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Nonlinear Markov switching analysis of economic and stock market dynamics for emerging market economies

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NONLINEAR MARKOV SWITCHING ANALYSIS OF ECONOMIC AND STOCK MARKET DYNAMICS FOR EMERGING MARKET ECONOMIES

BY

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To my parents, Nazife and Basri Baycan

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ABSTRACT

NONLINEAR MARKOV SWITCHING ANALYSIS OF ECONOMIC AND STOCK MARKET DYNAMICS FOR EMERGING MARKET ECONOMIES

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This dissertation 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. First, 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 study 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, we quantify the associations between business cycles across emerging markets and also with advanced G7 economies. The results identify distinct groups of emerging economies and stress the importance of using the information coming from other economies when constructing leading indicators and predicting turning points. Business cycles both for emerging markets and the advanced economies experience a high degree of commonality with the global recession of 2008.

CHAPTER 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 come as a result of government policy, financial crisis, political instability, and external shocks, which are common for emerging market economies. This analysis enables us to capture potential asymmetric behavior across business cycle phases, that is, within this method, low and high growth regimes, and recession states can display different duration, amplitude, and steepness.

Moreover, recent studies[1] emphasize the need for building different forward looking indicators of business cycles for emerging market economies. The related literature[2] on the relationship between the real economy and financial markets suggests 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, they use every piece of information as soon as economic data is available. As a result, the continuously updated assessments of market participants about the current state of the economy are well reflected in stock market movements. Therefore, building consistent

[1] See, for example, Pagan 2010 among others

[2] Empirical support in terms of interactions between financial and real markets are documented frequently in the literature by utilizing various econometric tools. Fama (1990), Schwert (1989, 1990), Chen (1991), Ferson and Harvey (1993), Cheung et al. (1997), and Binswanger (2000), Cheung and Ng (1998) and Maysami and Sim (2001) use both short and long run analyses to show this relationship between these two sectors.

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 study, we use a unified Markov switching framework to address the questions that 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 differences of these characteristic properties of emerging markets compared to the documented stylized facts of typical advanced economies? What are the relationships between 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 recession probabilities for the emerging and advanced G-7 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) uses a dataset that goes back for a century for ten developed countries and examine their properties. Stock and Watson (1999) examine the relationship between the U.S business cycle and several macroeconomic variables using the U.S. postwar data.

Synchronization of European business cycles is another area of focus that is highly analyzed. Artis, Kontolemis, and Osborn (1997), Krolzig (2001), Artis, Krolzig, Toro (2004) give evidence for a common European business cycle using the monthly industrial production data. Stock and Watson (2005) analyze the volatility, persistence, and synchronization of business cycles for the advanced G-7 economies.

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 a few applications in the literature for characterizing business cycles in different emerging market economies. Girardin (2005) utilizes nonlinear regime switching techniques to analyze quarterly business cycles for ten East Asian economies, including the emerging markets in the region. 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 examine 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 studies. The seminal work of Hamilton and Lin (1996) establishes the 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), and Altug and Bildirici (2012) argue that business cycles become more synchronized during recessions compared to expansions.

In this study, we present a systematic and consistent analysis of 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.

First, we characterize the dynamics of the 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 frequencies by employing hidden Markov switching 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 to officially monitor business cycles. We use a three state specification to obtain a convenient framework to decompose the non-recessionary state into high-growth and low-growth states, which enables us to further analyze the asymmetric behavior of the business cycles and to compare the characteristics of different phases of the economy for these emerging markets.

This section of our study closes the gap in the literature by classifying turning points and capturing the asymmetric behavior across different business cycle regimes for a diverse group of emerging markets using monthly data. We map the potential asymmetric behavior across business cycle phases in emerging markets, that is, within this framework, high and low growth regimes and recessionary phases can display different duration, amplitude, and steepness. Further, regarding classifying the turning points, this framework used in our study overcomes the shortcomings of a committee assessment, which has the drawbacks of being subjective and announcing the results with a lack of time.

Second, 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. We compute the characteristics of stock markets accounting for the asymmetric behavior across stock market phases for each country in our sample. It follows, then, we examine the dynamic relationship between business cycles and stock market fluctuations at monthly frequencies. Using the inference from the estimated regime probabilities for each of the countries, we examine the dynamic relationship between the smoothed probabilities of the stock market and the real economy that we obtained from the dynamic hidden Markov switching models. This analysis enables us to show the lead/lag relations of business cycles and stock market movements using this inference from the estimated regime probabilities.

This section of our study fills an important void in the literature given the results of Pagan (2010), who emphasizes the need for building forward looking indicators of business cycles for emerging market economies. Other than the paper of Senyuz, Yoldas, and Baycan (2012), we believe that this is the first study that employs a Markov switching framework to explicitly model cyclical dynamics of the stock markets and relate it to the business cycles in emerging market economies.

Third, we utilize the smoothed regime probabilities that we obtain from modeling each of the business cycles to understand how different or similar the business cycles are among individual emerging market economies as well as between emerging markets and advanced economies. We start analyzing the behavior of the pairwise contemporaneous correlations of the smoothed probabilities of recessionary states to uncover the common features of international linkages across national business cycles. To further analyze the synchronization of national business cycles, we also examine the corrected contingency coefficients, which is a non-parametric approach that documents the comovements of different business cycle regimes across the emerging and developed countries in our sample.

We also believe that this is the first study to utilize the Markov switching framework and employ inferences from the derived 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 a diverse group of emerging and G-7 countries.

Considering the dramatic policy changes and frequent financial crises in emerging market economies, this dissertation obtains a sound regime classification that is not overly 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.

Our results reveal the strong asymetric dynamics of business cycles in emerging markets and document the stylized facts of cyclical fluctuations for 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. 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 the long-run average rate. The estimated business cycle models of our study classify business cycle turning points and identify the individual crises in the emerging markets, as well as the more contagious 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.

Our results regarding the stock markets identify that the stock markets in our sample go through three distinct regimes characterized by different risk-return dynamics. We show that these three regimes for stock markets are characterized best by different mean and variance dynamics for the emerging economies. 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 typical advanced economies such as the U.S. for which bull markets are characterized by high returns and low volatility. In terms of the linkages between macroeconomics and finance, we find a consistent relationship between the real economies and the stock markets. To examine this relationship, we use the inference of regime probabilities that we calculated for the bear states of the stock markets and the recessionary states of the real economies. Our analysis of interrelations between 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; therefore, bear market peaks may be considered as a potential predictor of the recessions.

Next, our results quantify the associations of business cycles across emerging markets and advanced G-7 economies. We utilize the smoothed probabilities that we obtain from modeling 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 economies and between emerging markets and G-7 countries over the period between 1996 - 2012 and a subperiod of 2004 - 2012. Our results identify a distinct group of emerging economies. Furthermore, we show that business cycles both for emerging markets and the advanced economies experience a high degree of commonality when there is a large common disturbance affiliated with a global recession. During the sub period of 2004 - 2012, the results show very strong comovements among all countries, with considerably 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.

The remainder of the study is structured as follows. Chapter 2 reviews the empirical literature and discusses the distinction of our study from the prior work to give further insight about how this study can close the gap in the literature. Chapter 3 describes the employed methodology and the estimation procedure. This chapter also defines the data, and explains the intuitions behind choosing them. Chapter 4 presents the empirical results. Chapter 5 offers a brief summary and some concluding remarks.

CHAPTER 2

PREVIOUS WORK AND METHODOLOGICAL ISSUES

2.1. Introduction

This chapter is organized in three sections. Section 2.2 starts with a survey on the early studies that examine the stylized facts of the business cycles in the literature. These early studies primarily focus on economic history of advanced economies and summarize the qualitative features of their cyclical behaviors. The section then discusses the subsequent studies, which depart from these early qualitative analyses and employ more sophisticated quantitative techniques that take into account the more complex dynamics of business cycles.

The developments on computational statistics and time series methods have opened up new possibilities to further analyze the business cycle asymmetries. The section continues with a survey of the developments in the literature on the nonlinear Markov switching approach and its extensions over time. The section documents the studies in the literature that explain why Markov switching models and their extensions are superior compared to the other commonly used methods to characterize the business cycle fluctiations. We then discuss the studies comparing the Markov switching approach with the commonly used alternative frameworks of the Hodrick and Prescott (1997) and the non-parametric Harding and Pagan (2002, 2006) approaches. We then review the studies examining the ability of Markov switching models to generate real time probabilities for a real time track of business cycles.

The section next examines the studies that document the differences of business cycle characteristics in emerging markets compared to developed economies. Even though emerging markets have shown notable performances during the last two decades, the studies on business cycles for emerging economies have, until recently, been limited to descriptive studies and applications of the leading indicators methodology. We review these few studies employing contemporary frameworks in order to understand their cyclical fluctuations in the literature.

Section 2.3 starts by surveying the prior works that examine the transition mechanisms of financial indicators that affect real economic growth. The section discusses the studies that investigate the effects of different financial variables such as stock market prices, yield spread, interest rate levels, and money stocks on the real economy. We then focus on the prior studies that show evidence of systematic movements in excess stock returns that are related to estimates of the business cycles.

After we discuss the literature on the effects of financial instruments on the real economy, the section reviews the studies that argue how stock markets and economic activity are becoming more strongly linked in emerging markets during the recent years. We survey the related literature considering the advancements in stock markets of emerging market economies and increasing linkages of these stock markets with economic activity. We then highlight the fact that these previous studies, which analyze this relationship in emerging market economies, are lack of accounting for asymmetries.

Section 2.4 begins by discussing the studies examining the channels of cyclical transmission mechanisms across different countries. We first survey the literature regarding developed countries, where it is well documented in the prior work that they often contain some characteristics with each other that are common in economic activity. We then continue by considering the few existing studies that examine the similarities and differences of business cycle dynamics within emerging market economies.

We then consider the studies that employ nonlinear Markov switching methods to investigate the commonalities and differences of business cycles among individual emerging market economies as well as between emerging markets and advanced economies. Finally, we discuss the distinction of our study from the prior work to give further insight about how this study can close the gap in the literature.

2.2. Literature Review on the Cyclical Dynamics of the Real Economy

Understanding business cycles has always been important for policy makers and business professionals. Consequently, analyses on the cyclical fluctuations of the economy have been studied for many decades. The studies of Mitchell (1927) and Keynes (1936) are among the first and well known studies that compare and distinguish the phases of business cycles. They emphasize the asymmetric nature of business cycles and suggest that economic downturns are shorter, more severe, and more volatile compared to the expansions, whereas expansions are longer and more gradual. Burns and Mitchel (1946) define business cycles as the fluctuation in economic activity of nations that expansions followed by recessions, contractions, and revivals that merge into the expansion phase of the next cycle, where the sequence in not periodic, but recurrent. The business cycle empirical methodology of the National Bureau of Economic Analysis (NBER), which was founded in 1920s, still uses the definition of Burns and Mitchel (1946) as a fundamental for identification of business cycles.

The prior work in the literature vastly focuses on examining the stylized facts of the business cycles mostly for developed economies. Early studies rest on qualitative analyses to characterize and understand the business cycles properties. These early studies of economic fluctuations rest on the qualitative methods, and heavily focus on the role of advanced economies. Schumpeter (1934, 1939) suggests that external factors of economic change are the primary explanation of business fluctuations. In particular, he argues that technological innovations are the main reason for the existence of longer waves. He classifies different historical waves due to different innovations starting with the industrial revolution. Abramovitz (1950) examines manufacturers' inventories to explain the business cycle fluctuations. He discusses that these inventories cause fluctuations in the production of durable capital equipment and construction, and therefore have the main influence on business cycles. Gayer, Rostow, and Schwartz (1953) examine the historical business cycle fluctuations of the British economy. They divide the business cycles into major and minor fluctuations and distinguish the source of these two different types. On the other hand, Friedman and Schwartz (1963) argue that the change in nominal income is mainly due to the change in the money stock. They suggest that the stock of money displays a systematic cyclical behavior, where the rate of change in the money stock regularly reaches a peak and a trough just before the reference business cycle peaks and troughs. Then they make the point that stock of money is much more closely and systematically related to income over business cycles than it is related to investment or autonomous expenditures. Zarnowitz (1985, 2007) provides a rich extensive survey of further developments in early business cycle literature.

Subsequent studies depart from these early qualitative analyses and employ more sophisticated quantitative techniques that take into account more complex dynamics of business cycles. Sargent and Sims (1977) define a way of measuring multivariate business cycles using a dynamic factor model. They examine the cyclical behavior of a set of key time series variables of unobservable factors. Kydland and Prescott (1982) modify the equilibrium growth model to explain the cyclical variances of economic time series variables for the U.S. economy. They develop a competitive equilibrium model with productivity shocks to analyze the cyclical behavior and to explain the quantitative comovements and the serial correlation properties of the output. Hodrick and Prescott (1997) propose a procedure of filtering the U.S. macroeconomic time series to detrend. They present the time series as the sum of a smoothly varying trend component and a cyclical component. They find that the nature of the comovements of the cyclical components of macroeconomic time series is different from the comovements of the slowly varying components of the corresponding variable. They suggest that investment is around three times more volatile than output, while consumption is less volatile compared to output, and moreover they report that the volatility of total hours worked and output are similar. A comprehensive literature survey for the historical evolution of business cycle studies can be found in Altug (2009).

Developments on computational statistics and time series methods lead the way to further analyze the business cycle asymmetries. Modern econometric literature on modeling the nonlinearities for business cycles starts with Neftci (1982). He uses finite state Markov process to display the asymmetric behavior of unemployment rate over various phases of the business cycle. He documents that behavior of the unemployment rate is characterized by sudden jumps and slower drops. Hamilton (1989) refines his approach and proposes a model that accounts for the sudden changes in the behavior of a time series as the outcome of a Markov switching process, which is governed by an endogenous probability rule. This seminal paper of Hamilton utilizes a univariate model for the U.S. real GDP growth rate, where its mean switches between two regimes of recession and expansion. His results are highly correlated with the NBER dating.

Hansen (1992) extends Hamilton's paper and allows for switching not only in the mean parameter, but also in the residual variance and autoregressive parameters. His study distinguishes additional asymmetries variance and shows that variances in expansionary periods are different to the variances in recessionary periods. Allowing for a switching variance increases the models ability to account for a higher variability of growth rates both in recessions and expansions. Krolzig (1997) also modifies Hamilton's model and allows for a multivariate setup. Chauvet (1998) extends the method further using both dynamic factor and Markov switching approach in the same framework.

Sichel (1994) presents a comprehensive study of the presence of a third state, namely a high growth phase for the U.S. real GDP. Boldin (1996) and Clements and Krolzig (1998) extends the Hamilton model and allows switching for more than two regimes. Using an additional regime can distinguish further asymmetries in the model. Employing a third state enables us to decompose the expansionary state further two sub-states of high and low growth states.

Many studies in the literature document that Markov switching models are superior in describing the U.S. real GDP compared to alternative linear models. Galvão (2002), Clements and Krolzig (2004), and Kim, Morley, and Piger (2005) investigate linear and nonlinear models for their ability of reproducing the features of business cycles. Among others, Hansen (1992) and Kim, Morley and Piger (2005) conduct statistical tests to compare the ARIMA models with nonlinear alternatives and reject linearity in favor of several extended versions of the Hamilton model. Morley and Piger (2006) show that the regime-switching models seem to improve linear models in terms of the variability of growth rates that are observed for different business cycle phases. They suggest that employing certain Markov switching model specifications has the ability to substantially improve reproducing business cycle features over linear models.

Despite the fact that emerging market economies have shown remarkable performances during the last two decades, the previous studies in the literature heavily focus on examining the stylized facts of the business cycles mostly for developed economies. Backus and Kehoe (1993), for example, use a dataset that goes back for a century for ten developed countries and examine their properties. Stock and Watson (1999) examine the relationship between the U.S business cycle and several macroeconomic variables using the U.S. postwar data. As an important topic in the recent business cycle literature, economists also debated about whether or not a European business cycle exists as in the studies of Artis and Zhang (1997) or Artis, Kontolemis, and Osborn (1997). Artis, Marcellino, and Proietti (2003) present alternative ways to find the business cycle turning points in the Euro area. Stock and Watson (2005) analyze the volatility, persistence, and synchronization of business cycles for the advanced G-7 economies.

Ultimately, the ability of Markov switching models to capture the different characteristics of business cycle asymmetries has made them quite useful to investigate the role of nonlinearity in identifying, monitoring, and dating the turning points of national business cycles. The business cycle turning points are closely linked with the regime changes that driven by the nonlinear Markov switching models. Chauvet and Hamilton (2006) construct the business cycle chronology for the U.S. post World War II period. Their results for business cycle turning points are closely matched with the results of the business cycle dating committee of the NBER. Moreover, their results do not require a subjective discussion of a committee dating, but instead can be obtained using an objective, formal statistical method. Furthermore, their results become available significantly sooner than the results of the NBER.

Moreover, Markov switching analysis has several advantages compared to the other commonly used methods to characterize the business cycle characteristics. Markov switching models have the ability to overcome the drawbacks of these other commonly employed methods. One very popular method that is used to generate stylized facts of the business cycles is using the Hadrick - Prescott (HP) filter, which decompose the trend cycle. This method of Hodrick and Prescott (1997) measures the deviation of the series from its local trend. However, as Krolzig (1997) and Candelon and Metiu (2011) document, this approach was highly criticized in the literature. Krolzig (1997) criticizes this method suggesting that it is not clear how the turning points should be dated. In addition, he argues that it is also not clear how filtered data can be used for further analysis, e.g. for forecasts. Cogley and Nason (1995) shows that the HP filter is only optimal if the series are integrated of order two, and therefore can generate spurious cycles otherwise. Canova (1998) argues that choosing the value of smoothing parameter is debatable. Mise, Kim, and Newbold (2005) provide evidence that the smoothing filter is not optimal at the endpoints of the time series. This is particularly a disadvantage if the most recent pattern of the time series cycle is of particular interest.

Another popular method, probably as popular as the Markov switching approach in the literature, is the non-parametric Harding and Pagan approach (2002, 2006). Harding and Pagan (2002, 2006) formalize the traditional analysis of Burns and Mitchell (1946) for determining business cycle turning points. They improve Bry and Boschan (1971) algorithm and identify local peaks and troughs as local minimas and maximas in the path of different time series and try to identify an aggregate recession.

However, this nonparametric framework also has drawbacks compared to the Markov switching approach. This approach cannot identify any different state of the economy other than the recessions and expansions. In contrast, as we discussed earlier, a third regime is important to capture further asymmetries to identify a more realistic model for these countries. For example, this approach cannot identify the distinction between high and low growth phases, or a slowdown in an economy. As Helbling and Bayoumi (2003) and Bodart, Kholodilin, and Shadman-Mehta (2005) discuss, knowing only the direction of output comovements is not a comforting basis for a decision making for policymakers. Considering the ability of Markov switching approach of identifying multiple regimes and doing further analyze this relationship, it is superior in that respect to the Harding and Pagan approach (2002, 2006) about analyzing the business cycles.

In addition, another feature of the Markov switching approach is its ability to generate real time probabilities for a real time track. Using these filtered probabilities, it is also possible to monitor for an economic contraction and its severity on a timely basis by using the filtered probabilities obtained from the Markov Switching model. The filtered probabilities obtained from the Markov Switching model allow early recognition of the transition to a new cyclical phase, which can be used to set a signaling system against a crisis. A timely recognition of an economic contraction and its severity enables a government policy response that could reduce the amplitude and duration of the downturn. For example different monetary policies would have different effects on the economy depending on whether the economy is about to enter to an expansionary or recessionary state. Chauvet and Hamilton (2006), Chauvet and Piger (2002, 2008), and Hamilton (2011) tested the empirical consistency of Markov switching models in generating real time inferences for the U.S. business cycles. The results of Chauvet and Piger (2008) provide that the ability of formal rules to establish business cycle turning point dates in real time is more accurate with Markov switching models, as well as it identifies the troughs of business cycles with a larger lead compared to the nonparametric algorithm given in Harding and Pagan (2006). Hamilton (2011) documents that Markov switching time series models is the approach that gives the most clearly established real time track record compared to the alternatives.

Regarding the business cycles in emerging markets, it is well documented in the literature that the business cycle characteristics in emerging economies are different compared to the business cycle characteristics of developed countries. Historically, emerging markets experience larger and more persistent fluctuations than the developed countries. Cerra and Saxena (2005), Raddatz (2007), and Aiolfi, Catao and Timmermann (2011) try to explain the differences of business cycles of emerging and developed economies. According to the studies of Neumeyer and Perri (2005), Aguiar and Gopinath (2007), and Seoane (2011), volatility of consumption is larger than the volatility of output in emerging markets, while consumption follows a smoother path in developed economies. Moreover, they discuss that emerging markets have larger counter cyclical trade balances compared to the milder counter cyclical trade balances of developed economies. Calderón and Fuentes (2010) find that in emerging markets contractions are more frequent and deeper, while expansions are larger but more volatile among emerging markets compared to the advanced economies.

Although emerging market economies have shown remarkable performances during the last two decades and the prior work documents the different characteristics of emerging markets from developed economies, 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 a few applications in the literature for characterizing business cycles in different emerging market economies. Girardin (2005) utilizes nonlinear regime switching techniques to analyze quarterly business cycles for ten East Asian economies, including the emerging markets in the region. 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 (2012) detect business cycle turning points using quarterly GDP growth for a representative developed and emerging market economies. Rand and Tarp (2002) employ the non-parametric Bry-Boschan method for dating business cycles to examine the differences of developing countries' business cycles. Senyuz, Yoldas, 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.

This study fulfills the necessity and closes the gap in the literature by adequately modeling the state dependent dynamics of a diverse group of economies to reveal the characteristics of different phases of national business cycles, and provide further insights about these economies. We include the economies from different geographical areas of Europe, Asia, Central and South America, and Africa. Compared to the commonly employed two state specifications, we employ a three state specification to decompose the non-recessionary state into high-growth and low-growth states, which enables us to further analyze the asymmetric behavior of the business cycles and to compare the characteristics of different phases of the economy for these economies. In addition, regarding classifying the turning points, our study overcomes the drawbacks of a committee assessment, which has the disadvantages of being subjective and announcing the results with a lack of time.

2.3. Literature Review on the Interactions between Financial Markets and Real Economy

The existence of transition mechanisms through which financial indicators affect real economic growth has been extensively discussed in the economic literature. Different financial variables such as stock market prices, yield spread, interest rate levels, and money stocks to analyze this mechanism have been employed to predict the output growth. Chen (1991) presents the relationship between various financial investment opportunities and changes in macroeconomy. He argues that the term premium, the default premium, the short-term interest rate, and the market dividend-price ratio are indicators of the growth in the economy. Estrella and Mishkin (1998) examine the performance of interest rates, interest spreads, stock market prices, and monetary stocks to predict the U.S. recessions. The study evaluates the prediction performances from one to eight quarters ahead. Their findings show that stock prices are useful from one to three quarter horizons. Mili, Sahut, and Teulon (2012) utilize a nonlinear framework and show that global financial variables significantly affect real growth in the Euro area, particularly during periods of recession. Chauvet and Senyuz (2012) propose a joint dynamic econometric framework of the relationship between the yield curve and the economy to examine the predictive value of the yield curve to predict business cycle turning points at the monthly frequency.

