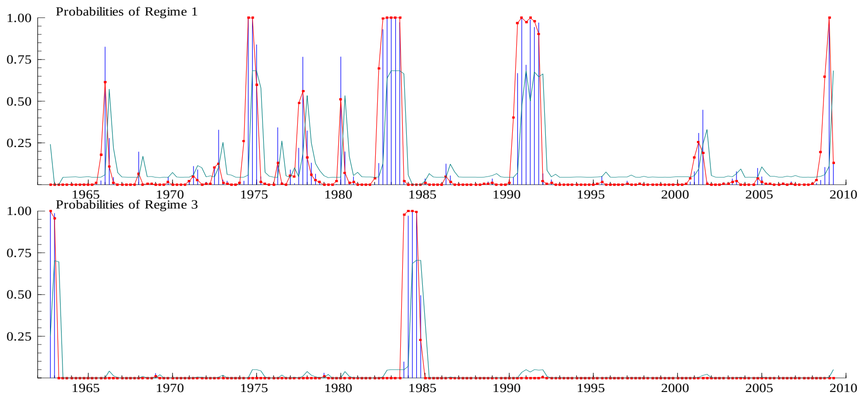
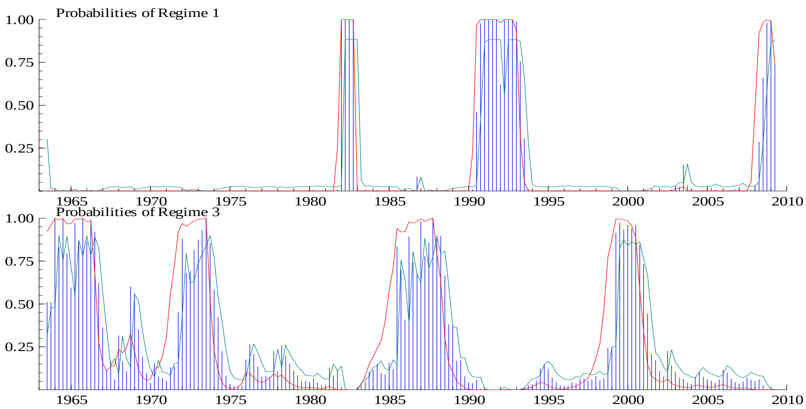

0.2
0
-0.2
1960
1980
2000
2020
Hong Kong: 1975-2009
0.1
0
-0.1
1980
1990
2000
2010
Singapore: 1986-2009
0.1
0
-0.1
1960
1980
2000
2020
South Korea: 1977-2009
0.2
0
-0.2
1980
1990
2000
2010
Taiwan: 1982-2009
0.2
0
-0.2
1990
2000
2010
Malaysia: 1993-2009
0.1
0
-0.1
1960
1980
2000
2020
South Africa: 1972-2009
0.1
0
-0.1
1980
1990
2000
2010
Turkey: 1989-2009
0.2
0
-0.2
1980
1990
2000
2010
Argentina: 1982-2009
0.1
0
-0.1
1990
2000
2010
Brazil: 1993-2009
0.1
0
-0.1
1980
1990
2000
2010
Chile: 1982-2009
0.1
0
-0.1
1980
1990
2000
2010
Mexico: 1983-2009
0.2
0
-0.2
1990
2000
2010
Uruguay: 1990-2009

