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NONLINEAR ANALYSIS OF BUSINESS CYCLES AND STOCK MARKET DYNAMICS: EVIDENCE FROM MALAYSIA, RUSSIA, BRAZIL, AND TURKEY

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Abstract

This study presents a systematic and consistent analysis, for the first time, for Malaysia, Russia, Brazil, and Turkey to characterize the dynamics of their business and stock market cycles, and the dynamic relationships between these cyclical interactions. First, the study charecterizes and provides benchmark chronologies of business and stock market cycles for the emerging market economies based on hidden Markov models that are robust to potential parameter instability. Second, the paper models the stock market dynamics and relates it to the business cycles for these economies. The spikes in probabilities of the bear states 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 ten months, implying that the stock market returns can be used as a forward looking indicator for these emerging market economies.

Keywords: Markov Switching Models, Business Cycles, Emerging Markets, Stock Markets

JEL Classifications: E32, C32.

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

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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 for a diverse group of emerging market economies, namely, Brazil, Malaysia, Russia, and Turkey: What are the characteristic properties of business cycle fluctiations and stock market movements in these emerging market economies when we account for the asymetric behavior across cyclical phases? What are the relationships between the dynamics of stock markets and business cycles in these emerging markets and can stock market movements be used to predict business cycle recessions in these countries? To answer these questions, we provide a systematic and consistent analysis for the first time for a diverse group of emerging market 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

[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.

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.

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, and the dynamic relationships between these cyclical interactions. 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 a diverse group of emerging market economies.

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 and discusses the data. Section 3 presents the empirical results for the real economy. Section 4 examines the analysis of the stock market and the relation between the economy and the stock market for emerging markets. Section 5 concludes.

2. The Model and Data

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

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

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 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.

This paper examines on a diverse group of emerging economies, including economies from Europe, Asia, and South America. We run the analyses for four emerging market economies: Brazil, Malaysia, Russia, and Turkey. The 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

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[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.
[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.

(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]

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

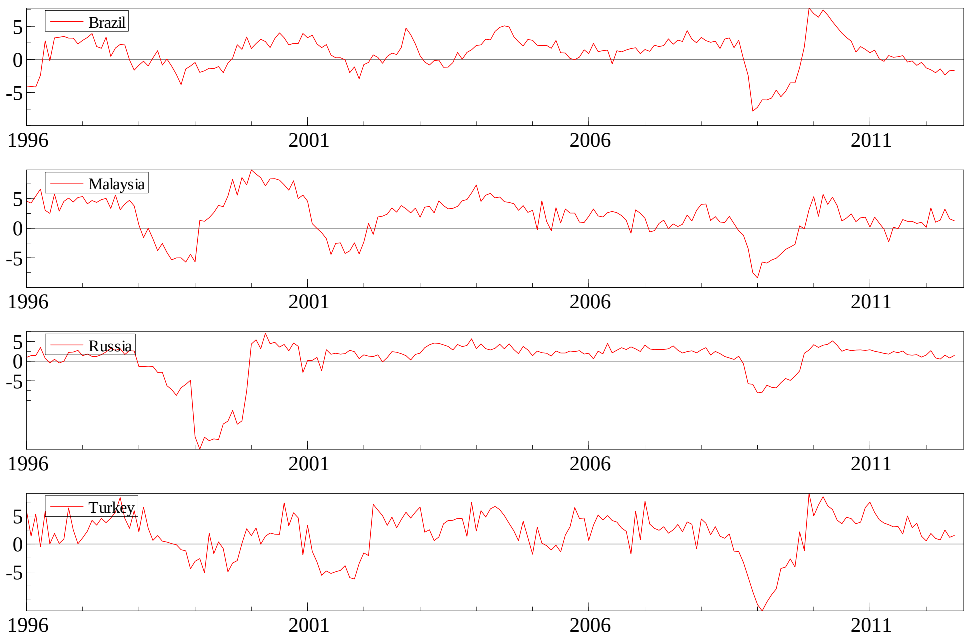

Figure 1 plots the growth rates of monthly industrial production for the emerging markets in our sample. We observe from Figure 1 that for all of the sample countries, the sharpest drop in growth rate of economic activity happens around 2008. The year on year growth rates of industrial production for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

3. Cyclical Dynamics of the Real Economy

We start our analysis with modeling the economic activity for emerging markets. The 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

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

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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.

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Table 1: MSMH(3) – AR(0) Results for Monthly IPI for Brazil and Russia

	Brazil	**Russia**
log-L	-383.65	-384.685
LRP	0.000	0.000
α_0	-2.80	-7.74
	(0.36)	(1.05)
α_1	0.36	1.80
	(0.19)	(0.10)
α_2	2.98	3.60
	(0.18)	(0.14)
σ_0	1.97	6.62
	(0.23)	(0.72)
σ_1	0.94	0.86
	(0.11)	(0.06)
σ_2	1.39	0.94
	(0.10)	(0.08)
p_{00}	0.89	0.92
	(0.05)	(0.04)
p_{10}	0.04	0.03
	(0.01)	(0.01)
p_{01}	0.06	0.02
	(0.03)	(0.01)
p_{11}	0.87	0.95
	(0.04)	(0.02)
p_{12}	0.06	0.05
	(0.02)	(0.03)
AIC	3.96	3.98
SC	4.14	4.18
HQ	4.04	4.06

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.

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Table 2: MSM(3)-AR(0) Results for Monthly IPI for Malaysia and Turkey

	Malaysia	**Turkey**
log-L	-413.21	-469.946
LRP	0.000	0.000
α_0	-4.17	-5.37
	(0.31)	(0.42)
α_1	1.58	0.80
	(0.19)	(0.43)
α_2	5.24	4.23
	(0.23)	(0.32)
σ	1.57	2.00
	(0.08)	(0.13)
p_{00}	0.89	0.86
	(0.05)	(0.06)
p_{10}		
p_{01}	0.03	0.06
	(0.01)	(0.03)
p_{11}	0.93	0.80
	(0.02)	(0.06)
p_{12}	0.06	0.08
	(0.03)	(0.04)
AIC	4.23	4.80
SIC	4.36	4.93
HQ	4.28	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.