Moreover, studies in the literature find evidence of systematic movements in excess stock returns that are related to estimates of the underlying state of the business cycle. These studies 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 about the future changes in economic activity lead the business cycle fluctuations. Among others, 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. As a result, they argue that stock market indices constitute potential leading indicators of economic activity and can be used for economic prediction. Chauvet (1998) represents the Stock market fluctuations and business cycles for the U.S. by building a nonlinear dynamic factor model at the monthly frequency. Their findings show that stock market factor leads the business cycle and can be used to identify turning points of an economy in real time. Beaudry and Portier (2006) argue that a shock that represents the news about future technological opportunities is captured in stock prices and this shock explains about half of the business cycle fluctuations. Perez-Quiros and Timmermann (1995) study the patterns and magnitude of variations in the mean and volatility of US stock returns around turning points of the business cycle. Senyuz (2011) presents a multivariate dynamic factor model that features Markov switching asymmetry to model the permanent and transitory components of the US economic activity and the stock market. Her study finds that the transitory stock market component signals recessions with an average lead of one quarter, whereas the market trend is correlated with the economic trend with varying lead/lag times. Senyuz, Yoldas, Baycan (2010) show that Turkish bear markets that are characterized by negative returns precede every recession in Turkish economy with an average lead time of nine months.

To summarize, the real economy and stock market relationship in the literature points out 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, these 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.

Regarding emerging markets, previous studies show that stock markets and economic activity in emerging economies are getting linked with a stronger connection. Garcia and Liu (1999) state that the average market capitalization after 1990 enormously increased for the emerging market economies. IMF World Economic Outlook Report (2011) and Levich (2001) document that the developing country stock markets surveyed by the International Finance Corporation back in 1982 had only a market capitalization of $67 billion. At that time this was only as big as 2.5 percent of the whole world market capitalization. However, by the end of 1999, the number of stock markets that International Finance Corporation had identified increased to eighty-one, which shows that the market capitalization exceeded $3 trillion, with an increase to 8.5 percent of the world equity market capitalization. Levich (2001) also shows that the predicted share of output for the five biggest emerging markets in the year 2020 is expected to be 16.1 percent, which is more than double of its 1992 share of 7.8 percent.

Moreover, recent studies[3] emphasize the need for building different forward looking indicators of business cycles for emerging market economies. Considering the rapidly developing stock markets in emerging markets and increasing connection of these stock markets with economic activity makes them even more important to investigate the relationship between these two sectors for the emerging markets. Muchaonyerwa (2011) constructs a Vector Error Correction model and finds a positive relationship between stock market performance and business cycles using monthly data for the period 2002-2009 in South Africa. Candelon and Metiua (2011) use cyclical filtering techniques and investigate the relationship between the stock market fluctuations and business cycles in eight Asian countries, namely China, Indonesia, Japan, Korea, Malaysia, the Philippines, Taiwan, and Thailand. They use cyclical filters and compare the cyclical components of the industrial production and stock market indices. Their results show that at cyclical frequencies stock markets lead business cycles by six months on average. Yuksel and Bayrak (2012) investigates the relation between the cyclical behaviors of stock market indices of industry, service, finance and technology sectors at Istanbul Stock Exchange and gross domestic product of Turkey between the 1998 January and 2011 September using the Hodrick and Prescott filter to determine the leading-lagging relation between obtained cyclical components. They document that the Turkish stock market leads the economy by about one quarter.

However, the previous studies in the literature looking for this relationship for emerging market economies are very limited, and the existing studies ignore the state dependent dynamics as they don't account for asymmetry in the responses to shocks. None of the studies in the literature explicitly model and characterize the stock market

[3] See, for example, Pagan (2010) among others

cycles using a nonlinear Markov switching approach to unravel the relationship between the stock market fluctuations and the business cycles for the emerging markets, except the study of Senyuz, Yoldas, and Baycan (2012) for Turkish economy. They document that the Turkish stock markets go through three distinct regimes characterized by different risk-return dynamics. They determine turning points of the economies and the stock markets and provide insight into their interrelations. The results show that bear markets that are characterized by negative returns precede every recession with an average lead time of nine months.

Following Senyuz, Yoldas, and Baycan (2012), this dissertation is the first study to explicitly model cyclical dynamics of the stock markets and relate it to the business cycles for a diverse group of emerging market economies using a nonlinear Markov switching approach. The results document the dynamic lead/lag relations of business cycles and stock market fluctuations for the first time, examining the state dependent dynamics of the asymmetrical cyclical relationships between the two sectors.

2.4. Literature Review on Business Cycle Synchronization

There is a growing literature investigating the business cycle linkages across different countries. Frankel and Roubini (2001) argue that policies of the industrialized countries lead the crises in emerging markets. They argue that trade is the most visible channel of this transmission as a fall in the income level of developed countries decreases their imports from developing countries. They discuss that economic prospects in each region of the world are affected strongly by the growth rate of the largest industrialized countries in that region. Camacho and Perez-Quiros (2006) propose a new framework to analyze pairwise business cycle synchronization across a given set of countries. The approach is based on multivariate Markov-switching procedures, and essentially determines the relative position of two countries' business cycles, which can be at some point between the two extreme cases of complete independence and perfect synchronization. An empirical application of this approach to the G-7 countries shows that these can be divided into two groups with distinct common business cycle dynamics, with one group consisting of Euro-zone countries (France, Germany, and Italy) and the other including English-speaking countries (Canada, the U.K., and the U.S.).

Regarding developed economies, it is often documented in the literature that they share some common characteristics in economic activity. Backus, Kehoe, and Kydland (1993), Baxter (1995), and Canova, Ciccarelli and Ortega (2007) show close linkages for the business cycles of advanced economies. Gregory, Head, and Raynauld (1997), Kose, Otrok, and Whiteman(2003), and Lumsdaine and Prasad (2003) document the commonalities of regional and country specific fluctuations for advanced economies. Synchronization of European business cycles is another area of focus that is highly analyzed. Artis, Kontolemis, and Osborn (1997), Krolzig (2001), Artis, Krolzig, Toro (2004) give evidence for a common European business cycle using the monthly industrial production data. They use the nonparametric corrected contingency coefficient approach to examine the strength of business cycle associations by quantifying the fraction of time that two country's business fluctuations are in the same state. Kose, Otrok, and Prasad (2008) employ a Bayesian dynamic latent factor model to estimate both common and country specific components in the main macroeconomic aggregates of the G-7 countries.

Their results verify that a common G-7 factor explains a larger fraction of output, consumption and investment volatility during the globalization period.

Nevertheless, relatively few studies have examined the similarities and differences of business cycle dynamics among emerging market economies. Some exceptions are Kose, Otrok, and Whiteman (2003), Girardin (2005), Aiolfi, Catao and Timmermann (2006, 2011), Kose, Otrok, and Prasad (2012), and Altug and Bildirici (2012). The study of Kose, Otrok, and Whiteman (2003) use a Bayesian dynamic factor framework and model the annual data of both developed and developing countries covering the period 1960–1992. They find that business cycles have a common component both in developed and developing countries; however, they suggest that this common component is more important in explaining business cycles of developed countries compared to the developing ones. Aiolfi, Catao and Timmermann (2011) develop a common factor approach to reconstruct new business cycle indices for Argentina, Brazil, Chile, and Mexico. They measure the cyclical synchronicity using the concordance index of Harding and Pagan (2002) and indicate that business cycles for these four Latin American countries displayed a reasonably high degree of synchronization throughout 1870–2004. Kose, Otrok, and Prasad (2012) employ a dynamic factor model and decompose fluctuations in output, consumption, and investment into different factors, namely, a global factor, country group factors, and country-specific factors. They find modest convergence of business cycle fluctuations both for advanced and emerging markets during the period 1985-2008. They also suggest that group specific factors are more important rather than the global factors in explaining cyclical fluctuations.

Recently, some few studies employ nonlinear Markov switching methods to analyze the importance of asymmetric state dependent dynamics on common factors in driving the degree of business cycle comovement. Girardin (2005) uses a regime-switching framework to examine the similarities of GDP growth-cycle features of 10 East Asian countries. He also documents that the relevance of a third business cycle regime of rapid growth has to be considered for the Asian countries alongside the usual regimes of recession and normal growth. The study provides the contemporaneous correlations of smoothed recession and rapid growth regime probabilities among East Asian economies for the 1978:3–2002:4 period and two subperiods around 1990. He concludes that the correlations of China with East Asian countries are stronger than the correlations with Japan. The most comprehensive analysis in the literature that examines the synchronization of business cycles both for developed and developing countries that using a nonlinear approach is the fruitful study of Altug and Bildirici (2012). Their study employs a Markov switching framework and documents the correlations of the recession probabilities for each of the sample countries and hence investigates the commonalities and differences of these economies' cyclical fluctuations. The study documents the episodes when national business cycles are globally synchronized. They suggest that analyzing the highly heterogeneous cyclical responses of individual countries may provide a valuable tool for understanding the nature of business cycle fluctuations worldwide.

Compared to the previous studies in the literature, including Altug and Bildirici (2012), our study utilizes hidden Markov models to characterize the cyclical fluctuations of the real economy and the financial markets, and use the inference from the generated regime probabilities to make comparisons among the countries in our sample. One advantage of using hidden Markov models is their robust structures that may have occurred due to major shifts in policy and frequent shocks to the economy. Employing hidden Markov models are particularly important for emerging market economies considering that they experience more frequent financial crises and dramatic policy changes. Moreover, compared to the other studies, we are running the analysis for a broader number of emerging market economies, which contains the countries such as, the Czech Republic, Peru, Poland, Russia, which are not analyzed in previous studies. In addition, for each of the countries in our sample, we use a different variable and a different frequency in our analysis. Previous studies use real gross domestic product data in a quarterly frequency to analyze the national business cycles of the countries. Our study, on the other hand, utilizes industrial production indices representing the real side of the economies in a monthly frequency. Industrial production indices measure the real growth rate of industrial production in an economy. Compared to the GDP based measures, which have the drawback of being available only in quarterly frequencies, industrial production index data is available in a monthly frequency. Furthermore, compared to the other studies, we use a long and different time horizon with two different subsamples. Finally, we also employ an additional analysis to uncover the features of the international linkages of business cycles using the inference from the regime probabilities that we obtain from our models. The few existing studies using this approach on emerging markets report only the pairwise contemporaneous correlations of the smoothed probabilities of recessionary states. On the other, we further analyze the synchronization of national business cycles by utilizing a non - parametric approach, namely, corrected contingency coefficient, to examine the comovements and associations of different business cycle regimes across different countries in our study.

CHAPTER 3

EMPIRICAL METHODOLOGY AND DATA

3.1. Introduction

This chapter presents the empirical strategies employed in the study to conduct a systematic and consistent analysis of characterizing the dynamics of business and stock market cycles of emerging markets, the dynamic relationships between these two cyclical fluctuations, and how different or similar the business cycles are among emerging market economies as well as between emerging markets and advanced economies.

Section 3.2 describes the formal framework of the Markov switching time series models, which enables us to identify different heterogeneous regimes that are characterized by different mean and variance structures. We investigate the basic properties of Markov switching models and show the statistical techniques for specification and estimation of the models to fit our data, which exhibits regime shifts in a stationary manner. Section 3.3 discusses the parameter estimation of the model. We investigate the filtered and smoothed regime probabilities, which provide us the information about the regime at time t and enables us to compute the maximum likelihood analysis to estimate the model parameters and apply the likelihood ratio tests. We then review the implementation of the Expectation Maximization algorithm and discuss its steps that enable the iteration to continue until convergence to a maximum.

Section 3.4 describes the data, and explains the intuitions behind employing them. In addition, the section discusses the appropriate data adjustments that are applied to bring data in a consistent and economically meaningful format.

3.2. The Models

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), exchange rates, e.g. Bekaert and Hodrick (1992), inflation, .e.g. Garcia and Perron(1996), interest rates, .e.g. Ang and Bekaert (2002), changes in government policy, e.g. Sims and Zha (2006) among others. When business cycles are modelled with the Markov switching time series framework, the parameters of the model depend on a stochastic and unobservable state variable that represents the different phases of the business cycle. These 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 $s_t \in \{1, \dots, M\}$ is a latent Markov processes that determines the state of the economy and $\alpha(s_t) = \alpha_i$ for $s_t = i$, $i \in \{1, \dots, M\}$. The description of Markov trend dynamics becomes complete after defining a probability rule for transition between different states. Following the common practice in the 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:

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

where p_{ij} denotes the probability that state i will be followed by state j and $i, j, k \in \{1, \dots, M\}$.

We can collect these transition probabilities in a *(M x M)* transition matrix, denoted as *P*. Each element in the transition matrix p_{ij} represents the probability that event i will be followed by event j.

$$(4) \qquad P = \begin{bmatrix} p_{11} & p_{21} & \cdots & p_{M1} \\ p_{12} & p_{22} & \cdots & p_{M2} \\ \vdots & \vdots & \cdots & \vdots \\ p_{1M} & p_{2M} & \cdots & p_{MM} \end{bmatrix}$$

By rules of probability, we have

$$\sum_{j=1}^{M} p_{ij} = 1 \quad \text{where} \quad i = 1,2,\dots,M \quad \text{and} \quad 0 \le p_{ij} \le 1$$

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

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

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,

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

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. Kim and Nelson (1999), Koop and Potter (2000), and Chauvet and Potter (2001) further investigate this result. As proposed in Chauvet (2002), Senyuz (2010), and Senyuz, Yoldas, and Baycan (2012), one way of handling the structural breaks is using a hidden Markov specification, where the

[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.

autoregressive terms in Equation (4) are set to zero.[5] In this case, the variable of interest, y_t, is a function of an integrated process that follows a Markov chain and a white noise process.

The model becomes:

$$(7) \qquad \begin{aligned} y_t &= n_t + z_t, \\ n_t &= \alpha(s_t) + n_{t-1} \\ z_t &= z_{t-1} + \varepsilon_t \end{aligned}$$

which yields the following model for the differenced series:

$$(8) \qquad \Delta y_t = \alpha(s_t) + \varepsilon_t$$

where the Markov chain holds its regularity assumptions of being ergodic, nonperiodic, irreducible, and homogeneous. The states of the model are serially correlated and this serial correlation is captured only through the serial dependence in the different regimes of the model.

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. It is particularly important for emerging markets as they have experienced major policy changes and went through stabilization programs which may have resulted in structural breaks in the data. As Calderon and Fuentes (2010) point out,

[5] See Chauvet (2002) for an application on Brazilian economy.

emerging market economies have higher macroeconomic volatility. Fluctuations in output, current account balances, and exchange rates in these economies are more frequent, sharper and sudden compared to advanced economies. 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.

This framework is also consistent with Pagan (2010), where he suggests that using simpler models can capture the asymmetries better in emerging markets, while more complex Markov switching models reflect convergence problems in getting estimates of the parameters due to the labeling identification issues. Moreover, Albert and Chib (1993), McConnell and Perez-Quiros (2000), Harding and Pagan (2001), Chauvet (2002) among others report that the first difference of output in the US and other countries is better modeled as a low autoregressive process. In particular, Albert and Chib (1993) employ Bayesian methods to estimate Hamilton's model and report that the best specification for changes in GDP is an AR(0) process, as the autoregressive coefficients are not statistically significant.

3.3. Estimation

The transition probabilities can be denoted by a (3×1) vector, $\hat{\xi}_{t|t}$, whose first element is $P\left(s_t = 1|\psi_t\right)$ where $\psi_t = \{\psi_{t-1}, y_t\}$ and ψ_{t-1} contains past values of y_t. If we knew the value of $\hat{\xi}_{t|t-1}$, then it would be straightforward to develop a forecast of the regime for t given the information at t-1 and bring together the terms for the probabilities of s_t= 0,1,2 in a vector denoted by $\hat{\xi}_{t|t-1}$ as follows:

(9) $$\hat{\xi}_{t|t-1} = \begin{bmatrix} P(s_t = 0|\psi_{t-1}) \\ P(s_t = 1|\psi_{t-1}) \\ P(s_t = 2|\psi_{t-1}) \end{bmatrix}$$

We can identify the probability law of the observed variable y_t conditional on s_t and ψ_{t-1} and collect them in a (3×1) vector η_t:

(10) $$\eta_t = \begin{bmatrix} f(y_t|s_t = 0, \psi_{t-1}) \\ f(y_t|s_t = 1, \psi_{t-1}) \\ f(y_t|s_t = 2, \psi_{t-1}) \end{bmatrix}$$

Given the past information ψ_{t-1}, we need the state variable s_t to find the density of y_t. However, the state variable s_t is unobservable. Therefore, we follow Kim and Nelson (2003) to overcome this problem and illustrate the calculations of the regime probabilities and hence to calculate the likelihood function, we consider two steps:

First, we drive the joint probability of y_t and s_t, conditional on the past information ψ_{t-1}. This joint density is given by the product:

(11) $$f(y_t, s_t = j|\psi_{t-1}) = f(y_t|s_t = j, \psi_{t-1})\Pr(s_t = j|\psi_{t-1}), \quad j = 1,2,...,\text{M}$$

where

(12) $$f\left(y_t \middle| s_t = j, \psi_{t-1}\right) = \frac{1}{\sqrt{2\pi\sigma_{S_t}^2}} \exp\left\{\frac{-(y_t - \mu_{S_t})}{2\sigma_{S_t}^{\ 2}}\right\}$$

Second, we find the marginal density of y_t . To get $f\left(y_t \middle| \psi_{t-1}\right)$, we integrate the unobservable state variable s_t out of the above joint density by summing over all possible values of s_t

(13) $$f\left(y_t \middle| \psi_{t-1}\right) = \sum_{S_t=0}^{M} f\left(y_t, \mathrm{s}_t \middle| \psi_{t-1}\right) = \sum_{s_t=0}^{M} f\left(y_t \middle| s_t = j, \psi_{t-1}\right) f\left(s_t = j \middle| \psi_{t-1}\right)$$

$$= \frac{1}{\sqrt{2\pi\sigma_0^2}} \exp\left\{\frac{-(y_t - \mu_0)}{2\sigma_0^{\ 2}}\right\} x\left(s_t = 0 \middle| \psi_{t-1}\right)$$

$$+ \frac{1}{\sqrt{2\pi\sigma_1^2}} \exp\left\{\frac{-(y_t - \mu_1)}{2\sigma_1^{\ 2}}\right\} x\left(s_t = 1 \middle| \psi_{t-1}\right) + \ldots$$

$$+ \frac{1}{\sqrt{2\pi\sigma_M^2}} \exp\left\{\frac{-(y_t - \mu_M)}{2\sigma_M^{\ 2}}\right\} x\left(s_t = M \middle| \psi_{t-1}\right)$$

And therefore the log likelihood function is calculated as:

$$(14) \qquad = \ln L = \sum_{t=1}^{T} \ln\{\sum_{S_t=0}^{M} f\left(y_t \middle| s_t = j, \psi_{t-1}\right) \Pr\left(s_t = j \middle| \psi_{t-1}\right)\}$$

This marginal probability above is a weighted average of conditional probabilities, given the unobservable state variables $s_t = 0,1,2...,\mathrm{M}$. However, the weighting factors of $\Pr\left(s_t = j \middle| \psi_{t-1}\right)$, $\forall j = 1,2,..M$ still need to be calculated to derive the marginal density of y_t and therefore to calculate the log likelihood functions. Yet, this is not possible without a priory assumption about the stochastic behavior of the unobservable state variables.

Therefore, Hamilton (1989) employs nonlinear filtering and smoothing techniques to make probabilistic inferences about the unobserved states. These filtered and smoothed state probabilities do not only provide inference about the regime at time t, but they also provide the necessary tool to compute the maximum likelihood analysis to estimate the model parameters and apply the likelihood ratio tests.

The filtered probabilities can be found using the equation (13) with a forward recursion at time $t = 1,...,T$ when initialized by the estimate of the initial value of the state variable s_0. Then the weighting terms $\Pr\left(s_t = j \middle| \psi_{t-1}\right)$, $\forall j = 1,2,...,M$ can be calculated using the transition probabilities.

Probability terms can be updated when yt is observed at the end of time t (or in other words at the end of the t-th iteration).

Such as:

(15) $$\Pr\left(s_t = j \middle| \psi_t\right) = \Pr\left(s_t = j \middle| \psi_{t-1}, y_t\right)$$

$$= \frac{f\left(s_t = j, y_t \middle| \psi_{t-1}\right)}{f\left(y_t \middle| \psi_{t-1}\right)}$$

(16) $$= \frac{f\left(y_t \middle| s_t = j, \psi_{t-1}\right) \Pr\left(s_t = j \middle| \psi_{t-1}\right)}{\sum_{s_t=0}^{M} f\left(y_t \middle| s_t = j, \psi_{t-1}\right) f\left(s_t = j \middle| \psi_{t-1}\right)}$$

And the weighting terms can be calculated by iterating these steps for $t = 1, 2..., T$

As a result, it is possible to argue that the probability of a recession given all available information at time t depends of two things: First, it depends on the relative likelihood of observing the variable in each different state, and second, it depends on the relative likelihood of a particular regime with respect to the information set of ψ_{t-1}, which is available in the previous period. The smoothed regime probabilities, which was developed by Kim (1994), uses different information set to reconstruct the time path of the states to provide inference. While filtered probabilities $P(s_t = j|\psi_t)$ are inferences about s_t conditional on information up to time t , smoothed probabilities $P(s_t = j|\psi_T)$ are inferences about s_t that use all the available information in the sample given the parameter estimates, where $t = 1, 2, \ldots, T$. Using the full sample substantially smooths out the temporary blips in the filtered estimates.

We follow Hamilton (1990) and use the Expectation Maximization (EM) algorithm along with the nonlinear filters to calculate the maximum likelihood estimates of the model parameters. Note that we do not impose any a priori restrictions on any of the model parameters and infer the states through statistical estimation. EM algorithm is introduced by Dempster, Laird, and Rubin (1977) as an alternative way of maximizing likelihood function when there are unobservable stochastic variables in a model. Application of the EM algorithm to Markov switching models are described in detail in Hamilton (1990), Krolzig (1997, 2003), and Kim and Nelson (2003). The EM algorithm is an iterative procedure and consists of two steps, namely, expectation and maximization. As Hamilton (1990) explains, one advantage of the EM algorithm is its robustness with respect to even poorly chosen starting values of the model parameters.

In the expectation step, the unobserved variables are estimated given the parameter estimates that are obtained from the iteration process. As Kim and Nelson (2003) points out, the expectation step is nothing more than obtaining the smoothing probabilities of the unobserved regime variable of the Markov switching model. The unobserved state variables are estimated by their weighting smoothed probabilities.

In the maximization step, conditional on the expectation of the unobserved states that we found in the first step, we maximize the likelihood function with respect to the model parameters[6]. Smoothed probabilities replace the conditional regime probabilities throughout the optimization process. Starting with arbitrary initial values of the parameters, each iteration increases the value of the likelihood function. This iteration continues until convergence to a maximum.

[6] See Kim and Nelson (2003) for a detailed derivation of the EM algorithm and its application to Markov switching models.

3.4. The Data

This paper examines on a large and diverse group of countries, including economies from different geographical areas of Europe, Asia, North and South America, and Africa. We run the analyses for 12 emerging market economies: Argentina, Brazil, Chile, Mexico, Peru, South Korea, Malaysia, the Czech 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 data set consists of seasonally adjusted monthly industrial production and daily returns on stock exchange indices. The sample period is January 1995 through July 2012, with a number of observations of 199 for each sample. Monthly industrial production indices are drawn from the Thomson Datastream database, and the International Financial Statistics (IFS) of the International Monetary Fund (IMF) database. Daily returns on stock exchange indices are drawn from the Morgan Stanley Capital International (MSCI) database in Thomson Datastream.