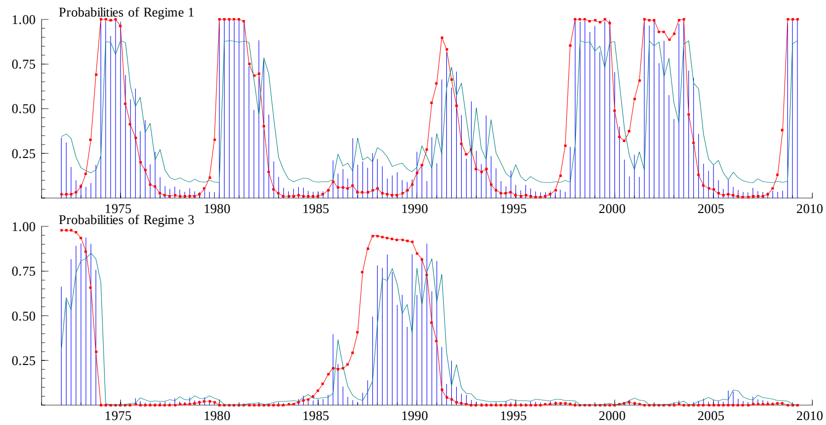
Figure 3



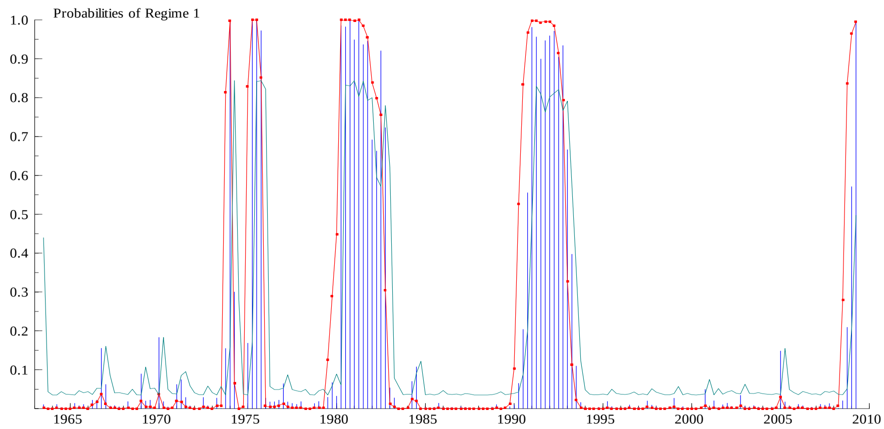
Australia



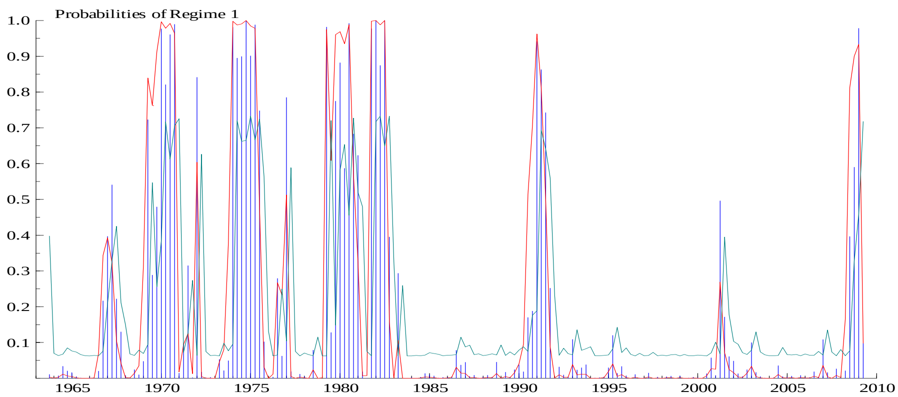
Canada



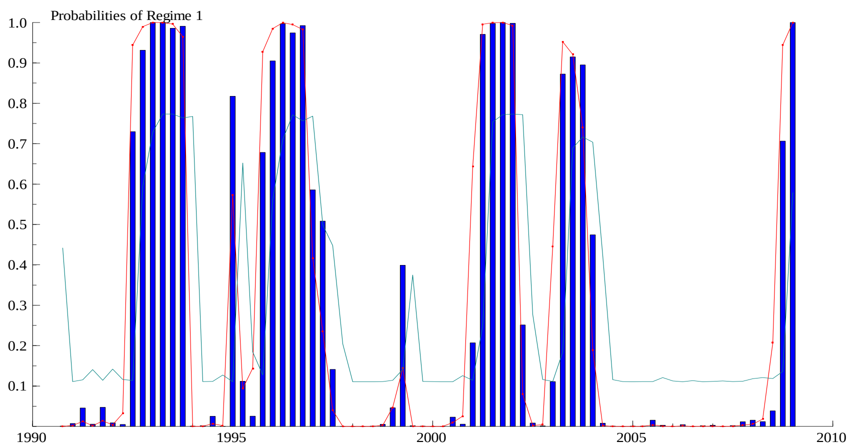
Japan



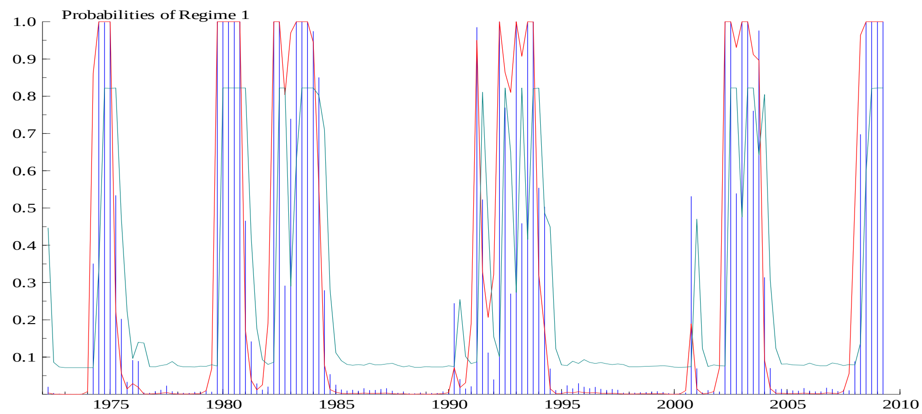
