Nonlinear Analysis of Business Cycles and Stock Market Dynamics for Emerging Market Economies

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Abstract

This paper presents a systematic and consistent analysis, for the first time, for a large and diverse group of emerging market economies to characterize the dynamics of their business and stock market cycles, the dynamic relationships between these cyclical interactions, and how different or similar the business cycles are among individual emerging market economies as well as between emerging markets and advanced economies. Fırst, the study charecterizes and provides benchmark chronologies of business and stock market cycles for a diverse group of emerging market economies based on hidden Markov models that are robust to potential parameter instability. We identify three states of business cycles and provide estimates of turning points based on monthly industrial production data. Crises that are characterized by sharp drops in economic activity are preceded by slowdowns and are typically followed by strong recoveries during which the economies grow above long-run average rate. Second, the paper explicitly models cyclical dynamics of the stock markets and relates it to the business cycles for a diverse group of emerging market economies. Stock markets go through three distinct regimes characterized by different risk-return dynamics. Findings present a consistent relationship between the real economies and the stock markets. The spikes in probabilities of the bear state of the stock market are highly correlated with the recessionary periods. Probabilities of stock market crashes increase before every recession and do not miss any of the business cycle peaks and correctly predict all recessions in the sample. The results suggest that bear markets characterized by negative returns precede every recession with a lead time between five to eleven months, implying that the stock market returns can be used as a forward looking indicator of emerging market economies. Third, the study quantifies the associations between business cycles across emerging markets and also with advanced G7 economies. The results identify distinct groups of emerging economies. Business cycles both for emerging markets and the advanced economies experience a high degree of commonality when there is a large common disturbance that is affiliated with a global recession.

Keywords: Markov Switching Models, Business Cycles, Emerging Markets, Stock Market, Business Cycle Synchronization

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1. Introduction

The dynamics of the global economy have dramatically shifted during the last two decades. First, trade volumes and financial linkages across countries have rapidly increased, deepening the globalization of markets. Second, the economic importance of emerging market economies has significantly increased, becoming key contributors to the growth of the global economy. In recent years, emerging economies have continued to enjoy higher economic growth rates compared to advanced economies. Observations over the last decade indicate a shift with regards to the leadership in economic growth from developed economies to developing countries, led by the emerging markets.

Because of the rising role of emerging economies, it has been an increasing concern for policy makers and business professionals to monitor the business cycles of these emerging market economies. However, only a few developed countries have institutions, such as the NBER Business Cycle Dating Committee for the U.S., that have been dating the expansions and recessions of their economies. Emerging market economies do not have these kinds of institutions to obtain official or universally accepted chronologies of their business cycles, which are essential for analysis and prediction of economic and financial dynamics of these countries. Moreover, decisions of these institutions that monitor business cycles have important drawbacks: They are released with various lags and are based on subjective discussions of the committee members. On the other hand, Markov switching models which are based on a probabilistic framework have been used extensively to determine and forecast turning points of cyclical phases since the seminal work of Hamilton (1989). These models typically assume a first order Markov process governed by an endogenous probability rule and provide timely and objective information on business cycle turning points, therefore overcoming the drawbacks of a committee dating. A particularly useful feature of this framework is its ability to capture frequent changes in data that may result due to government policy, financial crisis, political instability, and external shocks, which are common for emerging market economies. It is able to capture potential asymmetric behavior across business cycle phases, that is, within this framework, expansions or high growth phases and recessions or slowdowns can display different duration, amplitude, and steepness.

Moreover, recent studies[2] emphasize the need for building different forward looking indicators of business cycles for emerging market economies. The related literature[3] on the relationship between the real economy and financial markets suggest that when stock markets are efficient, they react to the present or future evolution of real economic activity. Because of the profit motive of financial market participants, participants use every piece of information as soon as economic data are available. Therefore, the continuously updated assessments of market participants about the current state of the economy are well reflected in stock market movements. Building consistent models to understand and characterize the dynamics of stock markets can give us further inference to analyze the relationship within these sectors of emerging economies.

In this paper, we use a unified Markov switching framework to address the questions arise for emerging market economies. We begin with an investigation of explicitly modeling the dynamics of business and stock market fluctuations: What are the characteristic properties of business cycle fluctiations and stock market movements in emerging market economies when we account for the asymetric behavior across cyclical phases? What are the relationships between

[2] See, for example, Pagan 2010 among others
[3] The literature provides empirical support for the interactions between financial and real markets by, Fama (1990), Schwert (1989, 1990), Chen (1991), Ferson and Harvey (1993), Cheung et al. (1997), and Binswanger (2000) for the U.S. Cheung and Ng (1998) and Maysami and Sim (2001) examine the ineractions for a group of countries. These studies include short- and long-run analyses, employing various econometric tools.

the dynamics of stock markets and business cycles in emerging markets and can stock market movements be used to predict business cycle recessions in these countries? We then turn to several examinations of synchronizations of smoothed probabilities of recessions for the emerging and advanced G7 countries: What are the differences and similarities of business cycle dynamics within emerging market economies? What are the features of international linkages for business cycles? To answer these questions, we provide a systematic and consistent analysis for the first time for a large and diverse group of emerging markets and advanced G-7 economies.

Although emerging market economies have shown remarkable performances during the last two decades, the prior work in the literature vastly focuses on examining the stylized facts of the business cycles mostly for developed economies. 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 several variables to characterize the 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 date Euro area business cycles.

On the other hand, the analysis of business cycles for emerging markets has been limited to descriptive studies and applications of the leading indicators methodology until recently. There are only few applications in the literature of the various approaches for characterizing business cycles in different emerging market contexts. Girardin (2005) examines quarterly GDP growth-cycles for 10 East Asian countries including Japan, China, and South Korea using regime-switching techniques. Senyuz (2003) conducts a formal analysis of Turkish business cycles using various regime-switching models, and Tastan and Yildirim (2008) emphasize the asymmetric behavior of business cycle phases and document the usefulness of nonlinear specifications in modeling output growth compared to linear alternatives. Altug and Bildirici (2010) detect business cycle turning points using quarterly GDP growth for a representative developed and emerging market economies. Rand and Tarp (2002) employ a non-parametric Bry-Boschan method for dating business cycles to examine the differences of developing countries' business cycles. Senyuz, Yoldas, and Baycan (2010) provide benchmark chronologies of growth, business, and stock market cycles in Turkey and examines their relationship based on hidden Markov models. Morudu (2011) uses Markov switching approach to build a South African business cycle forecast model for South African GDP.

Moreover, Hamilton and Lin (1996), Chauvet (1998), Chauvet and Potter (2000,2001), Whitelaw (1994), Perez-Quiros and Timmermann (1995), Fama and French (1989), Senyuz (2011) find evidence of systematic movements in excess stock returns that are related to estimates of the underlying state of the business cycle. The results suggest that stock market contractions usually begin some months before an economic recession starts and end before the trough. Therefore, stock market movements that are generated from the expectations of people about the future changes in economic activity lead the business cycle fluctuations. Nevertheless, the cyclical links between the two sectors have been investigated by only a few papers. The seminal work of Hamilton and Lin (1996) establishes the most robust stylized facts on cyclical interactions. The authors state that stock market downturns precede economic recessions, while stock market upswings anticipate business cycle expansions. Hence, stock market indices constitute potential leading indicators of economic activity and can be used for economic prediction. Chauvet (1999), and Senyuz, Yoldas, and Baycan (2010) show that stock market cycles seem to anticipate economic cycle turning points.

Another area of focus in the literature is examining the contemporaneous pairwise comparisons to identify the level of national business cycle synchronizations. Artis, Kontolemis and Osborn (1997), and Harding and Pagan (2002) use the non-parametric Bry-Boschan algorithms. Harding and Pagan (2006) identify and compare the turning points for national industrial productions for 12 advanced economies using a univariate setting. The studies of as Guha and Banerji (1998), and Bodman and Crosby (2002) utilize a univariate Markov switching framework to produce business cycle chronologies and consider their synchronizations. Artis, Krolzig, Toro (2004) use pairwise comparisons in a Markov switching setup and suggests a common European cycle. Furthermore, relatively few studies have examined the similarities and differences of business cycle dynamics within emerging market economies or documented their differences compared to those in advanced economies. Some exceptions are Kose, Otrok, and Prasad (2008), Altug and Bildirici (2012), and Aiolfi, Catao and Timmermann (2005). In addition, Canova, Ciccarelli, and Ortega (2007) show that business cycles tend to become more synchronized globally during recessions than expansions.

In this paper, we have a systematic and consistent analysis for a diverse group of emerging market economies on characterizing the dynamics of their business and stock market cycles, the dynamic relationships between these cyclical interactions, and how business cycles in emerging markets differ from those in advanced economies. We first characterize the dynamics of business cycles of the emerging countries using a Markov switching specification to the mean and variance. We construct the reference business cycle chronologies for the emerging economies at monthly frequency through hidden Markov models. Utilizing this framework enables us to have timely and objective information on business cycle turning points, which is particularly important for emerging market economies considering their lack of institutions for officially monitoring business cycles. We employ a three state specification to obtain a convenient framework to decompose the non-recessionary state into high-growth and low-growth states, which helps us to further analyse the asymmetric behaviour of the business cycles and to compare the characteristics of different phases of the economy for emerging markets.

We then explicitly model the stock market cycles and analyze the lead/lag relations of business cycles and stock market movements using inference from the estimated regime probabilities that we derive from each of the models. Our approach fills an important void in the literature given the results of Pagan (2010), who emphasize the need for building forward looking indicators of business cycles for emerging market economies. We believe that this is the first Markov switching framework which explicitly models cyclical dynamics of the stock market and relates it to the business cycle in emerging market economies.

We then utilize the smoothed probabilities that we obtain from modelling the business and stock market cycles to understand how different or similar the business cycles are among emerging market economies as well as between emerging markets and advanced economies. We also believe that this is the first study that utilizes the Markov switching smoothed probabilities to provide both the contemporaneous pairwise correlations and the nonparametric approach of corrected contingency coefficients of the recession probabilities over long periods of time for emerging markets.

Considering the dramatic policy changes and frequent financial crisis in emerging markets, it is cumbersome to obtain a sound regime classification that is not sensitive to model specification. Therefore, in our analyses we utilize hidden Markov models that are robust to potential structural breaks that may have occurred due to major shifts in policy and frequent shocks to the economy. Employing this approach is also useful in order to model the stock market dynamics given the extreme volatility in the equity prices due to the aforementioned events and potential abrupt changes in mean and variance parameters.

The rest of the paper is organized as follows. Section 2 presents the general form of the hidden Markov model used to quantify the dynamics of the real economy as well as the stock market. Section 3 discusses the data. Section 4 presents the empirical results for the real economy. Section 5 examines the analysis of the stock market and the relation between the economy and the stock market for emerging markets. Section 6 examines the international synchronization of business cycles. Section 7 concludes.

2. The Model

Markov-switching class of models provide a convenient framework to analyze time series with state dependent dynamics, such as GDP growth, e.g. Hamilton (1989), and interest rates, .e.g. Ang and Bekaert (2002). The regimes are driven by an unobservable stochastic state variable where some or all of the model parameters may take different values with respect to the regime prevailing at a given point in time. Let y_t denote the variable of interest that can typically be thought of as the sum of two components,

(1) $$y_t = n_t + z_t,$$

where n_t is the Markov trend term and z_t is the Gaussian component. The Markov trend is given by,

(2) $$n_t = \alpha(s_t) + n_{t-1},$$

where $s_t \in \{1, \ldots, M\}$ is a latent Markov processes that determines the state of the economy and $\alpha(s_t) = \alpha_i$ for $s_t = i$, $i \in \{1, \ldots, M\}$. The description of Markov trend dynamics becomes complete after defining a probability rule for transition between states. Following the common practice in this literature, we assume that the unobserved state variable, s_t, follows a first-order Markov-process, which implies that the current regime depends only on the regime prevailing one period ago. Formally, we have

(3) $$P[s_t = j | s_{t-1} = i, s_{t-2} = k, \ldots] = P[s_t = j | s = i] = p_{ij},$$

where p_{ij} denotes the probability that state i will be followed by state j and $i, j, k \in \{1, \ldots, M\}$. By rules of probability, we have $\sum_{j=1}^{M} p_{ij} = 1$.

The Gaussian component in Equation (2) is given by:

(4) $$z_t = z_{t-1} + \phi_1(z_{t-1} - z_{t-2}) + \cdots + \phi_r(z_{t-r} - z_{t-r-1}) + \varepsilon_t$$

where $\varepsilon_t / \sigma(s_t) \sim NID(0, 1)$ and is independent of n_{t+h}, $\forall h \geq 0$.[4] By differencing Equation (1) and substituting (4) we obtain,

(5) $$\Delta y_t = \alpha(s_t) + \phi_1(z_{t-1} - z_{t-2}) + \cdots + \phi_r(z_{t-r} - z_{t-r-1}) + \varepsilon_t$$

This model is able to identify regimes characterized by different means and variances. It is particularly suitable to model dynamics of emerging markets, in which economic activities and financial markets have been going through dramatic changes. However, if the underlying time series exhibits any structural breaks, the two unit root processes in the above model cannot distinguish regime shifts from a break. This result has been documented in McConnell and

[4] Note that this is the general form of the model. Under constant variance assumption, the model boils down to a mean-switching only specification.

Perez-Quiros (2000), who provide evidence for a variance break for the U.S. economy in 1984[5]. One way of handling the structural breaks is using a hidden Markov specification where the autoregressive terms in Equation (4) are set to zero.[6] This yields the following model for the differenced series,

(6) $$\Delta y_t = \alpha(s_t) + \varepsilon_t \, .$$

Emerging economies has experienced major policy changes and went through stabilization programs which may have resulted in structural breaks in the data. Estimating a hidden Markov specification makes it possible to model economic fluctuations and obtain a chronology of turning points that are immune to potential structural breaks. This choice is particularly relevant given the relatively short sample sizes at hand and the difficulty of properly identifying and accounting for breaks in finite samples. Therefore, we use this framework in order to identify cycles of the emerging market economies as well as their stock markets.

Following Hamilton (1990), we estimate the models using EM algorithm together with the nonlinear filter to find the maximum likelihood estimates of the model parameters. Note that we do not impose any a priori restrictions on model parameters and infer the states through statistical estimation. See Dempster, Laird and Rubin (1987) for a detailed description of the EM algorithm and Krolzig (1997) for its application to MS class of models.