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%. Once the economy is in a recession, the estimated probability of

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staying in the same regime for the next month is given in Table 3. The average durations and percentages of staying in the same state were calculated using the transition probabilities and reported in Table 4. These estimated transition probabilities of staying in the same state varies according to individual country characteristics.

Table 3. Estimated Markov probabilities of staying in the same state

	Brazil	**Malaysia**	**Russia**	**Turkey**
Regime 0	0.89	0.89	0.92	0.86
Regime 1	0.87	0.93	0.95	0.80
Regime 2	0.93	0.93	0.92	0.91

Note: Regime 0 represents the recession state, Regime 1 represents the low growth state, and the regime 2 represents the high growth state

Table 4. Average durations and percentages of staying in one state

	Brazil		**Malaysia**		**Russia**		**Turkey**	
	Percentage	Duration	Percentage	Duration	Percentage	Duration	Percentage	Duration
Regime 0	19.60	7.80	15.08	10.00	21.11	14.00	14.57	7.25
Regime 1	33.67	8.38	50.75	14.43	47.24	18.80	30.15	5.00
Regime 2	46.73	15.50	34.17	17.00	31.66	15.75	55.28	13.75

Note: Regime 0 represents the recession state, Regime 1 represents the low growth state, and the regime 2 represents the high growth state

Table 5: Dating of Business Cycles from the Smoothed Model Probabilities

Brazil			**Malaysia**			**Russia**			**Turkey**		
Peak	Trough	Duration (months)	Peak	Trough	Duration (months)	Peak	Trough	Duration (months)	Peak	Trough	Duration (months)
1996:1	1996:4	4	1998:4	1999:1	10	1998:1	1999:12	24	1998:12	1999:3	4
1998:8	1999:8	13	2001:5	2002:1	9	2000:12	2001:4	5	1999:8	1999:10	3
2001:10	2001:12	3	2008:11	2009:9	11	2008:10	2009:10	13	2001:3	2001:12	10
2008:11	2009:10	12							2008:10	2009:9	12
2012:1	2012:7	7									

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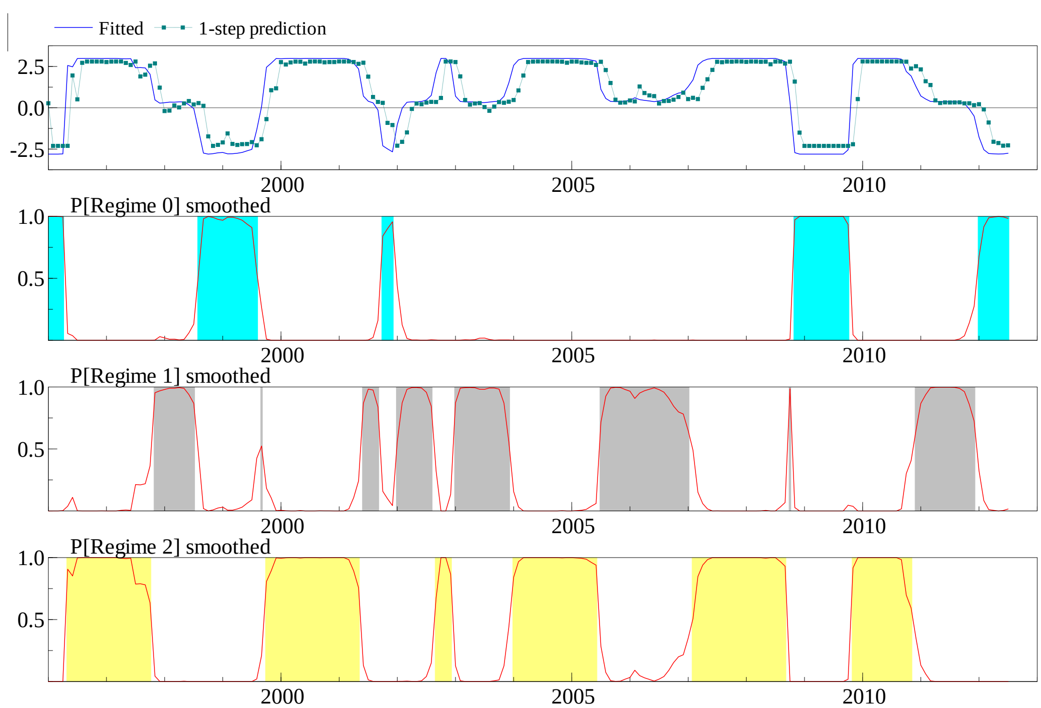
For the growth rates of monthly industrial production index for Brazil, we find that the three-state mean specification with constant variance adequately captures state dependent dynamics of the economy. The small value of the Davies upper bound along with the substantially different mean estimates and transition regime probabilities across different regimes document the strong asymmetry. Linearity is clearly rejected and the results are in favor of nonlinearity. Regarding determining the number of regimes, all three information criteria tests and modified likelihood ratio values comparing a 3 state versus a 2 state specification suggest that a 3 regime model fits better for Brazil. In addition, the results cannot reject the null hypothesis of invariant variance. The smoothed probabilities of all three states of the Brazilian economy are plotted in Figure 2. The economy has a monthly growth rate of around -2.80% from the same month of the previous year in a typical recession. The mean values for expansions are estimated to be around 0.36% and 2.98% for the low and high growth periods. Once the economy is in a recession, the probability of staying in the recession for the next month is 0.89. This implies an average duration of 7.8 months for recessions, which corresponds to 19.6% of the whole sample period. The transition probabilities for the expansion states are estimated to be 0.87 and 0.93, which imply longer durations of 8.38 and 15.5 months for low and high growth states, constituting 33% and 46% of the sample period. The smoothed probabilities of recessions implied by the model with respect to industrial production index identify five spikes in probabilities which are all associated with sharp declines in output. Three of them are longer than the 6-months rule; therefore three Brazilian crises are identified in our framework: 1998, 2008, and 2012. All these recessions are associated with sharp declines in economic activity, with the 2008 recession being the deepest one.

