The Role of Credit on Business Cycles

by

Burak Parlak

A Dissertation Submitted to the
Graduate School of Social Sciences and Humanities
in Partial Fulfillment of the Requirements for
the Degree of

Master of Arts

in

Economics

KOÇ ÜNİVERSİTESİ

February 25, 2023

The Role of Credit on Business Cycles

Koç University

Graduate School of Social Sciences and Humanities

This is to certify that I have examined this copy of a master's thesis by

Burak Parlak

and have found that it is complete and satisfactory in all respects,

and that any and all revisions required by the final

examining committee have been made.

Committee Members:

____

Asst. Prof. Cem Çakmaklı

____

Prof. Selva Demiralp

____

Asst. Prof. Han N. Özsöylev

Date: ______________________

To my family

ABSTRACT

The Role of Credit on Business Cycles
Burak Parlak
Master of Arts in Economics
February 25, 2023

This study investigates whether there is a direct and meaningful effect of credit-related variables on business cycles in terms of magnitude and duration, or not. The research also focuses on the possibility of structural changes caused by the coronavirus pandemic through the credit channel, compared to the pre-pandemic era. For these purposes, real GDP and total credit to private non-financial sector datasets that belong to 31 selected OECD countries were employed as input. The main model used on this study is hierarchical Markov mixture model with Bayesian simulation. To observe possible effects of credit-related variables on business cycles, time-varying transition probabilities were enabled in emphasized model by means of probit model. For the pre-pandemic era, credit-to-GDP ratio tends to decrease the magnitude of cycle whatever the current phase is. Another finding states that annual real credit growth leads to an increase in the magnitude of cycle for both phases during pre-pandemic periods. It can be said that there exists evidence for several effects of credit-related variables on business cycles even though some of them seem to be disappeared with the pandemic era.

ÖZETÇE

İş Döngülerinde Kredinin Rolü
Burak Parlak
Ekonomi, Yüksek Lisans
25 Şubat 2023

Bu çalışma, krediye ilişkin değişkenlerin iş döngüleri üzerinde genlik ve süre bakımından doğrudan ve anlamlı bir etkiye sahip olup olmadığını irdeler. Araştırma, aynı zamanda pandemi öncesi döneme kıyasla koronavirüs pandemisinin kredi kanalı vasıtasıyla sebep olduğu yapısal değişiklikler ihtimali üzerinde durur. Belirtilen amaçlar doğrultusunda, girdi olarak 31 OECD üye ülkesine ait reel GSYH ve finansal nitelik taşımayan özel sektör unsurlarına verilen toplam kredi adlı veri setleri kullanılmıştır. Bu çalışmada kullanılan ana model, Bayes simülasyonuna dayanan hiyerarşik Markov modelidir. Krediye ilişkin değişkenlerin iş döngüleri üzerindeki olası etkilerini gözlemlemek için probit modeli aracılığıyla zamanla birlikte değişen geçiş olasılıkları vurgulanan modelde kullanıma elverişli hale getirilmiştir. Pandemi öncesi dönem özelinde kredi/reel GSYH oranı, içinde bulunulan safha fark etmeksizin, iş döngüsünün genliğini artırma eğilimi göstermektedir. Diğer bir bulgu, pandemi öncesi periyotlarda yıllık reel kredi büyümesinin her iki safha için de iş döngüsünün genliğinde bir artışa sebep olduğunu belirtmektedir. Bazılarının pandemi dönemiyle birlikte kayboluyor gibi görünmesine rağmen krediye ilişkin değişkenlerin iş döngüleri üzerindeki çeşitli etkilerine dair bir bulgunun var olduğu söylenebilir.

ACKNOWLEDGMENTS

Firstly, I would like to express my sincere gratitude to my advisor Professor Cem Çakmaklı for his continuous support and valuable time throughout this study. Without his guidance and effort, this thesis could not reach a meaningful conclusion. I am also deeply thankful to Professor Selva Demiralp for her precious evaluations and feed-backs on the thesis, and to Professor Han Özsöylev for his unique support in this study.