3. Data

This paper examines on a large and diverse group of countries, including economies from Europe, Asia, Central and South America, and Africa. We run the analyses for 12 emerging market economies: Argentina, Brazil, Chile, Mexico, Peru, South Korea, Malaysia, the Czech

[5] Kim and Nelson (1999), Koop and Potter (2000), and Chauvet and Potter (2001) investigate this result.
[6] See Chauvet (2002) for an application on Brazilian economy.

Republic, Poland, Russia, Turkey, and South Africa. Besides these emerging markets, we also rest the analyses for advanced G-7 economies, namely USA, Japan, Germany, France, UK, Canada, and Italy in order to compare their results with the models that we build for the EMEs. Our macro data set consists of seasonally adjusted monthly industrial production indices and daily returns on stock exchange indices from 1995 to 2012. The data sets are drawn from the Datastream database, the IMF International Financial Statistics (IFS) database, and countries' own statistical offices. Following Stock and Watson (2005), we smoothed out high frequency movements in the different series of industrial production index by taking twelve-month averages of the annual month-to-month growth rates. For monthly frequencies, we calculate year on year growth rates, i.e., $\Delta IPI_t = 100[\ln(IPI_t) - \ln(IPI_{t-12})]$. For the stock exchange indices, we follow calculate monthly return series as the sum of continuously compounded daily returns and then smooth it out using the Hodrick-Prescott (HP) Filter (lambda = 10). Applying the HP filter eliminates the noisy component of stock returns and yields a smoother series that allows us to disentangle the component of stock returns that is strongly correlated with real activity.[7]

Figures 1 plot the growth rates of monthly industrial production for the emerging markets in our sample. We observe from Figure 1 that for most of the countries, the sharpest drop in growth rate of economic activity happens around 2008. The year on year growth rates of industrial production for each of the countries in our dataset fall at least at a rate of 5% or more in 2009.

4. Cyclical Dynamics of the Real Economy

[7] See Chauvet (1998/1999) for a similar approach in relating stock market dynamics to business cycles.

We start our analysis with modeling the economic activity for emerging markets. Our first objective is to reveal the characteristics of different phases of business cycles, and provide insight about the dynamics of the emerging market economies. We model business cycles for the emerging markets at monthly frequencies by focusing on the year on year growth rates. We first start modeling the nonlinear dynamics with a two state specification (M=2), however, this specification only helps to distinguish crisis episodes from all other times which are associated with varying growth rates. The results show that, the two-state specification is not very informative for identifying phases of the business cycles. Likelihood ratio and several information criteria tests are applied to compare between three versus two states for the number of regimes. The results are also in favour of three states for every country in our dataset. In that sense, for the growth rates of monthly industrial production index, we find that a three-state specification adequately captures state dependent dynamics of the economy. Therefore, we proceed with a three state specification that produces the estimates given in Table 1-2. Linearity is strongly rejected as implied by the upper bound on the p-value of the likelihood ratio test based on Davies (1987)[8].

Note that before deciding on this model, we also estimated several models incorporating autoregressive terms. We found that the implied chronology is very sensitive to lag structure, possibly due to structural breaks. Since the objective of our analysis is to identify business cycle phases and obtain a reliable business cycle chronology, rather than forecasting future recessions, we use hidden Markov switching models, which are robust to structural breaks as they provide a consistent classification of business cycle phases even in the case of potential parameter instability as shown in Chauvet (2002).

[8] See Hansen (1992) for another testing procedure where the supremum of the calculated standardized LR statistics is utilized.

The strong asymmetry is evident in the small value of the Davies upper bound and the substantially different mean estimates and regime probabilities across the states. Tables 1 and 2 show the results of growth rates with different mean and variance structures of different phases for each of the countries. Russia has the sharpest drop in industrial production with a value of 7.74%. The mean for expansions is estimated to be the highest for South Korea, with a percentage around 9.21%. Once the economy is in a recession, the estimated probability of staying in the same regime for the next month is given in Table 5. The average durations and percentages of staying in the same state were calculated using the transition probabilities and reported in table 9. These estimated transition probabilities of staying in the same state varies according to individual country characteristics. For Argentina, Brazil, Czech Republic, Malaysia, Peru, Poland, and Turkey the highest probability is for staying in the high growth regimes with average durations of 38, 15.5, 14.38, 17, 14.6, 21.8, 13.2 months, respectively. The estimated transition probability of staying in the low growth state is the highest for the countries Chile, Russia, South Africa, and South Korea, with average durations of 26, 18.8, 24, 33.5 months, respectively. The results are in line with business cycle stylized facts in terms of implying short and abrupt recession phases and longer and moderate expansion phases. Figure 3 plots the smoothed probabilities and figure 4 plots the filtered probabilities of the recessions implied by our models with respect to industrial production. The spikes in probabilities are all associated with sharp declines in output.

Since we want to obtain a chronology for business cycle turning points of emerging markets, we need a decision rule to convert these recession probabilities into a discrete variable that defines whether the economy is in an expansionary or recessionary state at a given point in time. Following the convenient in the literature, we define turning points based on whether the probability of being in a given regime is smaller or greater than 0.5. In particular, we assume that a business cycle peak occurs at month $t+1$ if the economy was in an expansion in month t, $\Pr[s_t = 1|\Omega_t] < 0.5$ where Ω_t denotes the information set at time t, and it enters a recession in $t+1$, $\Pr[s_{t+1} = 1|\Omega_t] \geq 0.5$. A business cycle trough occurs in month $t+1$ if the economy was in a recession in month t, $\Pr[s_t = 1|\Omega_t] \geq 0.5$, and it enters an expansion in month $t+1$, $\Pr[s_{t+1} = 1|\Omega_t] < 0.5$. This rule provides a reliable chronology because the probabilities produced by the models clearly identify the times when a recession is more likely to happen from those others when existing of an expansion is more likely. Also, following the NBER guideline, we define a recession as a general downturn in the economy for a minimum length of six months. This helps us to filter out very short-lived disturbances to the economy and instead consider longer contractions to label recessionary periods.

Applying this decision rule to the smoothed probabilities, we obtain monthly dating of business cycles of emerging markets. Table 7 presents the individual crises of the emerging market economies, as well as the more contagion crises in our sample set that has affected multiple economies, such as the 1997 Asian crisis, 1998 Russian Crisis, 2001 recession in the US, and lastly the 2008 sub-prime led financial crisis and the ensuing global recession that caused a significant decline in global economic activity. All these recessions are associated with sharp declines in economic activity with the most recent 2008 recession being the deepest one. We observe that recessions are short and abrupt while expansions are long and gradual, reflecting the well documented asymmetric behaviour of economic activity over different cyclical phases. Fluctuations in the industrial production growth rate that are large in magnitude are typical of the cyclical pattern in emerging market economies. The accelerated growth has most of the time been followed by a period of slowdown over the sample period.

5. Cyclical Dynamics of the Stock Market

We now turn our attention to cyclical dynamics of the stock markets and analyze the linkages between business and stock market cycles in emerging market economies. Following Chauvet (1999), we calculate monthly return series as the sum of continuously compounded daily returns and then smooth it out using the Hodrick-Prescott Filter (lambda = 10). Figure 2 plots the monthly filtered return series for each country.

We start with the identification of episodes characterized by different mean and variance dynamics in the stock markets of the emerging economies in our sample. For this purpose, we estimate various Markov switching specifications using monthly returns of stock exchanges from January 1996 to July 2012. We find that a three state specification provides an adequate fit for all countries. Table 8 presents the maximum likelihood estimates from this specification. Russia again has the sharpest drop for returns with a mean value for bear markets of 12.31%. Argentina and Malaysia follow Russia with contractions of 6.29% and 4.39% respectively. Turkey has the highest mean growth for returns with a value of 8.93% and Russia follows Turkey with 7.23%. For Chile, South Korea, and Turkey, the times during which the stock market performs well above the average also seems to be the most volatile state of the market, with variance estimates of 3.46, 7.02, and 13.61, respectively. This is different from documented stylized facts of a typical advanced economy such as the U.S. for which bull markets are characterized by high returns and low volatility, e.g. Hamilton and Lin (1996), and Guidolin and Timmerman (2006). Volatility of the bear state, which is associated with negative returns, is higher than that of the normal state, which is characterized by moderate positive returns, reflecting increased uncertainty during periods of low returns.

Figure 4 plots the smoothed probabilities of the bear market regimes along with the recessions implied by the models of industrial production. We clearly see that spikes in probabilities of the bear state of the stock market are highly correlated with the recessionary periods. Probabilities of stock market crashes increase before every recession in the sample. The smoothing probabilities of the bear markets correctly predict all recessions in the sample. Although the bear markets do not miss any business cycle peaks, they sometimes produce false signals which are not followed by recessions. This is consistent with the documented results for the US and other advanced economies, e.g. Chauvet (1998/1999) and Senyuz (2011).

We proceed with a full-sample analysis to assess the accuracy of the estimated probabilities and gain more insight into the relation between the economies and the stock markets. We use the regime classification determined by the macro model estimated at the monthly frequencies and the smoothed probabilities of the stock market model in order to assess the lead/lag relation between turning points. For comparison, we use the quadratic probability score (QPS) as proposed in Diebold and Rudebusch (1989), which is similar to the mean squared error measure. Let $\{N_{1,t}\}_{t=1}^{n}$ denote the stock market model generated probabilities, which take values in the [0,1] range, and $\{N_{2,t}\}_{t=1}^{n}$ denote a binary variable representing the monthly business cycle chronology, such that $N_{2,t}$ equals 1 in recessions and 0 otherwise. Then, the QPS is given by

(7) $$QPS_i = \frac{2}{n}\sum_{t=1}^{n}\left(N_{1,t} - N_{2,t+i}\right)^2, \quad i = 0,1, \dots 12.$$

Table 10 presents the QPS values for lead times of the stock market ranging from 0 to 12 months. The QPS takes a value between 0 and 2 where 0 corresponds to perfect accuracy. The smoothed probabilities of the bear state yield the lowest QPS at horizons between 5 and 11.

6. Business Cycle Synchronization

This section makes comparisons of different business cycles and quantifies the dynamics of global cyclical linkages by examining the smoothed probabilities for the emerging and G7 economies that we obtained from the dynamic Markov switching models. We analyze how business cycles in emerging market economies are different or similar within each other and compared to the advanced G7 economies. We try to answer whether or not the economic fluctuations are globally synchronized, and which countries or country groups are more synchronized compared to the others for the time period 1996-2012 and a sub period of 2004-2012.

To uncover the features of the international linkages of business cycles, first we analyze the behavior of the pairwise contemporaneous correlations of the smoothed probabilities of recessionary states. Most of these correlations are statistically significant, indicating that most of these markets are in the same regime state during the sample period.

To further analyze the synchronization of national business cycles, we next utilize a non - parametric approach, namely, corrected contingency coefficient, to examine the comovements of different business cycles regimes across the countries in our study. We follow Artis, Krolzig, Torro (2004) and compare the expansion and contraction frequencies of two series. Results give us the association between the business cycle regimes using the corrected contingency coefficient. We again use the estimations of smoothed probabilities that we obtained from our model to examine the business cycle characterizations and regime classifications. We employ a binary time series variable that we obtain using the smoothed probabilities of recessionary states that we estimated for each country. Using these regime classifications, we denote 1 for recessionary regime states and 0 for moderate and high growth regime states. To convert these recession probabilities into a discrete variable, we utilize the same decision rule that we employed in order to obtain the regime chronologies and define the turning points of emerging markets.

To calculate these corrected contingency coefficients, we first classify our binary variables for each pair of countries i and j. We start measuring the statistics for X^2, which is frequently used to test the dependence level of variables.

$$\chi^2 = \sum_{i=0}^{1} \sum_{j=0}^{1} \frac{[n_{ij} - n_{i.} n_{.j} \;/\; N]^2}{n_{i.} n_{.j} \;/\; N} \tag{8}$$

where n_{ij} stands for the frequencies that overlap both for a pair of countries i and j. The subtotals of these overlapping frequencies are denoted as $n_{i.}$ and $n_{.j}$. Then the contingency coefficient is given with the following formula:

$$CC = \sqrt{\frac{\chi^2}{N + \chi^2}} \tag{9}$$

In order to obtain a statistic that lies between 0 -100, we correct this formula for each pair of countries (2x2 dimensions each) using the following formula:

$$CC_{corr} = \frac{CC}{\sqrt{0.5}} 100 \tag{10}$$

If two binary series are independent, then n_{ij} and $n_{i.} n_{.j}$ become the same and the percentage of association converts to 0. With complete dependence, the CC becomes $\sqrt{0.5}$ and the corrected contingency coefficient becomes 100, which means a complete association. In this case two countries have complete dependence and they are in the same regime for every time period, suggesting that the business cycle turning point dates are identical.

Tables 11 - 14 display contemporaneous pairwise correlations of smoothed probabilities of the recessionary state regimes among emerging countries and between emerging markets and G7 countries, over the 1996:0 – 2012:07 period and a subperiod of 2004:01-2012:07 respectively. Moreover, Tables 15 - 18 report the corrected contingency coefficients of binary variables that we obtain from the smoothed probabilities of recessionary regimes among emerging countries and between emerging markets and G7 countries, again over the 1996:0 – 2012:07 period and a subperiod of 2004:01-2012:07 respectively. Crises of emerging markets were contagion up to a degree, but this contagion is generally among some of these emerging economies. Results show that the 1997 East Asian crisis and the 1998 Russian Crisis do not affect the economy globally. Japan is the only G7 country that was affected from the East Asian crisis. Other G7 countries were not affected from the crises that emerging economies suffered. The crises of emerging markets in our sample period were not severe and contiguous for the advanced economies. The 2001 recession in the US was more contiguous for many of the advanced and emerging countries. However, the results clearly show that the recession of 2008 creates a true disturbance factor that can be identified as a global recession that both advanced and emerging markets experienced.

The results identify some distinct group of countries within emerging economies and between emerging markets and advanced G7 countries. Both the contemporaneous correlations and the corrected contingency coefficients give the largest values across the East Asian Economies of Malaysia, South Korea, and Japan. Moreover, they have relatively low degree of synchronicity measures with many other emerging markets in our sample. All contingency coefficients among these countries are higher than 85.4% with significant contemporaneous correlation 0.79. The cause may be the result of the increasing trade among the East Asian countries. The highest association in this group is between South Korea and Malaysia with a contingency coefficient value of 89% and a contemporaneous correlation value of 0.84.