UK



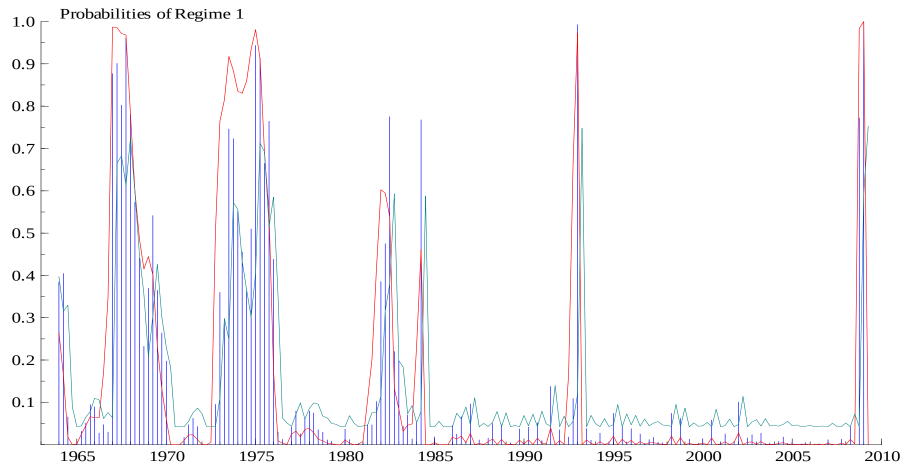
US



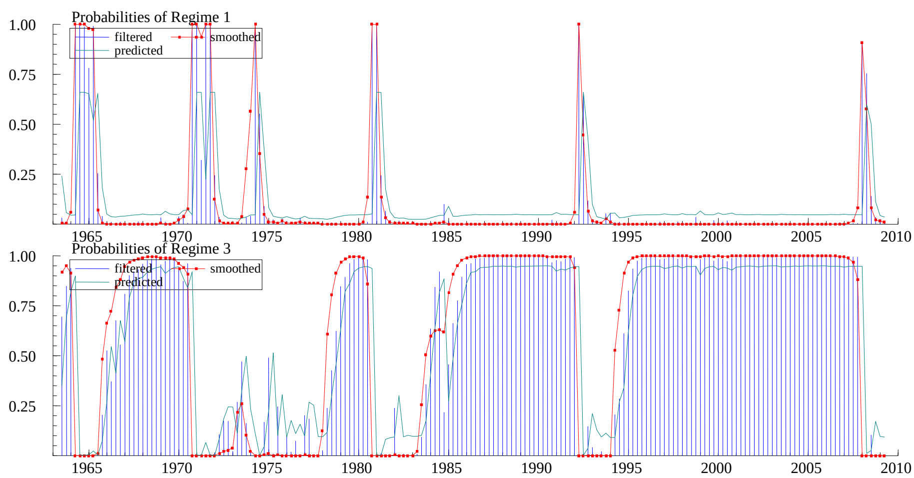
Austria



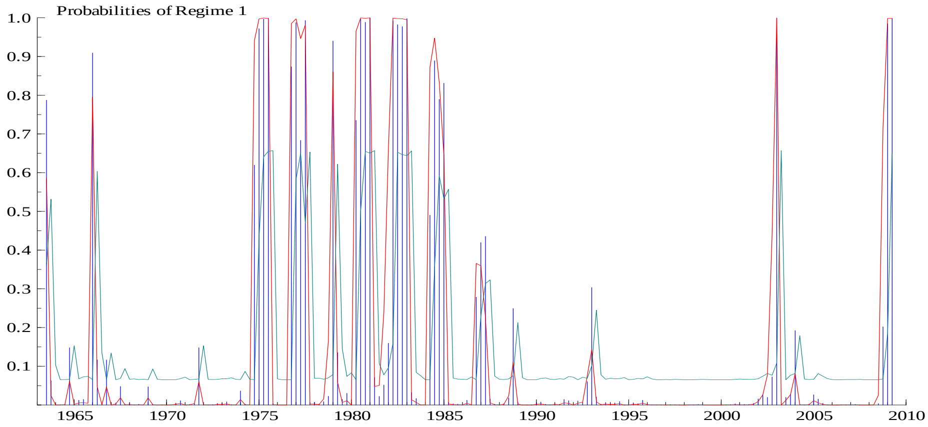
France



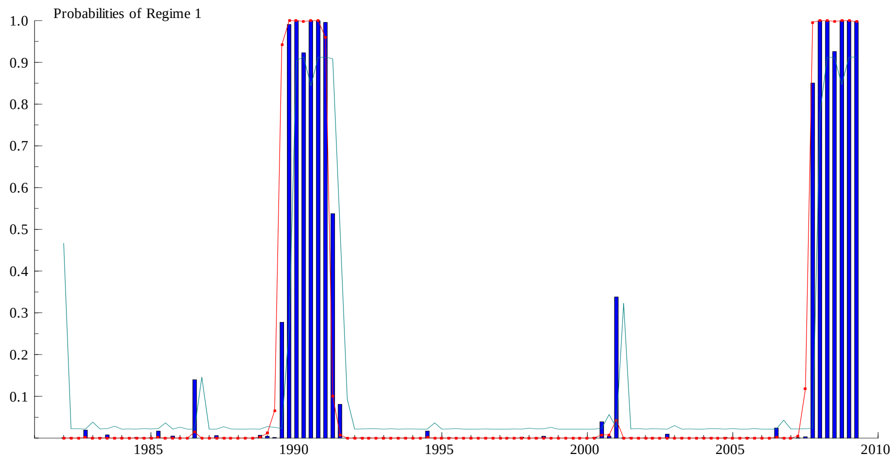
Germany



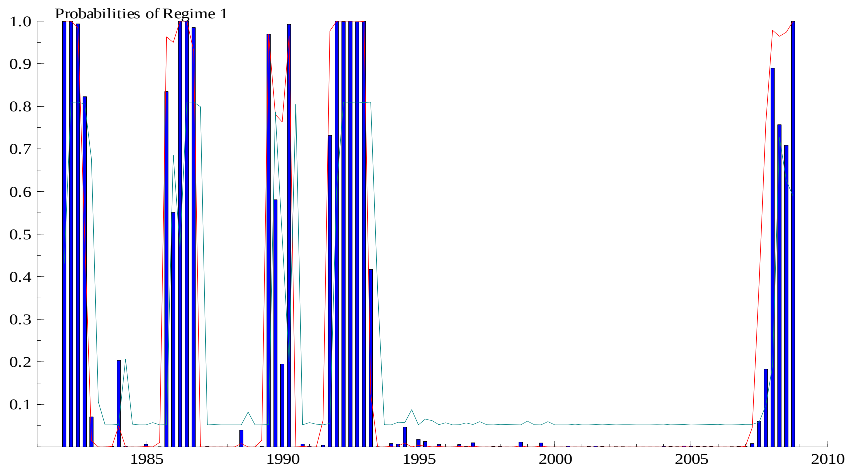