Figure 2: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Brazil



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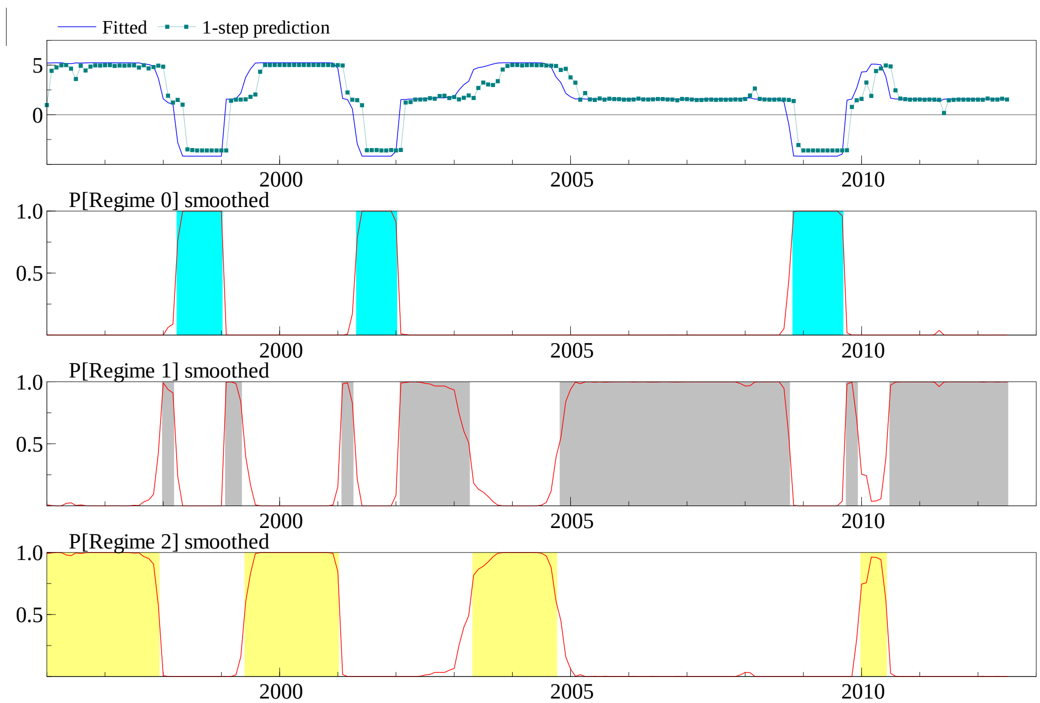
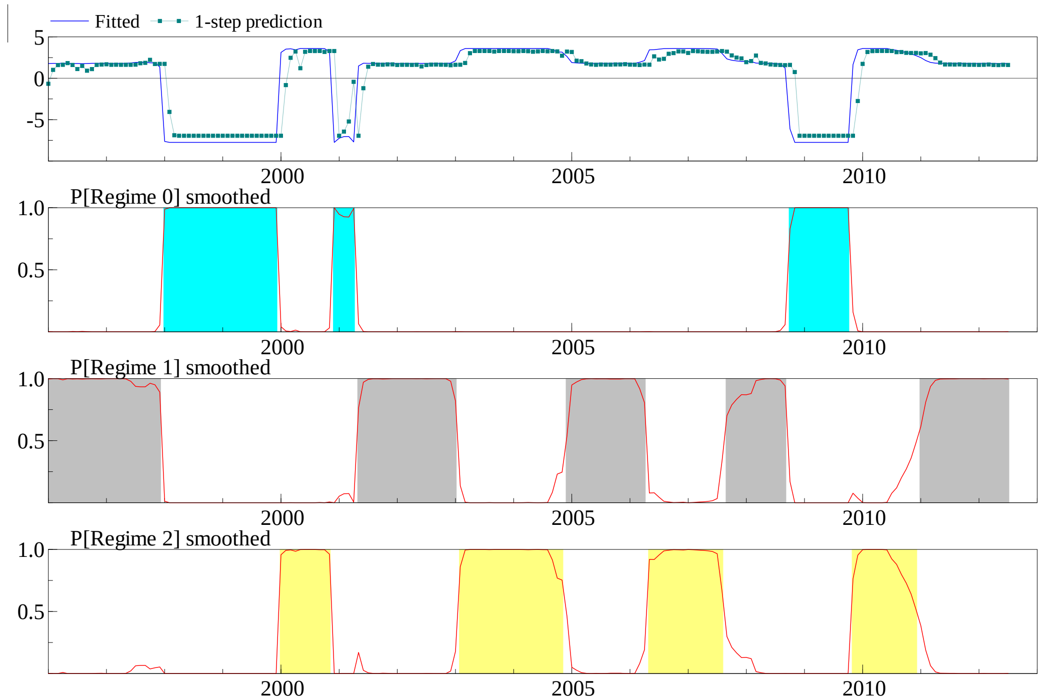
The results for the Malaysian economy reveal three different phases of industrial production growth. The results also favor the existence of regime dependent variances. Linearity is strongly rejected. The recessionary state corresponds to a monthly growth rate of -4.17%, the high growth state corresponds to a monthly growth rate of 5.24%, and the low growth state corresponds to a monthly growth rate of 1.58% The estimated Markov probabilities of staying in the same regime for recession, low and high growth states are persistent with the values of 0.89, 0.93, and 0.93 respectively. We find that the expected duration of a recession is around 10 months, with a percentage of 15.08. Of the three regimes, the expected duration of a high-growth regime is the longest with an average of 17 months and a percentage of 34.17. And finally, the expected duration of a low-growth regime is around 14.43 months, with a percentage of 50.75. Figure 3 shows the sequence of the smoothed probabilities for each of Malaysia's different regime. Dating of the Malaysian economy based on these smoothed model probabilities identify the 1998-1999, 2001-2002, and 2008-2009 recessions in Malaysia.

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



For the Russian growth rates of monthly industrial production index, we find that the 3-state mean specification with regime dependent variance adequately captures state dependent dynamics of the economy. The variance of the recessionary state is the highest in Russia compared to the other emerging markets. Results also document strong asymmetry based on the Davies upper bound values. The estimated conditional means are -7.74, 1.80, and 3.60 for the recession, low and high growth states, respectively. Transition probabilities are statistically significant with the values of p_{00}= 0.92, p_{11}=0.95, and p_{22}= 0.92. The average durations are 14, 18.8, and 15.75 months for recessionary, low, and high growth states, while the average percentages are: 21.14%, 47.24%, and 31.66%, respectively. Figure 4 shows the sequence of the smoothed probabilities for each different regime of Russia. The model identifies the 1998-1999 and 2008-2009 Russian crises.