Mexico and the U.S. have the second strongest association in our sample following the highest association of the East Asian economies. Both countries have a corrected contingency coefficient of 82.3% and their pairwise correlation is 0.74. This high association can arise due to NAFTA, however, pairwise correlations and contingency coefficients are relatively lower with Mexico and Canada, with an only about 53.8% association and 0.42 correlation rates. The 53.8% value is still higher than the generally accepted threshold value of 50%, which still suggests an association even it is weaker than the association with the U.S.

Russia, Poland, and the Czech Republic are also another distinct group that appears to have high contemporaneity and association among each other with large significant contemporaneous correlations and contingency coefficients. All contingency coefficients among these countries are higher than 76% with significant contemporaneous correlation 0.69, with the highest association value of 81% and contemporaneous correlation of 0.70 between the Czech Republic and Russia. The Czech Republic also has a strong regime comovement with Germany with a value of 78.6% and a significant contemporaneous correlation value of 0.69.

We also observe a high degree of concordance and strong significant pairwise contemporaneous correlations among Turkey, Brazil, and Argentina, which are the emerging markets that have experienced much volatility and crisis starting from the beginning of our samples. Their transition probabilities for each of the states are also very similar. The contagionary effects of crisis during the end of the 1990's may be an important source of fluctuations in the emerging economies.

On the other hand, we cannot conclude that the emerging markets are driven solely by national factors. Many emerging countries, such as Argentina, Mexico, Poland, South Korea, and Turkey, show both moderate correlations and associations with the US economy with contingency coefficients above 50% and significant pairwise correlations above 0.44. Moreover, we also cannot conclude that regional driving factors are always important. The contingency coefficients and contemporaneous correlations are weak among some of the emerging markets that can be considered in the same region, such as the Latin American countries of Argentina, Chile, and Peru. For example, the corrected contingency coefficient is only 42% between Argentina and Chile, and also 49% between Peru and Argentina.

Altug and Bildirici (2011) and Canova, Ciccarelli, and Ortega (2007) argue that business cycles become more synchronized during recessions compared to expansions. Their results state that declines in economic activity have common timing and dynamics, both within and across countries. The results show that business cycles both for emerging markets and the advanced economies experience a high degree of commonality when there exists a large common disturbance that is affiliated with a global recession. When we observe the sub period of 2004-2012, the results show very strong comovements among all countries. The corrected contingency coefficients and contemporaneous pairwise correlations show very high level of increases. The average values of contingency coefficients for the 1996-2012 period are 61% among EMEs, 60% between EMEs and G7 economies, and 60% overall. When we observe the 2004-2012 subperiod, these values increase to 86.3% among EMEs, 86% with EMEs and G7 countries, and 86.1% overall.

The results suggest the existence of a world factor both for emerging and advanced economies that drives the cyclical fluctuations. The results show that a large common disturbance that is affiliated with global recessions is the main factor that drives this common cycle. The 2008 financial crisis is a good example for this worldwide association of business cycles. Results suggest that policy makers should be alert for the turning points that are resulting from external factors. This stresses the importance of using the information coming from the other countries when constructing leading indicators and predicting the turning points. However, as explained above, the results also show the existence of idiosyncratic factors, which affect the national business cycles of individual countries and attribute to the lack of synchronization among them. As Aolfi et al. (2010) discuss, one reason for the dissimilarities on national business cycles may be the differences in terms of trade shocks due to the dissimilarities for these countries' export compositions. Another reason for the different economic forces at play may be the political and institutional differences of each country faces.

7. Concluding Remarks

We analyze cyclical dynamics of the emerging market economies, which have shown increasing growth performances during the last two decades. We use hidden Markov models that are robust to potential structural breaks, which are typical of emerging markets, and identify turning points of business and stock market cycles. We find that recessions are associated with sharp drops in economic activity and are usually very short-lived, whereas expansions that typically start with strong recoveries are much longer. Our business cycle models estimated at the monthly frequency identify the individual crises of the emerging market economies, as well as the more contagion crises in the sample that have affected multiple economies, such as the 1997 Asian crisis, 1998 Russian Crisis, 2001 recession in the US, and lastly the 2008 sub-prime led financial crisis and the ensuing global recession.

We identify three regimes for stock markets of the emerging economies characterized by different mean and variance levels. We find that bull markets in Turkey, South Korea, and Chile that are characterized by high returns are also the most volatile, which is different from documented stylized facts of a typical advanced economy such as the U.S. for which bull markets are characterized by high returns and low volatility. In terms of macro-finance linkages, our analysis on interrelations of the economy and the stock market reveals that bear market peaks in the emerging markets consistently lead the beginnings of recessions with an in-sample average of five to eleven months, and therefore may be considered as a potential predictor of the recessions.

We utilize the smoothed probabilities that we obtained from modelling the business cycles to understand how different or similar the business cycles are across emerging market economies as well as between emerging markets and advanced economies. We examine the corrected contingency coefficients and contemporaneous pairwise correlations of smoothed probabilities of the recession states among emerging countries and between emerging markets and G7 countries, over the 1996 - 2012 period and a subperiod of 2004 - 2012. The results identify distinct group of emerging economies. Besides, business cycles both for emerging markets and the advanced economies experience a high degree of commonality when there is a large common disturbance that is affiliated with a global recession. During the sub period of 2004-2012, the results show very strong comovements among all countries, with considerable higher contingency coefficients and pairwise correlations compared to the whole sample period. The results stress the importance of using the information coming from other economies when constructing leading indicators and predicting turning points.

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FIGURES

Figure 1: Year on Year Growth Rates of Monthly Industrial Production
(January 1996-July 2012)

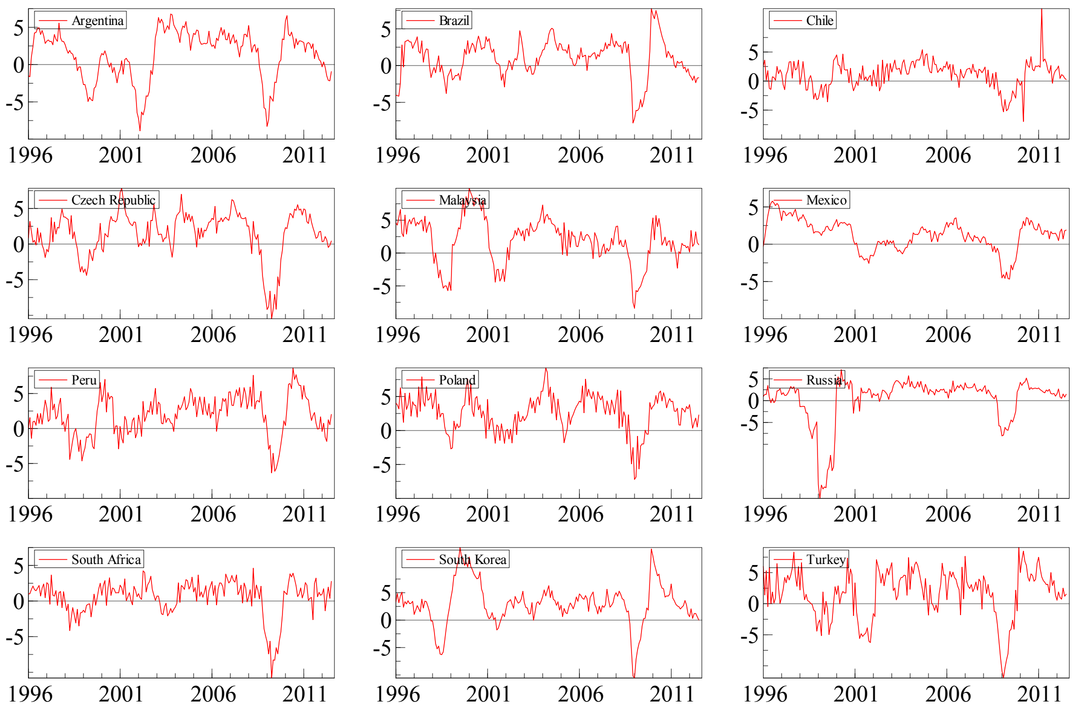


Figure 2: MSCI Monthly Returns of Stock Exchanges
(January 1996 – July 2012)