Italy



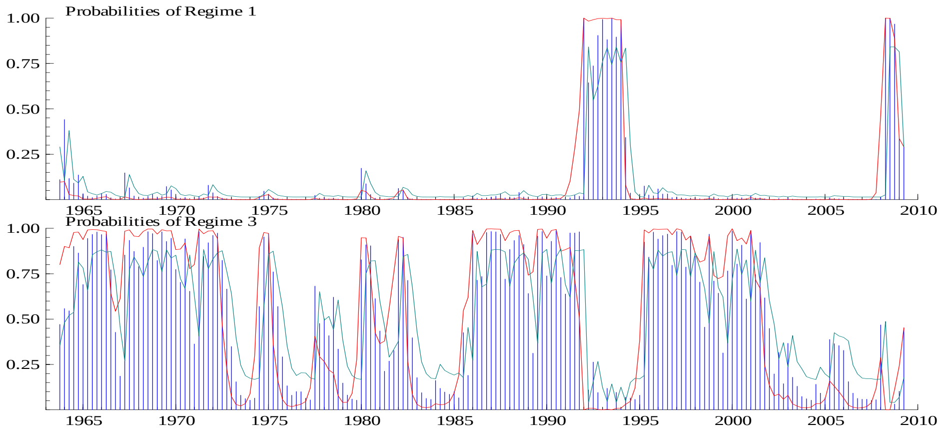
Netherlands



Finland



Greece



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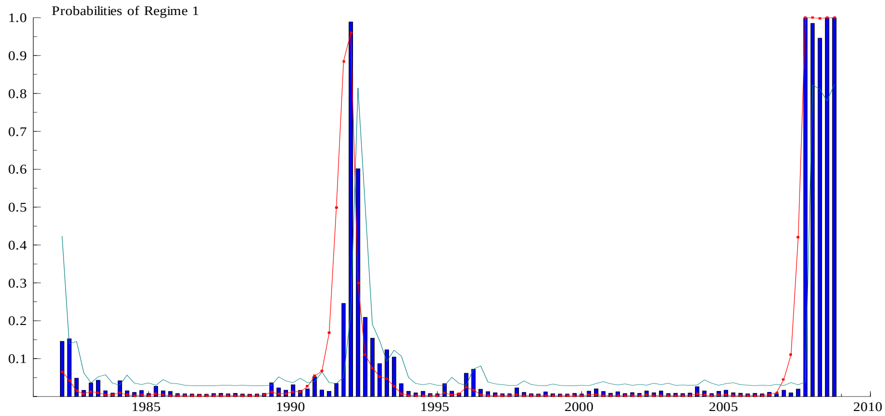

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