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



For the Turkish economy, we find that the growth a rate of monthly industrial production index is best characterized by a three-state specification. In addition, we find that the null hypothesis of invariant variance cannot be rejected. The results are also in favor of regime dependent variance. The small value of the Davies upper bound, along with the substantially different mean estimates and transition regime probabilities across different regimes, suggests strong asymmetry. The Turkish economy has a monthly growth rate of around -5.37% in a typical recession. The mean values for expansions are estimated to be around 0.80% and 4.23% for the low and high growth periods. Once the economy enters into a recession, the probability of staying in the recession for the next month is 0.86. This implies an average duration of 7.25 months for recessions, which corresponds to 14.57% of the whole time. Among the three regimes, the high growth regime has the longest average duration. The transition probabilities for the expansion states are estimated to be 0.80 and 0.91, which imply durations of 5 and 13.75 months for low and high growth states, constituting about 30.15% and 55.28% of the sample period. The smoothed probabilities of all three states of the Turkish economy are plotted in Figure 5. The model identifies the Turkish crises that start in 1998, 2001, and 2008.

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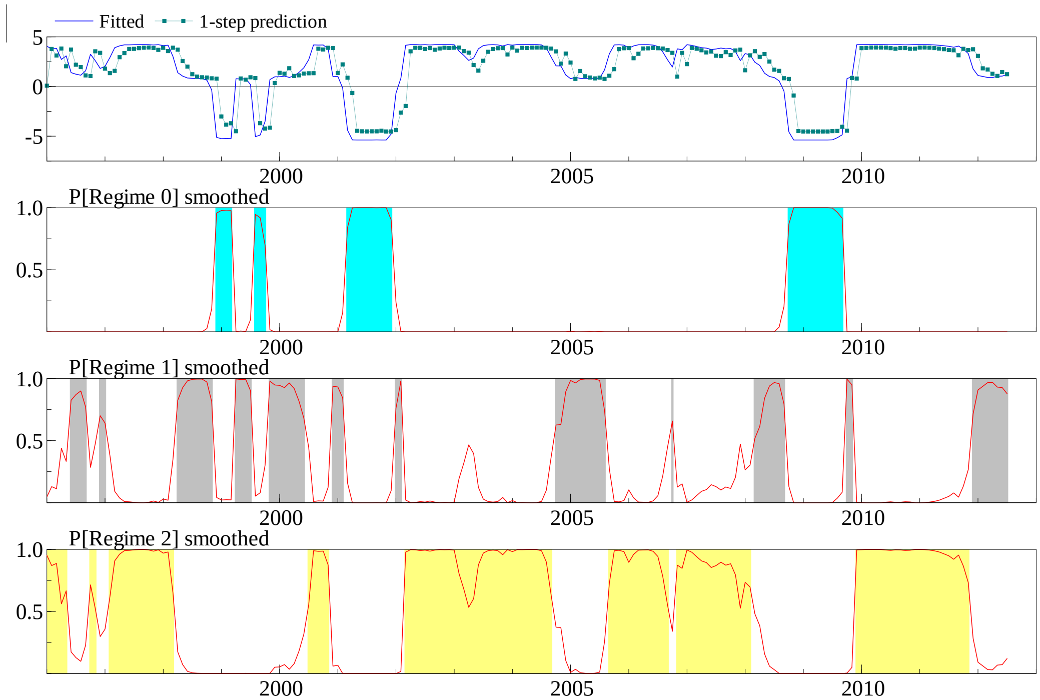
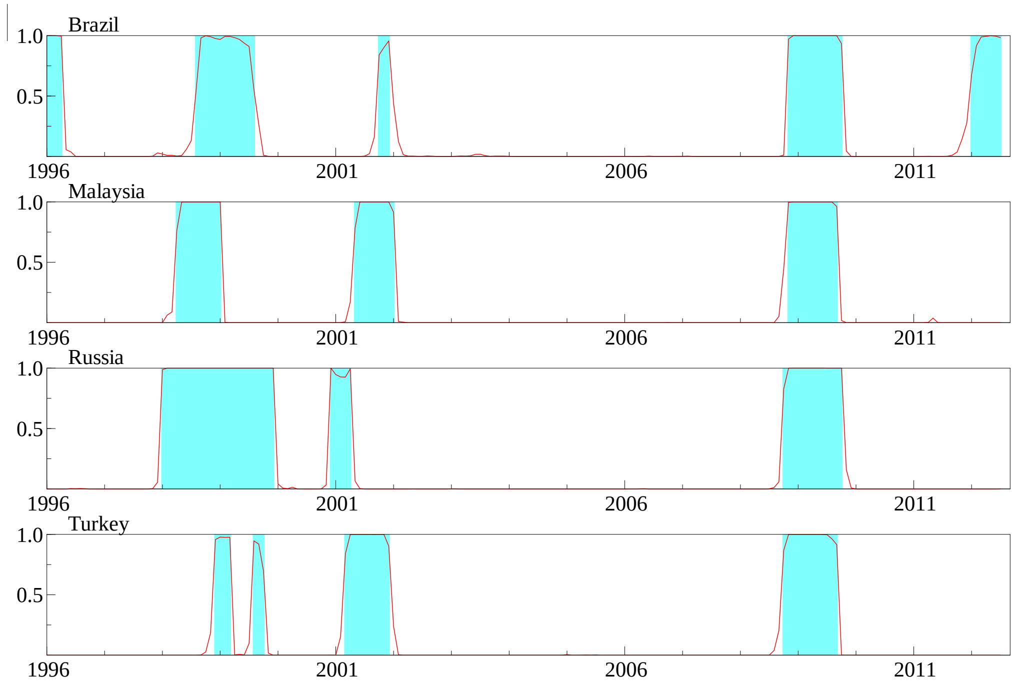
Figure 5: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Turkey