Industrial production index is a widely used variable that is employed to characterize the real economy in the literature. This economic indicator measures the real growth rate of industrial production in an economy. Because the data takes into account of the key cyclical sectors, such as the manufacturing sector, it plays an important role in distinguishing the turning points of cyclical fluctuations. Artis, Kontolemis and Osborne (1997), Harding and Pagan (2002), Artis, Krolzig and Toro (2004), Berger de Haan and Inklaar (2005), Savva, Neanidis and Osborn (2010), and Altug, Tan, Gencer (2012) among others use industrial production index data to examine business cycle characteristics, utilizing both parametric and nonparametric approaches.

Using industrial production data has some advantages compared to the GDP based measures. First, the GDP based measures suffer from the drawback of being available only in quarterly frequencies. Industrial production index data, on the contrary, is available in monthly frequencies. Because the GDP based measures are only available in quarterly frequencies, and also considering the lags in the collection and revision of the data, these shortcomings of GDP based measures result with further delays in reporting the data. In addition, the industrial production data does not only has the advantage of being available in monthly frequencies, but as Candelon, and Metiu (2011) points out, it is also less subject to revisions. Besides, Chauvet and Hamilton (2006) suggest that measures available on a monthly basis produce better inferences for business cycles.

The MSCI Price indices measure the daily price performance of markets for each of the countries in our sample. The price returns of the index capture the sum of its constituents' free float-weighted market capitalization returns. The free float methodology market capitalization is calculated by taking the equity's price and multiplying it by the number of shares readily available in the market. Instead of using all of the shares outstanding like the full-market capitalization method, the free-float method excludes locked-in shares such as those held by promoters and governments.

As Morley and Piger (2012) discuss, it is useful to make a distinction between the fluctuations in business cycles and fluctuations in seasonal patterns, even though they may be related to each other up to some degree. Therefore, we seasonally adjust our dataset of monthly industrial production and daily returns on stock exchange indices by using the ratio-to-moving average method. Employing seasonally adjusted data implicitly treats the seasonal patterns as independent or, at least, not marginally relevant for making inferences about business cycle fluctuations.

Following Stock and Watson (2005), we smooth 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 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] As explained in section 3.2, we model each of these series using univariate hidden Markov models. As Hamilton (2010) suggests, using a univariate model has the advantage of giving more robustness with respect to the changes than a more elaborate specifications. The growth rates of monthly industrial production for the emerging markets in our sample are plotted in Figure 1. The monthly filtered return series for each country are plotted in Figure 2. 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.

We examine the presence of unit roots in the data with the Augmented Dickey-Fuller test (the ADF test) proposed in Dickey and Fuller (1981) and the Phillips Perron (the PP test) proposed in Phillips Perron (1998). First, test statistics fail to reject the unit

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

root hypothesis for any of the industrial production and stock exchange series. Then stationarity is achieved after taking twelve-month averages of the annual month-to-month growth rates of the industrial production and calculating filtered monthly return series as the sum of continuously compounded daily returns, as all series were modeled as in equation (7) and transformed to their difference as in equation (8). Table 1 presents the results of the unit root tests for industrial production indices for the emerging market economies. Table 2 shows the unit root test results for the G7 economies. Table 3 provides the results of the unit root tests for the monthly filtered return series. All results reject the unit root hypothesis both with the ADF and PP tests.

CHAPTER 4

EMPIRICAL RESULTS

4.1. Introduction

This chapter provides the empirical results of this systematic and consistent analysis, which is able to account for the state dependent dynamics. We conduct the analysis and document the results in three main sections.

Section 4.2 examines the cyclical dynamics of the real economy. This section first applies several specification tests to find individual models that best reveal the characterization of individual dynamics for each of the countries in our sample. Then we report the comparisons of the findings among different country groups. We then provide classifications for the business cycle turning points that identify the individual crises of the emerging markets, as well as the more contagious crises in the sample that have affected multiple economies. Finally, the individual characteristics of state dependent dynamics are further examined in this section for each of the emerging economies in our sample.

Section 4.3 examines the cyclical dynamics of the stock markets for the emerging market economies. This section explicitly models and characterizes the stock market cycles using adequate regime switching specifications, and identifies the bear, bull, and moderate return states. We first compare the findings among different stock markets of emerging markets, and then further examine the individual characteristics of state dependent dynamics of stock market returns. We report the different characteristics of the stock markets in emerging markets compared to the documented stylized facts of typical advanced economies. Furthermore, for the first time in the literature, this section examines and quantifies the dynamic relationship between the smoothed probabilities of the stock market and the real economy for the 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. Empirical results document that bear market peaks can be considered as a potential predictor of the recessions.

Section 4.4 quantifies the associations between business cycles across emerging markets and advanced G-7 economies. Again for the first time in the literature, this section examines both the corrected contingency coefficients and contemporaneous pairwise correlations of smoothed regime probabilities that we obtain from modeling each of the national business cycles in our sample to understand how different or similar the business cycles are among individual emerging market economies, as well as between emerging markets and advanced economies. The section quantifies the associations across different business cycles, and tries to answer whether or not the economic fluctuations are globally synchronized, and which countries or country groups are more synchronized compared to the others over the period between 1996-2012, and a sub period of 2004-2012. In addition to the idiosyncratic and regional factors, the section investigates the effect of a large common disturbance that is affiliated with a global recession.

4.2. Cyclical Dynamics of the Real Economy

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 further insights about these economies. We model business cycles for the emerging markets at monthly frequencies by focusing on the year on year growth rates of industrial production index.

4.2.1. Examining Nonlinearity, Number of Regimes, and Regime Dependent Variance

We first apply several specification tests to find individual models that best fit to reveal the characterization of individual dynamics for each of the countries in our sample. By using the specification tests, our aim is to choose the number of regimes, and to examine heteroscedasticity to identify whether or not the variance structure also switches with respect to different regimes. We also test the null hypothesis of linearity against the alternative of nonlinear Markov switching specifications.

We use a variety of approaches to identify the best models representing the dynamics of each of the emerging and advanced economies in our sample. We start by using visual inspection of the data. Then we employ Akaike Information (AIC), Hannah-Quinn (HQ) and Schwarz Bayesian Information (SIC) penalized likelihood model selection criteria tests. Finally, we use the modified likelihood ratio tests that are proposed by Garcia and Perron (1996), and Ang and Bekaert (2002). The reason that we need to use modified likelihood ratio tests is due to the problem of unidentified nuisance parameters. This problem arises because the transition probabilities are not identified under the null. These unidentified nuisance parameters prohibit the use of conventional distribution theory as the conventional regularity conditions of identical zero scores and singular variance-covariance-matrices do not hold.

4.2.1.1. Determining the number of regimes

We conduct tests for each country to examine whether a two or a three state specification best captures the characteristic dynamics of the economies. Because the standard asymptotic distribution theory cannot be invoked as explained above, along with the other information criteria tests, we rely on the modified likelihood ratio test of Ans and Bekaer (2002) to choose the number of regimes for each of the models. According to this approach, the degrees of freedom of the models are adjusted according to the nuisance parameters. The corrected degrees of freedom is calculated as the summation of the number of restrictions obtained from the model for two regimes ($p_{11}+p_{12} = 1$ and $p_{22}+p_{22} = 1$), and the nuisance parameters in each model that cannot be identified under the null. For the third regime, these include the regime dependent parameters plus the transition probabilities (p_{31}, p_{32}) of the third regime.

We first start modeling the nonlinear dynamics with a two state specification; 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. After performing this modified likelihood ratio statistic of Ans and Bekaer (2002), which is conditioned on the value of the nuisance parameters, and also conducting the penalized likelihood model selection criteria tests of AIC, SIC, and HQ to select the best specification, the results suggest that a three state specification captures state dependent dynamics better than the two-state specifications. Therefore, we proceed with a three state specification that produces the estimates given in Tables 4, 5, 6, and 7.

4.2.1.2 Regime Dependent Heteroscedasticity

We also employ the same specification tests to decide for the allowance of heteroscedasticity both for the emerging and G-7 economies. For the emerging countries in our sample, the null hypothesis of invariant variance $(\sigma_0^2 = \sigma_1^2 = \sigma_2^2)$ cannot be rejected for Argentina, Chile, Malaysia, Peru, Poland, and Turkey. The results are reported in Table 4. On the other hand, the results are in favor of regime dependent variance for Brazil, the Czech Republic, Mexico, Russia, South Africa, and South Korea as reported in Table 5. For the advanced G-7 economies of France, Italy, Japan, and the USA, the results are in favor of heteroscedasticity with regime switching variances as reported in Table 6. The rest of the G-7 countries, namely Canada, Germany, and the UK are reported in Table 7 and the results are in favor of invariant variances for these countries that are not sensitive to different states of the economy. Whenever an economy is characterized with a regime dependent variance, then the variance during the contraction of industrial production index is higher than that during the low or high growth phases in all of the emerging markets and G-7 economies. Russia has the largest variance during a recession among the emerging market economies, while Japan has the largest variance among the G-7 countries.

4.2.1.3 Asymmetries of the Business Cycles:

We also compare our nonlinear Markov switching models with linear specifications. However, conducting a test of linearity is complicated because of the parameters that are not identified under the null hypothesis. The reason is that, as mentioned before, we don't have the standard asymptotic $\chi 2$ distribution for the likelihood ratio tests. Davies (1987) proposes an approach to overcome this problem when testing for linearity. Following Garcia and Perron (1996) to show this approach[8], we denote the likelihood ratio statistic with $\hat{\tau}$, the number of coefficients in the mean that vanish under the null with m, and the number of transition probabilities that vanish under the null with q.

It is possible to formulate the conventional likelihood ratio test as:

$$P\left[\chi^2(m+q) > \hat{\tau}\right] \tag{1}$$

While the approximate upper bound is shown as:

$$P\left[\chi^2(q) > \hat{\tau}\right] + 2\hat{\tau}^{1/2}\exp\left\{\left(\tfrac{q}{2}-0.5\right)\log(\hat{\tau}) - \tfrac{\hat{\tau}}{2} - \tfrac{q}{2}\log(2) - \log\Gamma(\tfrac{q}{2})\right\} \tag{2}$$

Tables 4, 5, 6, 7, and 11 present these p-values of the upper bound for the likelihood ratio test of linearity based on Davies (1987) for each of the countries that we model. Linearity is clearly rejected in favour of nonlinear Markov switching models for

[8] Further discussion on conducting the linearity test can be found in Terasvirta (2006), and in Doornik and Hendry (2009)

all of the emerging and developed countries in our sample. The strong asymmetry is evident in the small value of the Davies upper bound and in the substantially different mean estimates and regime probabilities across the states.

Note that before deciding on model (7)-(8) defined in Chapter 3, 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 as explained in Chapter 3. 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).

4.2.2 Estimation

Maximum likelihood estimations of the selected models, along with the transition probabilities for emerging market economies, are given in Table 4 and 5. Estimation results of the chosen models for G-7 economies are shown in Tables 6 and 7. The models are estimated with the expectation maximization algorithm discussed in Chapter 3. The numbers in parentheses give the asymptotic standard errors. Russia has the sharpest drop in industrial production index with a value of 7.74%. The mean for expansions is estimated to be the highest for South Korea, with a percentage of 9.21%. For all the emerging and developed economies that are characterized with regime dependent variances, estimated variances of the recessions are higher than variances of low and high growth regimes. These results document that recessionary states are the most volatile states compared to the low and high growth states both for the emerging and advanced economies.

We also visualize the implications of the chosen models for the statistical characterization of the emerging market business cycles. Figure 3 plots the time paths of smoothed probabilities of being in a recession, while Figure 4 plots the time paths of smoothed probabilities of being in a recession for the emerging economies. Figures 3 through 14 plot the time paths of smoothed full sample probabilities for recessionary, low growth, and high growth regimes of the emerging market economies. As we discussed in Chapter 3, the filtered probabilities represent an optimal inference using only the current information up to time *t*. The smoothed probabilities of being in the recessionary state 0, low growth state 1, or the high growth state 2 are based on the full information of the sample. The spikes in probabilities of the recessionary states are all associated with sharp declines in output.

4.2.3 Determining the Duration and Persistence:

We can determine the duration of each regime by using the diagonal elements of equation (14) in Chapter 3. These diagonal elements denote the transition probabilities of being in the same state both in the current and the previous period. Using this information, we can find the average length of a particular regime lasts on average. Following Kim and Nelson (2003), calculation of these durations can be shown as follows:

Let j denote the current state ($s_t = j$), and D denote the duration of state j. Then:

(3) $$D=1,\ \text{if } s_t = j \text{ and } s_{t+1} \neq j;\ \Pr[\mathrm{D}=1]=(1-p_{jj})$$

(4) $$D=2,\ \text{if } s_t + s_{t+1} = j \text{ and } s_{t+2} \neq j;\ \Pr[\mathrm{D}=2]=p_{jj}(1-p_{jj})$$

(5) $$D=3,\ \text{if } s_t + s_{t+1} + s_{t+2} = j \text{ and } s_{t+3} \neq j;\ \Pr[\mathrm{D}=3]=p^2{}_{jj}(1-p_{jj})\ \ldots$$

Following these steps, the expected duration of state j can be derived as follows:

(6) $$E(D_j)=\sum_{j=1}^{\infty} \mathrm{j}\Pr[\mathrm{D}=j]$$

$$=1\times(1-p_{jj})+2\times p_{jj}(1-p_{jj})+3\times p^2{}_{jj}(1-p_{jj})+\ldots$$

(7) $$E(D_j)=\frac{1}{1-p_{jj}}$$

In particular, we can calculate the expected duration of the recessionary state ($s_t = 0$), low growth state ($s_t = 1$), and the high growth state ($s_t = 2$) with the following equations:

(8) $$E(D_0)=\frac{1}{1-p_{00}}$$

$$(9) \qquad E(D_1) = \frac{1}{1 - p_{11}}$$

$$(10) \qquad E(D_2) = \frac{1}{1 - p_{22}}$$

These estimated transition probabilities of staying in the same state vary according to individual country characteristics. Using the transition probabilities from Table 5 and the above equations of (8), (9), and (10), along with the equation (4) in Chapter 3, Table 9 reports the calculations of average durations and percentages of staying in the same regime.

When emerging market economies enter expansionary phases, the durations of high state expansions are briefest in South Africa, their length being equal to an average of 6.5 months, which corresponds to 6.53% of the whole sample period. On the contrary, Argentina continues expanding in the high growth state for the longest period, with an average duration of 38 months, which corresponds to 57.29% of the whole sample period. Among the emerging markets in our study, the recessionary regime persists the longest in Mexico with an average duration of 29 months. Turkey has the lowest average duration for recessions, with an average duration of 7.25 months. 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.

4.2.4 Turning Point Analysis

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 convention 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, $\Pr[s_t = 0|\Omega_t] < 0.5$ where Ω_t denotes the information set at time t, and it enters a recession in $t+1$, $\Pr[s_{t+1} = 0|\Omega_t] \geq 0.5$. A business cycle trough occurs in month $t+1$ if the economy was in a recession in month t, $\Pr[s_t = 0|\Omega_t] \geq 0.5$, and it enters an expansion in month $t+1$, $\Pr[s_{t+1} = 0|\Omega_t] < 0.5$. 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 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 10 presents the individual crises of the emerging market economies, as well as the more contagious crises in our sample set 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 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 behavior 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. Most of the time, the accelerated growth has been followed by a period of slowdown over the sample period.

4.2.5 Business Cycle Analyses of Individual Country Characteristics

In the previous sections, we reported the results considering the big picture both for the emerging markets and G-7 economies, including the comparisons of the findings among different country groups. In this section, we provide further results to examine individual characteristics of state dependent dynamics of each emerging market economy in more detail.

Table 4 and 5 present regime dependent maximum likelihood mean and variance estimations of the selected models, transition probabilities, AIC, HQ and SIC penalized likelihood model selection criteria tests, Likelihood Ratio statistics, and the Davies upper bound p-values for each of the emerging market economies in our dataset. The numbers in parenthesis give the asymptotic standard errors. Figure 27 plots the smoothed recession probabilities, while Figure 28 plots the sequence of filtered probabilities of recessionary periods. The sequence of the smoothed probabilities for each different regime, along with the fitted values and one-step-ahead predictions, is shown in Figures 3 through 14 for each of the emerging market economies in our sample.

Table 8 shows the estimated Markov probabilities of staying in the same regime. Using the transition probabilities from Table 4 and 5, and the equations (8), (9), and (10), along with the equation (4) in chapter 3, Table 9 reports the calculated average durations and percentages of staying in each particular state.

4.2.5.1 Argentina

For the growth rates of monthly industrial production index for Argentina, 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 Argentina. In addition, the results cannot reject the null hypothesis of invariant variance. The monthly mean growth rate of industrial production is around -4.9% for state 0, which has an expected duration of 9.3 months as implied by the 0.88 transition probability estimate of staying in this regime once it prevails. This state represents the crises periods during which economic activity has dropped sharply. The economy stays in this recession state 14% of the time. The mean growth rates of states 2 and 3 are 0.26% and 3.6% per year respectively, characterizing the low and high growth regimes. Among the three regimes, regime 3 has the longest duration of more than 38 months, which corresponds to 57.2% of the whole sample period. The smoothed probabilities of each state and the fitted values along with the one-step-ahead predictions for Argentina are plotted in Figure 3. The model identifies the Argentinian crises of 1999, 2001-2002, and 2008-2009. Of these, the longest recessionary regime is the most recent one, of 2008.

4.2.5.2 Brazil

For the Brazilian economy, we find that the growth 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. Linearity is strongly rejected in favor of asymmetry. 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.

4.2.5.3 Chile

The results for Chile are in favor of strong asymmetry. Consideration of all the model tests suggests a 3-regime model for Chile. Figure 5 plots these regimes along with the fitted values and one-step-ahead predictions. The estimated conditional means are 2.27, 0.98, and 2.81 for the recession, low, and high growth states, respectively. The hypothesis of homoscedasticity cannot be rejected. Transition probabilities are statistically significant and provide insight about the average durations and percentages of staying in each individual state. Estimated Markov probabilities are highly persistent with the values of p_{00}= 0.93, p_{11}=0.96, and p_{22}= 0.94. The average durations are 15, 26, and 21.67 months for recessionary, low, and high growth states, while the average percentages are: 15.08%, 52.26%, and 32.66%, respectively. The model identifies the1998-1999 and 2008-2010 Chilean crises.

4.2.5.4 The Czech Republic

For the Czech Republic, the results are in favor of nonlinearity and the specification tests suggest a 3-state specification with respect to the industrial production growth. Parameter estimates of the chosen Markov switching model report the conditional means of -2.27%, 0.98%, and 2.81% for the recession, low, and high growth states, respectively. Variance of a recessionary state is the highest compared to the low and high growth states. The recessionary regime persists on average for about 11.50 months, with an overall percentage of 11.56. The high growth regime is the most persistence state compared to the others. The persistent of low and high growth regimes are about 9.57 and 14.38 months, with respective percentages of 43.72% and 44.72%. The smoothed probabilities for each of the states are given in Figure 6. The model identifies the crises of 1998-1999 and 2008-2009 for the Czech Republic.

4.2.5.5 Malaysia

The results reveal three different phases of industrial production growth in the Malaysian economy. The results also favor the existance 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 7 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.

4.2.5.6 Mexico

We identify three states of Mexican business cycles. Specification tests reject linearity. In addition, the null hypothesis of invariant variance cannot be rejected. The results are in favor of heteroscedasticity. The mean growth rates are -1.14% during recessions, 1.44% during the low growth regimes, and 3.44% during the high growth regimes. The variance of the percentage change in output takes its highest value in the recession periods. Using the estimates of the transition probabilities given in Table 4, we analyze the persistence of each regime, finding that each regime appears highly persistent. Figure 8 shows the different states for Mexican economy based on the smoothed probabilities The model identifies the Mexican crises that start in 2001 and 2008. The probability that a month of depression will be followed by another month of depression is 95% for Mexico, while this probability is 92% both for the low and high growth states. Average durations and percentages of staying in each individual state are: 29 months with a percentage of 29.15 for recessions, 12 months with a percentage of 42.21 for low growth regimes, and 14.25 months with a percentage of 28.64 for high growth regimes.

4.2.5.7 Peru

When we apply the analysis for Peru with year on year growth rates of monthly industrial production index, the specification tests are in favor of a three-state specification with constant variance. Results give strong evidence for the asymmetric character of the economy. During recessionary periods, manufacturing output of Peru contracts at a monthly rate of -2.75%, whereas it grows by about 0.94% and 4.16% in the low and high phases of the expansions. The transition probability for the recession state is 0.90, which is lower than that of the high phase of expansions, 0.92. The implied average duration of a recession is approximately 13 months, whereas it is 9.44 months for low growth states and 14.67 months for high growth states. The average percentages of staying in one state for recession, low, and high growth regimes are 13.07%, 42.71%, and 44.22% respectively. The smoothed probabilities of each regime are plotted in Figure 9. Using the dating rule with the smoothed probabilities, the model identifies the recessions of 1998-1999 and 2009.

4.2.5.8 Poland

For the growth rates of monthly industrial production index for Poland, we find that the three-state mean specification with constant variance adequately captures state dependent dynamics of the economy. The hypothesis of homoscedasticity cannot be rejected. The estimated conditional mean growth rates are -1.53 %, 1.69%, and 4.37% for the recession, low and high growth states, respectively. Transition probabilities are statistically significant with the values of 0.87 for recessions, 0.85 for low growth, and 0.94 for high growth states. Average durations and percentages of staying in each individual state are calculated using these transition probabilities. We find that the expected duration of a recession is around 10 months, with a percentage of 15.08. The expected duration of a high-growth regime is the highest with an average of 21.8 months and a percentage of 54.77. And finally, the expected duration of a low-growth regime is around 8.57 months, with a percentage of 30.15. Figure 10 shows each different regime for the Polish economy based on the smoothed probabilities. The model identifies the Polish crises of 2001-2002 and 2008-2009.

4.2.5.9 Russia

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 11 shows the sequence of the smoothed probabilities for each different regime of Russia. The model identifies the 1998-1999 and 2008-2009 Rusiian crises.

4.2.5.10 South Africa

The results for South Africa are in favor of strong asymmetry. The model specification tests suggest a 3-regime model. Additionally, the results are in favor of regime dependent variances. Parameter estimates of the chosen Markov switching model report the conditional means of -2.86%, 1.30%, and 3.24% for the recession, low, and high growth states respectively. We find that the expected duration of a recession is around 14 months, with a percentage of 21.11. The expected duration of low-growth regime is the highest with an average of 24 months and a percentage of 72.36. And finally, the expected duration of a high-growth regime is around 6.5 months, with a percentage of 6.53. Figure 12 shows the different states for South African economy based on the smoothed probabilities. The model identifies the South African crises that start in 2001 and 2008.