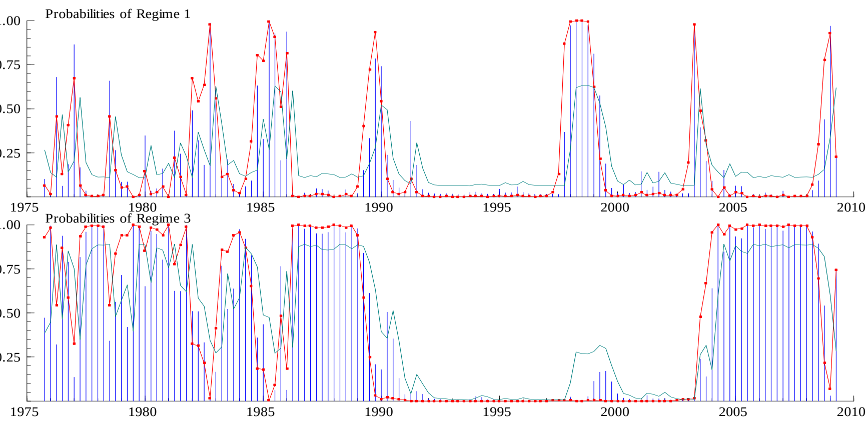

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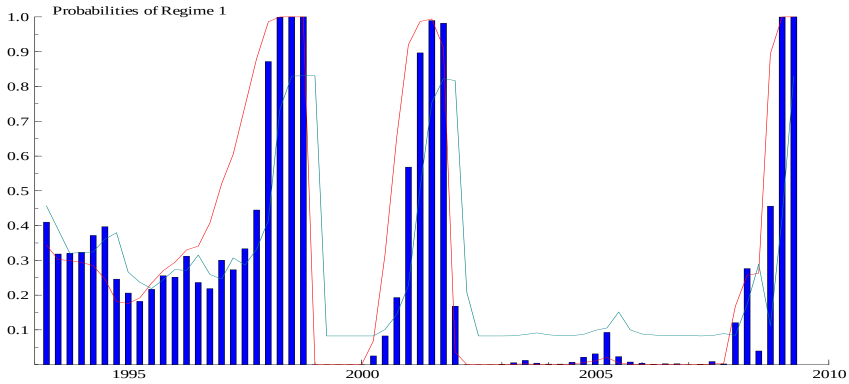

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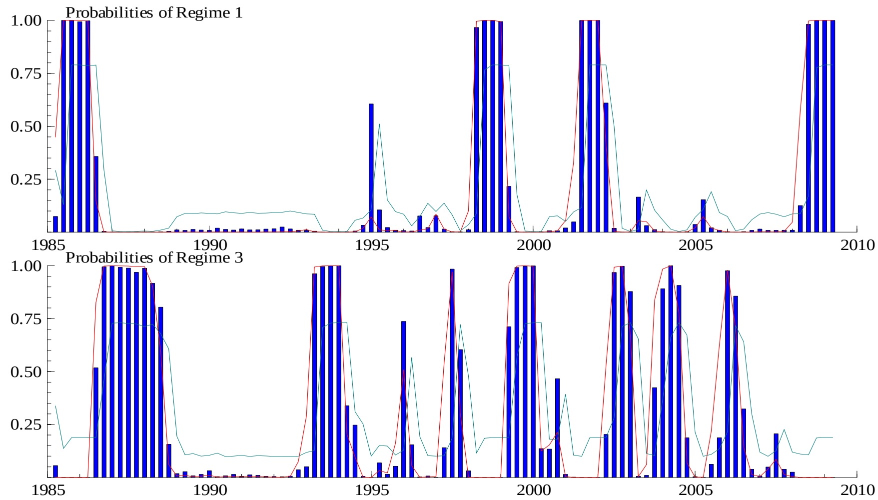