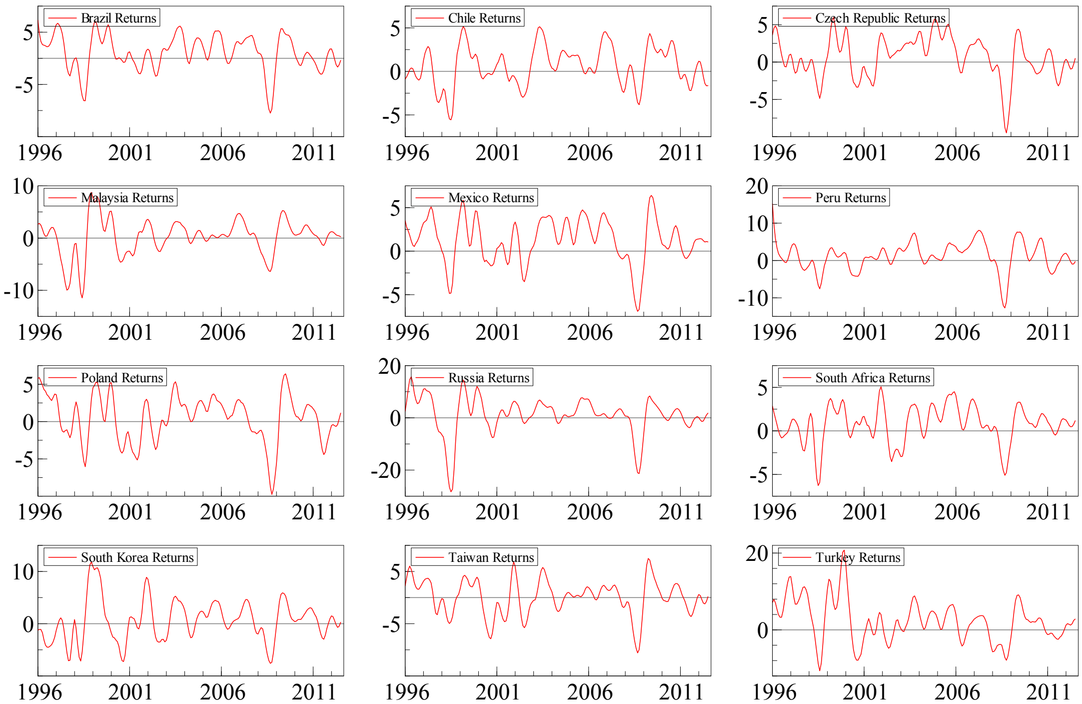


Figure 3: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Argentina

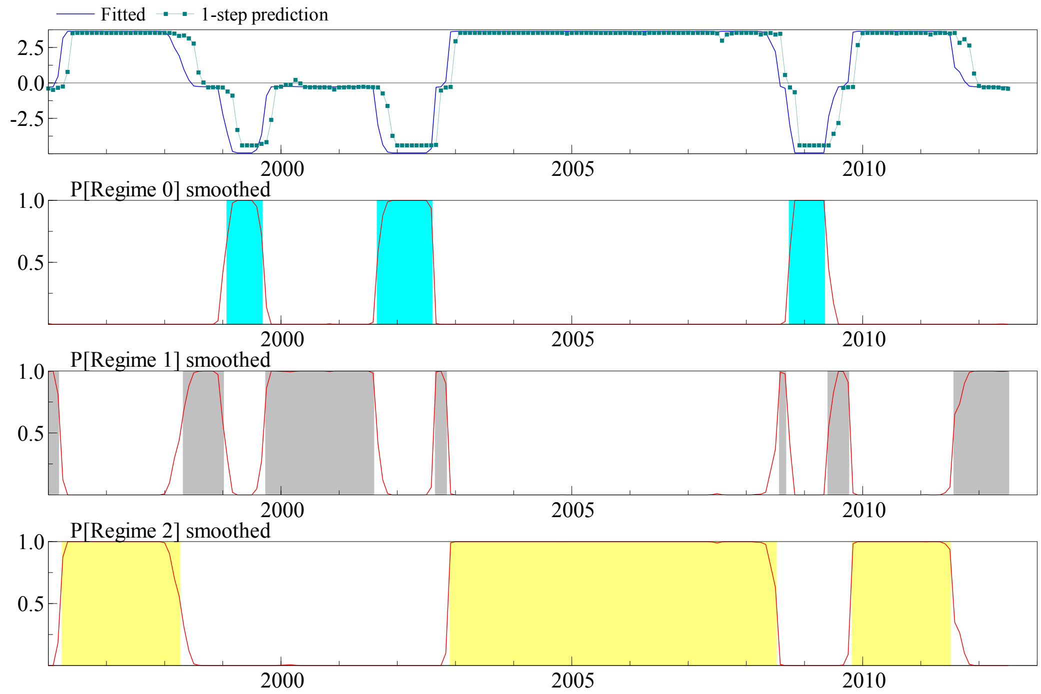


Figure 4: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Brazil

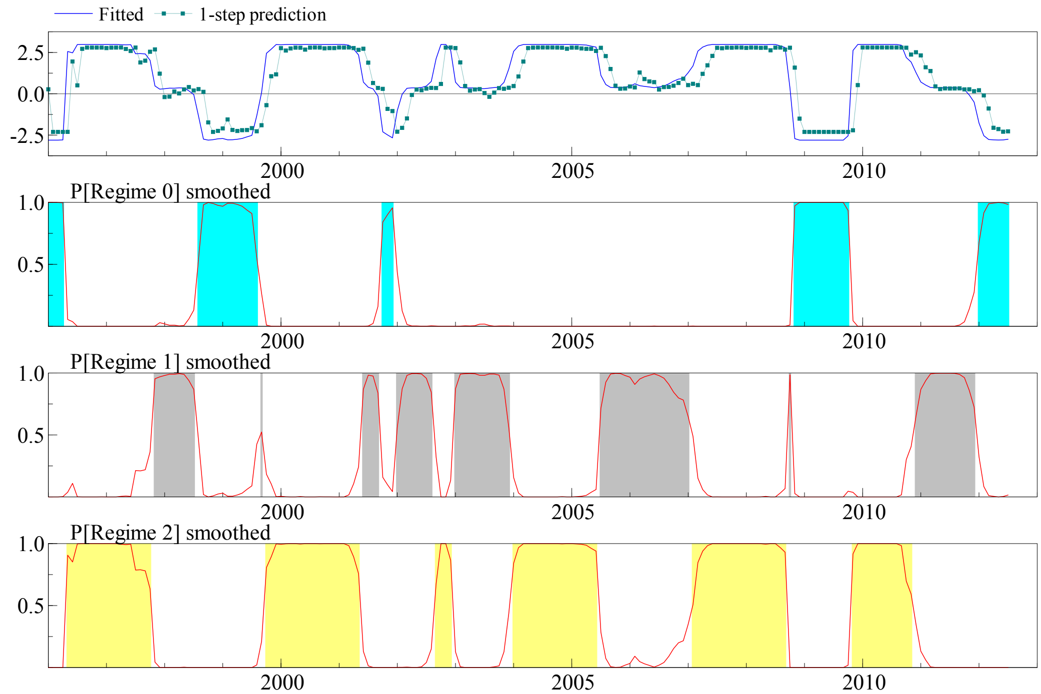


Figure 5: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Chile

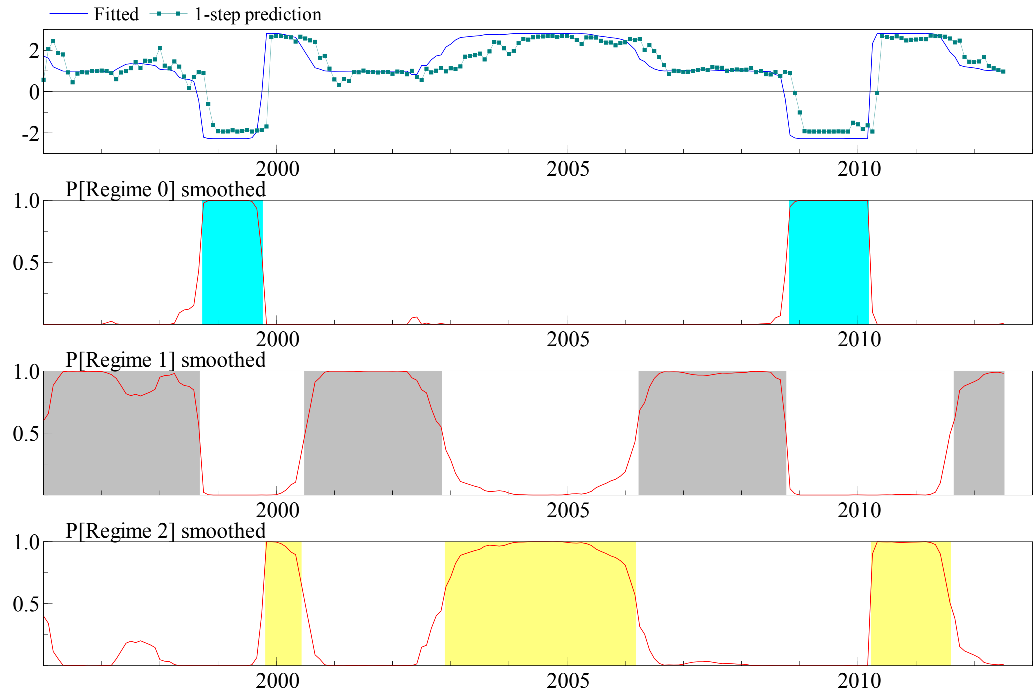


Figure 6: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Czech Republic

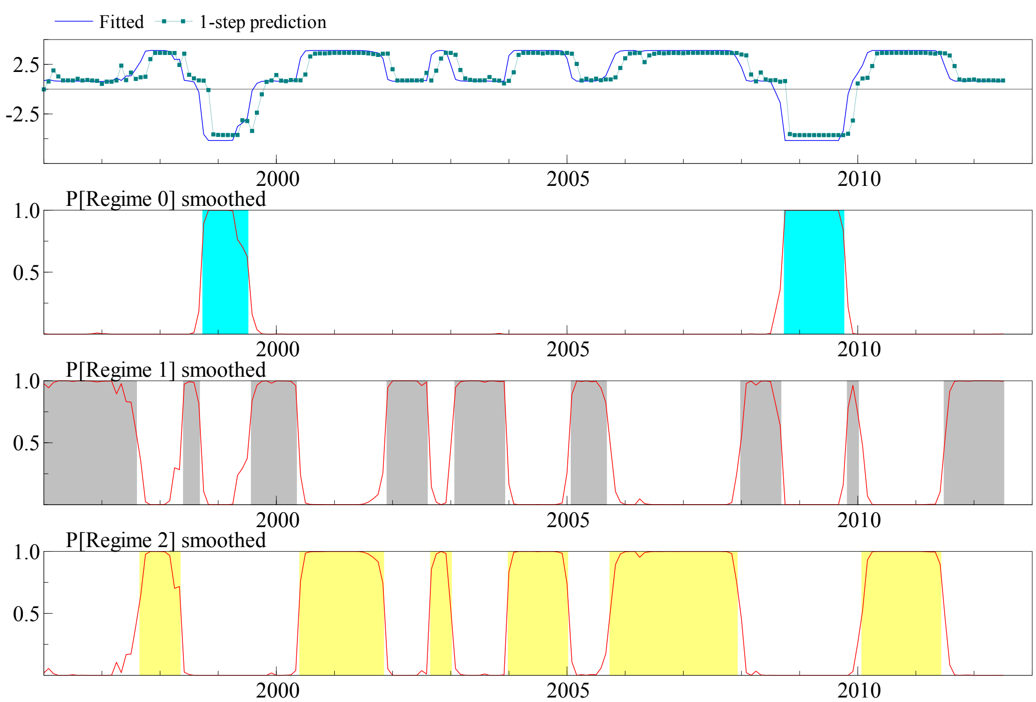


Figure 7: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Malaysia

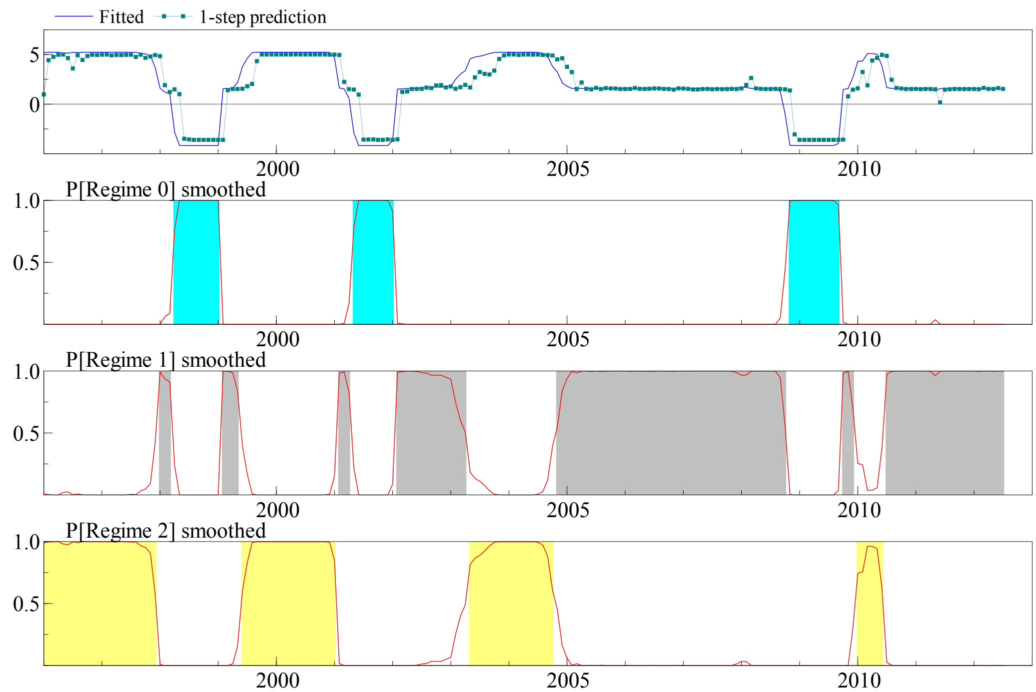


Figure 8: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Mexico

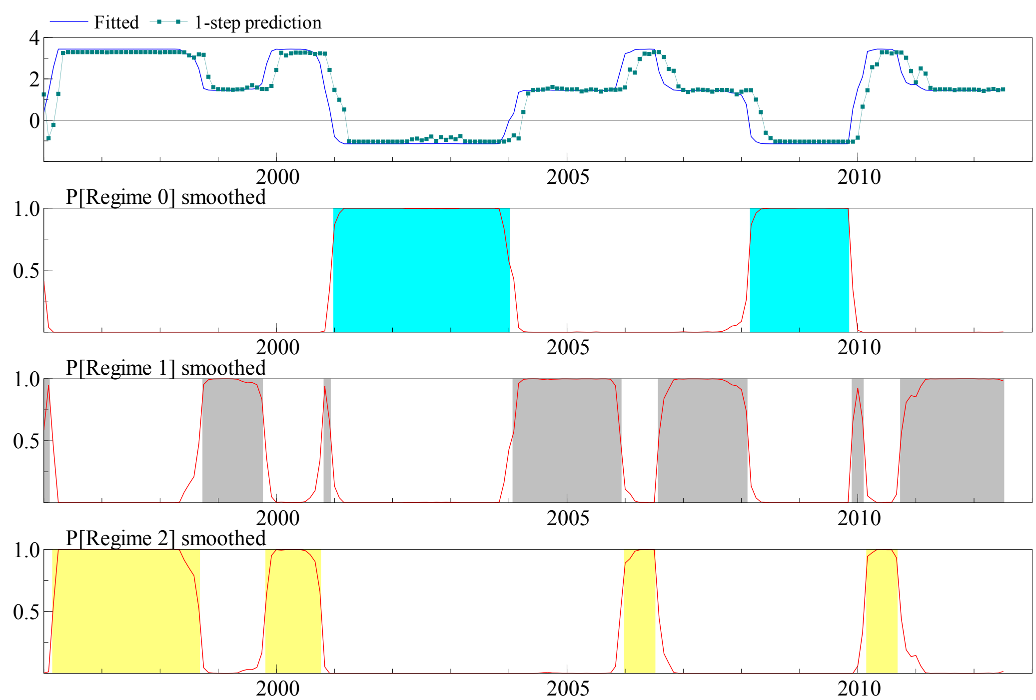


Figure 9: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Peru