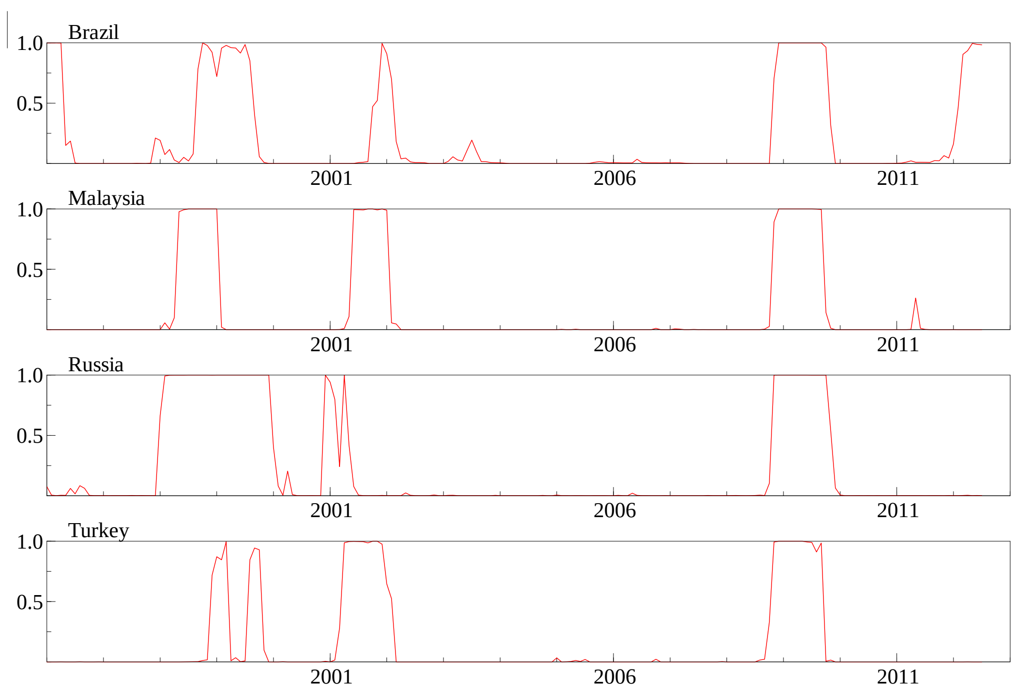
The results are in line with business cycle stylized facts in terms of implying short and abrupt recession phases and longer and moderate expansion phases. Figure 6 plots the smoothed probabilities and Figure 7 plots the filtered probabilities of the recessions implied by our models with respect to industrial production. The spikes in probabilities are all associated with sharp declines in output.

Figure 6: 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 7: Filtered Probabilities of Recessions in EMEs (January 1996 - July 2012)



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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, $\Pr\left[s_t = 1|\Omega_t\right] < 0.5$ where Ω_t denotes the information set at time t, and it enters a recession in $t+1$, $\Pr\left[s_{t+1} = 1|\Omega_t\right] \geq 0.5$. A business cycle trough occurs in month $t+1$ if the economy was in a recession in month t, $\Pr\left[s_t = 1|\Omega_t\right] \geq 0.5$, and it enters an expansion in month $t+1$, $\Pr\left[s_{t+1} = 1|\Omega_t\right] < 0.5$. 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 the emerging markets. Table 5 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 the emerging market economies. The accelerated growth has most of the time been followed by a period of slowdown over the sample period.

4. 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 the 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 6 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%. Turkey has the highest mean growth for returns with a value of 8.93% and Russia follows Turkey with 7.23%.

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Table 6: Results for Monthly Returns of Emerging Markets

	Brazil	**Malaysia**	**Russia**	**Turkey**
log-L	-409.69	-401.36	-526.35	-505.63
LRP	0.000	0.000	0.000	0.000
α_0	-4.13	-4.39	-12.31	-3.80
	(0.56)	(0.42)	(2.04)	(0.42)
α_1	0.24	0.57	0.59	2.15
	(0.15)	(0.11)	(0.20)	(0.23)
α_2	4.15	3.81	7.23	8.93
	0.17	(0.30)	(0.49)	(0.56)
σ_0	2.73	2.76	8.06	2.55
	(0.34)	(0.28)	(1.22)	(0.25)
σ_1	1.05	0.80	1.74	1.52
	(0.10)	(0.08)	(0.15)	(0.16)
σ_2	1.39	1.82	3.14	3.69
	(0.11)	(0.17)	(0.32)	(0.35)
p_{00}	0.81	0.91	0.88	0.88
	(0.07)	(0.04)	(0.06)	(0.04)
p_{10}		0.08	0.08	
		(0.03)	(0.15)	
p_{01}	0.07	0.04	0.03	0.07
	(0.03)	(0.02)	(0.01)	(0.03)
p_{11}	0.84	0.88	0.91	0.86
	(0.04)	(0.03)	(0.04)	(0.04)
p_{12}	0.08	0.12	0.09	0.10
	(0.03)	(0.04)	(0.03)	(0.04)
AIC	4.21	4.13	5.40	5.18
SC	4.38	4.29	5.28	5.34
HQ	4.28	4.20	5.47	5.24

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.

The results for the stock markets of Brazil are in favor of strong asymmetry. Figure 8 shows the sequence of the smoothed probabilities for each different regime of Brazilian stock markets. Variance of a bear state is the highest compared to the moderate returns and bull states. The estimated conditional means are -4.13, 0.24, and 4.15 for the bear, moderate returns, and bull states, respectively. Estimated Markov Probabilities are highly persistent with the values of p_{00}= 0.81, p_{11}=0.84, and p_{22}= 0.91. The average durations are 5.33, 6.38, and 12 months for bear, moderate, and bull states, while the average percentages are 16.08%, 41.71%, and 42.21%, respectively.