I am also grateful to The Scientific and Technological Research Council of Türkiye for the BİDEB 2210/A National MSc/MA Scholarship which made my expenditures during graduate studies affordable.

I cannot neglect the role of my friends from graduate class on this process. Many thanks to the successful researchers of the future. I also want to express my thanks to my manager for his encouraging comments and his understanding.

I am indebted to my teacher from primary school who provided me a desire to learn and the importance of curiosity.

Lastly, I would like to express my deepest appreciation to my family for their unlimited support and guidance started from my very first steps.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

NOMENCLATURE

MNM	Markov Normal Mixture
HMNM	Hierarchical Markov Normal Mixture
BIS	Bank of International Settlements
OECD	Organisation for Economic Co-operation and Development
NBER	National Bureau of Economic Research
TVP	Time-Varying Probability

Chapter 1

INTRODUCTION

The relationship between business cycles and financial conditions has been the focal point of many researchers in field of macroeconomics. Especially after several financial crises, the question whether financial conditions mainly determined by credit levels (or, credit growth) have considerable influence on the business cycles in terms of magnitude (depth) and duration has became the subject which should be investigated for further policy responses. Most of the related studies in the literature (e.g., [Gourinchas and Obstfeld, 2012] and [Kaminsky and Reinhart, 1999]) focus especially on the "recession" phase of business cycles to observe the role of credit-related variables on the predictability of these periods and on the size of economic downturn. As opposed to these studies, in this research, "good times" (that is, "expansion" phase) of various economies are also investigated from the perspective of credit conditions. Moreover, main phases that construct business cycles (i.e., expansion and recession) are decomposed into sub-states in order to examine the impact of credit during the different types of main phases.

Another fundamental issue that had been studied in this research is the implementation of credit expansion (stimulus) programs during the Covid-19 pandemic. Additional to these credit expansion programs, unprecedented levels of fluctuations in real global output (that is, business cycles with large magnitude) experienced at this period, can be treated as the fresh topic in terms of the impact of credit measures on business cycles. To maintain sustainable economic and financial conditions and to mitigate drastic effects of Covid-19 on these conditions, fiscal and monetary authorities (i.e., governments and central banks) had implemented several economic stimulus packages. For instance, the European Central Bank had put "pandemic emergency purchase program(PEPP)" into action with the purpose of providing households, firms and governments an access to funding (via loose borrowing conditions). The ECB had also announced the third series of "targeted long-term refinancing operations (TLTRO III)" in order to support lender-borrower relationship between banks and actors in real economy during the coronavirus pandemic. According to [Kose et al., 2021], private debt levels in emerging markets and their "single-year" growth rates recorded at the early stage of Covid-19 pandemic were "unprecedentedly" high for the past fourty-year period. The similar phenomenon can be found in an advanced economy such as the United States. (see Figure A.12)

The connection between credit-related variables and business cycles had been investigated in several papers of which findings were similar to ones in this research. For example, [Jordà et al., 2013] stated that expansionary periods with high levels of credit are more likely followed by sluggish recovery and severe recessionary periods by analyzing recession phases of advanced countries occurred far before the pandemic. In another paper, [Claessens et al., 2012] had studied the modifications in business cycle structure within different financial conditions (also called "financial cycles"). They concluded that there are meaningful linkages between business cycles and financial conditions. They stated that recessionary periods coincided with financial breakdown are greater in terms of magnitude and duration compared to the other recessions. On the expansion side, credit booms (or, credit growth with fast pace) during recoveries more probably lead to strong expansionary periods.

On the contrary to papers emphasized above, the broad data sets that contain observations from post-pandemic era, are used in this study. The inclusion of samples from both pandemic and post-pandemic periods might lead to a new insight on the interaction between credit-related variables and business cycles. Beyond the wide range of data sets employed in this study, the content of these data can be advantageous. Having observations belong to countries from diverse economic and geopolitical conditions can be thought as the strong aspect of data sets. Moreover, Gibbs sampling, the commonly used Bayesian simulation method, is employed in this study to make inference. Similar to the aforementioned studies, this research has following main findings: (a) countries with high credit-to-GDP ratio just before the recessionary period are more likely to experience long-lasting recession phase for pre-pandemic era, (b) credit-to-GDP ratio acts as a smoothing factor, that is, it prevents the existence of deep sub-states for both main phases, (c) annual real credit growth has positive impact on the expected duration of recession phase whereas it affects duration of expansion regime adversely for both pre-pandemic and full sample, and (d) real credit growth during the recession phase leads to an increase in the probability of being in mild recession instead of deep recession which might make credit stimulus programs implemented in pandemic reasonable.