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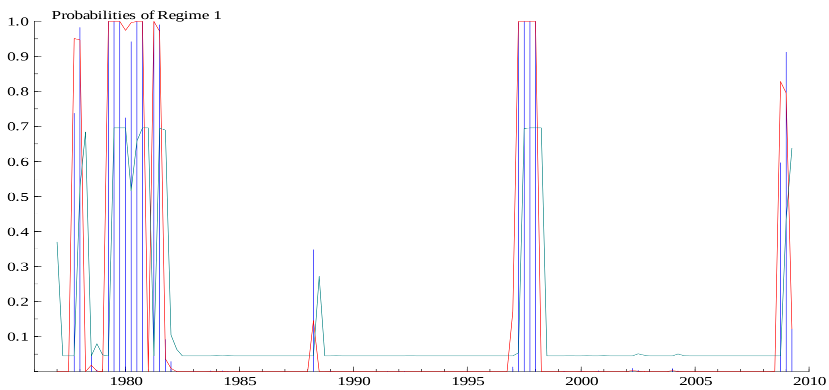

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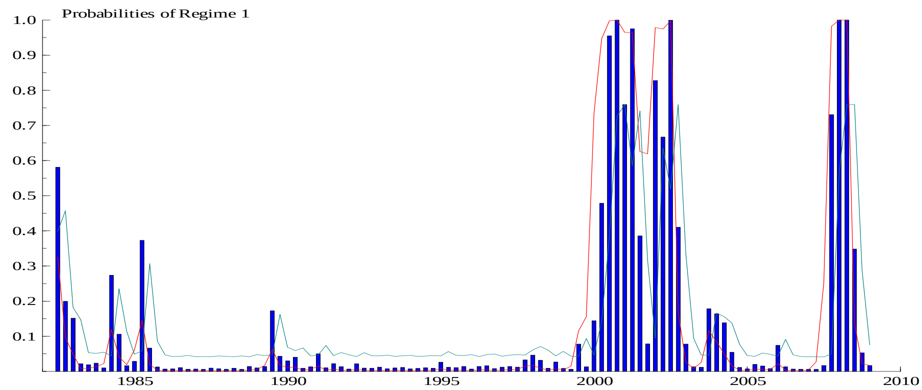

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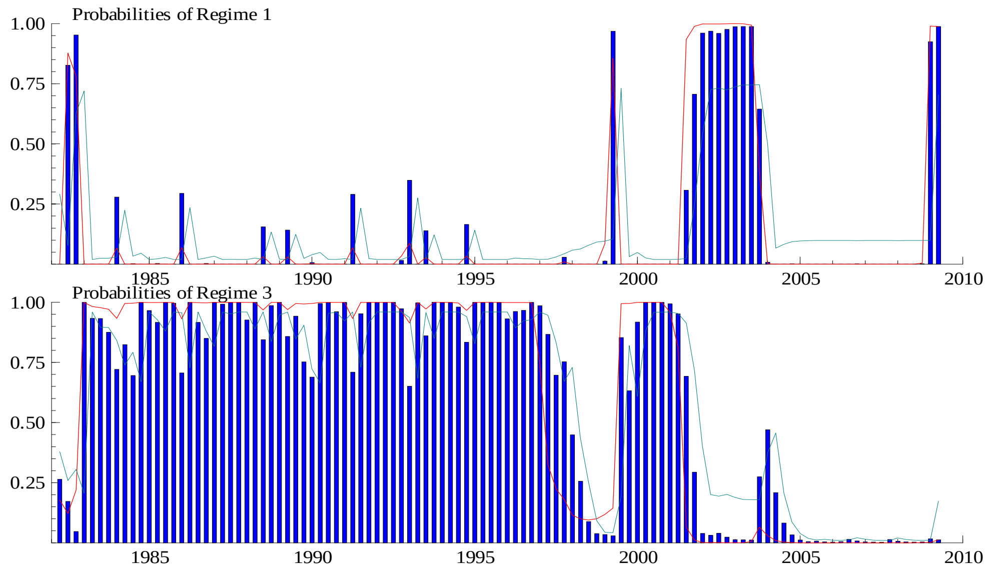