4.2.5.11 South Korea

For South Korea, the results with respect to the industrial production growth suggest nonlinearity. The specification tests suggest a three-state specification. The results are also in favor of the regime dependent variances. The mean growth rates are -1.83% during recessions, 3.10% during low growth regimes, and 9.21% during the high growth regimes. The variance of the percentage change in output takes its highest value in the recession periods. The transition probability for the recession state is 0.92, which is less than that of the low phase of expansion, 0.97. The implied average duration of a recession is approximately 12.33 months, whereas it is 33.5 months for low growth states, and 14 months for high growth states. The average percentages of staying in one state for recession, low, and high growth regimes are 18.59%, 67.34%, and 14.07% respectively. Figure 13 shows each different regime for South Korean economy based on the smoothed probabilities. The model identifies the crises of 1997-1999, 2001, and 2008-2009.

4.2.5.12 Turkey

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 14. The model identifies the Turkish crises that start in 1998, 2001, and 2008.

4.2.6 Main Findings

Overall, we have considered the big picture including the comparisons of findings among different country groups, and we provided further results to examine individual characteristics of state dependent dynamics of emerging economies. Results reveal the strong asymmetric dynamics of business cycles in emerging markets and document the stylized facts of cyclical fluctuations for a diverse group of emerging economies. Crises of emerging markets 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 the long-run average rate. Our estimated business cycle models classify business cycle turning points and identify the individual crises in the emerging markets, as well as the more contagious crises in the sample that have affected multiple economies, such as the 1997 Asian crisis, the 1998 Russian Crisis, the 2001 recession in the US, and lastly the 2008 sub-prime led financial crisis and the ensuing global recession. The results are in line with business cycle stylized facts in terms of implying short, abrupt recession phases and longer, moderate expansion phases. 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. 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 patterns in emerging market economies. Almost every period of accelerated growth has been followed by a period of slowdown during the years in our sample.

4.3. 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 again use several approaches to identify the best models that represent the dynamics of each of the emerging market stock market returns in our sample. We begin by visually inspecting the data. Then we employ AIC, HQ and SIC penalized likelihood model selection criteria tests. We then use the modified likelihood ratio tests that are proposed by Garcia and Perron (1996), and Ang and Bekaert (2002). As explained in section 4.2, the reason that we need to use modified likelihood ratio tests is due to the problem of unidentified nuisance parameters.

We find that a three-state specification with switching mean and variance adequately captures state dependent dynamics of the stock market returns for all countries. Table 8 provides these p-values of the upper bound for the likelihood ratio test of linearity based on Davies (1987) for each of the countries that we model. Linearity is clearly rejected in favor of nonlinear Markov switching models for all of the stock markets in the emerging economies in our sample. The strong asymmetry is evident in the small value of the Davies upper bound in and the substantially different mean estimates and regime probabilities across the negative, moderate, and high returns states.

After we characterize all the stock markets with regime dependent variances, we then analyze how the variance structure behaves according to the negative, moderate, and high returns phases of the stock markets. Among the emerging market economies, Russia has the largest variance during a negative returns state, while Chile has the lowest variance for the same bear markets state. For the bull market regimes, Turkey has the highest variance while South Africa has the lowest value. For Chile, South Korea, and Turkey, the periods during which the stock market performs well above the average also seem 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. For the rest of the emerging markets, volatility of the bear state is the highest, reflecting increased uncertainty during periods of low returns.

Of all these countries, Russia, again, has the sharpest drop for returns with a mean value of -12.31% for the bear market regime. Argentina and Malaysia follow Russia with mean values 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%.

When emerging market economies enter bull state phases, the duration of high returns states is briefest in Poland, its length being equal to an average of 6.83 months, which corresponds to 20.6 % of the whole sample period. On the contrary, the Czech Republic continues to stay in the bull markets state for the longest period, with an average duration of 16.5 months, which corresponds to 44.72% of the whole sample period. Among the emerging markets in our study, the negative returns state of the bear market phase persists the longest for Poland on average of 12.67 months, with a corresponding average of 38.19% of the whole period. Brazil has the lowest average duration for the bear state, with an average duration of 5.33 months, or 16.08% of the whole sample period.

4.3.1 Stock Market Analyses of Individual Country Characteristics

After reporting the overall results and comparisons of the findings among different stock markets of emerging markets, in this section we provide further results to examine the individual characteristics of state dependent dynamics of stock market returns for each of the emerging markets in our dataset.

Table 8 presents regime dependent maximum likelihood mean and variance estimations of the selected models, transition probabilities, AIC, HQ and SIC penalized likelihood model selection criteria tests, Likelihood Ratio statistics, and the Davies upper bound p-values for each of the emerging market stock markets. The numbers in parentheses give the asymptotic standard errors.

Figure 29 plots the sequence of smoothed probabilities for the bear states of the stock markets. The sequence of the smoothed probabilities for each different regime, along with the fitted values and one-step-ahead predictions are shown in Figures 15 through 26 for each of the emerging market stock markets in our sample.

Table 12 shows the estimated Markov probabilities of staying in the same returns regime. Using the transition probabilities from Table 8 and the equations (8), (9), and (10), along with the equation (4) in chapter 3, Table 13 reports the calculated average durations and percentages of staying in each particular state for the stock markets of emerging markets.

4.3.1.1 Argentina

For the Argentinian stock markets, we find that the three-state mean specification with regime dependent variance adequately captures state dependent dynamics of the filtered returns. Linearity is strongly rejected in favor of asymmetry. The smoothed probabilities of bear, moderate, and bull states and the fitted values along with the one-step-ahead predictions for Argentinian stock market returns are plotted in Figure 15. The monthly mean growth rate of filtered returns is around -6.29% for state 0, which has an expected duration of 9.4 months as implied by the 0.91 transition probability estimate of staying in this regime once it prevails. This state represents the bear markets during which stock market has dropped sharply. 23.6% of the time the stock market stays in this bear markets state. The mean growth rates of States 2 and 3 are 0.59% and 4.94% per year respectively, characterizing the moderate return and bull market regimes.

4.3.1.2 Brazil

The results for the stock markets of Brazil are in favor of strong asymmetry. Figure 16 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.

4.3.1.3 Chile

The results for the stock markets of Chile are in favor of nonlinearity. The smoothed probabilities of each of the stock market states are given in Figure 17. Parameter estimates of the chosen Markov switching model report the conditional means of -2.59%, 0.09%, and 2.68% for the bear, moderate returns, and bull states, respectively. Variance of the bull state is the highest compared to the low and high return states, which is different from documented stylized facts of a typical advanced economy, where the bull markets are characterized by high returns and low volatility. The bear regime persists on average for about 6.50 months, with an overall percentage of 19.60. The bull regime is the most persistence state compared to the others. The persistence of bear and bull regimes are about 6.50 and 12 months, with respective percentages of 19.60% and 42.21%.

4.3.1.4 The Czech Republic

Figure 18 shows the sequence of the smoothed probabilities for each different stock market regimes of the Czech Republic. The results reveal three different phases of filtered returns in the Czech stock market. The mean growth rates are -3.58% during bear states, -0.42% during moderate returns states, and 2.82% during the bull states. The variance of the percentage change in returns takes its highest value in the bear market periods. The transition probability for the bear state is 0.83, which is lower than that of the bull state, 0.93. The implied average duration of a bear state is approximately 6.40 months, whereas it is 6.80 months for moderate return states, and 16.50 months for bull market states. The average percentages of staying in one particular state for bear, moderate returns, and bull regimes are 16.08%, 34.17%, and 44.72% respectively.

4.3.1.5 Malaysia

Figure 19 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.

4.3.1.6 Mexico

Figure 20 plots each of the three states for Mexican stock markets based on the smoothed probabilities. The results for Mexico are in favor of strong asymmetry. The estimated conditional means are -1.92, 1.03, and 3.65 for the low, moderate and high return states respectively. Estimates of the transition probabilities are statistically significant and provide insight about the average durations and percentages of staying in each individual state. Transition probabilities have the values of p_{00}= 0.88, p_{11}=0.75, and p_{22}= 0.86. The average durations are 8.83, 4, and 7.09 months for bear, moderate, and bull market states, while the average percentages are 26.63%, 34.17%, and 39.20% respectively.

4.3.1.7 Peru

Figure 21 shows the sequence of the smoothed probabilities for each different regime of Peru. Linearity is strongly rejected and the results give us strong evidence for the asymmetric character of the stock market. During bear state periods, monthly stock market returns in Peru contracts at a monthly rate of -4.16% whereas it grows by about 0.52% and 4.56% in moderate and high return phases of stock markets. The transition probability for the bear state is 0.87, which is lower than that of the high phase of bull state, 0.89. The implied average duration of a bear state is approximately 7.6 months, whereas it is 6.31 months for moderate returns states, and 9.88 months for bull market states. The average percentages of staying in one state for bear, moderate, and bull states are 19.10%, 41.21%, and 39.70%, respectively.

4.3.1.8 Poland

For the growth rates of monthly stock market returns for Poland, we find that the three-state mean specification with switching variance adequately captures state dependent dynamics of the economy. Figure 22 shows each different regime for the Polish economy based on the smoothed probabilities. The estimated conditional mean growth rates are -2.71%, 1.50%, and 4.31% for the bear, moderate returns and bull states, respectively. Transition probabilities are statistically significant with the values of 0.91 for low returns state, 0.86 for moderate returns, and 0.84 for high return states. Average durations and percentages of staying in each individual state are calculated using these transition probabilities. We find that the expected duration of a bear state is around 12.67 months, with a percentage of 38.19. The expected duration of a bull regime is 6.38 months and has a percentage of 20.60. And finally, the expected duration of a moderate returns regime is around 6.83 months, with a percentage of 41.21.

4.3.1.9 Russia

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 23 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.

4.3.1.10 South Africa

Figure 24 shows each different regime for the South African stock market based on the smoothed probabilities. Results also document strong asymmetry based on the Davies upper bound values. The mean growth rates are -2.93% during low return states, 0.61% during moderate returns states, and 3.04% during the high returns states. The variance of the bear state is the lowest in South Africa compared to the other emerging markets. The variance of the percentage change in stock market takes its highest value in the bear state periods. The transition probability for the bear state is 0.86, which is less than that of the moderate returns, 0.89. The implied average duration of a bear state is approximately 7.50 months, whereas it is 9.42 months for moderate returns states and 7 months for high returns states. The average percentages of staying in one state for bear, moderate returns, and bull market regimes are 15.08%, 56.78%, and 28.14% respectively.

4.3.1.11 South Korea

The smoothed probabilities for all three states of the South Korean stock market are plotted in Figure 25. Linearity is clearly rejected and the results are in favor of asymmetry. Parameter estimates of the chosen Markov switching model report the conditional means of -3.33%, 0.90%, and 5.78% for the low return, moderate return, and high return states, respectively. Variance of a bear state is the highest compared to the moderate and high return states. The bear market regime persists on average for about 10.14 months, with an overall percentage of 35.68. This regime is the most persistence state compared to the others. The persistence of moderate and high growth regimes are about 7.33 and 9.33 months, with respective percentages of 44.22% and 28.14%. Variance of the low return state is the highest compared to the moderate and high return states, which is different from documented stylized facts of a typical advanced economy.

4.3.1.12 Turkey

Results document strong asymmetry based on the Davies upper bound values. The smoothed probabilities of each of the states are given in Figure 26. 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. Similar to Chile and South Korea, variance 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.

4.3.2 Relationship between Stock Market and Real Economy

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 relationship 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 let $\{N_{2,t}\}_{t=1}^{n}$

denote a binary variable representing the monthly business cycle chronology, such that $N_{2,t}$ equals 1 during recessions, and 0 otherwise.

Then, the QPS is given by

$$(11) \qquad QPS_i = \frac{2}{n}\sum_{t=1}^{n}\left(N_{1,t} - N_{2,t+i}\right)^2, \quad i = 0,1,\ldots 12$$

Table 10 presents the QPS values for lead times of the stock markets ranging from 0 to 12 months for each of the emerging markets in our sample. The QPS takes a value between 0 and 2, where 0 corresponds to perfect accuracy. The minimum QPS value is achieved when the loss function is minimized. The smaller the value of QPS is, the more accurate the correspondence is between the monthly business cycle chronologies that we provide using monthly industrial production data, and the stock market model generated smoothed probabilities. We find that the smoothed probabilities of the bear state yield the lowest QPS at horizons between 5 and 11. Therefore, 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.

4.4. Business Cycle Synchronization

This section makes comparisons of different business cycles and quantifies the dynamics of global cyclical linkages for the emerging and G-7 economies by examining the smoothed probabilities obtained from the dynamic Markov switching models. We analyze how business cycles in emerging market economies are different from or similar to each other and the advanced G-7 economies. To do this, we utilize the smoothed regime probabilities that we obtain from modelling each of the national business cycles in our sample. We quantify the associations across different business cycles, and 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 over the period between 1996-2012 and a sub period of 2004-2012.

4.4.1 Quantifying the Business Cycles Associations

To uncover the features of international linkages across national business cycles, first we analyze the behavior of the pairwise contemporaneous correlations of the estimated smoothed probability sequences of recessionary states, which are affiliated with each of the national business cycles in our sample. The pairwise contemporaneous correlations measure the synchronization strength by providing the degree of clustering of the turning points among national business cycles. Most of these correlations are statistically significant, indicating that most of these economies are in the same regime during the sample period.

To further analyze the synchronization of national business cycles, we next utilize a non - parametric approach, namely the corrected contingency coefficient, to measure the comovements of different business cycle regimes across the countries in our study. The corrected contingency coefficients examine the strength of association by quantifying the fraction of time that two countries' business fluctuations are in the same state. We follow Artis, Krolzig, and Torro (2004) and compare the expansion and contraction frequencies of the two series. We again use the estimations of smoothed probabilities, obtained by modeling national business cycle models, to examine their characterizations and regime classifications. Then, we employ a binary time series variable for the smoothed probabilities of recessionary states, which 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 employed in obtaining 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 by measuring the statistics for X^2, which is frequently used to test the dependence level of variables.

(12) $$\chi^2 = \sum_{i=0}^{1}\sum_{j=0}^{1} \frac{[n_{ij} - n_{i.}n_{.j} / N]^2}{n_{i.}n_{.j} / N}$$

where n_{ij} stands for the frequencies that overlap both countries in the pair 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:

(13) $$CC = \sqrt{\frac{\chi^2}{N + \chi^2}}$$

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:

(14) $$CC_{corr} = \frac{CC}{\sqrt{0.5}} 100$$

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 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 14 through 17 display contemporaneous pairwise correlations of smoothed probabilities of the recessionary regimes among emerging countries and between emerging markets and G-7 countries, over the 1996:01 – 2012:07 period and a subperiod of 2004:01 – 2012:07. Moreover, Tables 18 through 21 report the corrected contingency coefficients of binary variables, that we obtain from the sequences of smoothed probabilities of recessionary regimes, among emerging countries and between emerging markets and G-7 countries, again over the 1996:01 – 2012:07 period and a subperiod of 2004:01 – 2012:07.

Results show that crises of emerging markets are contagious 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 did not affect the economy globally. Japan is the only advanced G-7 country that was affected by the East Asian crisis. Other G-7 countries were not affected by these two crises that emerging economies suffered. The crises that were caused by the emerging markets were not severe or contagious for the advanced economies over our sample period. The 2001 recession in the U.S. was more contagious for many of the advanced and emerging economies. However, the results clearly show that the recession of 2008 creates a true disturbance factor that can be identified as a global recession, both for advanced and emerging market economies.

The results identify some distinct group of countries within emerging economies and between emerging markets and advanced G-7 countries. Both the contemporaneous pairwise correlations and the corrected contingency coefficients give the largest values across the East Asian Economies of Malaysia, South Korea, and Japan. Moreover, they have a relatively low degree of synchronicity with many other emerging markets in our sample. All contingency coefficients among these countries are higher than 85.4%. In addition, contemporaneous pairwise correlations are all significant with a minimum value of 0.79. This result may be related to the increasing trade among the East Asian countries. The highest degree of association in this group is between South Korea and Malaysia

,with a contingency coefficient of 89% and a significant contemporaneous correlation value of 0.84.

Mexico and the U.S. have the second strongest degree of association in our sample following the highest degree of association among the East Asian economies. These countries have a corrected contingency coefficient of 82.3%, and their contemporaneous pairwise correlation is significant with a value of 0.74. The reason for this high association can be due to NAFTA. However, contemporaneous pairwise correlations and corrected contingency coefficients are relatively lower between Mexico and Canada, with a value of 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 a mild association even though it is weaker than Mexico's association compared to the U.S.

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 many throughout our entire sample period. Their transition probabilities for each of the states are also very similar. The contagionary effects of crises 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 regional driving factors are always important. The contingency coefficients and contemporaneous correlations are weak among some emerging markets within 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. Nor can we 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 U.S. economy with contingency coefficients above 50% and significant pairwise correlations above 0.44.

Altug and Bildirici (2012) and Canova, Ciccarelli, and Ortega (2007) argue that business cycles become more synchronized during recessions compared to expansions. Their results report that declines in economic activity have common timing and dynamics, both within and across countries. When we observe the sub-period of 2004-2012, the results show very strong comovements among all countries. The results show that business cycles both for emerging markets and the advanced economies experience a high degree of commonality when a large common disturbance exists that is affiliated with a global recession. 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 emerging markets, 60% between emerging and G-7 economies, and 60% overall. However, when we observe the 2004-2012 sub-period, these values jump up to 86.3% among emerging market economies, 86% between emerging markets and G-7 economies, and 86.1% overall.

These results suggest the existence of a common factor both for emerging and advanced economies that gives direction to the cyclical fluctuations. The findings 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. The results suggest that policy makers should also be aware of 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 give evidence for the role of national and regional factors, which affect business cycles of individual countries and contribute to the lack of synchronization among them. As Aolfi et al. (2010) discuss, one reason for the dissimilarities of national business cycles may be the differences in terms of trade shocks due to the dissimilarities of these countries' export compositions. Another reason for the different economic forces at play may be the political and institutional differences that are unique to individual countries.

CHAPTER 5

CONCLUSION

This dissertation 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.

First, the study closes the gap in the literature by adequately modeling the state dependent dynamics and accounting for the asymmetric behaviour 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. The study adequately map the state dependent dynamics and classify the turning points across different business cycle regimes for a large and diverse group of countries, including economies from different geographical areas of Europe, Asia, Central and South America, and Africa, using monthly data. Considering the significantly increasing economic importance of these emerging markets in the rapidly changing dynamics of the global economy, we reveal the differences in business cycle characteristics of these emerging economies compared to the developed countries. Compared to the commonly employed two state specifications, we employ a three state specification in the study to decompose the non-recessionary state into high-growth and low-growth states. This enables us to adequately capture the state dependent dynamics and analyse the asymmetric behaviour of individual business cycles even further and to compare the characteristics of different phases of the economy for each of these economies. 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.

The second part of the dissertation, for the first time in the literature, uses a Markov switching approach and explicitly models cyclical dynamics of the stock markets and relates it to the business cycles for a diverse group of emerging market economies. This is the first study in the literature 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. Considering the fact that continuously updated assessments of market participants about the current state of the economy are well reflected in stock market movements, when stock markets are efficient, they react to the present or future evolution of real economic activity. Therefore, to further 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. We then compute the characteristics of stock markets accounting for the asymmetric behavior across stock market phases for each country in our 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.

Third, part of the study utilizes the hidden Markov switching framework and employs inferences from the derived smoothed probabilities to uncover the features of international linkages across national business cycles over long periods of time for a diverse group of emerging and G-7 countries. We start analysing the behavior of the pairwise contemporaneous correlations of the smoothed probabilities of recessionary states to uncover the common features of international linkages across national business cycles. To further analyze the synchronization of national business cycles, we also examine the corrected contingency coefficient, which is a non-parametric approach that documents the comovements of different business cycle regimes across the emerging and developed countries in our sample. We utilize the smoothed probabilities that we obtain from modelling the business cycles using monthly data for industrial production to quantify the associations of business cycles across different emerging markets and advanced G-7 economies over the period between 1996 - 2012 and a sub period of 2004 - 2012.

We utilize the Markov Switching framework to model the state depended dynamics of the business cycles and stock market fluctuations of the emerging markets. Considering the dramatic policy changes and frequent financial crises in emerging market economies, we obtain a sound regime classification that is not overly sensitive to model specification utilizing hidden Markov models, which are robust to potential structural breaks that may have occurred due to major shifts in policy and frequent shocks to the economy. Given the extreme volatility in the equity prices, employing this approach is also useful modeling the stock markets. We use the Expectation Maximization algorithm along with the nonlinear filters to calculate the maximum likelihood estimates of the model parameters without imposing any a priori restrictions on any of the model parameters and infer the states through statistical estimation. The estimated parameters of the model depend on a stochastic and unobservable state variable that represents different phases of the business cycles and stock market fluctuations of each emerging market, where model parameters may take different values with respect to the regime prevailing at a given point in time.

The results of the first section 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 findings are in line with business cycle stylized facts in terms of implying short and abrupt recession phases with sharp drops in economic activity and are typically followed by strong recoveries during which the economies grow above the long-run average rate, reflecting the well documented asymmetric behaviour of economic activity over different cyclical phases. Our estimated business cycle models classify business cycle turning points and identify the individual crises in the emerging markets, as well as the more contagious 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. 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. Moreover, the smoothed probabilities that we obtain utilizing the nonlinear Markov switching models in the section develop inference for further analyses in the study.

The results for the second part of the study identify that the stock markets in our sample go through three distinct regimes, namely bear, bull, and moderate returns states, each are characterized by different risk return dynamics. The findings identify the individual characteristics of state dependent dynamics of stock market returns for each of the countries in our sample. We report the different characteristics of the stock markets in emerging markets compared to the documented stylized facts of typical advanced economies. For Chile, South Korea, and 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 eleven months, implying that the stock market returns can be used as a forward looking indicator of emerging market economies.

The results of the third section identify some distinct group of countries among emerging economies and between emerging markets and advanced G-7 countries. Results show that crises of emerging markets are contagious up to a degree, but this contagion is generally limited among some of these emerging economies. The crises that were caused by the emerging markets were not severe or contagious for the advanced economies over our sample period. However, findings clearly show that the recession of 2008 creates a true disturbance factor that can be identified as a global recession, both for advanced and emerging market economies. During the sub period of 2004 - 2012, the results show very strong comovements among all countries, with considerably higher contingency coefficients and pairwise correlations compared to the whole sample period. The findings suggest that policy makers should also be aware of the turning points that are resulting from external factors and stress the importance of using the information coming from other countries when constructing leading indicators and predicting the turning points. Moreover, the results also present the role of national and regional factors due to the political and institutional differences, which affect the national business cycles of individual countries and cause a lack of synchronization among them.