The overall structure of this paper can be summarized as follows: In Chapter 2, data sets and related data manipulation processes are introduced. The main data employed in this study is "National Accounts, GDP by Expenditure: Constant Prices" obtained from the FRED, database belonging to Federal Bank of St. Louis. For the formation of credit-related variables, the data named "Total Credit to Private Non-financial Sector" from BIS database is employed. The detailed explanations about the content and range of these data sets are expressed in this chapter. In addition, distributional properties of main phases are constructed and analyzed by means of the non-parametric business cycle dating algorithm. The extraordinary nature of the Covid-19 pandemic in terms of the recorded real output growth rates is emphasized to justify the use of additional layers in the econometric model.

The econometric model and its components are explained in the Chapter 3. Since business cycles are formed by two main phases, it can be said that the regime-switching model and its derivatives fit well into the purpose of this study. Thus, firstly, the definition of the regime-switching model(that is, base model) including Markov process and corresponding notations are given in detail. As an extension, probit model and its theoretical background are summarized in order to understand how time-varying transition probabilities are constructed within the specified model. Lastly, the Gibbs sampling algorithm, one of the most common Markov Chain Monte Carlo methods, and its implementation on the hierarchical model are described.

The demonstration and the interpretation of simulation findings can be found in Chapter 4. At the beginning of this chapter, the data set from which credit-related variables are derived, is introduced. Descriptions with mathematical expressions for each variable are also added. The table that contains descriptive statistics about the generated variables, can be seen from the mentioned chapter in order to compare pre-pandemic sample and full sample at first glance. Initially, the empirical results obtained from the hierarchical model with fixed transition probabilities are interpreted in terms of estimated business cycle durations and mean values. Smoothed probabilities for the United States and Turkey are also investigated (and, evaluated) within the historical perspective. Then, by allowing time-varying transition probabilities, findings belong to the modified hierarchical model are examined in order to seek any relationship between credit measures and business cycles. Simulation results and smoothed (hence, filtered) probabilities are illustrated via tables and figures at succeeding pages after the interpretation section.

Chapter 2

DATA

2.1 Data Characteristics

Within the scope of the study, firstly, real output values are required in order to observe business cycles and turning points for each country. Thus, it can be said that the main data of this study contains real Gross Domestic Product values with varying periods in quarterly basis. This data set can be obtained from the FRED (the database belongs to Federal Reserve Bank of St.Louis) in the exact name "National Accounts: GDP by Expenditure: Constant Prices".

Since the Markov mixture model is designed for real GDP growth rates, the original data should be properly transformed into the relevant format via another MATLAB program. For the model, the real output data of thirty one predetermined OECD countries (listed from Australia to the United States) were taken into consideration.[1] Both advanced economies and emerging markets from main regions, at which economic activities are intensified (such as trade and monetary unions), are included in the data.

After the data transformation, we have real output growth rates in standardized form (emphasized in *Distribution of Growth Rates*) for specified countries. However, the number of country-level data elements varies from a country to another. Due to such differences in sample size, we can follow the same format established by [Gadea Rivas and Perez-Quiros, 2015] to investigate empirical results as a whole.

[1]The detailed list can be observed in the Appendix.

Following the same method emphasized before, the chain-like data can be employed as an input for the econometric model. "Chain-like" means that growth rate data for each country are ordered in the proper way:

Let c denote the specific country (where $c = 1, ..., 31$), and t represent the time period (or, quarter) where $t = 1, ..., N_c$ for the country c. N_c can also be considered as the sample size of the country c. Hence, the final data can be described as below:

$$Y = \Big\{ y_{1,1}, ..., y_{N_1,1}, ..., y_{1,c}, ..., y_{t,c}, ..., y_{N_c,c}, ..., y_{1,31}, ..., y_{N_{31},31} \Big\}$$

where $y_{t,c}$ indicates the real output growth rate for country c at time period t.