Figure 8: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Brazil

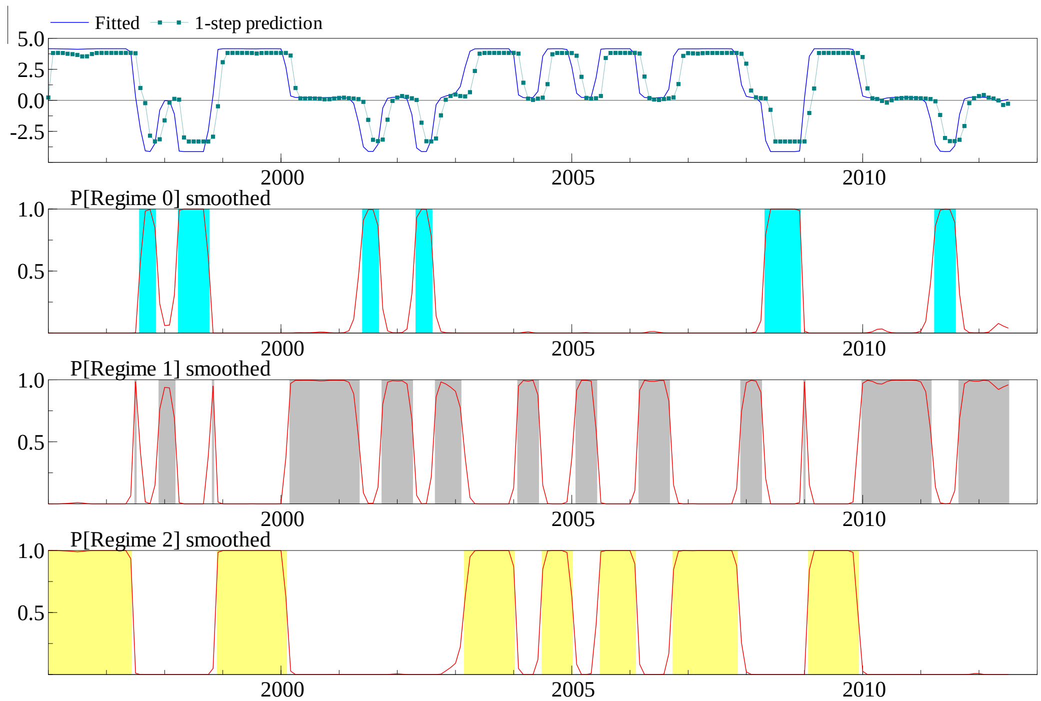
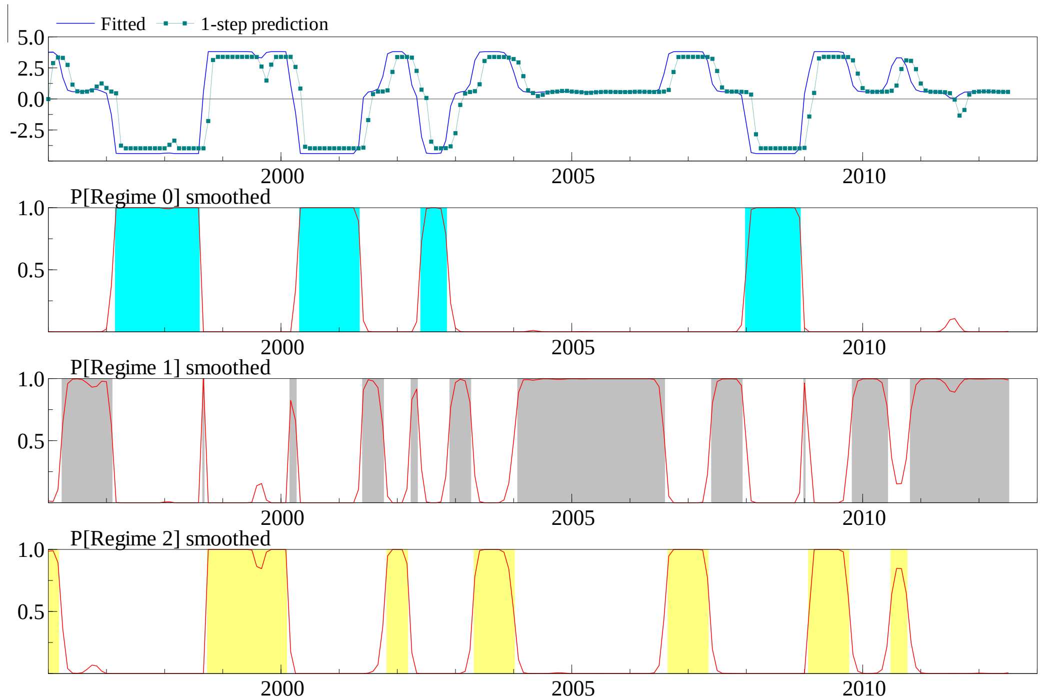


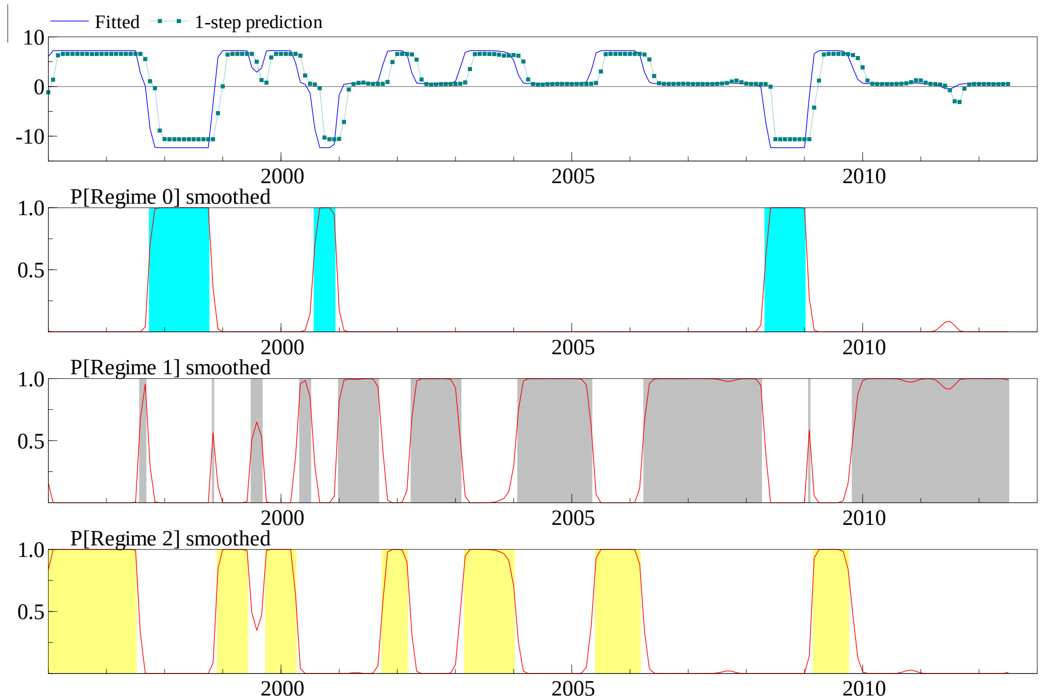
Figure 9 shows each different regime for Malaysian stock markets based on the smoothed probabilities. Results also document strong asymmetry based on the Davies upper bound values. During low returns periods, stock market returns of Malaysia contracts at a monthly rate of -4.39% whereas it grows by about 0.57% and 3.81% in moderate and high returns phases of stock markets. Each regime appears highly persistent. The probability that a month of bear state will be followed by another month of bear state is 91% for Malaysia, while this probability is 88% for the moderate and 87% for the high return states. Average durations and percentages of staying in each individual state are 12.25 months with a percentage of 24.62 for bear states, 8.55 months with a percentage of 47.24 for moderate return regimes, and 8 months with a percentage of 28.14 for high return states.