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FIGURES

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

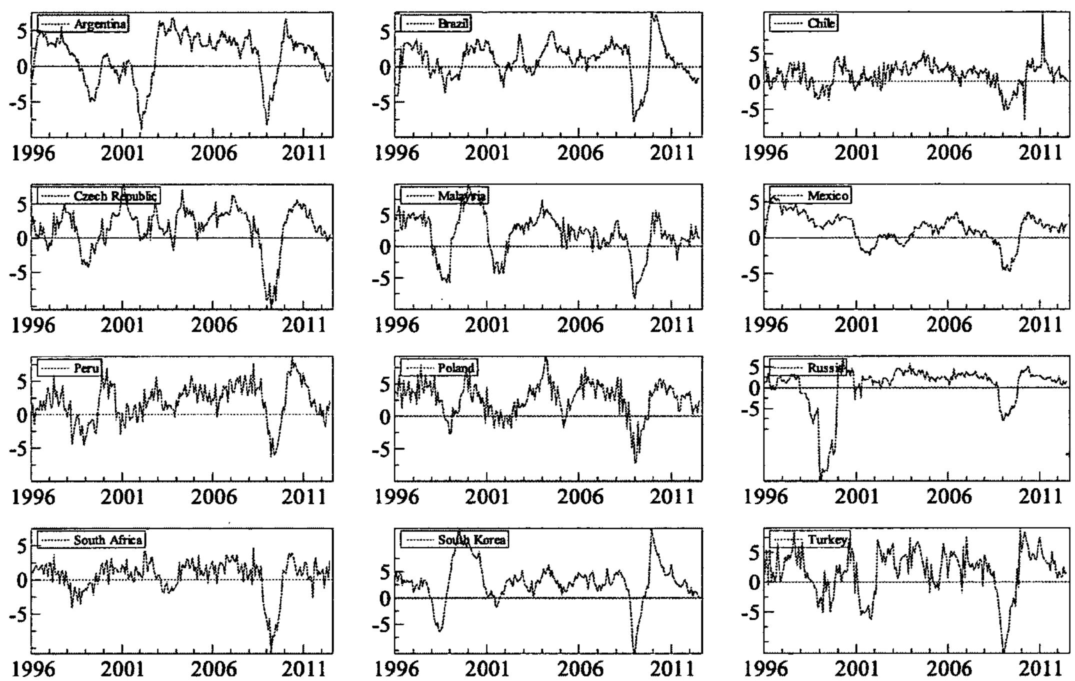


Figure 2: MSCI Monthly Returns of Stock Exchanges
(January 1996 – July 2012)