The second data set mainly needed for model with time-varying transition probabilities may be called "credit-to-GDP ratio". As seen from its name, this data consist of total credit level expressed quarterly in terms percentage of the output. To obtain credit-to-GDP data set, the Bank of International Settlements (BIS) Statistics Warehouse which contains various data sets from international banking to policy rates, can be used. However, the data imported from the source stated before has to be modified in order to prevent any mismatch with the format of growth rate data (Y). Since the data set contain credit ratio values for many countries(even the ones that are not in the scope of our study), the data manipulation (simply, filtering) is needed to construct the final version. For data arrangement and manipulation, R programming language that has comprehensive libraries were utilized. Similar to the real output growth data, country-level sample size varies depending on idiosyncratic characteristics of country. On the other hand, the credit ratio data set usually have more observations than ones in the growth rate data set. In other words, credit ratio data of the country include entries from earlier quarter, if any adjustment is not applied. The detailed explanation of the data set called credit-to-GDP ratio can be found in the section at which empirical results are reported.

2.2 Construction of Business Cycles

As stated in the former section, output (or, real GDP) growth rates of the specified countries are transformed into the suitable data format. Although output growth rates are obtained via data manipulation, classification of these elements in terms of different business cycle phases is the required step for the model implementation. Hence, an algorithm which detects turning points called as peak and trough, should be employed.

There exist non-parametric and parametric business cycle dating algorithms. The non-parametric business cycle dating algorithm is mainly based on the practical definition of recession whereas parametric one includes a statistical model such as Markov-switching model. Both types of dating algorithm and their performance were investigated by [Harding and Pagan, 2003]. In this study, the non-parametric business cycle dating algorithm, called Bry-Boschan Algorithm [Bry and Boschan, 1971], is preferred to specify peak and trough points. Following the definition[2] of recession and expansion stated by NBER Business Cycle Dating Committee, that is responsible for dating U.S. business cycles, growth rates are grouped in appropriate part depending on their location with respect to nearest peak and trough points.

In order to evaluate results (i.e. business cycle dates) obtained from the non-parametric algorithm, turning point dates stated by NBER Business Cycle Dating Committee are considered as control data, like [Harding and Pagan, 2003] did. From the Table 2.1, it can be observed that there may be small mismatch (which does not exceed three quarters) between turning point dates stated by NBER and results obtained from the algorithm due to the methodological distinction. To visualize cycle dates specified by the algorithm, recession periods in U.S. economy are represented with the gray-colored bars in Figure 2.1. As shown in the same figure, recession periods constructed by the algorithm are able to capture periods in which decline in the U.S. real GDP had been experienced.

[2] *A recession can be defined as the period between a peak of economic activity and its subsequent trough whereas an expansion is explained as the period from the trough to the following peak.*

Table 2.1: The Comparison of U.S. Business Cycle Dates

Peak		**Trough**	
NBER	Algorithm	NBER	Algorithm
1969 Q4	1969 Q3	1961 Q1	1960 Q4
1973 Q4	1973 Q4	1970 Q4	1970 Q4
1980 Q1	1980 Q1	1975 Q1	1975 Q1
1981 Q3	1981 Q3	1980 Q3	1980 Q3
1990 Q3	1990 Q3	1982 Q4	1982 Q1
2001 Q1	2001 Q2	1991 Q1	1991 Q1
2007 Q4	2008 Q2	2001 Q4	NA
2019 Q4	2019 Q4	2009 Q2	2009 Q2
NA	2021 Q4	2020 Q2	2020 Q2