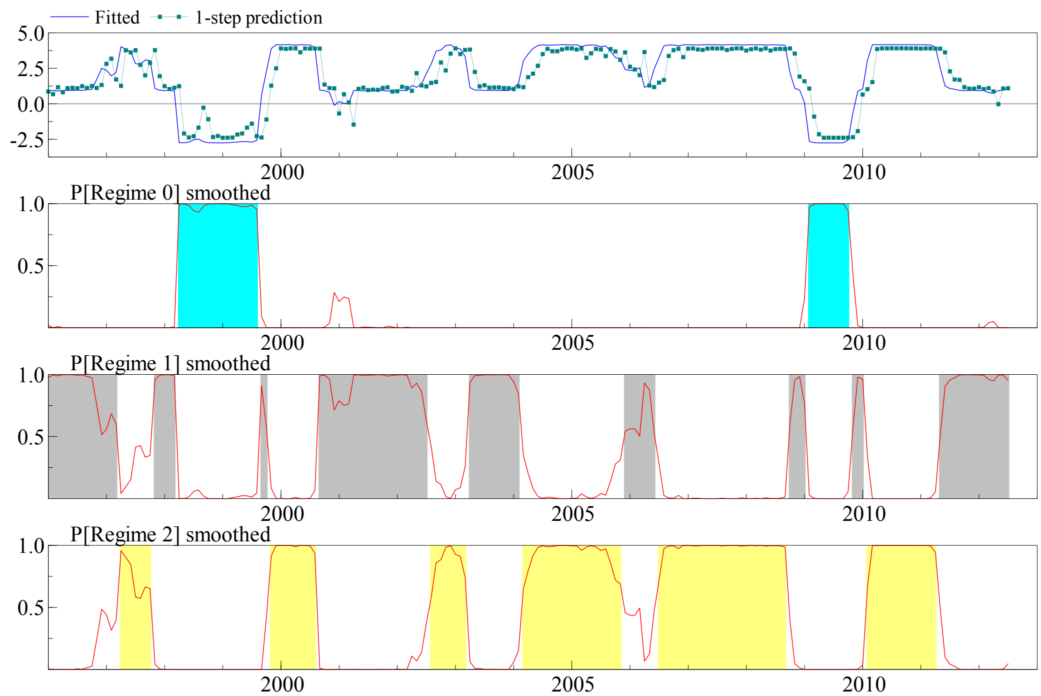


Figure 10: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Poland

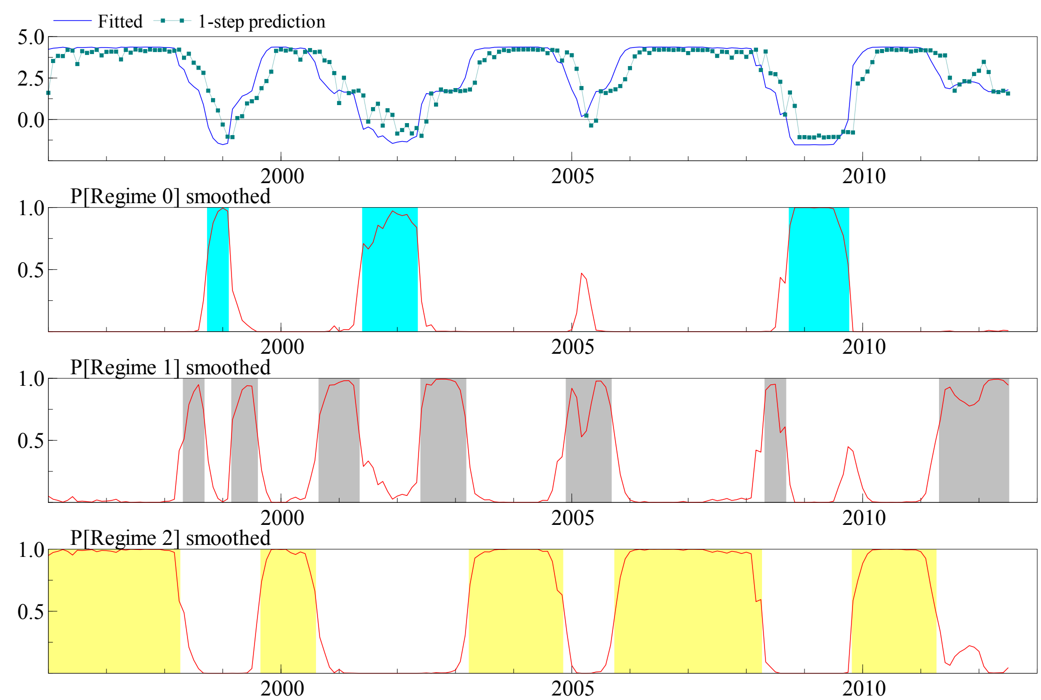


Figure 11: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Russia

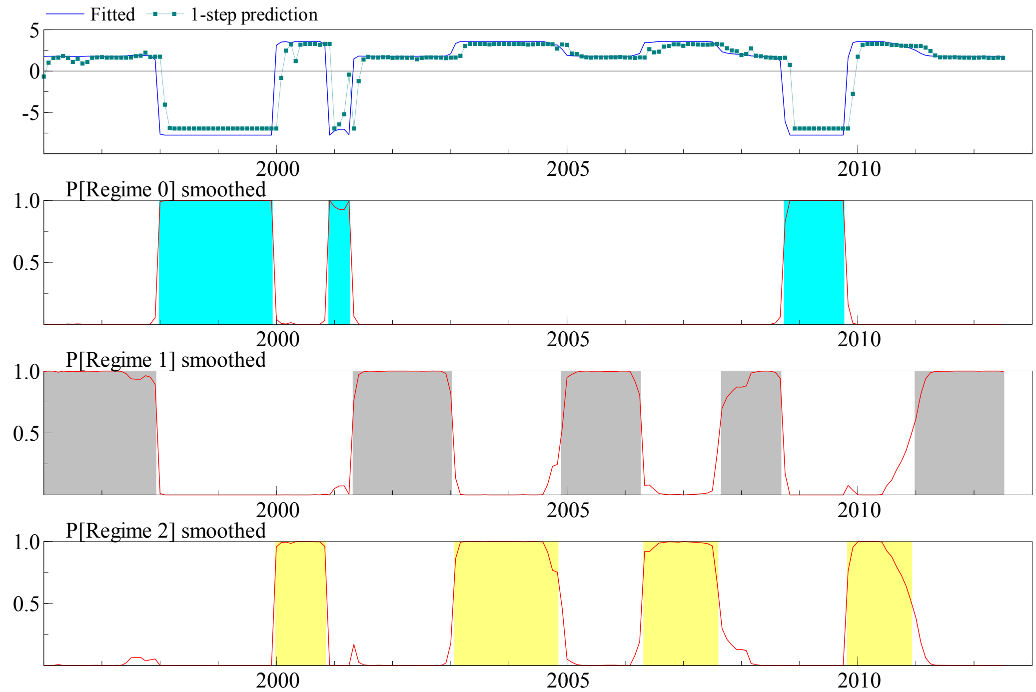


Figure 12: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of South Africa

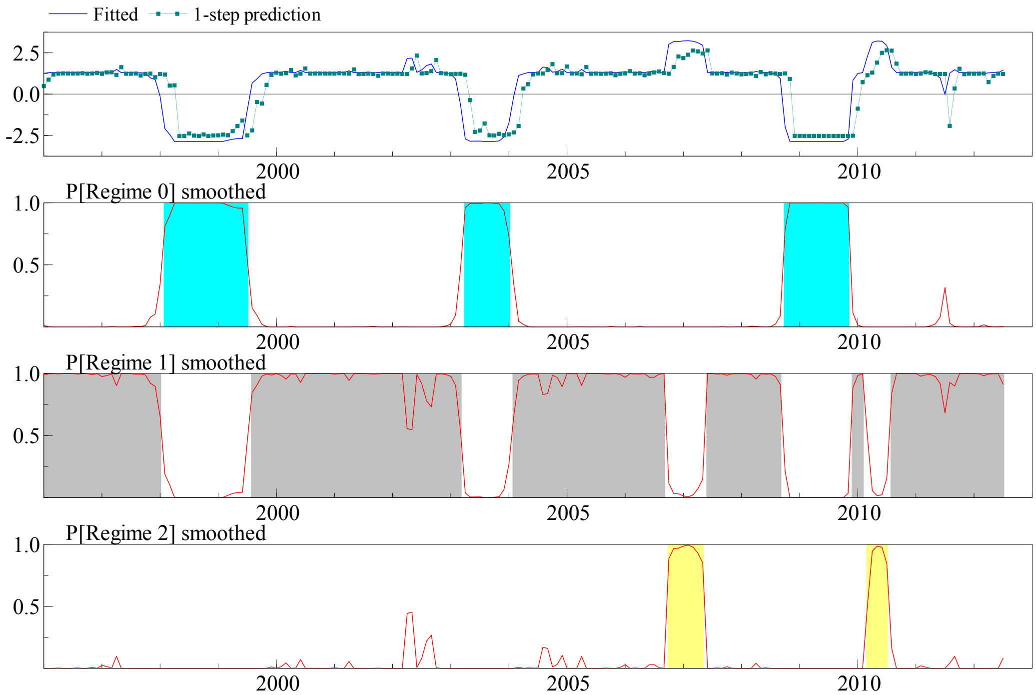


Figure 13: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of South Korea

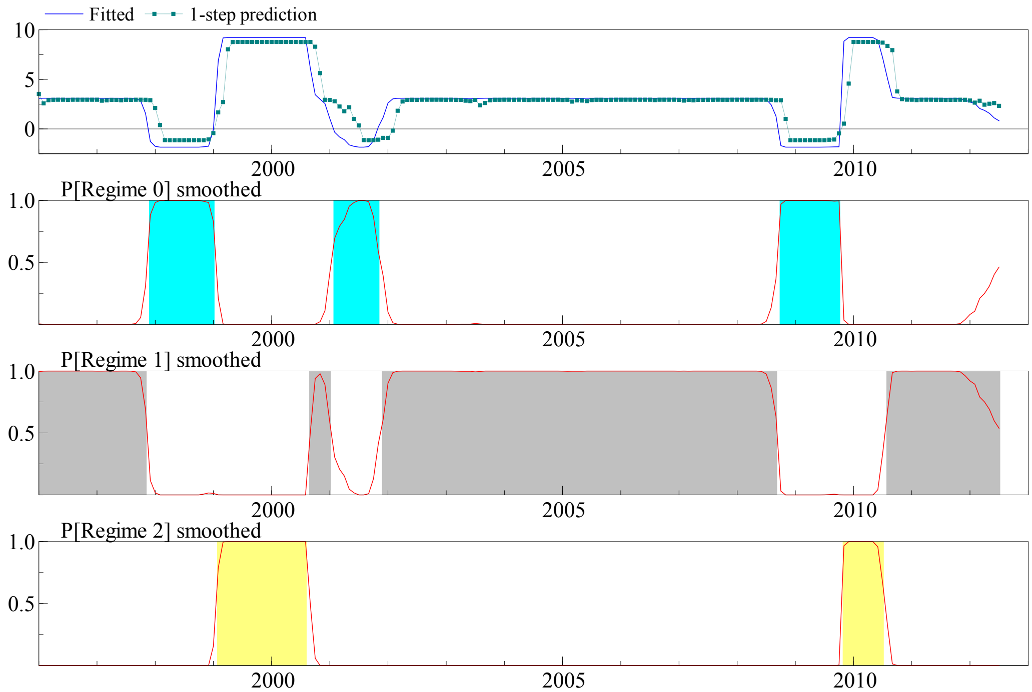


Figure 14: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Turkey

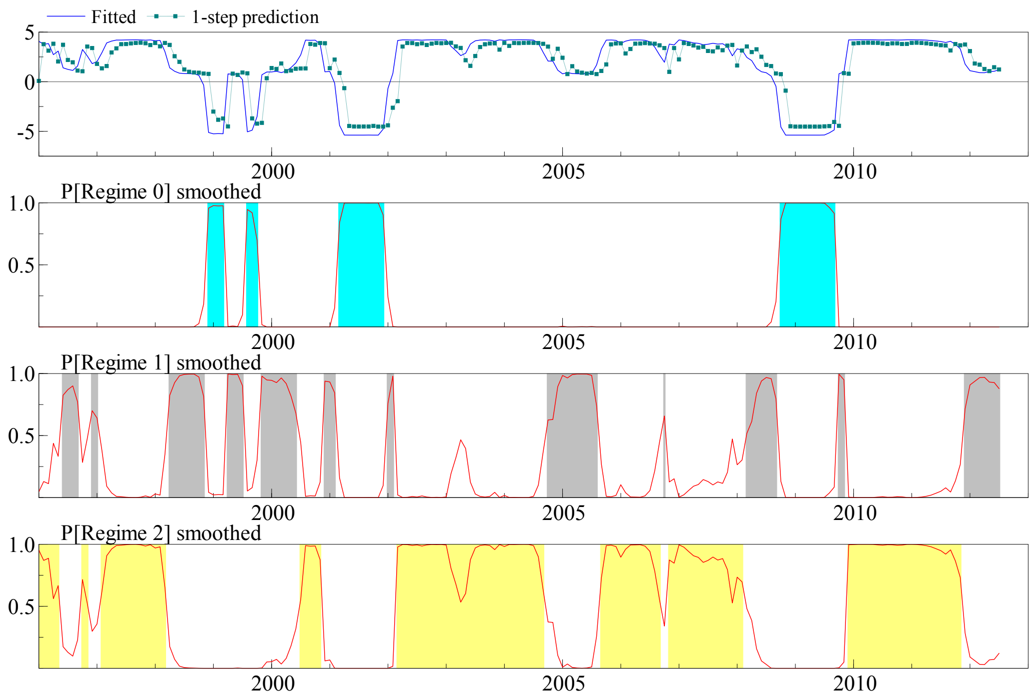


Figure 15: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Argentina

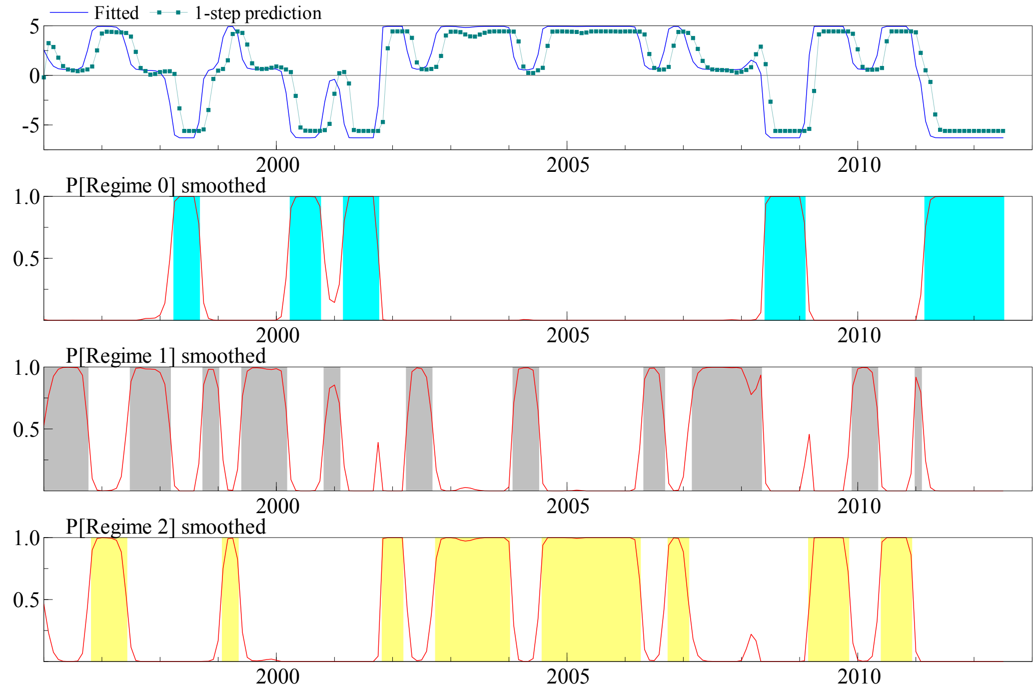


Figure 16: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Brazil

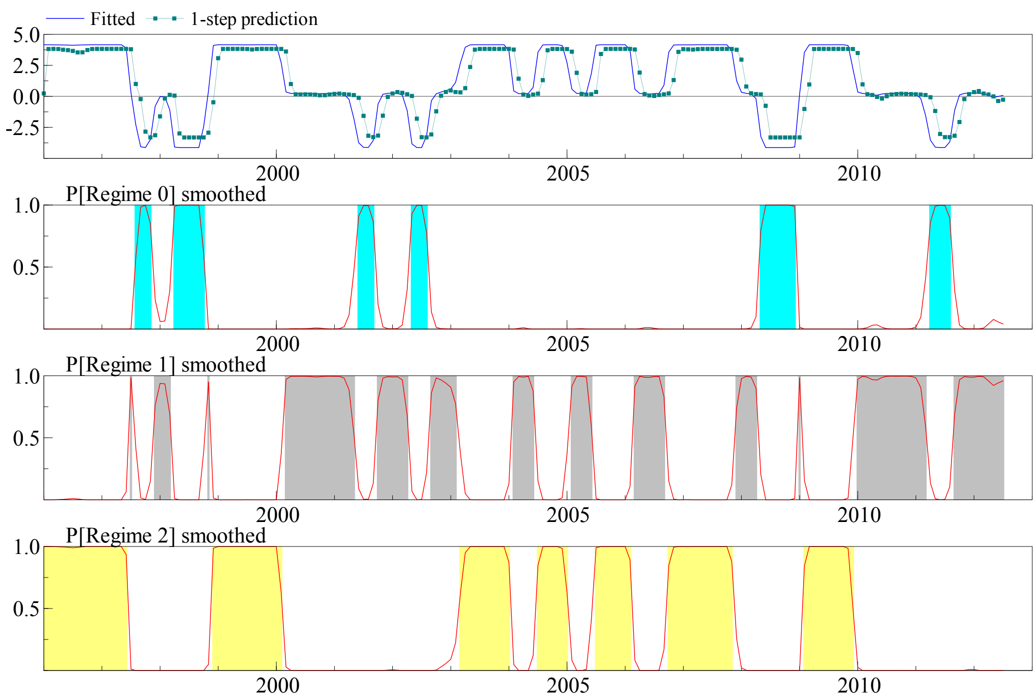