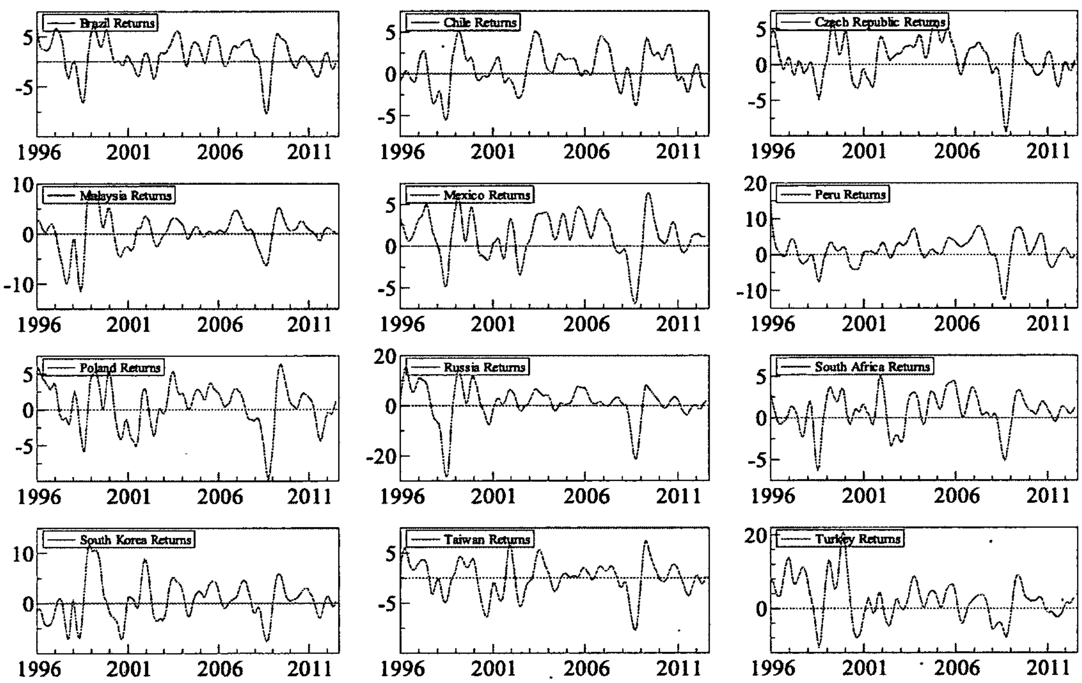


Figure 3: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Argentina

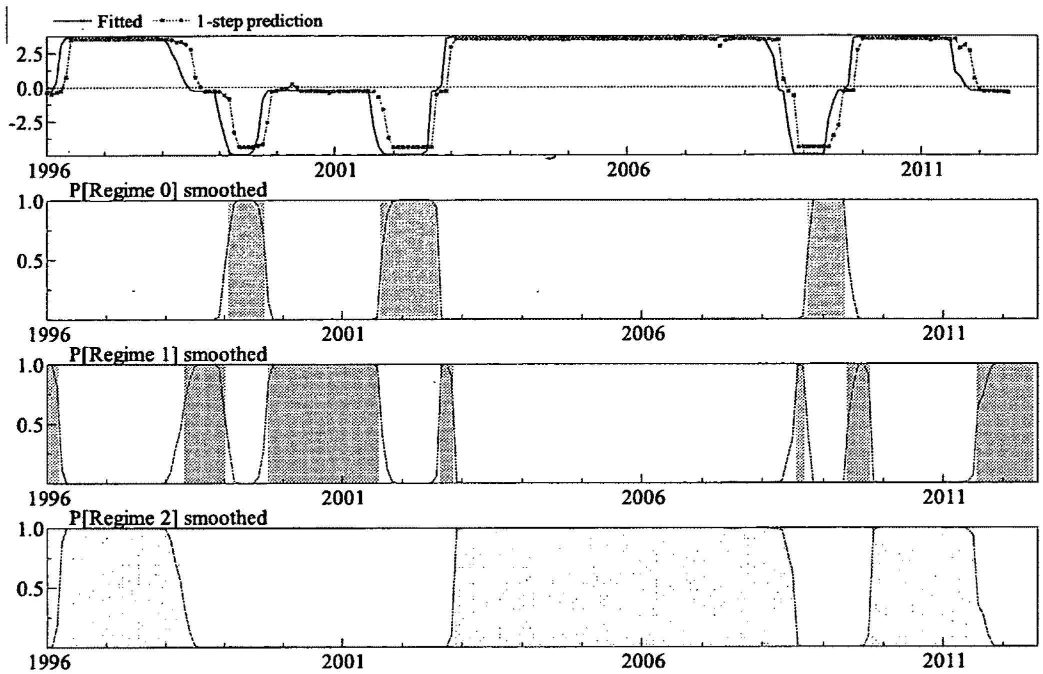


Figure 4: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Brazil

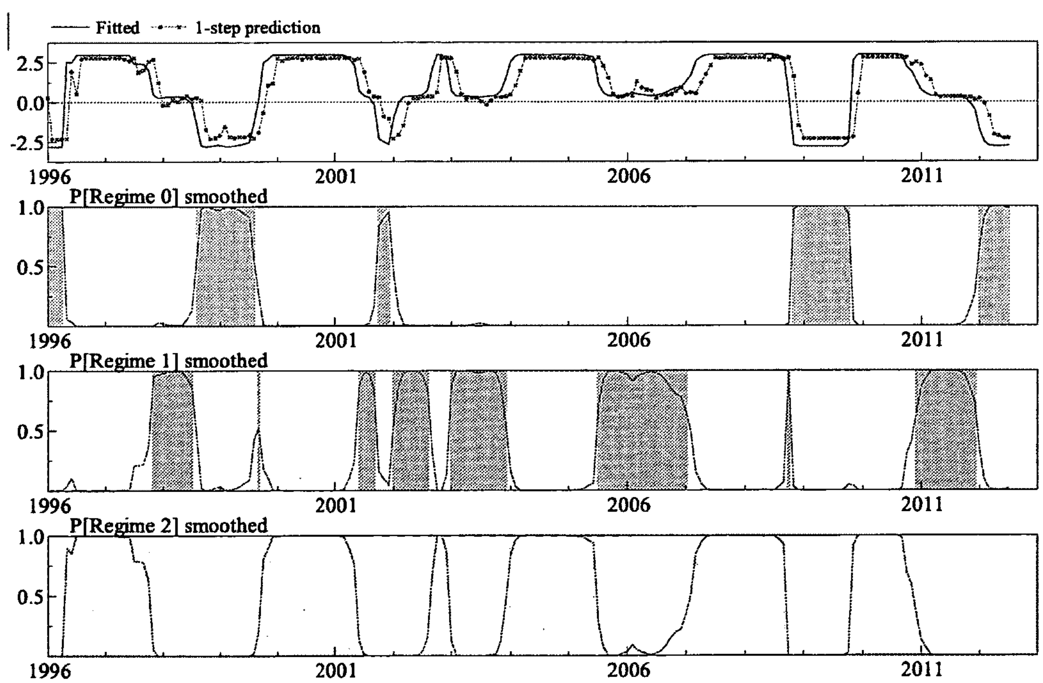


Figure 5: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Chile

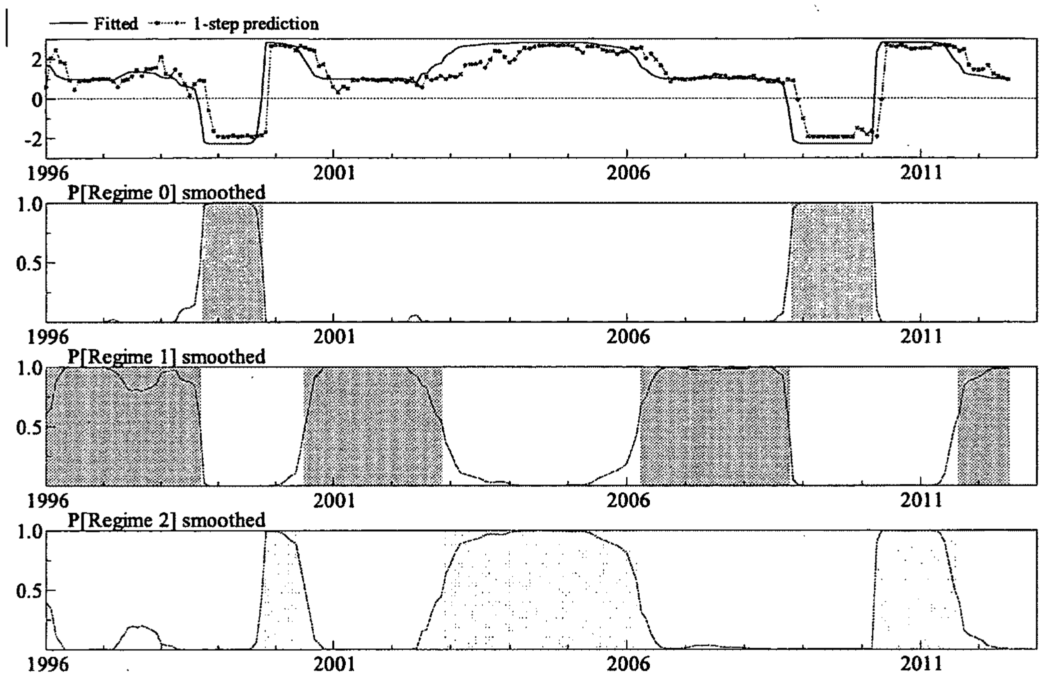


Figure 6: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Czech Republic

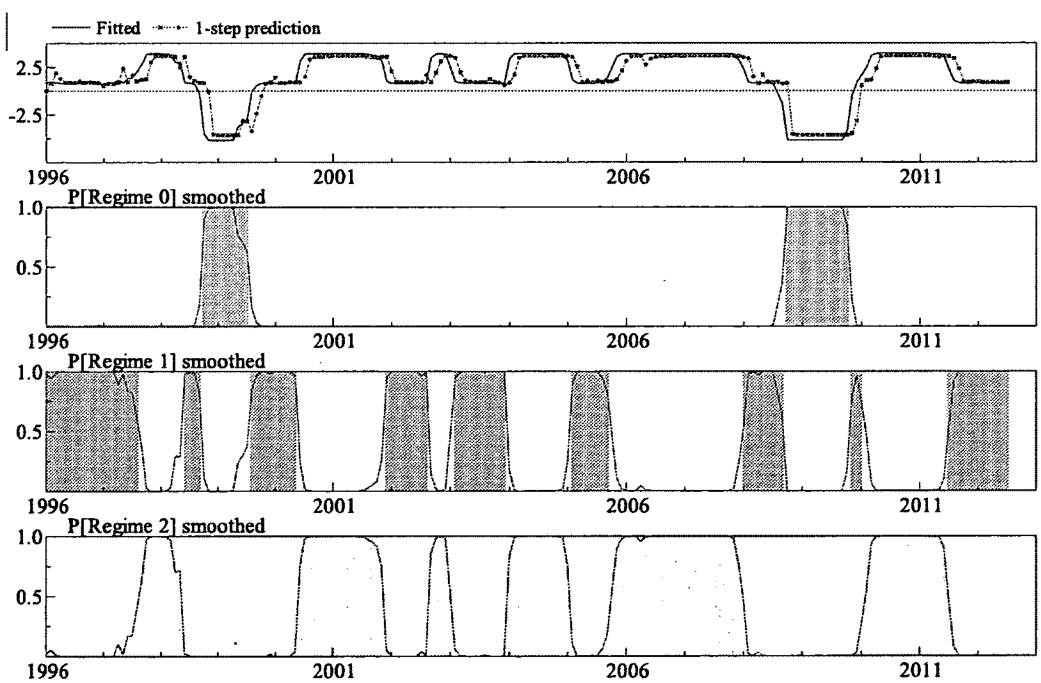


Figure 7: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Malaysia

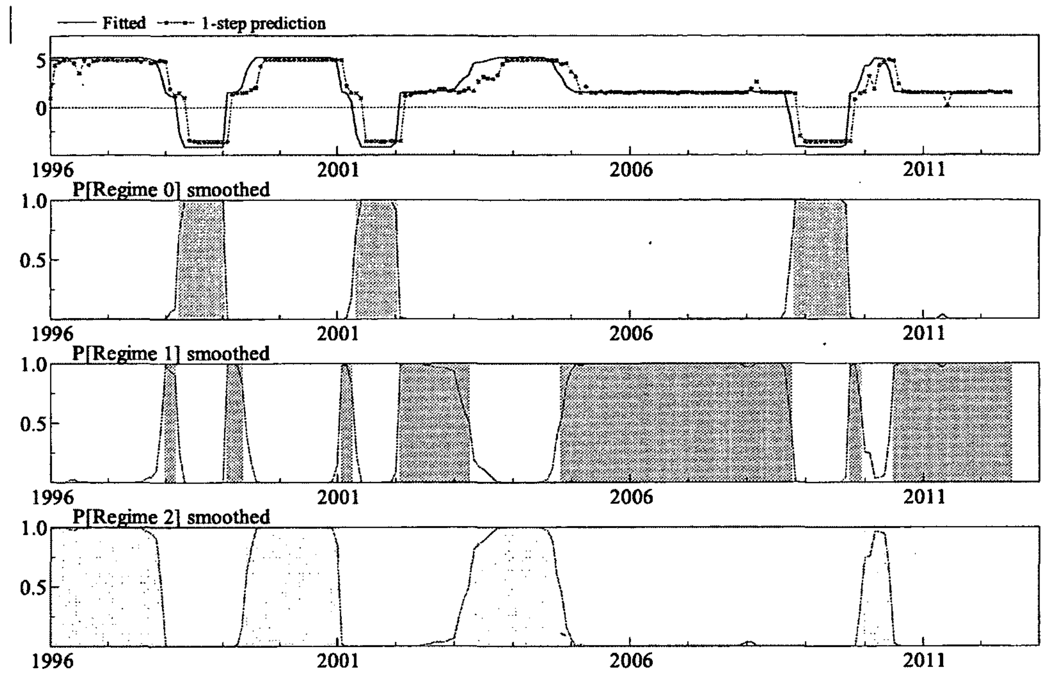


Figure 8: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Mexico

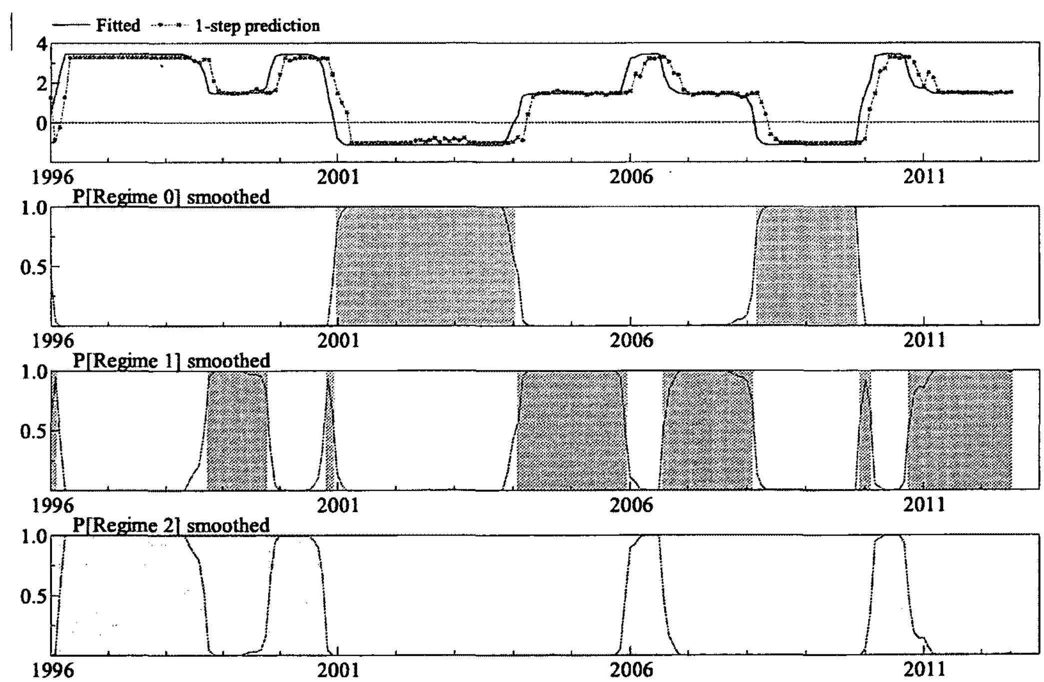


Figure 9: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Peru

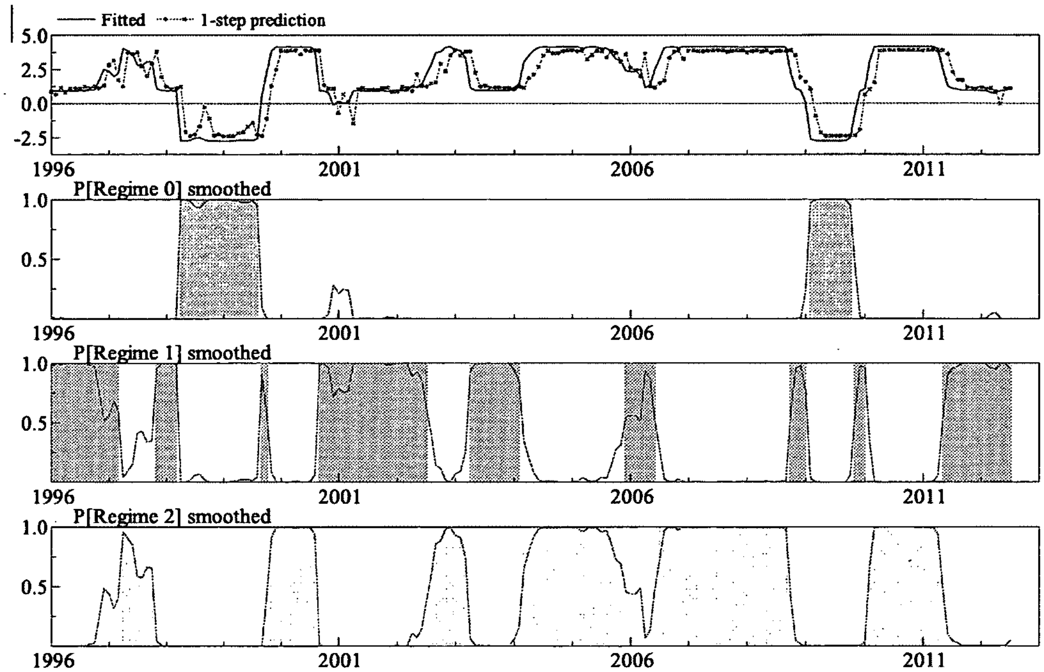


Figure 10: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Poland

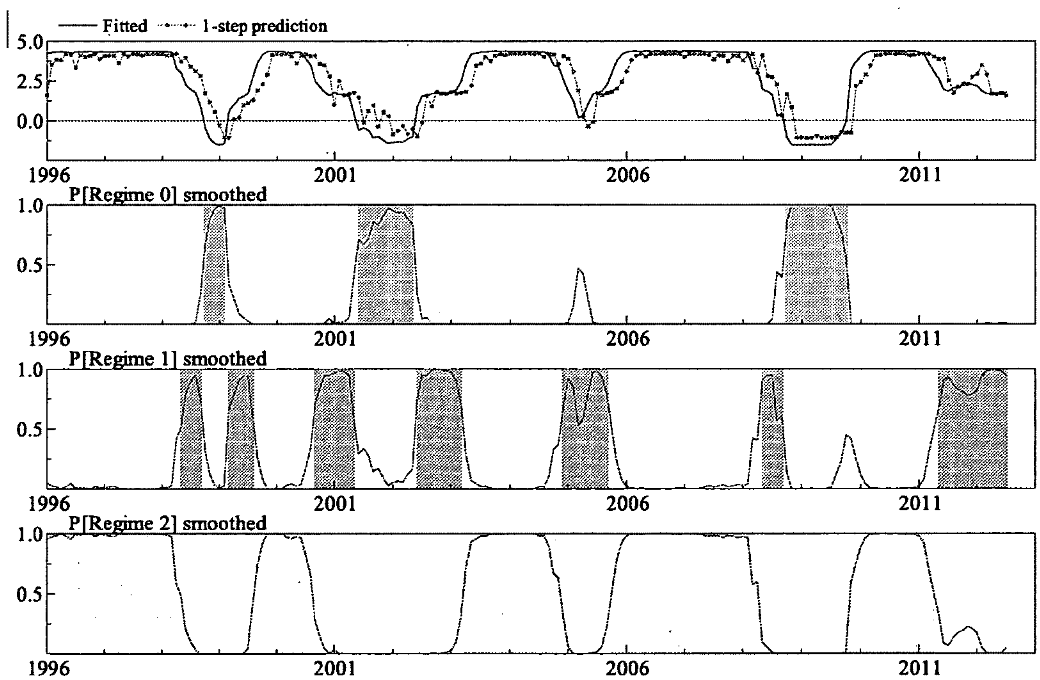


Figure 11: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Russia

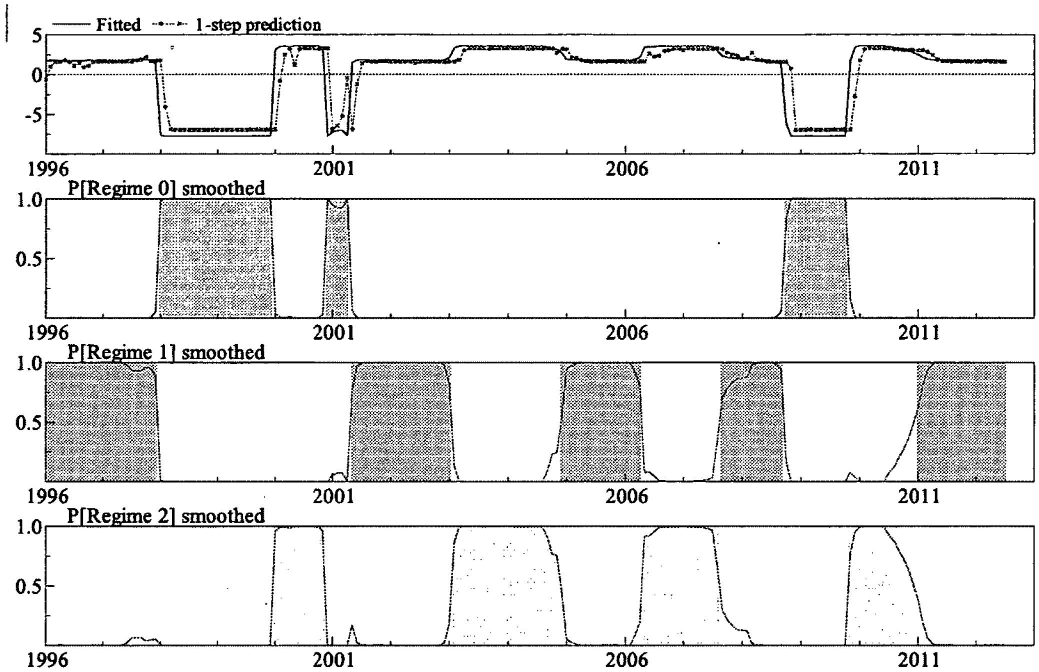


Figure 12: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of South Africa

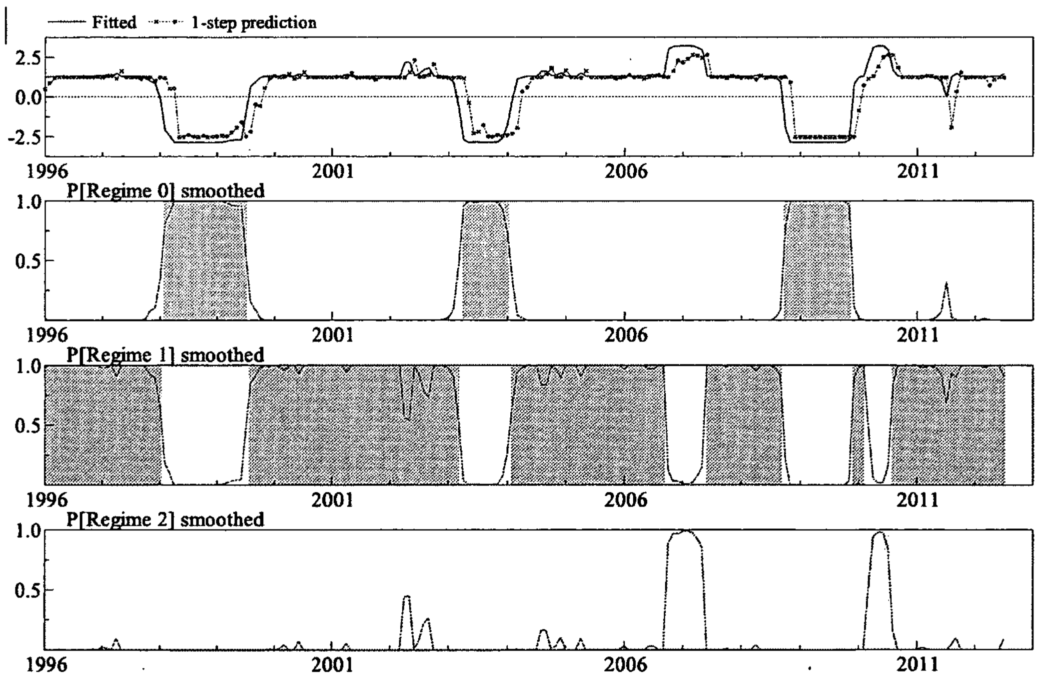


Figure 13: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of South Korea

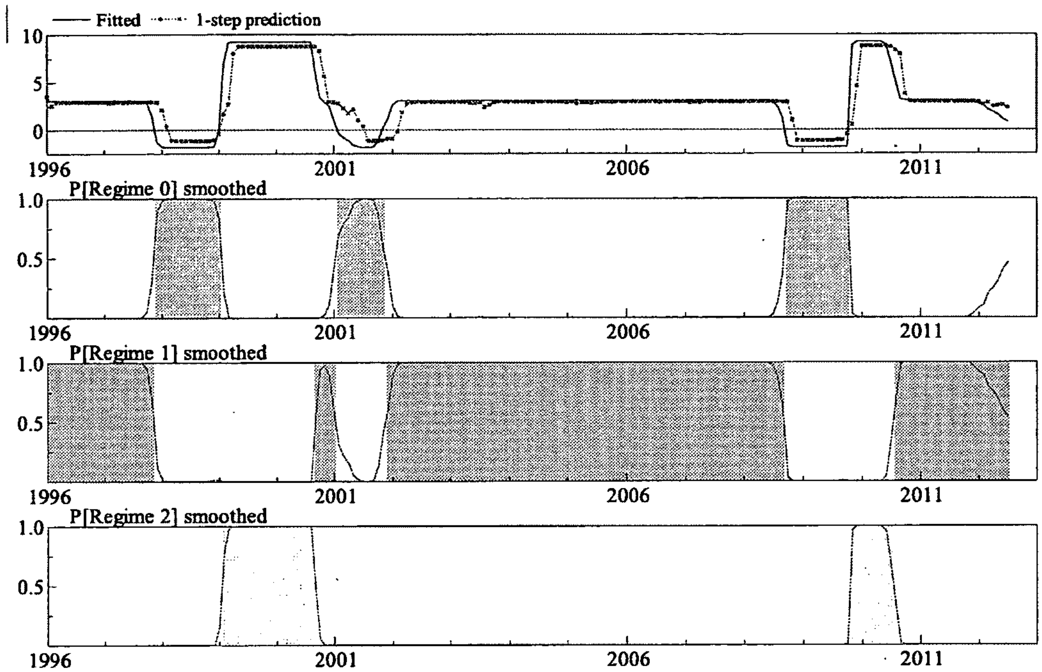


Figure 14: Business Cycle Smoothed Probabilities of Recession, Low, and High Growth States, Fitted Values, and one-step-ahead Predictions of Turkey