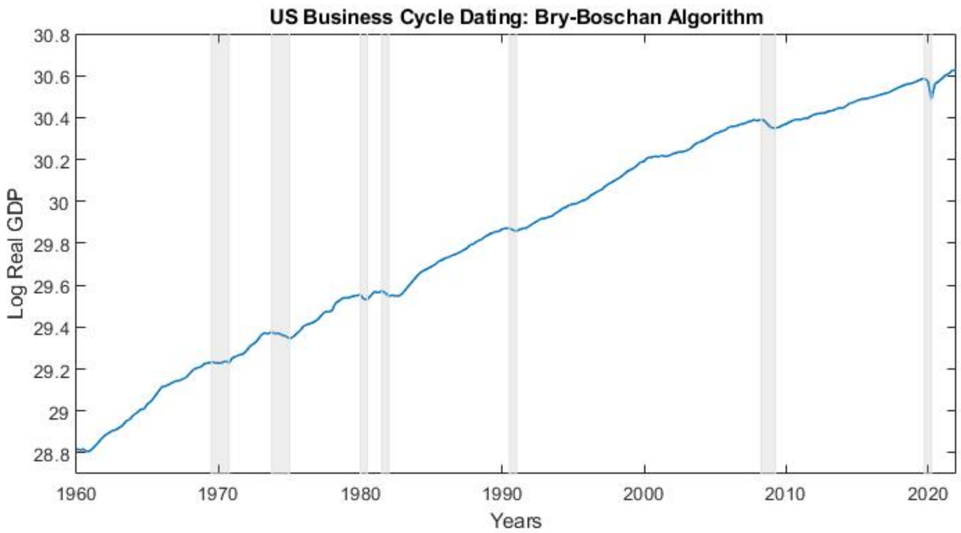


Figure 2.1: Implementation of the Bry-Boschan Algorithm on U.S. Real GDP Data including quarters between 1960 Q1 and 2022 Q3

Note: Shaded areas represent the period between two consecutive peak and trough points (from peak to trough according to the definition of recession) obtained via the algorithm.

2.3 Distribution of Growth Rates

In previous section, output growth rates were divided into recession and expansion phases via non-parametric business cycle dating algorithm. As a result, data elements can be observed separately for each phase. To investigate the distribution of the growth rates (i.e., extreme values, central tendency measures and overall shape), the simple method may be using histograms. As seen from the Figure 2.2, growth rate distributions for both recession and expansion phases cannot be included in the form of normal distribution simply due to absence of symmetry with respect to the mean value represented with black dashed line in both figures 2.2.a and 2.2.b.

According to the skewness values for each distribution, it can be said that distribution of the recession phase has negative skewness (left-skewed) whereas the one belongs to expansion phase has positive skewness (right-skewed). The distribution of the growth rates labeled as ”recession” has longer left tail (hence, left-skewed) which denotes the presence of deep recession cases. On the ”expansion” side, we can encounter the high levels of real GDP growth that represent exceptional ”growth” phases. These extreme values will constitute the reason behind the use of hierarchical model which will be emphasized later.

As an addition, the effect of Covid-19 pandemic on the statistical properties cannot be neglected. Since V-shaped fluctuations in real GDP growth, that is, sharp and successive movements in opposite directions occurred during the pandemic, there are additional extreme values (or, tail elements) in both phases. The aforementioned movement in the real GDP growth can be seen clearly through the Figure 2.4 at which data for the United States and Germany were illustrated as instance. Another evidence for such increase in tail elements can be deducted from scatter plots 2.5 and 2.6 at which real output growth rates are illustrated. In Figure 2.5, it is obvious that only growth rates experienced in the pandemic (most effective in the first half of 2020) are included in the left side of the threshold (that is, 2.5^{th} percentile) represented by blue dashed line. Similarly, majority of the observations from ”expansion” phase, that exceed the threshold (determined by 99^{th} percentile) in red dashed line, were occurred during the Covid-19 pandemic, as seen from Figure 2.6.

Hence, it can be claimed that the sharp swings emerged during pandemic led to an increase in number of tail elements for both recession and expansion phases.(In other words, the pandemic magnified the asymmetry in distributions as explained with the term "skewness".)