Figure 17: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Chile

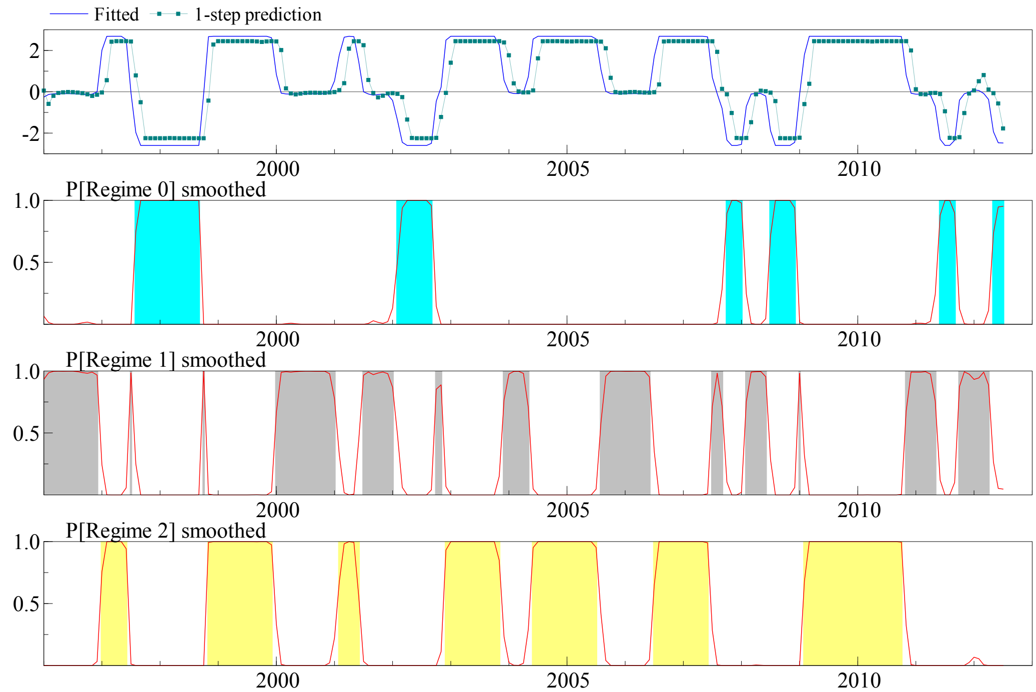


Figure 18: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Czech Republic

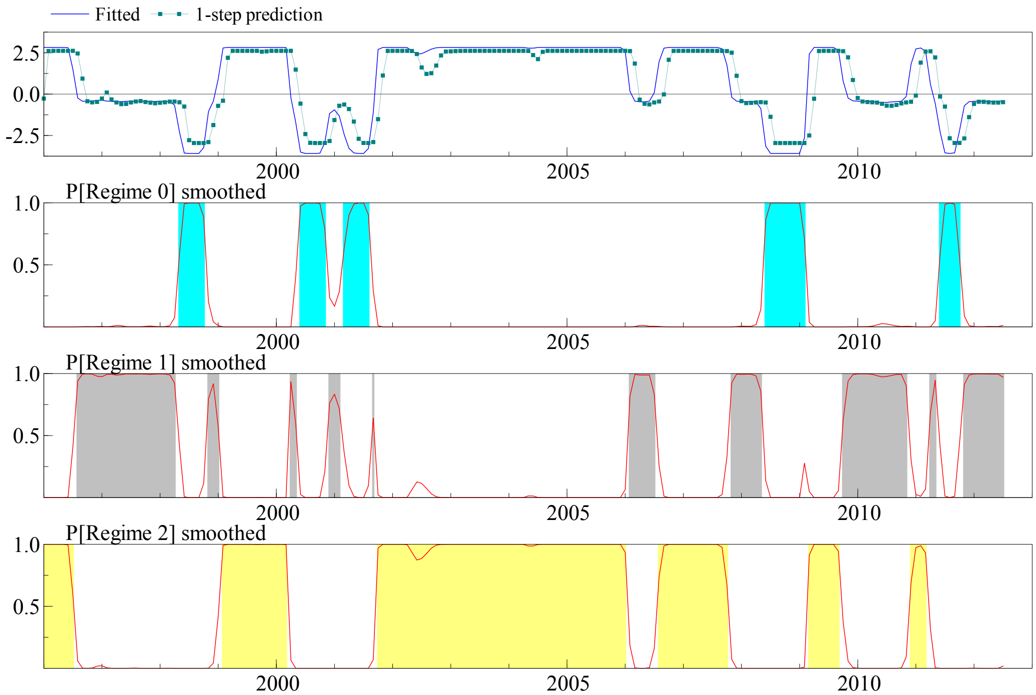


Figure 19: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Malaysia

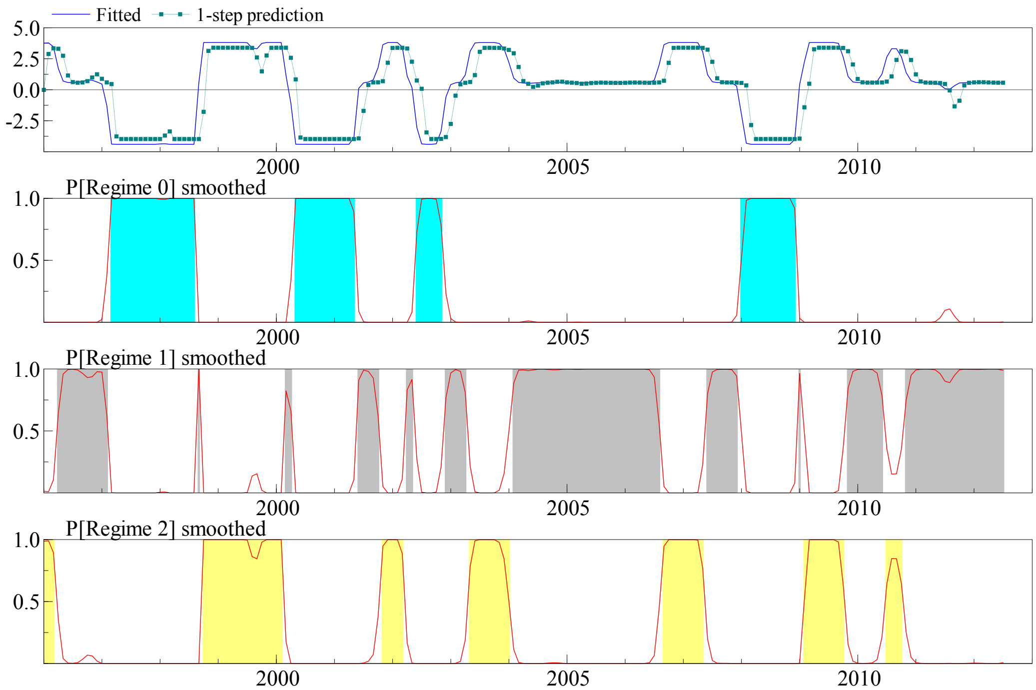


Figure 20: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Mexico

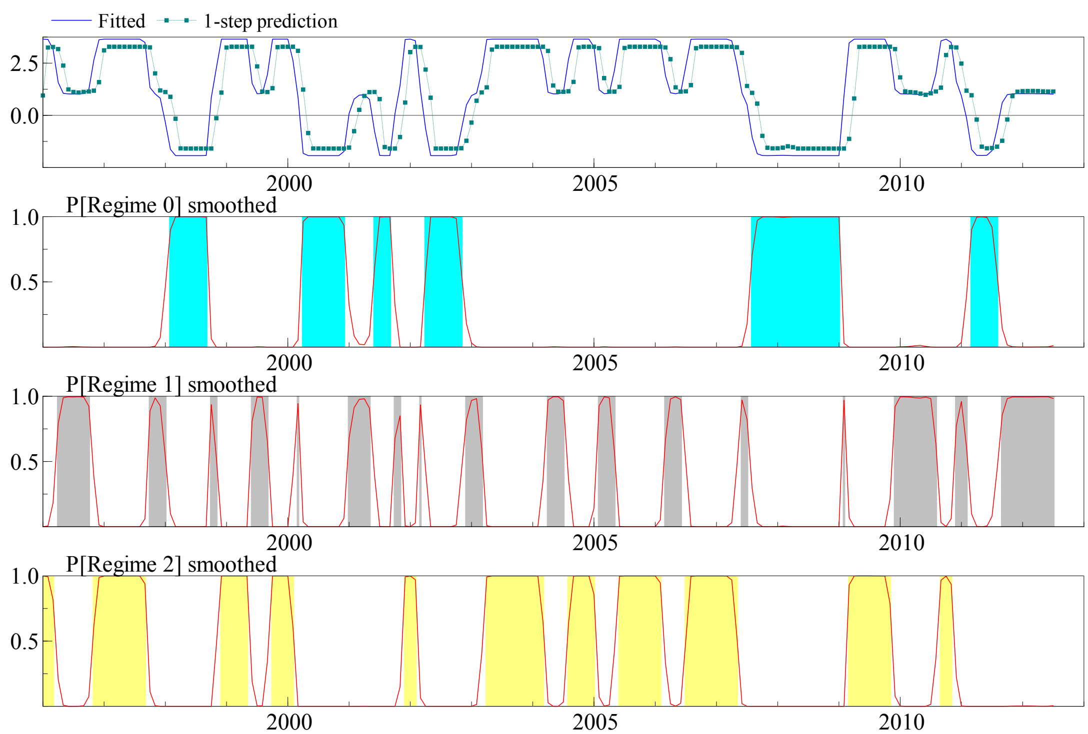


Figure 21: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Peru

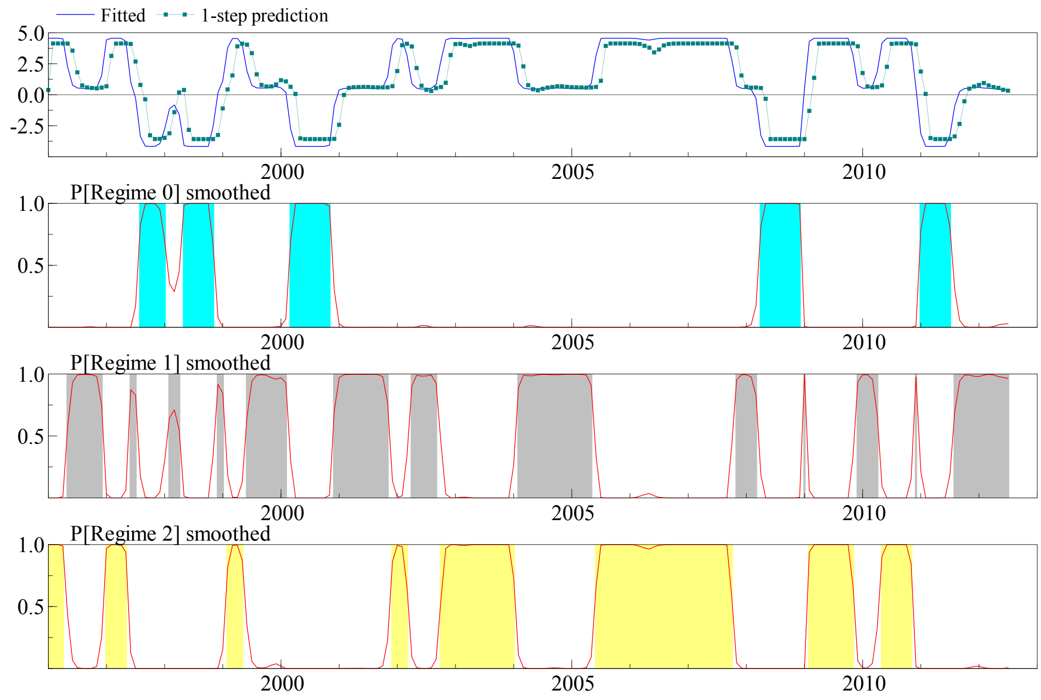


Figure 22: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Poland

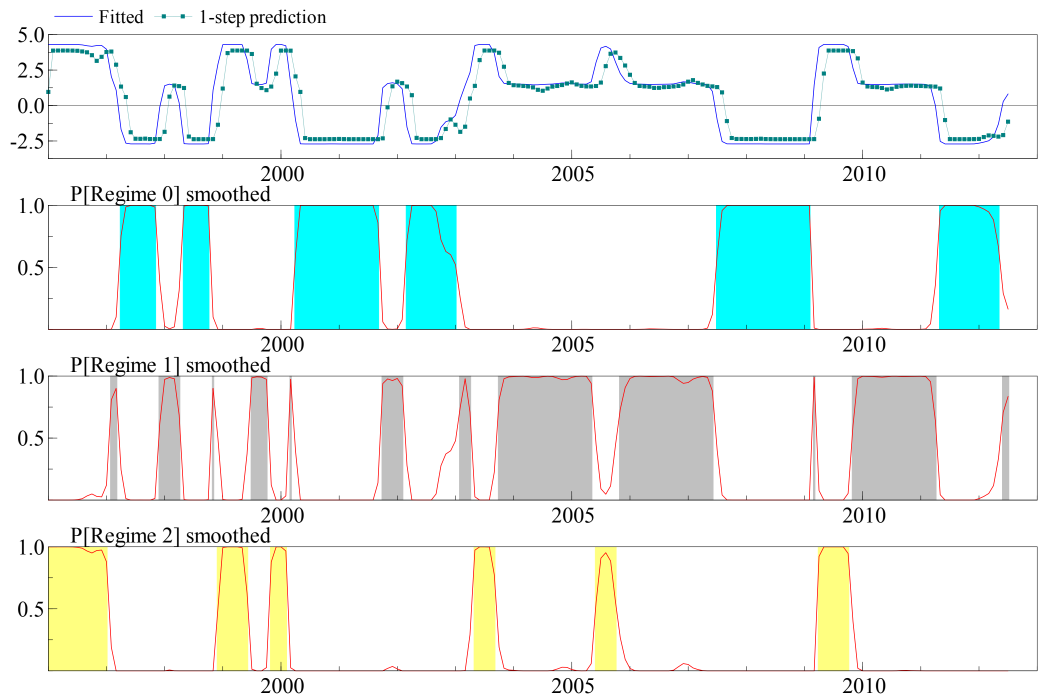


Figure 23: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Russia

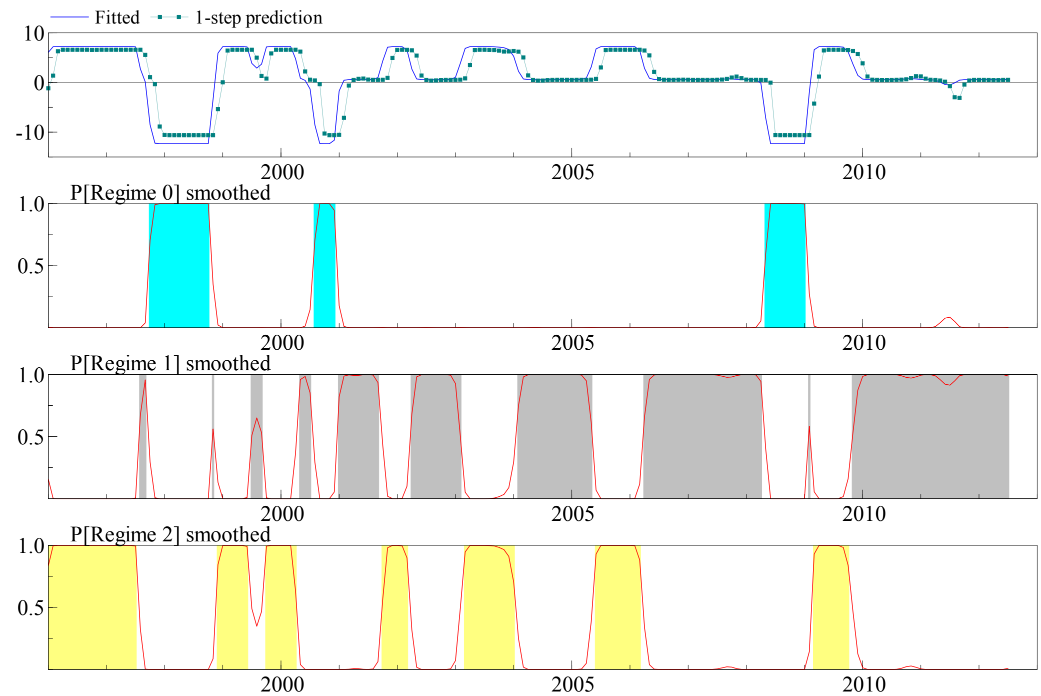