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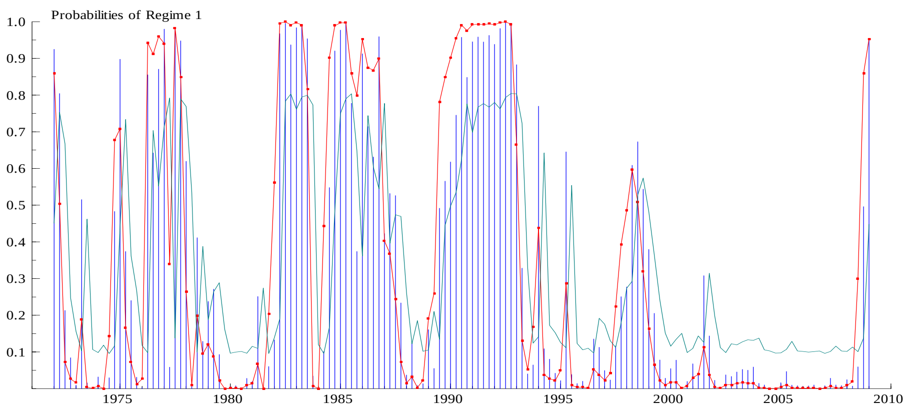
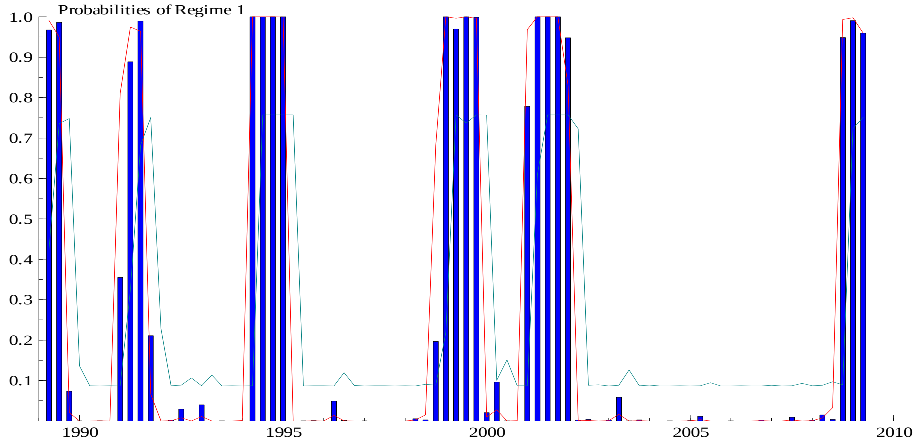


S. Africa



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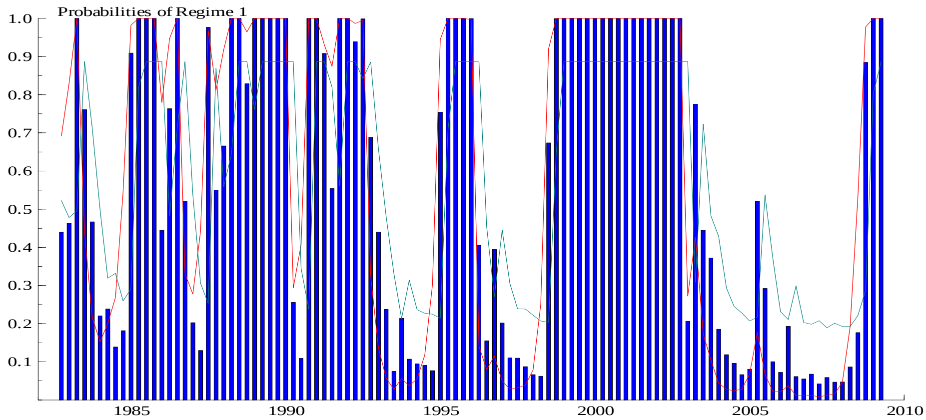