During the investigation of real GDP growth rate distribution, country-specific cases were neglected. However, we can observe distinct growth rates for each country even under the identical conditions. In other words, a country, depending on whether it is a member of emerging market or advanced economy club, can experience different levels of real GDP decline or increase in response to the same recessionary (or, expansionary) pressure. In order to construct reasonable categorization and to emphasize common characteristics, we should try to remove idiosyncratic specifications among countries contained in data set[3] by means of standardization, as [Gadea Rivas and Perez-Quiros, 2015] did before. This approach can be explained with these three consecutive steps:

1. Calculate the mean and standard deviation of the whole data, and denote these values as μ_d and σ_d, respectively

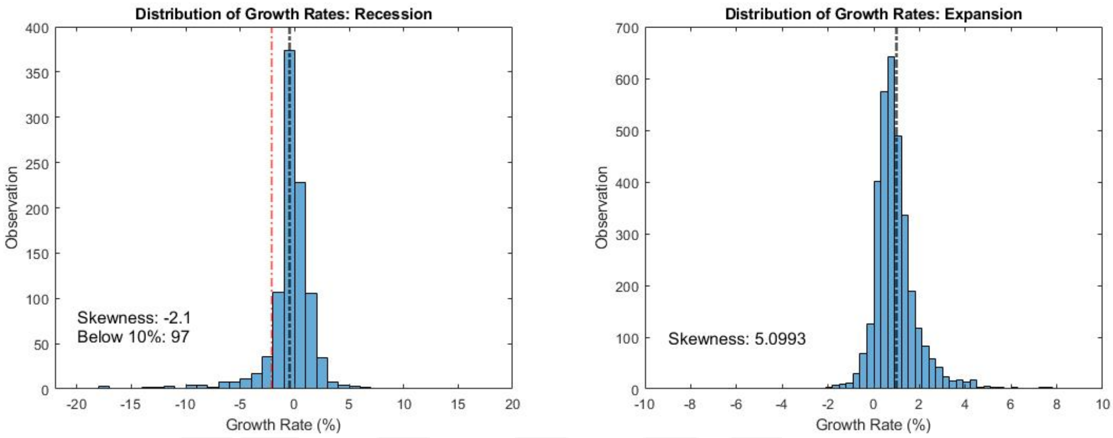
2. For each country ($c = 1, 2, ..., 31$) in data set, calculate the mean (μ_c) and standard deviation (σ_c) of country-specific data

3. Modify every element of real GDP growth data (represented with $t = 1, ..., N_c$) according to the standardization formula given below:

$$\widetilde{y_{t,c}} = \left(\frac{y_{t,c} - \mu_c}{\sigma_c}\right) * \sigma_d + \mu_d$$

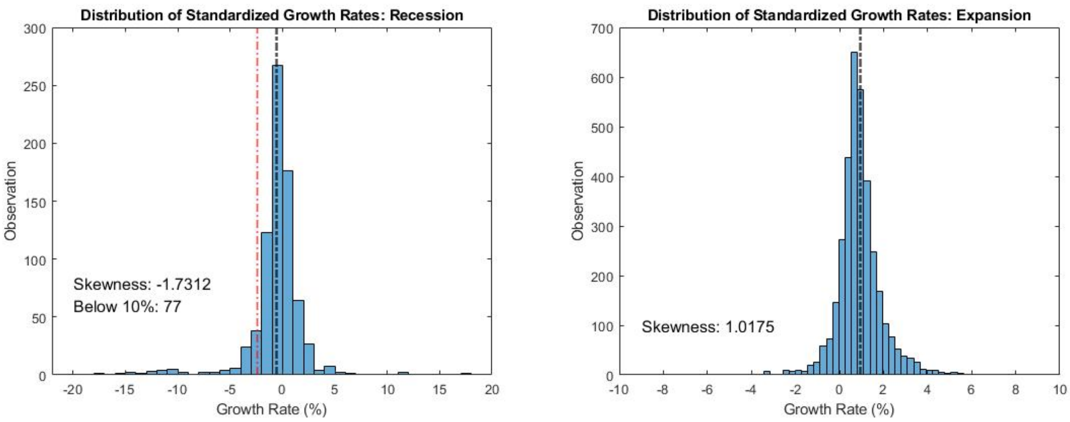
Hence, the distribution for standardized data can be observed in Figure 2.3. At these histograms, the improvement in the skewness value (that is, getting closer to zero), especially of expansion phase, may indicate a decrease in the number of tail elements and an increase in symmetry with respect to the recalculated mean.