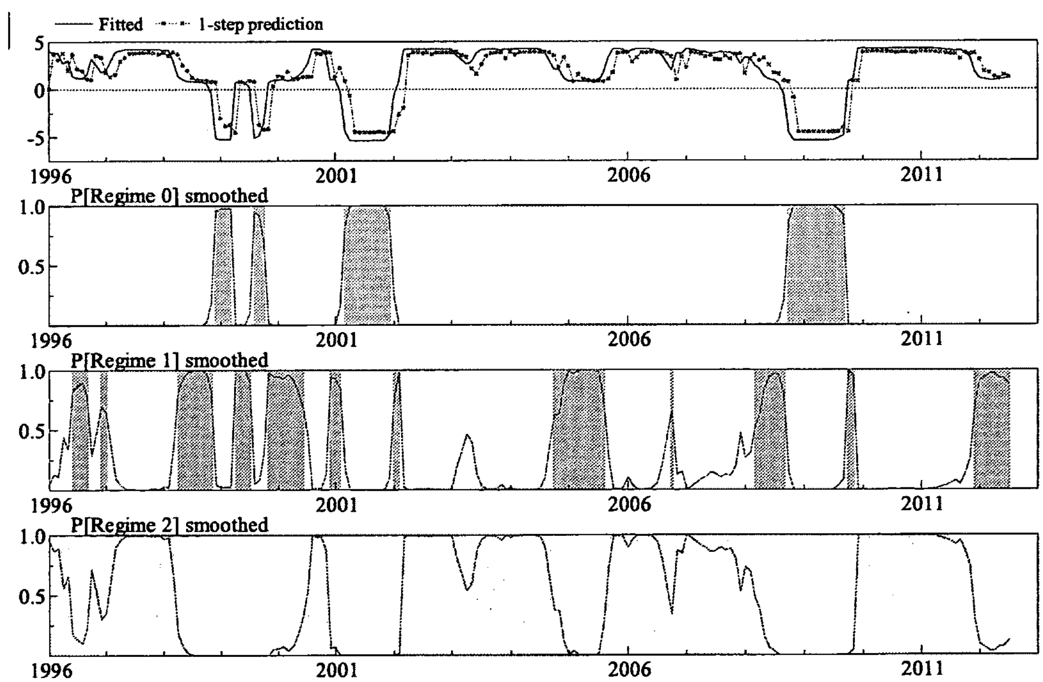


Figure 15: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Argentina

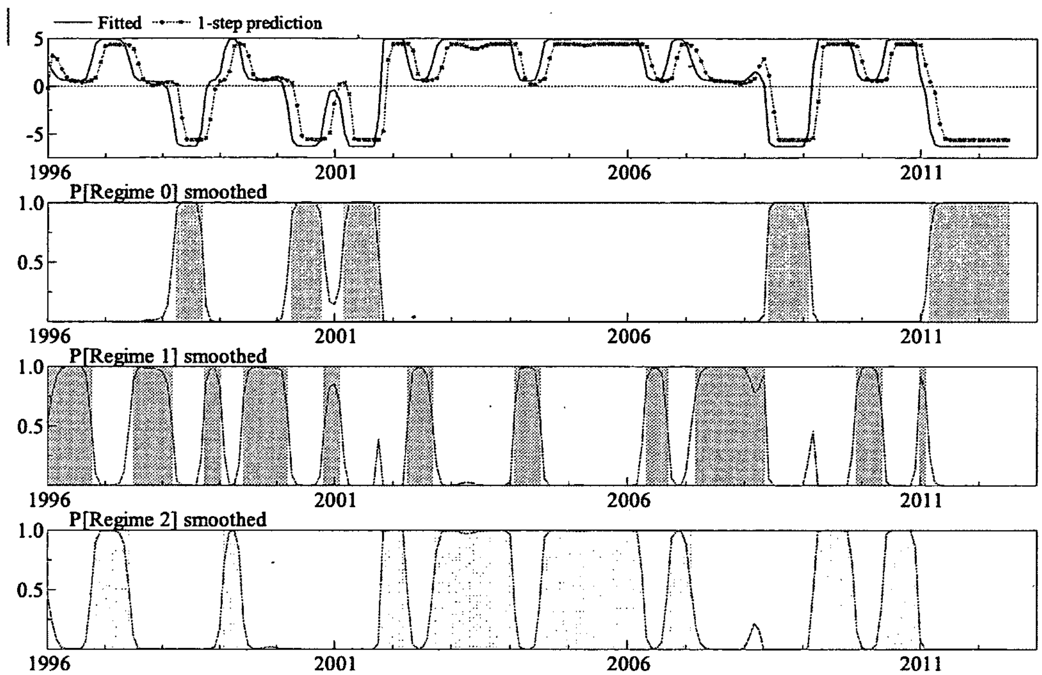


Figure 16: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Brazil

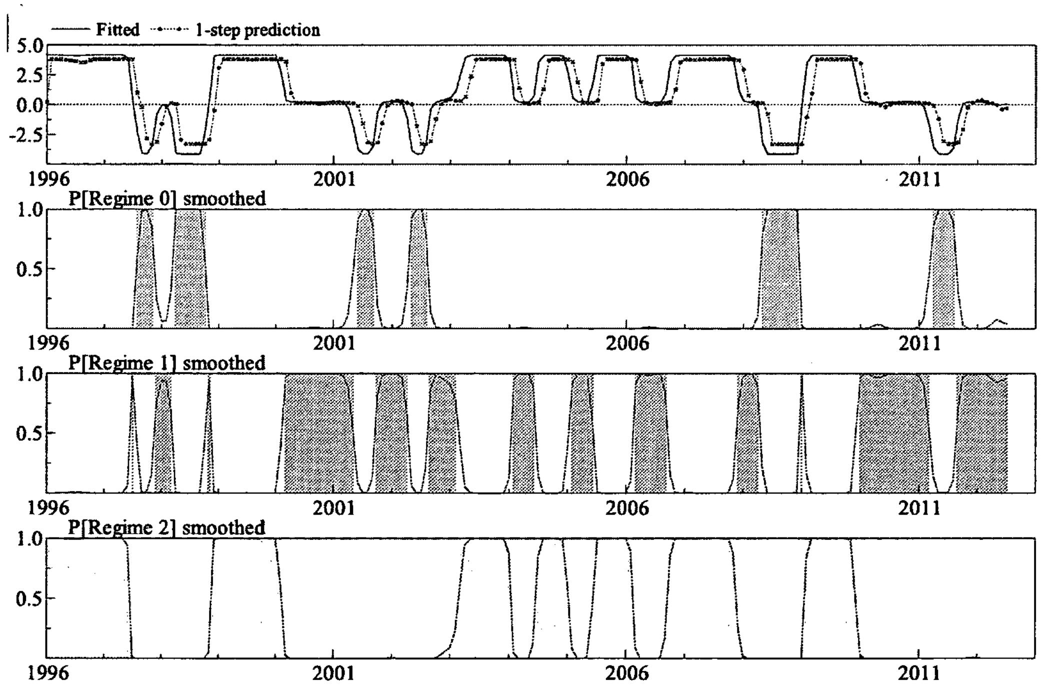


Figure 17: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Chile

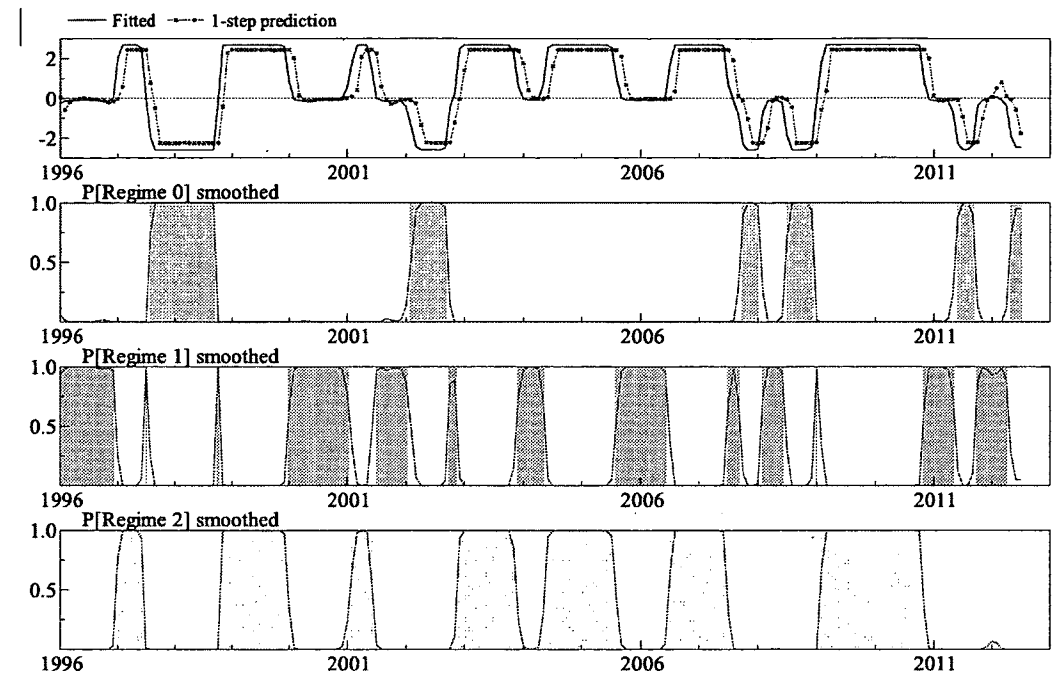


Figure 18: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Czech Republic

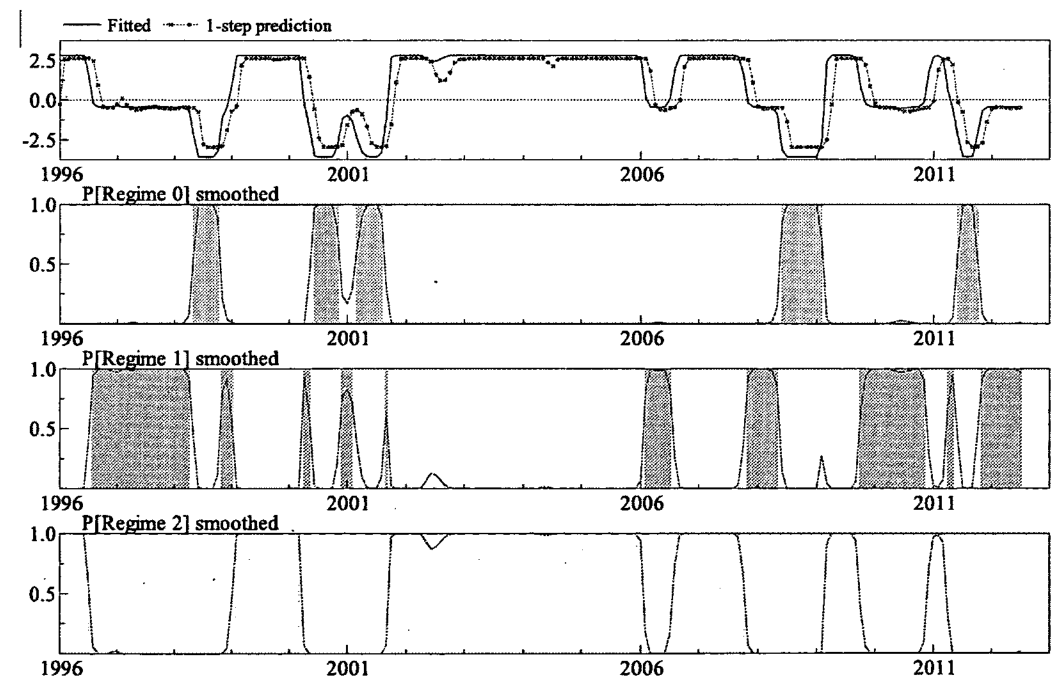


Figure 19: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Malaysia

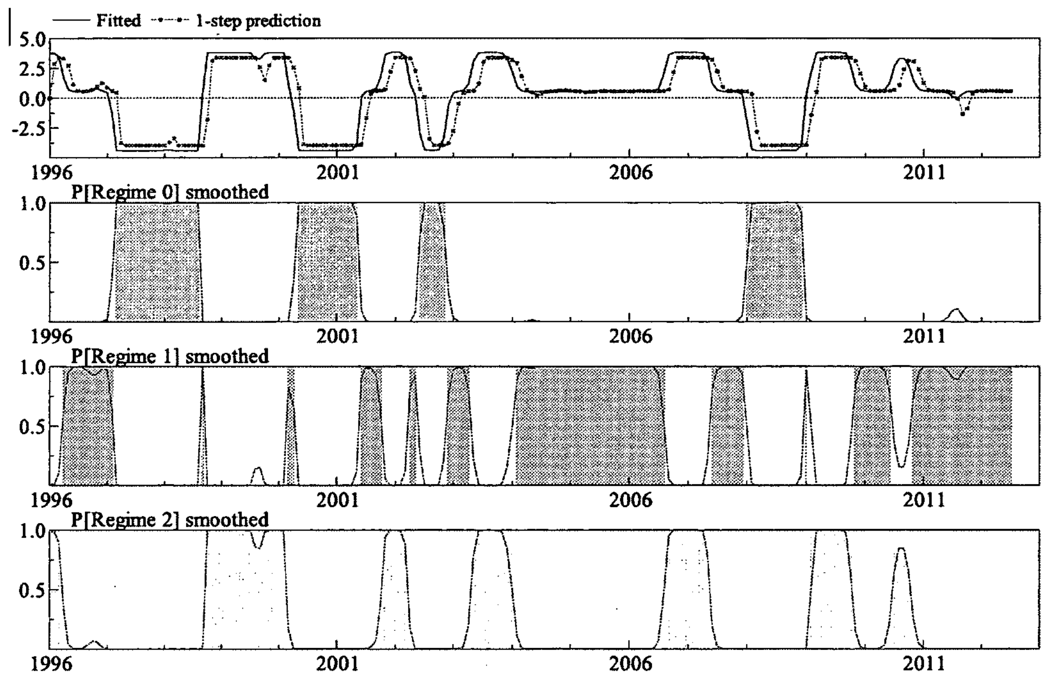


Figure 20: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Mexico

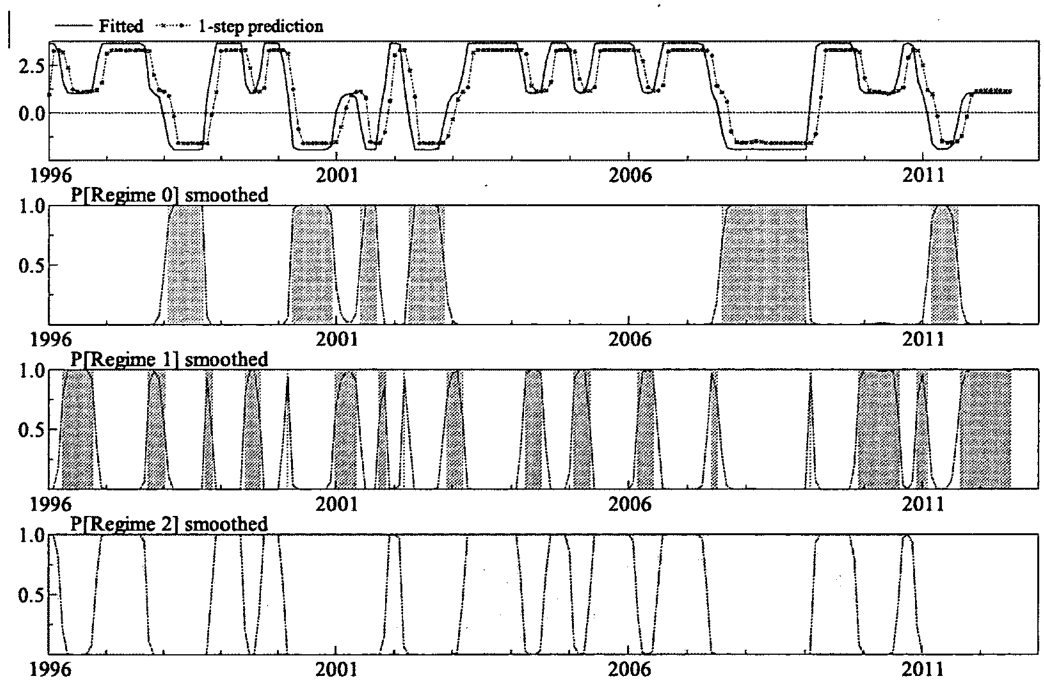


Figure 21: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Peru

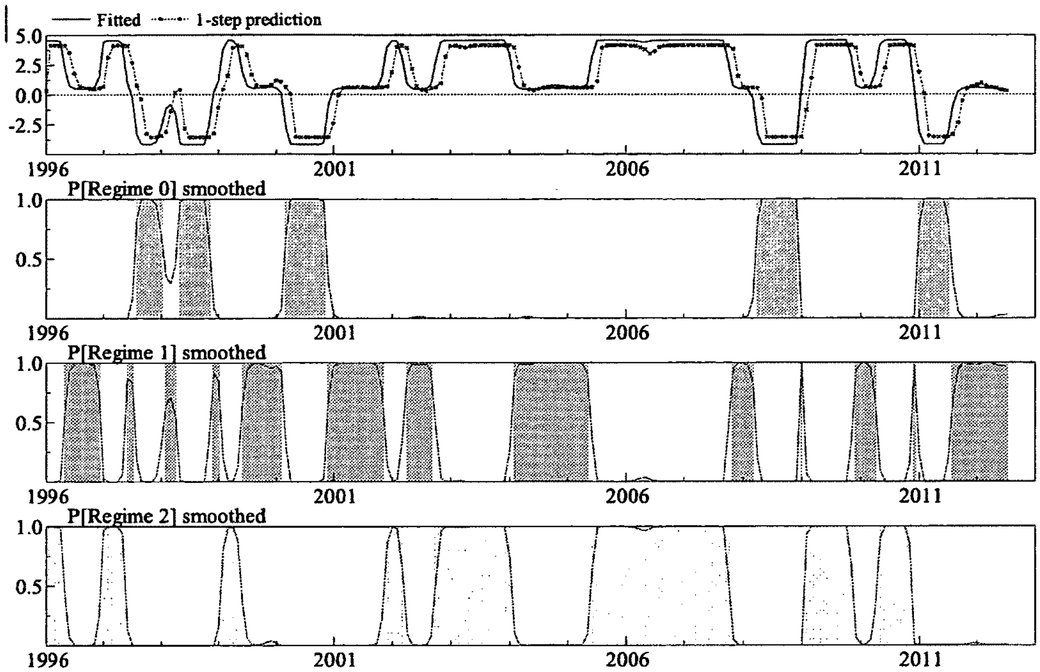


Figure 22: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Poland

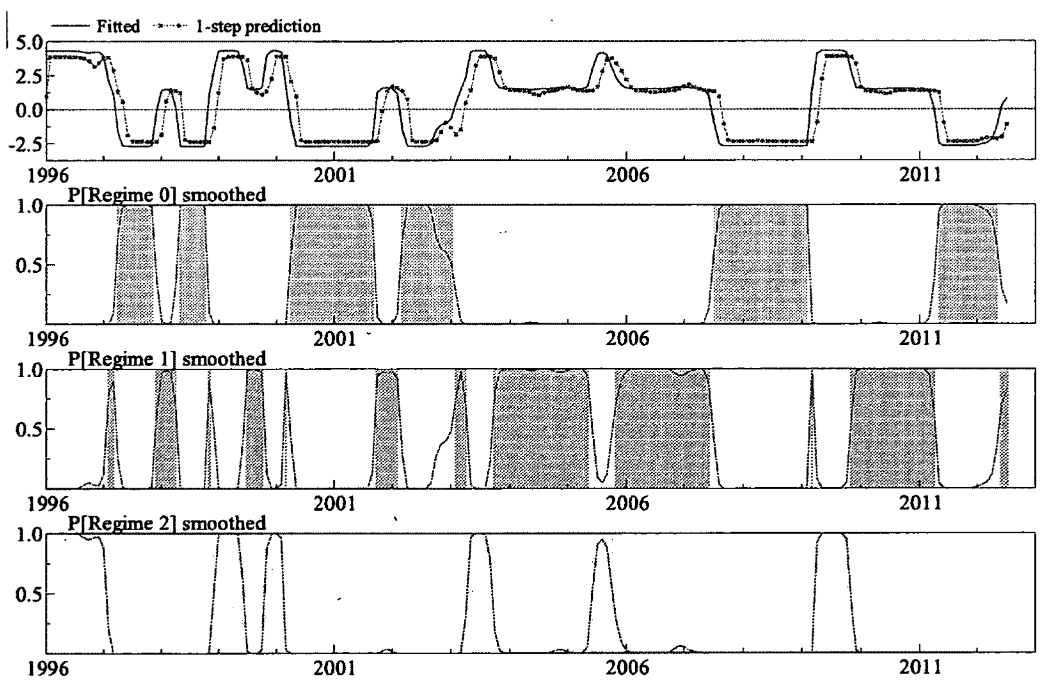


Figure 23: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Russia

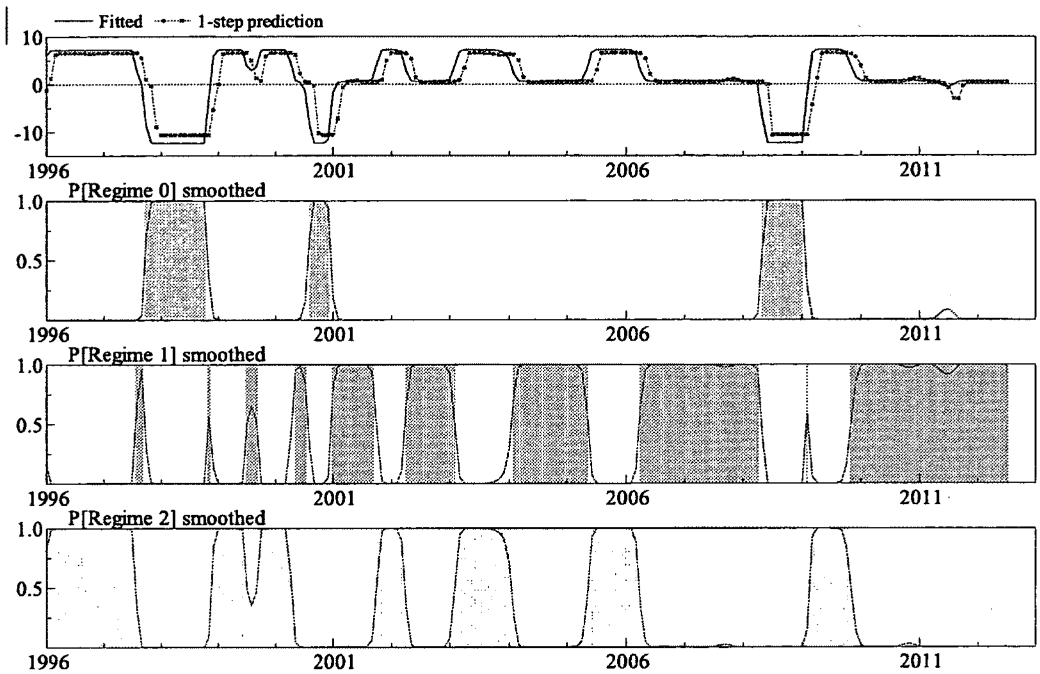


Figure 24: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of South Africa

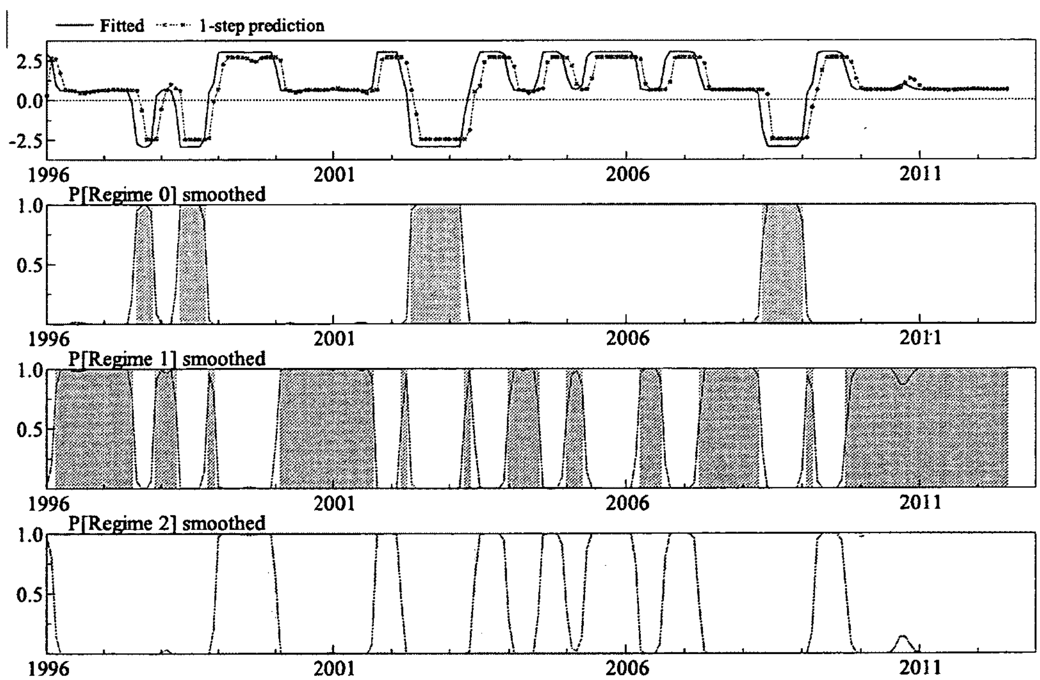


Figure 25: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of South Korea

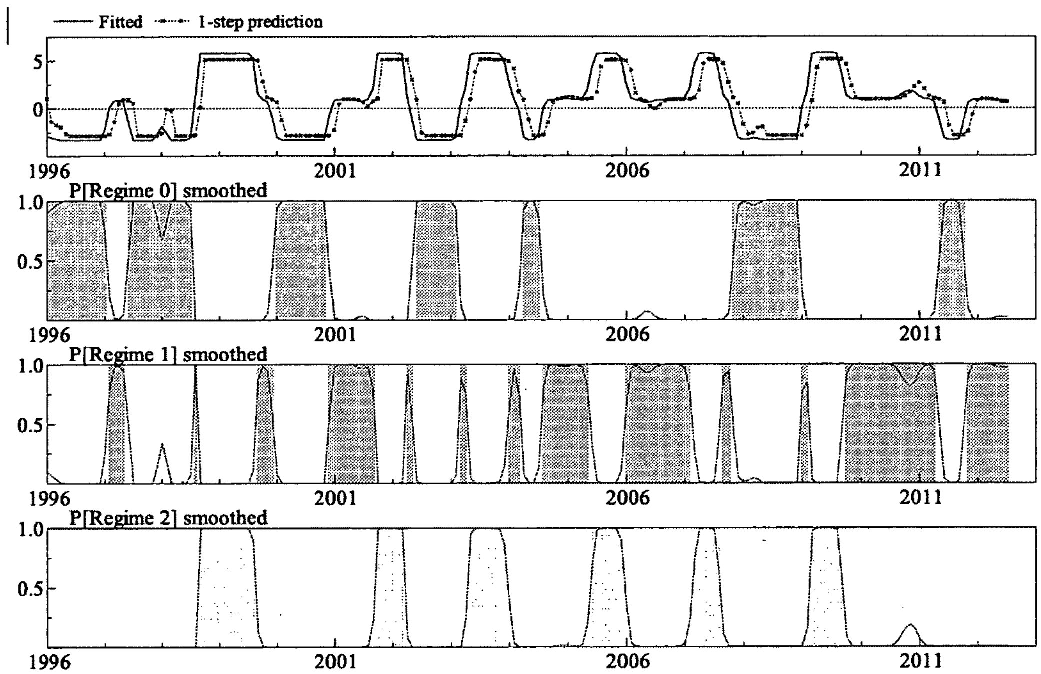


Figure 26: Stock Market Smoothed Probabilities of Bear, Normal, and Bull Market States, Fitted Values, and one-step-ahead Predictions of Turkey

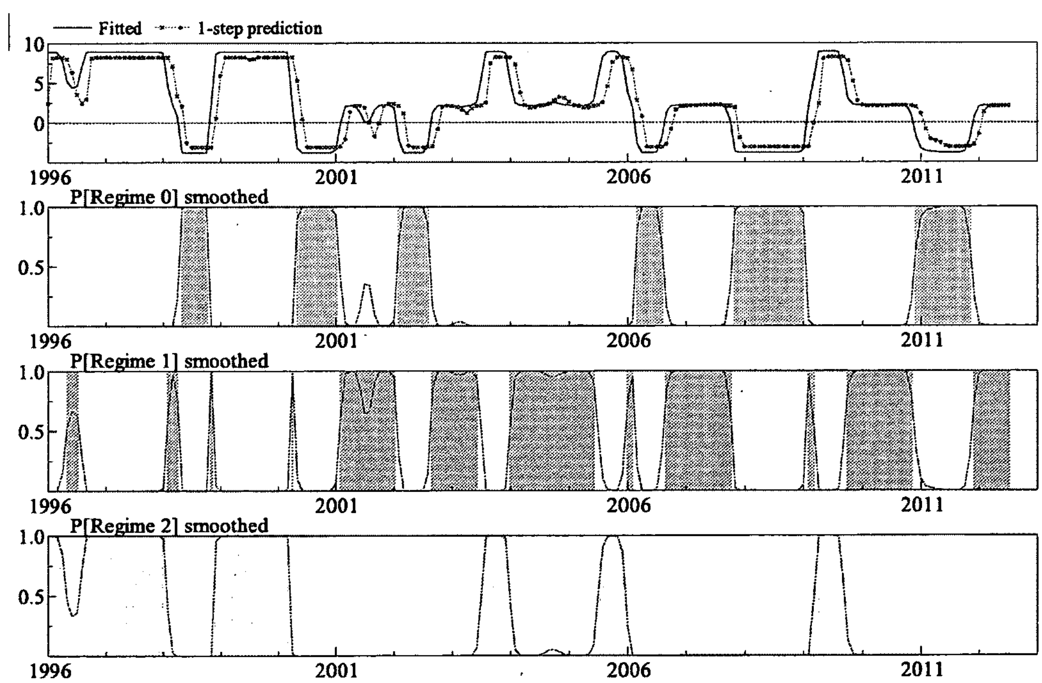
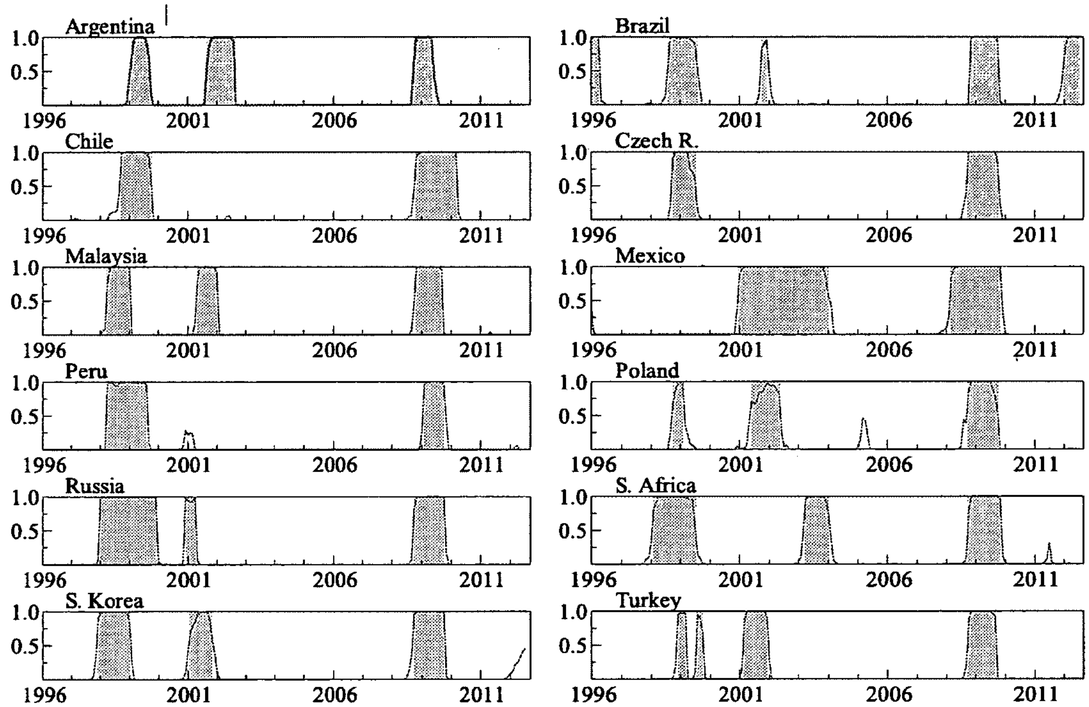


Figure 27: Smoothed Probabilities of Recessions and Business Cycle Dating based on Monthly Industrial Production of EMEs (January 1996 - July 2012)



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)

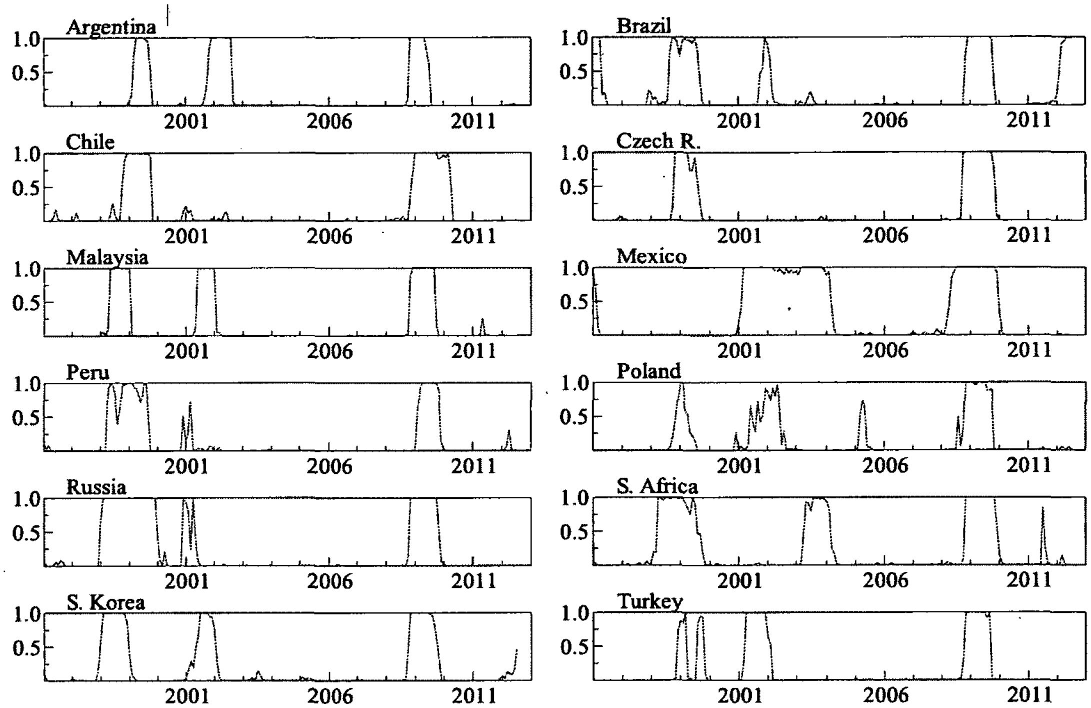
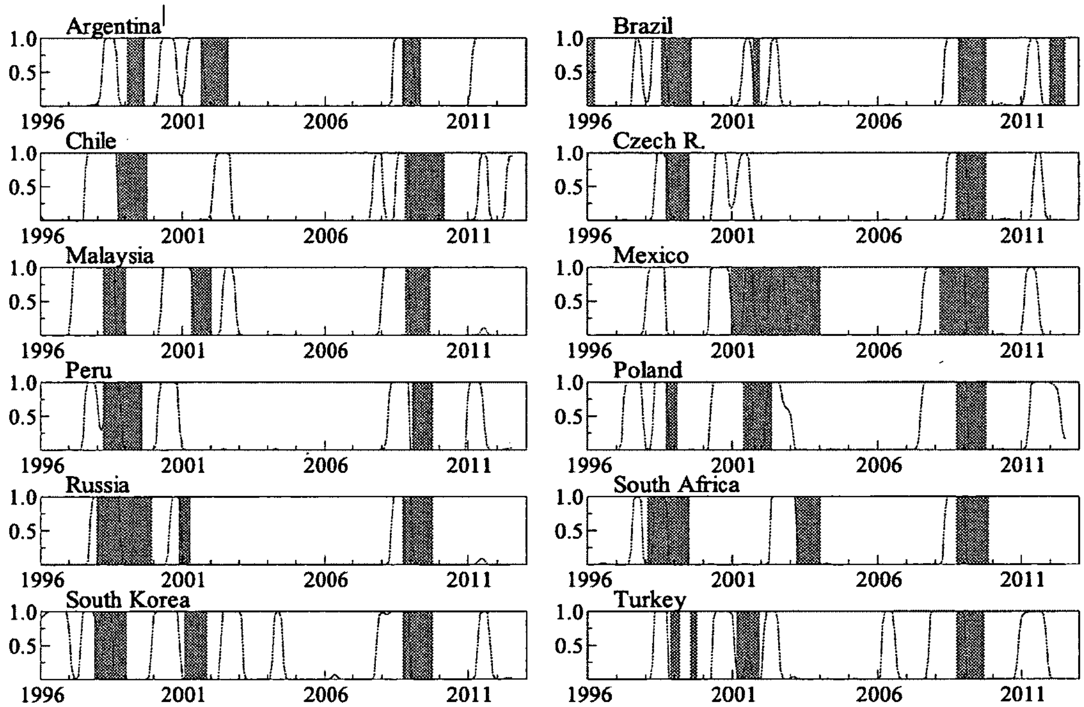
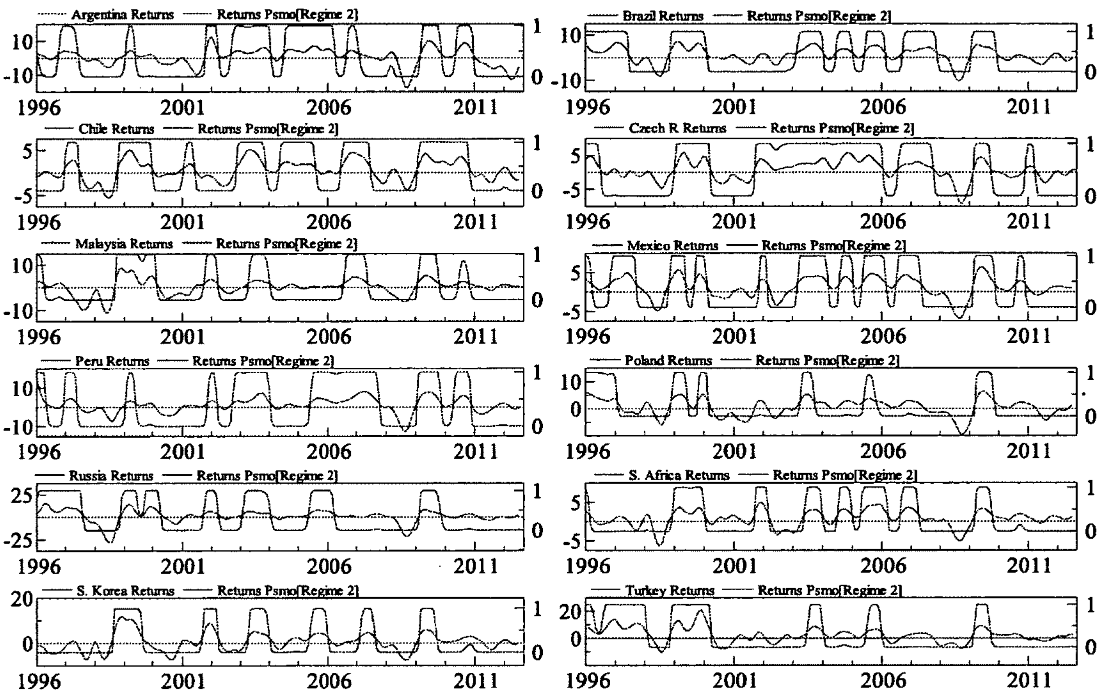


Figure 29: Smoothed Probabilities of Bear Market from the Stock Market Model and Recessions



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.