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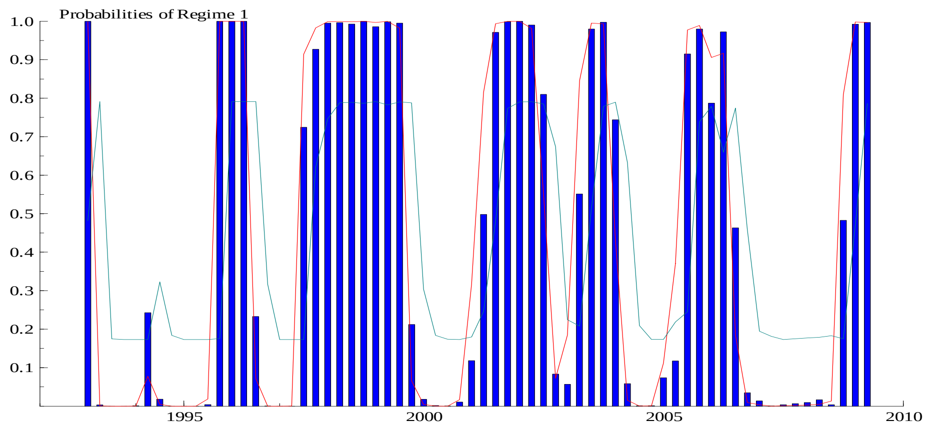

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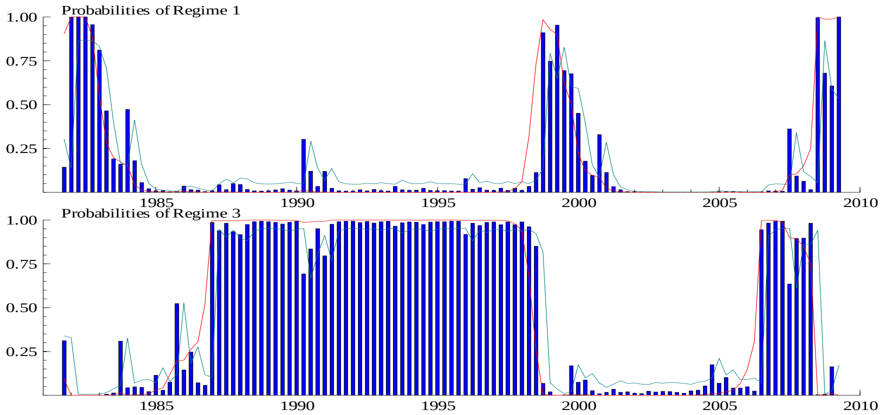

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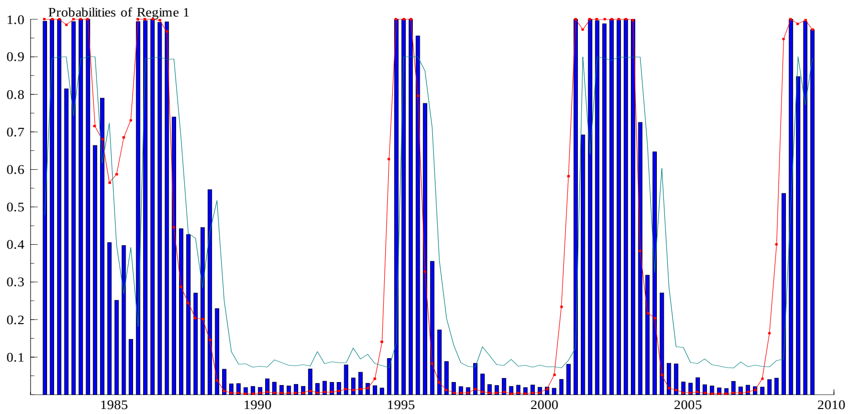
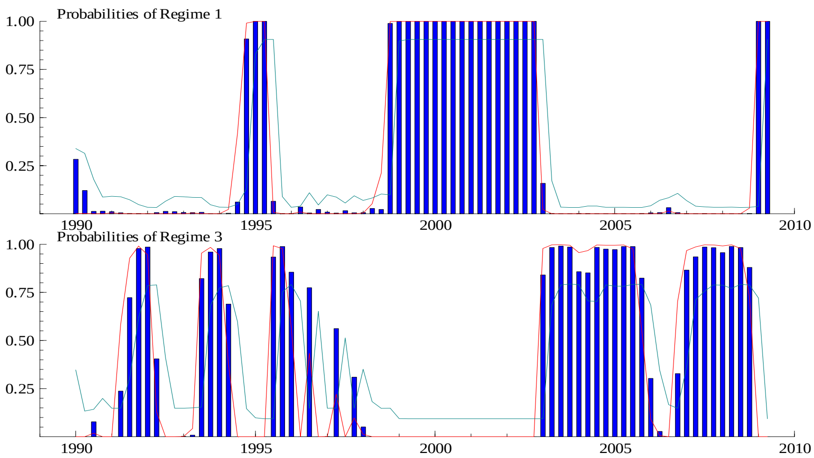


Mexico



Uruguay

Figure 4: Smoothed and Filtered Probabilities of a Recession