[3] For details see section 2.1: *Data Characteristics*



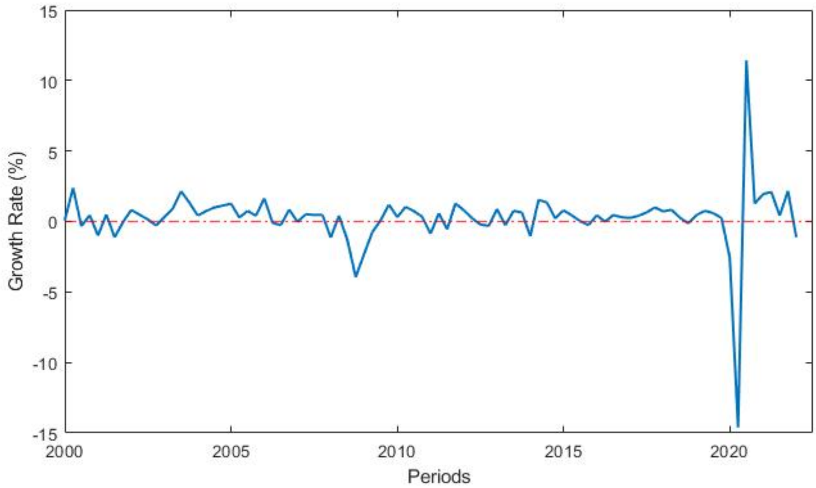
(a) Recession (b) Expansion

Figure 2.2: Histograms for growth rates occurred in both phases

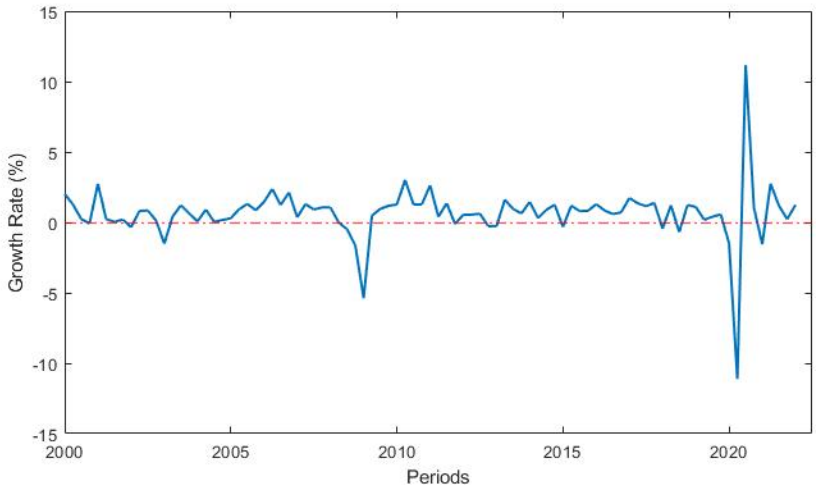


(a) Recession (b) Expansion

Figure 2.3: Histograms for standardized growth rates



(a) Real GDP Growth: the United States



(b) Real GDP Growth: Germany

Figure 2.4: Real GDP growth for the US and Germany between 2000 Q1 - 2022 Q1
Note: The red dashed line represents the growth rate of zero percentage.