Figure 9: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Malaysia



For the Russian growth rates of monthly stock market returns, we find that the three-state mean specification with regime dependent variance adequately captures state dependent dynamics of the stock markets. Linearity is strongly rejected in favor of asymmetry. Figure 9 shows the sequence of the smoothed probabilities for each different regime of Russia. The variance of the bear state is the highest in Russia compared to the other emerging markets. The estimated conditional means are -12.31, 0.59, and 7.23 for the low, moderate, and high return states, respectively. Transition probabilities are statistically significant with the values of p_{00}= 0.88, p_{11}=0.91, and p_{22}= 0.90. The average durations are 9, 10.40, and 9.71 months for bear, moderate returns, and bull states, while the average percentages are: 13.57%, 52.26%, and 34.17%, respectively.

Figure 10: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Russia



For Turkish stock markets, results document strong asymmetry based on the Davies upper bound values. The smoothed probabilities of each of the states are given in Figure 11. The small value of the Davies upper bound, along with the substantially different mean estimates and transition regime probabilities across different regimes, suggest strong asymmetry. The Turkish stock market has a monthly growth rate of around -3.80% in a typical low returns state. The mean values for moderate returns and bull states are estimated to be around 2.15% and 8.93%. Once the stock market enters a low returns phase, the probability of staying in the bear state for the next month is 0.88. This implies an average duration of 9.17 months for bear states, which corresponds to 27.64% of the whole time. Among the three regimes, the high returns regime has the longest average duration. The transition probabilities for the moderate and high return states are estimated to be 0.86 and 0.89, which imply durations of 7.33 and 9.33 months. These states correspond to 44.22% and 28.14% of the sample period. Variance value of the bull state is the highest compared to the low and high return states. 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.

Figure 11: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Turkey

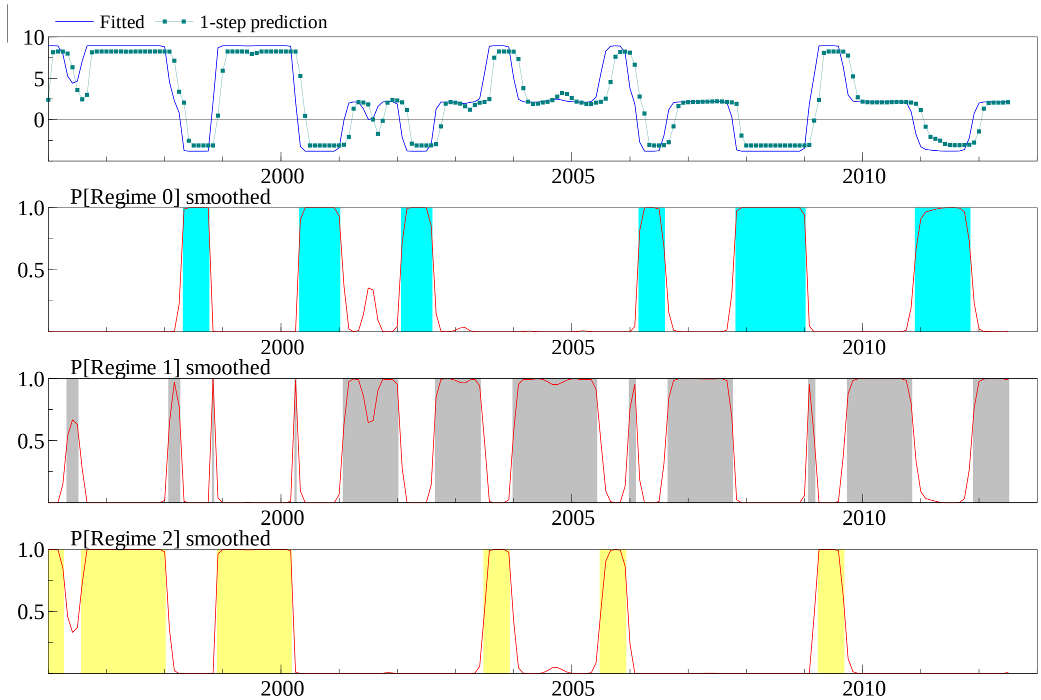


Figure 12 plots the smoothed probabilities of the bear market regimes along with the recessions implied by the models of industrial production. We clearly see that spikes in probabilities of the bear state of the stock market are highly correlated with the recessionary periods. Probabilities of stock 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).