Figure 24: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of South Africa

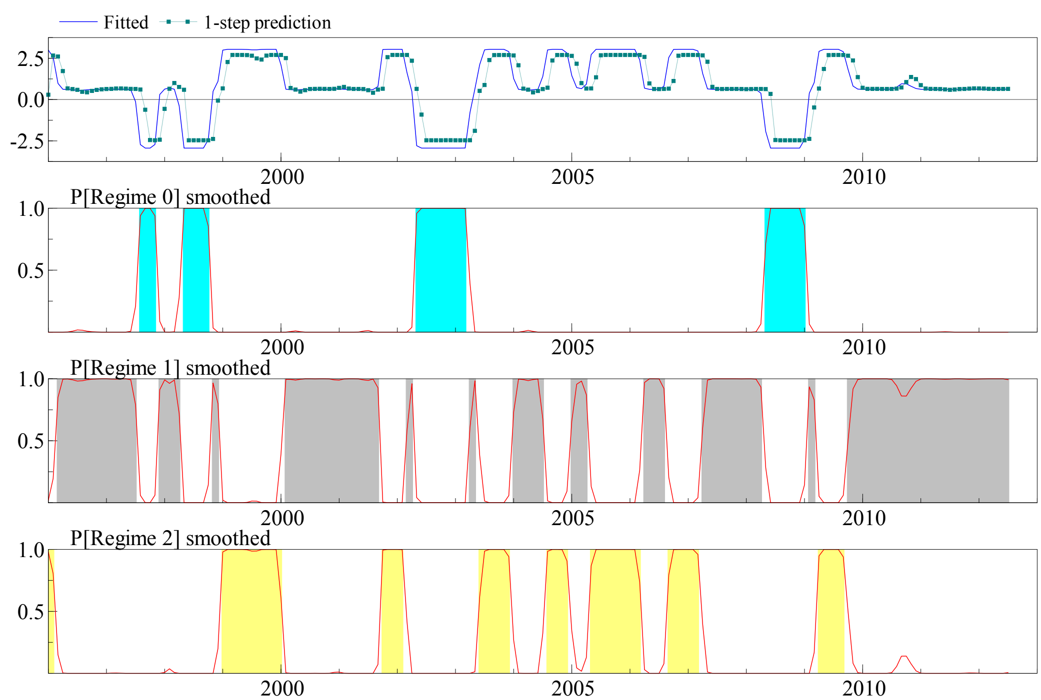


Figure 25: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of South Korea

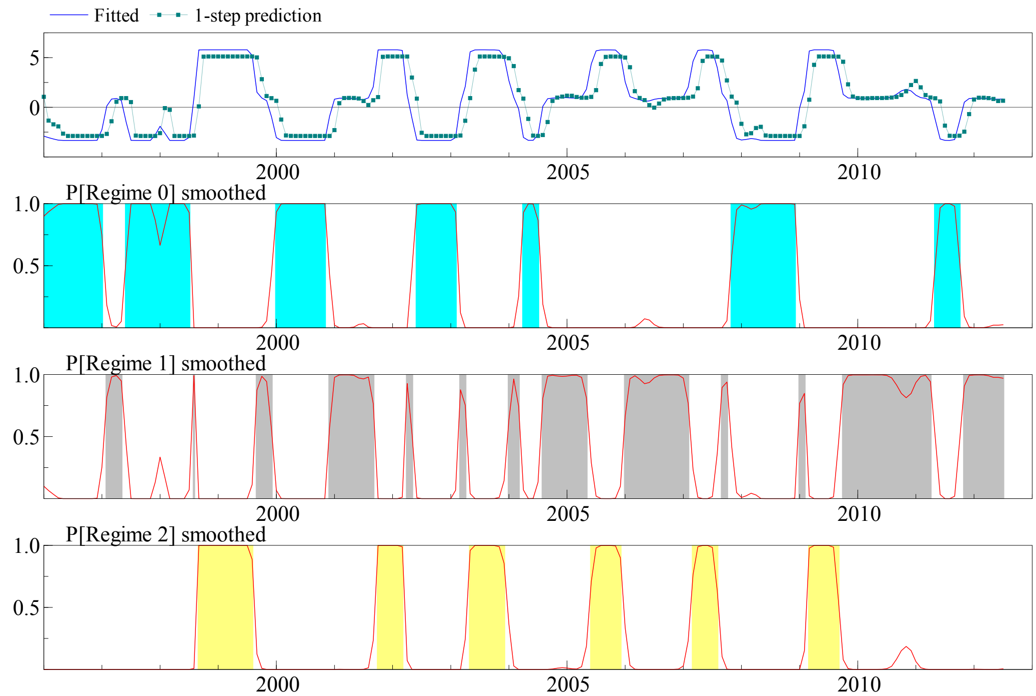


Figure 26: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Turkey

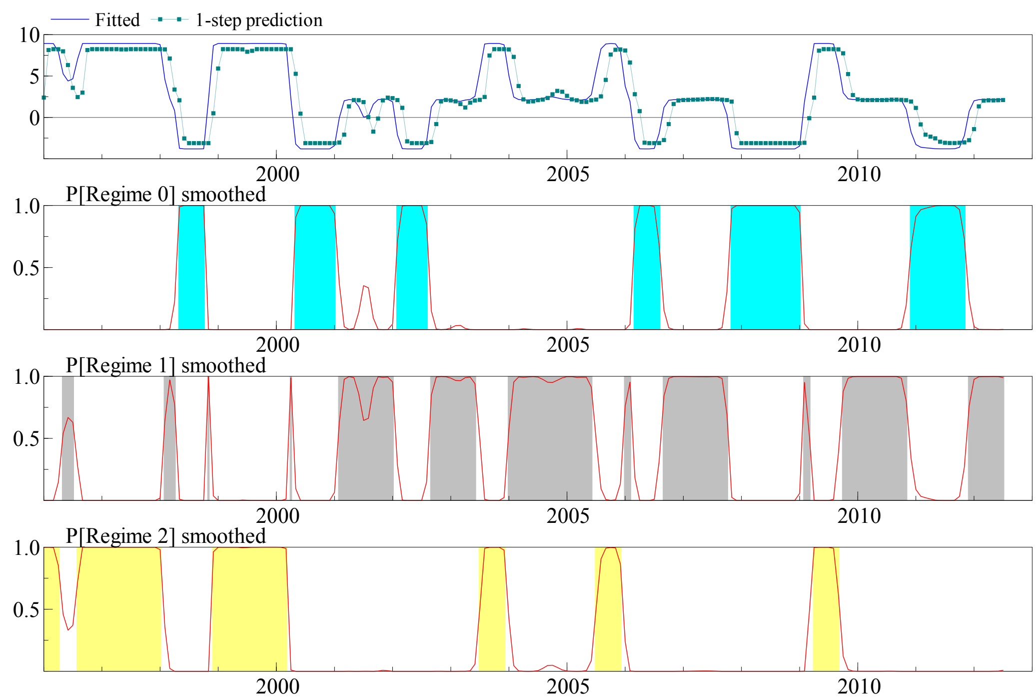
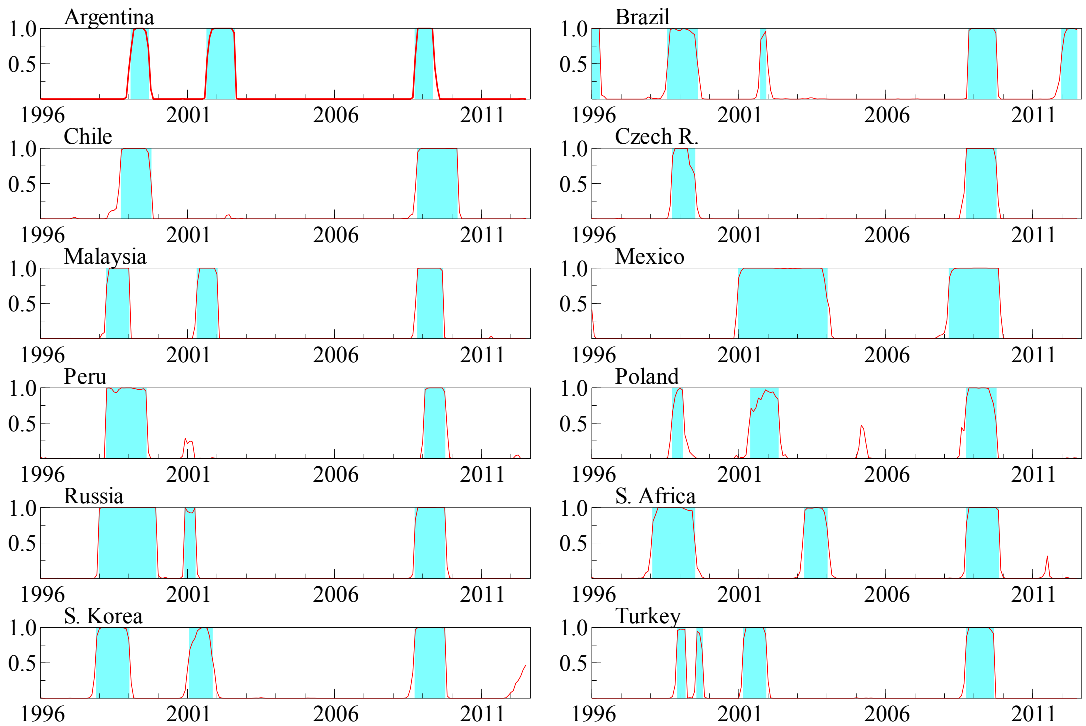


Figure 27: Smoothed Probabilities of Recessions and Business Cycle Dating based on Monthly Industrial Production of EMEs (January 1996 - July 2012)



Notes: Recessions are determined based on the probability rule and denoted by the shaded areas. These periods are characterized by negative mean growth rate at the monthly frequency.

Figure 28: Filtered Probabilities of Recessions in EMEs (January 1996 - July 2012)