Table 8. Estimated Markov Probabilities of Staying in the Same Business Cycle State for Emerging Economies

	Argentina	Brazil	Chile	Czech R	Malaysia	Mexico	Peru	Poland	Russia	S Africa	S Korea	Turkey
Regime 0	0.88	0.89	0.93	0.90	0.89	0.95	0.90	0.87	0.92	0.91	0.92	0.86
Regime 1	0.89	0.87	0.96	0.90	0.93	0.92	0.88	0.85	0.95	0.94	0.97	0.80
Regime 2	0.97	0.93	0.94	0.92	0.93	0.92	0.92	0.94	0.92	0.73	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 9. Average Durations and Percentages of Staying in one Business Cycle State for Emerging Economies

	Argentina		Brazil		Chile		Czech R		Malaysia		Mexico	
	Percentage	Duration	Percentage	Duration	Percentage	Duration	Percentage	Duration	Percentage	Duration	Percentage	Duration
Regime 0	14.07	9.33	19.60	7.80	15.08	15.00	11.56	11.50	15.08	10.00	29.15	29.00
Regime 1	28.64	8.14	33.67	8.38	52.26	26.00	43.72	9.57	50.75	14.43	42.21	12.00
Regime 2	57.29	38.00	46.73	15.50	32.66	21.67	44.72	14.38	34.17	17.00	28.64	14.25

	Peru		Poland		Russia		S Africa		S Korea		Turkey	
	Percentage	Duration	Percentage	Duration	Percentage	Duration	Percentage	Duration	Percentage	Duration	Percentage	Duration
Regime 0	13.07	13.00	15.08	10.00	21.11	14.00	21.11	14.00	18.59	12.33	14.57	7.25
Regime 1	42.71	9.44	30.15	8.57	47.24	18.80	72.36	24.00	67.34	33.50	30.15	5.00
Regime 2	44.22	14.67	54.77	21.80	31.66	15.75	6.53	6.50	14.07	14.00	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 10: Dating of Business Cycles from the Smoothed Model Probabilities

Argentina			**Brazil**			**Chile**			**Czech R.**		
Peak	Trough	Duration (months)	Peak	Trough	Duration (months)	Peak	Trough	Duration (months)	Peak	Trough	Duration (months)
1999:2	1999:9	8	1996:1	1996:4	4	1998:10	1999:10	13	1998:10	1999:7	10
2001:9	2002:8	12	1998:8	1999:8	13	2008:11	2010:3	17	2008:10	2009:10	13
2008:10	2009:5	8	2001:10	2001:12	3						
			2008:11	2009:10	12						
			2012:1	2012:7	7						

Malaysia			**Mexico**			**Peru**			**Poland**		
Peak	Trough	Duration (months)	Peak	Trough	Duration (months)	Peak	Trough	Duration (months)	Peak	Trough	Duration (months)
1998:4	1999:1	10	2001:1	2004:1	37	1998:4	1999:8	17	1998:10	1999:2	5
2001:5	2002:1	9	2008:3	2009:11	21	2009:2	2009:10	9	2001:6	2002:5	12
2008:11	2009:9	11							2008:10	2009:10	13

Russia			**South Africa**			**South Korea**			**Turkey**		
Peak	Trough	Duration (months)	Peak	Trough	Duration (months)	Peak	Trough	Duration (months)	Peak	Trough	Duration (months)
1998:1	1999:12	24	1998:12	1999:3	4	1997:12	1999:1	14	1998:12	1999:3	4
2000:12	2001:4	5	1999:8	1999:10	3	2001:2	2001:11	10	1999:8	1999:10	3
2008:10	2009:10	13	2001:3	2001:12	10	2008:10	2009:10	13	2001:3	2001:12	10
			2008:10	2009:9	12				2008:10	2009:9	12

Table 11: Results for Monthly Stock Market Returns of Emerging Markets

	Argentina	Brazil	Chile	Czech R.	Malaysia	Mexico
log-L	-491.82	-409.69	-328.34	-372.26	-401.36	-356.73
LRP	0.000	0.000	0.000	0.000	0.000	0.000
α_0	-6.29	-4.13	-2.59	-3.58	-4.39	-1.92
	(0.70)	(0.56)	(0.21)	(0.47)	(0.42)	(0.28)
α_1	0.59	0.24	-0.09	-0.42	0.57	1.03
	(0.23)	(0.15)	(0.09)	(0.12)	(0.11)	(0.11)
α_2	4.94	4.15	2.68	2.82	3.81	3.65
	(0.30)	0.17	(0.13)	(0.14)	(0.30)	(0.14)
σ_0	4.05	2.73	1.15	2.14	2.76	1.86
	(0.43)	(0.34)	(0.13)	(0.28)	(0.28)	(0.18)
σ_1	1.35	1.05	0.62	0.77	0.80	0.59
	(0.14)	(0.10)	(0.06)	(0.08)	(0.08)	(0.08)
σ_2	2.22	1.39	1.86	1.34	1.82	1.03
	(0.18)	(0.11)	(0.09)	(0.10)	(0.17)	(0,09)
p_{00}	0.91	0.81	0.85	0.83	0.91	0.88
	(0.04)	(0.07)	(0.05)	(0.07)	(0.04)	(0.04)
p_{10}	0.06			0.12	0.08	
	(0.03)			(0.05)	(0.03)	
p_{01}	0.06	0.07	0.08	0.07	0.04	0.09
	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
p_{11}	0.83	0.84	0.82	0.86	0.88	0.75
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)
p_{12}	0.11	0.08	0.08	0.06	0.12	0.13
	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)
AIC	5.05	4.21	3.40	3.85	4.13	3.68
SC	5.23	4.38	3.56	4.04	4.29	3.85
HQ	5.12	4.28	3.46	3.92	4.20	3.75

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 11: Results for Monthly Stock Market Returns for Emerging Markets (Continues)

	Peru	Poland	Russia	S. Africa	S. Korea	Turkey
log-L	-443.69	-399.91	-526.35	-312.87	-450.20	-505.63
LRP	0.000	0.000	0.000	0.000	0.000	0.000
α_0	-4.16	-2.71	-12.31	-2.93	-3.33	-3.80
	(0.56)	(0.32)	(2.04)	(0.29)	(0.27)	(0.42)
α_1	0.52	1.50	0.59	0.61	0.90	2.15
	(0.13)	(0.17)	(0.20)	(0.08)	(0.17)	(0.23)
α_2	4.56	4.31	7.23	3.04	5.78	8.93
	(0.27)	(0.20)	(0.49)	(0.13)	(0.45)	(0.56)
σ_0	3.04	2.18	8.06	1.45	2.02	2.55
	(0.09)	(0.18)	(1.22)	(0.19)	(0.17)	(0.25)
σ_1	0.92	0.99	1.74	0.75	1.11	1.52
	(0.09)	(0.10)	(0.15)	(0.05)	(0.11)	(0.16)
σ_2	2.24	1.03	3.14	0.80	2.65	3.69
	(0.18)	(0.12)	(0.32)	(0.08)	(0.28)	(0.35)
p_{00}	0.87	0.91	0.88	0.86	0.89	0.88
	(0.05)	(0.03)	(0.06)	(0.06)	(0.03)	(0.04)
p_{10}			0.08			
			(0.15)			
p_{01}	0.06	0.07	0.03	0.03	0.08	0.07
	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)
p_{11}	0.84	0.86	0.91	0.89	0.83	0.86
	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)
p_{12}	0.10	0.15	0.09	0.14	0.13	0.10
	(0.03)	(0.05)	(0.03)	(0.04)	(0.05)	(0.04)
AIC	4.55	4.11	5.40	3.24	4.62	5.18
SC	3.85	4.28	5.28	3.41	4.79	5.34
HQ	3.75	4.18	5.47	3.31	4.69	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.

Table 12 . Estimated Markov Probabilities of Staying in the Same State for Stock Market Filtered Returns

	Argentina	Brazil	Chile	Czech R	Malaysia	Mexico	Peru	Poland	Russia	S Africa	S Korea	Turkey
Regime 0	0.91	0.81	0.85	0.83	0.91	0.88	0.87	0.91	0.88	0.86	0.89	0.88
Regime 1	0.83	0.84	0.82	0.86	0.88	0.75	0.84	0.86	0.91	0.89	0.83	0.86
Regime 2	0.88	0.91	0.91	0.93	0.87	0.86	0.89	0.84	0.90	0.85	0.86	0.89

Note: Regime 0 represents the bear state, Regime 1 represents the normal returns state, and the regime 2 represents the bull growth state

Table 13. Average Durations and Percentages of Staying in the Same State for Stock Market Filtered Returns

	Argentina		Brazil		Chile		Czech R		Malaysia		Mexico	
	Percentage	Duration	Percentage	Duration	Percentage	Duration	Percentage	Duration	Percentage	Duration	Percentage	Duration
Regime 0	23.62	9.40	16.08	5.33	19.60	6.50	16.08	6.40	24.62	12.25	26.63	8.83
Regime 1	38.69	7.00	41.71	6.38	38.19	5.85	34.17	6.80	47.24	8.55	34.17	4.00
Regime 2	37.69	9.38	42.21	12.00	42.21	12.00	44.72	16.50	28.14	8.00	39.20	7.09

	Peru		Poland		Russia		S Africa		S Korea		Turkey	
	Percentage	Duration	Percentage	Duration	Percentage	Duration	Percentage	Duration	Percentage	Duration	Percentage	Duration
Regime 0	19.10	7.60	38.19	12.67	13.57	9.00	15.08	7.50	35.68	10.14	27.64	9.17
Regime 1	41.21	6.31	41.21	6.83	52.26	10.40	56.78	9.42	41.21	6.31	44.22	7.33
Regime 2	39.70	9.88	20.60	6.83	34.17	9.71	28.14	7.00	23.12	7.67	28.14	9.33

Note: Regime 0 represents the bear state, Regime 1 represents the normal returns state, and the regime 2 represents the bull growth state

Table 14: Evaluation of the Stock Market Turning Point Signals

	QPS$_i$											
i	**Argentina**	**Brazil**	**Chile**	**Czech**	**Malaysia**	**Mexico**	**Peru**	**Poland**	**Russia**	**S.Africa**	**S.Korea**	**Turkey**
12	0.3558	0.2648	0.2828	0.3563	0.2374	0.3646	0.2776	0.4256	0.3204	0.2615	0.4216	0.3556
11	0.3447	0.2631	**0.2648**	0.3226	0.2153	0.3447	0.235	**0.4191**	0.2974	0.1971	**0.4169**	0.3467
10	**0.3202**	0.2553	0.3143	0.2891	0.1942	0.3219	**0.1953**	0.4417	0.2744	0.1561	0.4402	**0.3462**
9	0.3379	**0.2424**	0.3545	0.2514	**0.1846**	**0.3208**	0.1974	0.437	0.2488	**0.1485**	0.4601	0.3733
8	0.3502	0.2647	0.3787	0.2312	0.2058	0.3394	0.2191	0.4277	0.227	0.1679	0.4788	0.3783
7	0.3618	0.2794	0.3977	**0.2285**	0.2445	0.3622	0.256	0.4554	0.2048	0.1881	0.4968	0.4012
6	0.3764	0.2835	0.4164	0.2296	0.2846	0.3957	0.296	0.4842	0.1831	0.2122	0.5165	0.4375
5	0.4014	0.3021	0.4349	0.2382	0.3244	0.4343	0.3357	0.5184	**0.1581**	0.2525	0.5656	0.4692
4	0.4268	0.3347	0.4541	0.2419	0.3843	0.4731	0.375	0.5659	0.1572	0.3069	0.6235	0.5213
3	0.4612	0.3902	0.4869	0.2786	0.4435	0.5115	0.413	0.6286	0.1892	0.3666	0.6814	0.578
2	0.5084	0.4543	0.5305	0.3178	0.5021	0.5495	0.4454	0.6762	0.2429	0.4244	0.7388	0.6359
1	0.5563	0.5213	0.5773	0.3566	0.56	0.587	0.4704	0.7141	0.3021	0.4644	0.7841	0.6919
0	0.6038	0.5855	0.6237	0.395	0.6175	0.6229	0.4739	0.751	0.3609	0.5022	0.8208	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.

Table 15: Contemporaneous Pairwise Correlations of the Smoothed Probabilities of Being in a Recession for the Sample Period 1996:01 – 2012:07 (Among Emerging Markets)

	Argentina	Brazil	Chile	Czech R	Malaysia	Mexico	Peru	Poland	Russia	S Africa	S Korea	Turkey
Argentina	1											
Brazil	0.4872**	1										
Chile	0.4141**	0.6383**	1									
Czech R	0.5186**	0.7121**	0.8461**	1								
Malaysia	0.3675**	0.5296**	0.4579**	0.5626**	1							
Mexico	0.3899**	0.1310**	0.151**	0.2507**	0.3650**	1						
Peru	0.3680**	0.6307**	0.7363**	0.7513**	0.5867**	0.0744	1					
Poland	0.6439**	0.5632**	0.5332**	0.6989**	0.7511**	0.5183**	0.4491**	1				
Russia	0.3847**	0.5284**	0.6829**	0.7024**	0.5344**	0.1288	0.7927**	0.4248**	1			
S Africa	0.3050**	0.4983**	0.6260**	0.700**	0.5348**	0.3164**	0.730**	0.4230**	0.6803**	1		
S Korea	0.2328**	0.4867**	0.4282**	0.5531**	0.8438**	0.340**	0.5731**	0.6288**	0.6800**	0.5681**	1	
Turkey	0.5180**	0.5095**	0.549**	0.6207**	0.7175**	0.4493**	0.4246**	0.7563**	0.5225**	0.3660**	0.6601**	1

Note: ** denotes 5% significance level

Table 16: Contemporaneous Pairwise Correlations of the Smoothed Probabilities of Being in a Recession for the Sample Period 1996:01 – 2012:07 (Between Emerging Countries and G–7 Economies)

	Argentina	Brazil	Chile	Czech R	Malaysia	Mexico	Peru	Poland	Russia	S Africa	S Korea	Turkey
Canada	0.3601**	0.5093**	0.6324**	0.7112**	0.5251**	0.4207**	0.4800**	0.5845**	0.4797**	0.5290**	0.5237**	0.5445**
France	0.3490**	0.4505**	0.6472**	0.7097**	0.4913**	0.4352**	0.4264**	0.5773**	0.4591**	0.5111**	0.5141**	0.5348**
Germany	0.3369**	0.5111**	0.5868**	0.6900**	0.5187**	0.3868**	0.5075**	0.5758**	0.4725**	0.4887**	0.5198**	0.5345**
Italy	0.2401**	0.5583**	0.4931**	0.5666**	0.3576**	0.3398**	0.308**	0.4563**	0.3199**	0.362**	0.4522**	0.4012**
Japan	0.3756**	0.4000**	0.3871**	0.5037**	0.7947**	0.4197**	0.4886**	0.7333**	0.5389**	0.4991**	0.8416**	0.6156**
UK	0.3792**	0.5349**	0.6043**	0.7225**	0.5496**	0.4004**	0.4761**	0.609**	0.4951**	0.5061**	0.5456**	0.5672**
USA	0.4443**	0.2793**	0.3230**	0.3961**	0.5441**	0.7472**	0.1951**	0.7098**	0.268**	0.1952**	0.5393**	0.6394**

Note: ** denotes 5% significance level

Table 17: Contemporaneous Pairwise Correlations of the Smoothed Probabilities of Being in a Recession for the Sample Period 2004:01 – 2012:07 (Among Emerging Markets)

	Argentina	Brazil	Chile	Czech R	Malaysia	Mexico	Peru	Poland	Russia	S Africa	S Korea	Turkey
Argentina	1											
Brazil	0.6035**	1										
Chile	0.5980**	0.6037**	1									
Czech R	0.8130**	0.7267**	0.8098**	1								
Malaysia	0.8429**	0.7358**	0.7772**	0.948**	1							
Mexico	0.6033**	0.5027**	0.6573**	0.786**	0.7046**	1						
Peru	0.5377**	0.6789**	0.7410**	0.8200**	0.7928**	0.6442**	1					
Poland	0.831**	0.6984**	0.7589**	0.9656**	0.9404**	0.7559**	0.7687**	1				
Russia	0.8077**	0.7477**	0.8199**	0.9920**	0.9482**	0.7570**	0.8409**	0.9514**	1			
S Africa	0.751**	0.6880**	0.8247**	0.9370**	0.8838**	0.7886**	0.8189**	0.8813**	0.9415**	1		
S Korea	0.7865**	0.8412**	0.7728**	0.9722**	0.9174**	0.7426**	0.8023**	0.9366**	0.9693**	0.899**	1	
Turkey	0.8560**	0.7089**	0.7649**	0.9633**	0.9898**	0.7248**	0.7637**	0.9542**	0.9516**	0.8851**	0.9304**	1

Note: ** denotes 5% significance leveL

Table 18: Contemporaneous Pairwise Correlations of the Smoothed Probabilities of being in a Recession for the Sample Period 2004:01– 2012:07 (Between Emerging Countries and G–7 Economies)

	Argentina	**Brazil**	**Chile**	**Czech R**	**Malaysia**	**Mexico**	**Peru**	**Poland**	**Russia**	**S Africa**	**S Korea**	**Turkey**
Canada	0.7480**	0.7445**	0.8506**	0.9320**	0.9092**	0.7493**	0.8748**	0.8829**	0.9487**	0.9487**	0.8996**	0.8831**
France	0.7422**	0.666**	0.8761**	0.9352**	0.8658**	0.7861**	0.796**	0.881**	0.9294**	0.933**	0.8968**	0.8783**
Germany	0.6946**	0.7420**	0.7852**	0.9002**	0.8899**	0.6850**	0.9115**	0.8637**	0.922**	0.871**	0.8839**	0.8599**
Italy	0.5808**	0.8478**	0.6769**	0.7564**	0.6774**	0.6706**	0.6284**	0.7259**	0.7283**	0.7247**	0.8343**	0.696**
Japan	0.6564**	0.5646**	0.6778**	0.8474**	0.7695**	0.7485**	0.6845**	0.821**	0.8164**	0.8013**	0.8092**	0.7884**
UK	0.776**	0.7781**	0.8102**	0.944**	0.9437**	0.7107**	0.8624**	0.9153**	0.9679**	0.9041**	0.9291**	0.9136**
USA	0.6068**	0.5117**	0.7098**	0.7916**	0.7087**	0.9653**	0.6490**	0.7616**	0.7617**	0.7593**	0.7487**	0.7289**

Note: ** denotes 5% significance level

Table 19: Corrected Contingency Coefficients of Binary Variables that are obtained from The Smoothed Probabilities of Recessionary Regimes among Emerging Countries for the Sample Period 1997:01 – 2012:07

	Argentina	Brazil	Chile	Czech R	Malaysia	Mexico	Peru	Poland	Russia	S Africa	S Korea	Turkey
Argentina	1											
Brazil	54.667	1										
Chile	49.45	73.269	1									
Czech R	61.872	80.52	89.28	1								
Malaysia	42.389	63.203	53.787	63.910	1							
Mexico	49.831	14.240	18.443	30.092	46.46	1						
Peru	42.467	75.807	78.72	84.558	71.568	6.591	1					
Poland	68.772	63.203	62.20	76.09	83.028	63.487	54.770	1				
Russia	47.591	65.267	76.445	81.016	63.734	18.0	84.818	52.702	1			
S Africa	38.954	62.145	70.372	81.016	63.734	42.937	82.100	52.702	78.557	1		
S Korea	29.756	54.188	49.798	64.652	88.974	46.387	67.475	75.28	78.779	67.59	1	
Turkey	62.044	60.967	67.432	69.420	78.053	55.270	51.299	81.229	65.178	46.10	76.620	1

Table 20: Corrected Contingency Coefficients of Binary Variables that are obtained from the Smoothed Probabilities of Recessionary Regimes between Emerging Countries and G – 7 Economies for the Sample Period 1997:01 – 2012:07

	Argentina	Brazil	Chile	Czech R	Malaysia	Mexico	Peru	Poland	Russia	S Africa	S Korea	Turkey
Canada	40.937	61.636	75.166	78.531	64.63	53.895	57.019	70.091	59.238	64.365	63.338	65.719
France	43.394	56.353	74.907	78.778	59.616	52.89	52.253	70.150	58.966	63.788	63.203	66.173
Germany	38.329	62.221	70.412	78.646	64.516	49.905	62.581	70.412	59.910	59.910	63.865	65.573
Italy	29.770	66.638	59.382	64.091	44.425	43.289	38.078	54.623	42.336	46.988	47.00	50.839
Japan	43.028	46.881	44.05	55.653	85.406	52.33	58.187	80.439	62.76	59.759	88.252	67.346
UK	43.403	64.56	72.871	81.158	67.412	51.951	59.685	72.871	62.204	62.204	66.232	68.485
USA	56.749	34.575	41.13	47.00	65.306	82.384	22.29	81.186	35.492	27.196	66.73	73.468

Table 21: Corrected Contingency Coefficients of Binary Variables that are obtained from the Smoothed Probabilities of Recessionary Regimes among Emerging Countries for the Sample Period 2004:01 – 2012:07

	Argentina	**Brazil**	**Chile**	**Czech R**	**Malaysia**	**Mexico**	**Peru**	**Poland**	**Russia**	**S Africa**	**S Korea**	**Turkey**
Argentina	1											
Brazil	64.912	1										
Chile	63.625	72.554	1									
Czech R	85.823	82.915	86.705	1								
Malaysia	82.767	83.163	86.820	95.171	1							
Mexico	68.799	61.718	72.569	83.328	78.187	1						
Peru	55.207	77.123	80.784	89.288	87.223	72.199	1					
Poland	85.823	82.915	86.705	100.00	95.171	83.328	89.288	1				
Russia	85.823	82.915	86.705	100.00	95.171	83.328	89.288	100.00	1			
S Africa	81.323	77.505	87.000	95.781	90.803	87.81	84.814	95.781	95.781	1		
S Korea	85.823	82.915	86.705	100.00	95.171	83.328	89.288	100.00	100.00	95.781	1	
Turkey	88.286	79.96	83.772	97.697	97.52	80.849	84.484	97.697	97.697	93.400	97.697	1

Table 22: Corrected Contingency Coefficients of Binary Variables that are obtained from the Smoothed Probabilities of Recessionary Regimes between Emerging Countries and G – 7 Economies for the Sample Period 2004:01 – 2012:07

	Argentina	**Brazil**	**Chile**	**Czech R**	**Malaysia**	**Mexico**	**Peru**	**Poland**	**Russia**	**S Africa**	**S Korea**	**Turkey**
Canada	77.431	82.915	91.891	95.294	95.171	83.328	89.288	95.294	95.294	95.781	95.294	92.47
France	81.323	77.505	91.869	95.781	90.803	78.187	84.814	95.781	95.781	95.86	95.781	93.400
Germany	73.146	83.163	86.820	95.171	94.502	78.187	94.306	95.171	95.171	90.803	95.171	91.855
Italy	67.312	90.120	76.300	81.780	76.645	75.440	70.686	81.780	81.780	81.402	81.780	79.302
Japan	71.968	65.825	76.340	86.577	81.44	79.503	75.412	86.577	86.577	86.384	86.577	84.106
UK	80.005	85.823	89.460	97.697	97.52	80.849	91.722	97.697	97.697	93.400	97.697	94.934
USA	70.349	63.738	79.826	84.926	79.784	95.309	73.773	84.926	84.926	84.672	84.926	82.449