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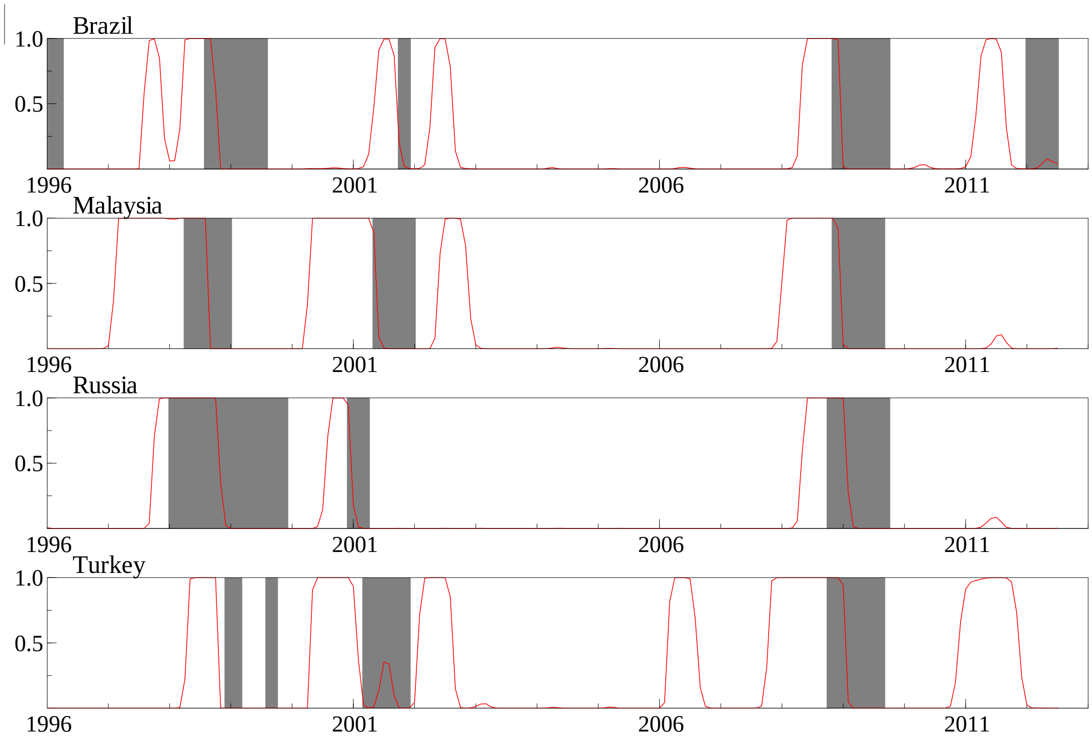
Figure 12: Smoothed Probabilities of Bear Market from the Stock Market Model and Recessions



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

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

Table 7 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 10.

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Table 7: Evaluation of the Stock Market Turning Point Signals

		QPS_i		
i	**Brazil**	**Malaysia**	**Russia**	**Turkey**
12	0.2648	0.2374	0.3204	0.3556
11	0.2631	0.2153	0.2974	0.3467
10	0.2553	0.1942	0.2744	**0.3462**
9	**0.2424**	**0.1846**	0.2488	0.3733
8	0.2647	0.2058	0.227	0.3783
7	0.2794	0.2445	0.2048	0.4012
6	0.2835	0.2846	0.1831	0.4375
5	0.3021	0.3244	**0.1581**	0.4692
4	0.3347	0.3843	0.1572	0.5213
3	0.3902	0.4435	0.1892	0.578
2	0.4543	0.5021	0.2429	0.6359
1	0.5213	0.56	0.3021	0.6919
0	0.5855	0.6175	0.3609	0.716

Notes: The table reports Quadratic Probability Scores (QPS) of the stock market Bear state probabilities in signaling recessions for horizon, i. Positive values of i indicate leads of stock market compared to business cycle peaks. We do not report the values where i takes negative values, i.e. the stock market lags the economy given that the leading behavior of the stock market is obvious from Figure 4. QPS values for that case are much higher than the values reported above.

5. Concluding Remarks

The study analyzes and characterizes the cyclical dynamics of a diverse group of emerging market economies. 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. The study closes the gap in the literature by adequately modeling the state dependent dynamics and accounting for the asymmetric behavior of national business cycles across cyclical phases to reveal the characteristics of different phases of national business cycles, and provide further insights about these economies. Compared to the commonly employed two state specifications, the paper employs a three state specification to decompose the non-recessionary state into high-growth and low-growth states. Moreover, we construct the reference business cycle chronologies for the emerging market economies at monthly frequencies by utilizing Markov switching models. Because of emerging market economies' lack of institutions to officially monitor business cycles, utilizing this framework is particularly important for these countries to have timely and objective information on business cycle turning points. Therefore, this framework used in the study also overcomes the shortcomings of a committee assessment, which has the drawbacks of being subjective and announcing the results with a lack of time. Moreover, finding the filtered probabilities of the estimated nonlinear models, we obtain inference that we can be utilized for further analyses.

Next, the study employs a Markov switching approach and explicitly models cyclical dynamics of the stock markets and relates it to the business cycles of emerging market economies. This is the first study in the literature

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that quantifies the dynamic relationship between the smoothed probabilities of the stock market and the real economy for a diverse group of emerging markets using the inference of regime probabilities that are calculated for the bear states of the stock markets and the recessionary states of the real economies. To understand this dynamic relationship, we explicitly model and characterize the stock market cycles using a three state specification with changing mean and variance to identify the bear, bull, and moderate return states. Then the study computes the characteristics of stock markets accounting for the asymmetric behavior across stock market phases for each country in the sample. Using the inference from the estimated regime probabilities for each of the countries, we examine the dynamic predictive relationship between the smoothed probabilities of the stock market and the real economy that we obtained from the dynamic Markov switching models for each of the countries at monthly frequencies.

The results reveal the strong asymmetric dynamics of business cycles and document the stylized facts of cyclical fluctuations in a diverse group of emerging economies. The results identify three states of business cycles and provide estimates of turning points based on monthly industrial production data. The estimated business cycle models classify business cycle turning points and identify the individual crises in these emerging markets. All the spikes in smoothed recession probabilities for the economies in our sample are associated with sharp declines in output. All these recessions are associated with sharp declines in economic activity with the most recent 2008 recession being the deepest one.

The results then identifies that the stock markets in the sample go through three distinct regimes, each are characterized by different risk return dynamics. The findings reveal the individual characteristics of state dependent dynamics of stock market returns for each of the countries in our sample. For Turkey, the periods during which the stock market performs well above the average also seem to be the most volatile state of the market. 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. In terms of macroeconomics and finance linkages, we present a consistent relationship between the real economies and the stock markets. The results show 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. The smoothing probabilities of the bear markets 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 ten months, implying that the stock market returns can be used as a forward looking indicator of emerging market economies.

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