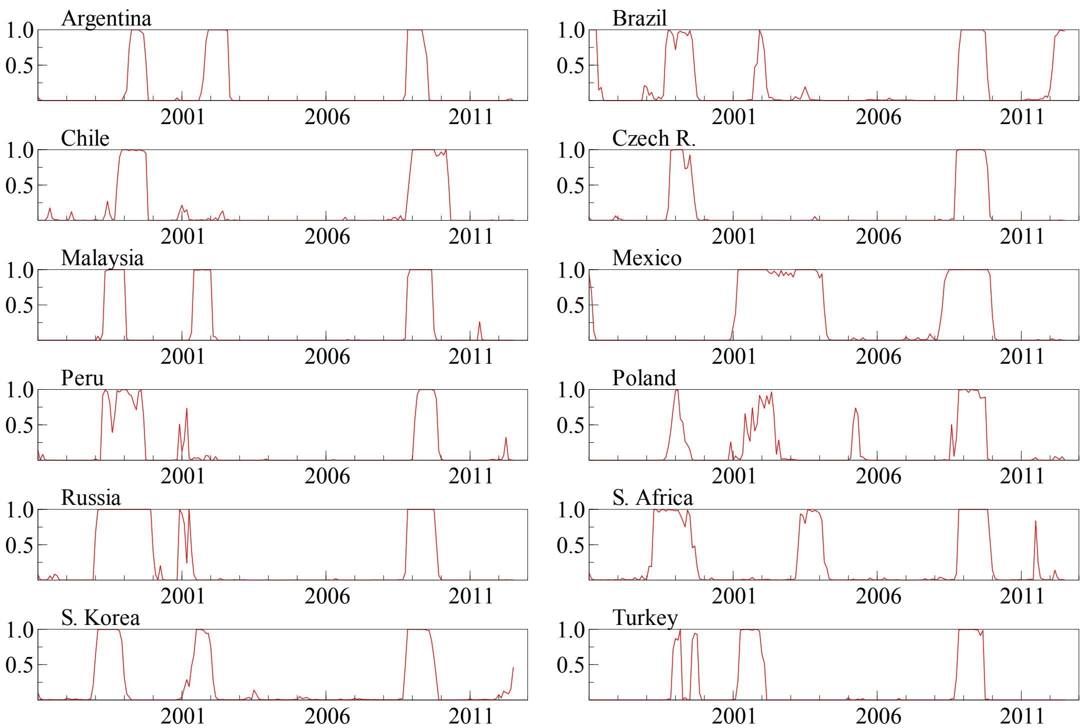
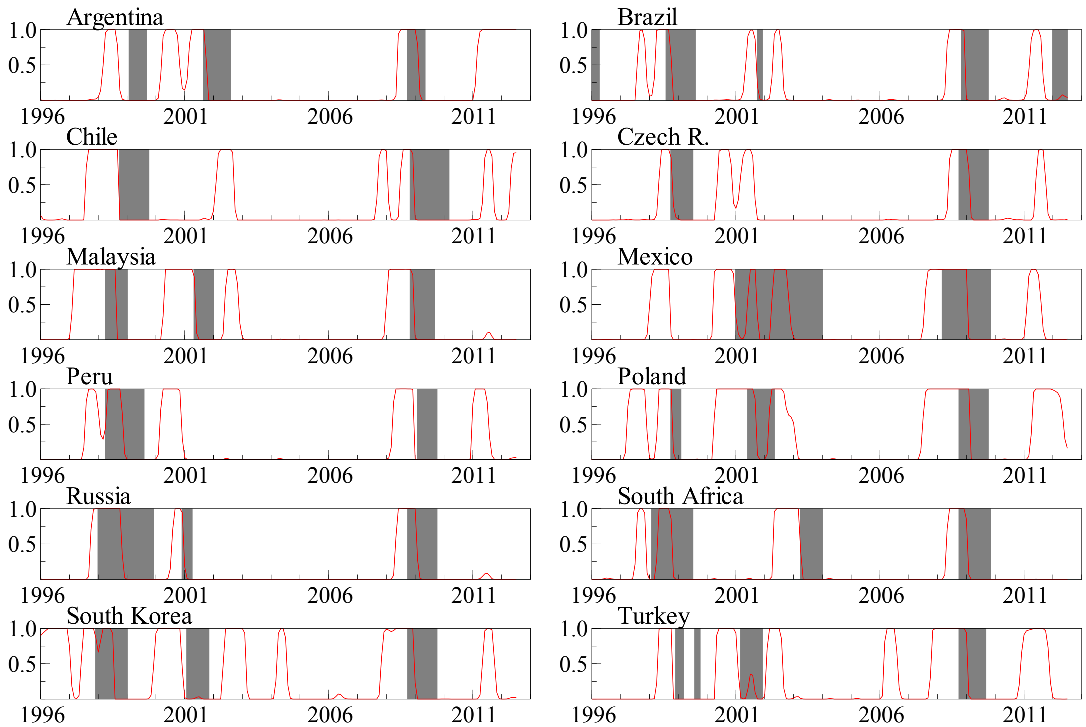
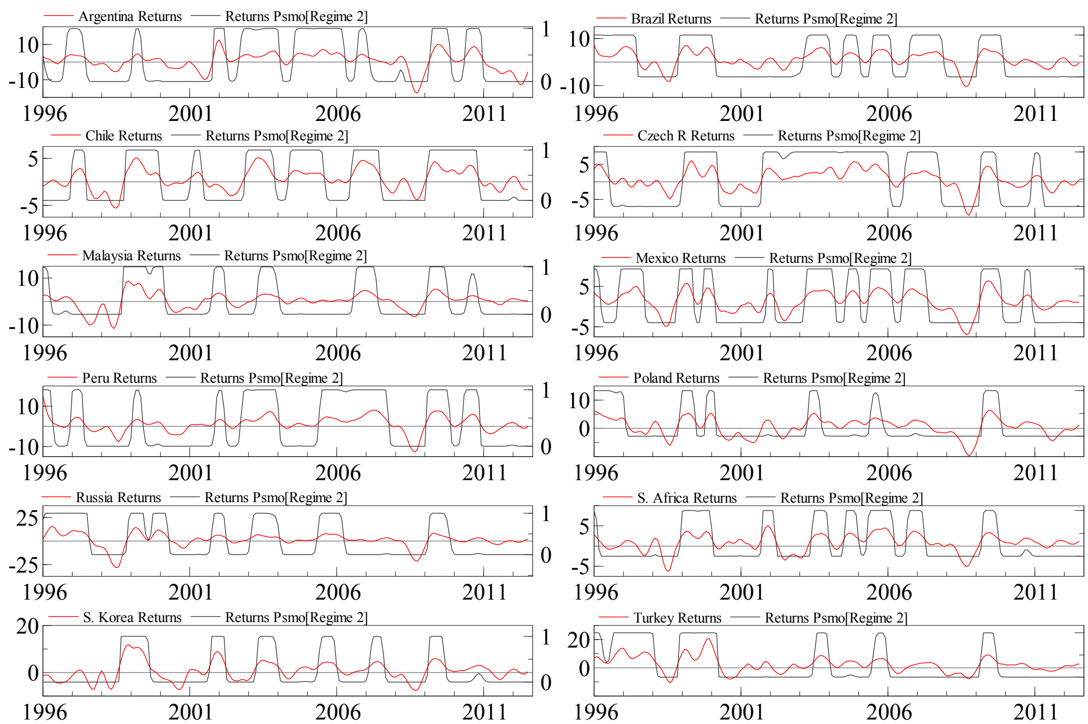


Figure 29: Smoothed Probabilities of Bear Market from the Stock Market Model and Recessions



Notes: The solid lines represent smoothed probabilities of bear market and the shaded areas denote the recessions determined based on the probability rule

Figure 30: Smoothed Probabilities of High Return State from the Stock Market Models and filtered returns of MSCI Returns



Note: Red line represents HP filtered returns and the black line is the smoothed probability of the bear state.

TABLES

Table 1. Unit Root Tests for IPI (Emerging markets)

Test	Test Statistics						Critical Value 5%
	Argentina	Brazil	Chile	Czech	Malaysia	Mexico	
ADF	-2.3227	-3.4954	-3.0174	-2.4152	-3.0658	-2.1283	-1.9425
PP	-2.8697	-3.9111	-6.4807	-3.1113	-3.0658	-2.3378	

Test	Test Statistics						Critical Value 5%
	Peru	Poland	Russia	S Africa	S Korea	Turkey	
ADF	-2.8113	-2.3771	-2.7530	-4.6204	-2.5380	-3.4657	-1.9425
PP	-3.7492	-3.5129	-2.9674	-5.2554	-2.7569	-4.7922	

Note: ADF and PP denote the Augmented Dickey Fuller and Phillips Perron tests. Lags used in the computation of statistics are automatically chosen by Eviews with respect to SIC criterion. The asymptotically equivalent critical values for the test statistics are taken from MacKinnon (1996).

Table 2. Unit Root Tests for IPI (G-7 countries)

Test	Test Statistics							Critical Value 5%
	Canada	France	Germany	Italy	Japan	UK	USA	
ADF	-3.204	-3.293	-4.099	-2.191	-2.782	-2.530	-2.125	-1.9425
PP	-2.128	-3.271	-3.047	-3.182	-3.522	-2.941	-2.425	

Note: ADF and PP denote the Augmented Dickey Fuller and Phillips Perron tests. Lags used in the computation of statistics are automatically chosen by Eviews with respect to SIC criterion. The asymptotically equivalent critical values for the test statistics are taken from MacKinnon (1996).

Table 3. Unit Root Tests for Stock Market Returns (Emerging markets)

Test	Test Statistics						Critical Value 5%
	Argentina	Brazil	Chile	Czech	Malaysia	Mexico	
ADF	-3.9043	-3.8666	-4.1070	-3.9240	-3.8391	-3.5075	-1.9425
PP	-3.8766	-4.1354	-3.6217	-3.7872	-3.8292	-3.5815	

Test	Test Statistics						Critical Value 5%
	Peru	Poland	Russia	S Africa	S Korea	Turkey	
ADF	-4.3266	-3.8187	-4.6385	-3.5906	-4.3960	-3.1781	-1.9425
PP	-4.7696	-4.0709	-3.7508	-4.0954	-3.8336	-3.6311	

Note: ADF and PP denote the Augmented Dickey Fuller and Phillips Perron tests. Lags used in the computation of statistics are automatically chosen by Eviews with respect to SIC criterion. The asymptotically equivalent critical values for the test statistics are taken from MacKinnon (1996).

Table 4: MSMH(3) – AR(0) Results for Monthly IPI for EMEs

	Brazil	**Czech R.**	**Mexico**	**Russia**	**S. Africa**	**S. Korea**
log-L	-383.65	-385.86	-299.97	-384.685	-371.54	-418.26
LRP	0.000	0.000	0.000	0.000	0.000	0.000
α_0	-2.80	-5.17	-1.14	-7.74	-2.86	-1.83
	(0.36)	(0.76)	(0.20)	(1.05)	(0.44)	(0.72)
α_1	0.36	0.80	1.44	1.80	1.30	3.10
	(0.19)	(0.18)	(0.09)	(0.10)	(0.11)	(0.16)
α_2	2.98	3.90	3.44	3.60	3.24	9.21
	(0.18)	(0.14)	(0.15)	(0.14)	(0.19)	(0.44)
σ_0	1.97	2.81	1.45	6.62	2.66	3.47
	(0.23)	(0.45)	(0.13)	(0.72)	(0.29)	(0.41)
σ_1	0.94	1.29	0.63	0.86	1.14	1.36
	(0.11)	(0.11)	(0.06)	(0.06)	(0.09)	(0.10)
σ_2	1.39	1.15	0.96	0.94	0.53	2.01
	(0.10)	(0.09)	(0.93)	(0.08)	(0.13)	(0.31)
p_{00}	0.89	0.90	0.95	0.92	0.91	0.92
	(0.05)	(0.06)	(0.02)	(0.04)	(0.04)	(0.04)
p_{10}	0.04			0.03		0.02
	(0.01)			(0.01)		(0.01)
p_{01}	0.06	0.02	0.03	0.02	0.02	0.02
	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
p_{11}	0.87	0.90	0.92	0.95	0.94	
	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	
p_{12}	0.06	0.07	0.07	0.05	0.26	0.07
	(0.02)	(0.02)	(0.03)	(0.03)	(0.16)	(0.04)
AIC	3.96	3.97	3.11	3.98	3.83	4.30
SC	4.14	4.14	3.85	4.18	4.00	4.46
HQ	4.04	4.04	3.75	4.06	3.90	4.37

Notes: The sample period is January 1996 - July 2012. LRP denotes the upper bound for the p-value of the likelihood ratio test of linearity based on Davies (1987). Standard errors are reported in parenthesis.

Table 5: MSM(3)-AR(0) Results for Monthly IPI for EMEs

	Argentina	**Chile**	**Malaysia**	**Peru**	**Poland**	**Turkey**
log-L	-373.65	-391.03	-413.21	-409.23	-414.32	-469.946
LRP	0.000	0.000	0.000	0.000	0.000	0.000
α_0	-4.93	-2.27	-4.17	-2.75	-1.53	-5.37
	(0.32)	(0.31)	(0.31)	(0.33)	(0.56)	(0.42)
α_1	-0.26	0.98	1.58	0.94	1.69	0.80
	(0.23)	(0.19)	(0.19)	(0.30)	(0.51)	(0.43)
α_2	3.64	2.81	5.24	4.16	4.37	4.23
	(0.13)	(0.22)	(0.23)	(0.25)	(0.19)	(0.32)
σ	1.31	1.53	1.57	1.51	1.62	2.00
	(0.06)	(0.08)	(0.08)	(0.08)	(0.09)	(0.13)
p_{00}	0.88	0.93	0.89	0.90	0.87	0.86
	(0.06)	(0.04)	(0.05)	(0.06)	(0.07)	(0.06)
p_{10}					0.11	
					(0.04)	
p_{01}	0.05	0.03	0.03	0.03	0.06	0.06
	(0.02)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)
p_{11}	0.89	0.96	0.93	0.88	0.85	0.80
	(0.04)	(0.02)	(0.02)	(0.04)	(0.06)	(0.06)
p_{12}	0.02	0.05	0.06	0.07	0.05	0.08
	(0.01)	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)
AIC	3.83	4.01	4.23	4.19	4.25	4.80
SIC	3.96	4.14	4.36	4.32	4.40	4.93
HQ	4.02	4.06	4.28	4.24	4.31	4.85

Notes: The sample period is January 1996 - July 2012. LRP denotes the upper bound for the p-value of the likelihood ratio test of linearity based on Davies (1987). Standard errors are reported in parenthesis.

Table 6: MSMH(3) – AR(0) Results for Monthly IPI for G-7 Countries

	France	**Italy**	**Japan**	**USA**
log-L	-263.09	-324.66	-404.52	-228.14
LRP	0.000	0.000	0.000	0.000
α_0	-5.40	-6.32	-5.21	-2.44
	(0.63)	(0.77)	(0.74)	(0.30)
α_1	0.05	-0.46	1.45	0.91
	(0.06)	(0.09)	(0.08)	(0.05)
α_2	1.81	1.82	2.61	2.32
	(0.10)	(0.12)	(0.99)	(0.07)
σ_0	2.31	3.59	4.38	1.80
	(0.44)	(0.53)	(0.45)	(0.21)
σ_1	0.75	0.88	0.86	0.45
	(0.04)	(0.06)	(0.06)	(0.03)
σ_2	0.64	0.90	4.01	0.58
	(0.06)	(0.07)	(0.57)	(0.05)
p_{00}	0.93	0.95	0.91	0.94
	(0.06)	(0.04)	(0.04)	(0.03)
p_{01}	0.00	0.01	0.03	0.02
	(0.00)	(0.01)	(0.01)	(0.01)
p_{11}	0.97	0.95		0.94
	(0.01)	(0.02)		(0.02)
p_{12}	0.06	0.06	0.11	0.03
	(0.03)	(0.02)	(0.07)	(0.02)
AIC	2.74	3.36	4.15	2.39
SC	2.91	3.52	4.30	2.55
HQ	2.81	3.43	4.21	2.46

Notes: The sample period is January 1996 - July 2012. LRP denotes the upper bound for the p-value of the likelihood ratio test of linearity based on Davies (1987). Standard errors are reported in parenthesis.

Table 7: MSM(3) – AR(0) Results for Monthly IPI for G-7 Countries

	Canada	**Germany**	**UK**
log-L	-128.81	-359.99	-195.15
LRP	0.000	0.000	0.000
α_0	-1.21	-8.87	-4.47
	(0.11)	(0.41)	(0.15)
α_1	0.82	0.33	-0.62
	(0.04)	(0.18)	(0.07)
α_2	1.79	3.01	0.61
	(0.05)	(0.21)	(0.07)
σ	0.40	1.27	0.54
	(0.02)	(0.06)	(0.02)
p_{00}	0.91	0.90	0.91
	(0.07)	(0.09)	(0.07)
p_{01}	0.01	0.00	0.01
	(0.00)	(0.00)	(0.01)
p_{11}	0.95	0.95	0.93
	(0.02)	(0.02)	(0.02)
p_{12}	0.03	0.05	0.04
	(0.02)	(0.02)	(0.02)
AIC	1.37	3.69	2.04
SC	1.50	3.83	2.17
HQ	1.42	3.75	2.09

Notes: The sample period is January 1996 - July 2012. LRP denotes the upper bound for the p-value of the likelihood ratio test of linearity based on Davies (1987). Standard errors are reported in parenthesis.