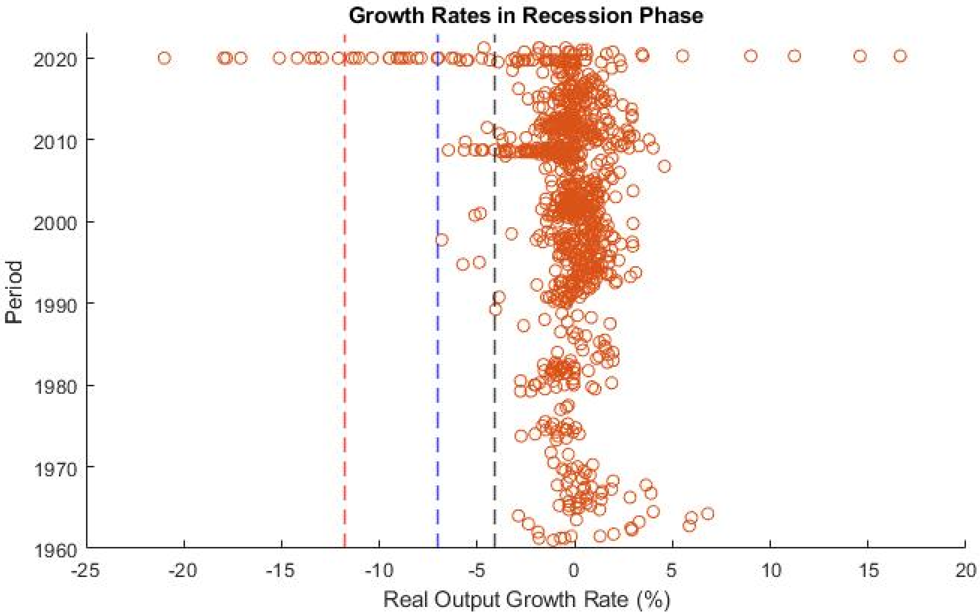


Figure 2.5: Non-standardized real output growth rates included in recession phase

Note: Dashed lines from right to left represents $5^{th}, 2.5^{th}$ and 1^{st} percentile thresholds of the recession sample, respectively. The number of observations smaller than these percentile values are calculated as 50, 25 and 10 since the sample size of recession phase is 999.

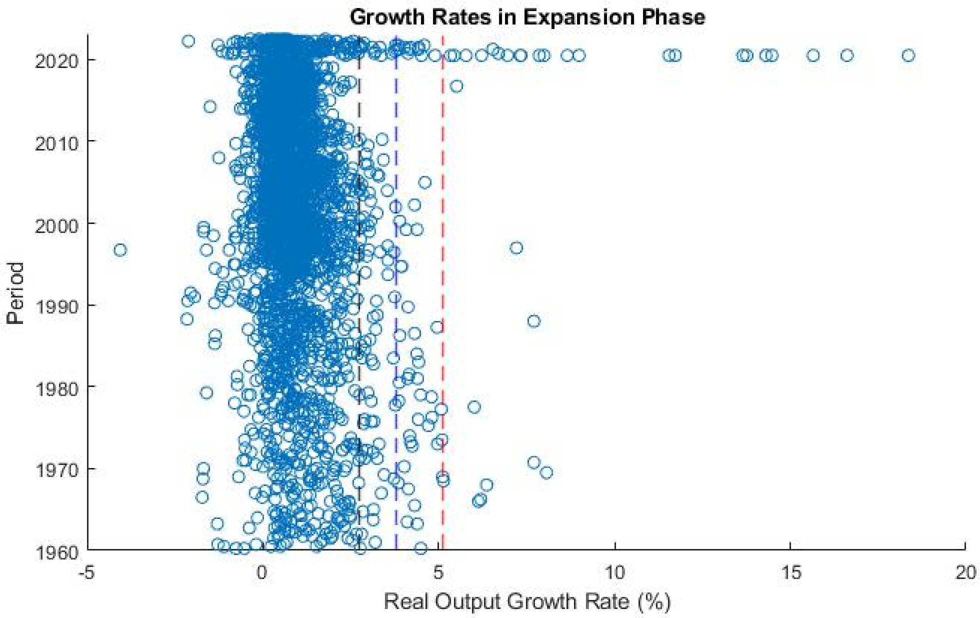


Figure 2.6: Non-standardized real output growth rates included in expansion phase

Note: Dashed lines from left to right represents $95^{th}, 97.5^{th}$ and 99^{th} percentile thresholds of the recession sample, respectively. The number of observations greater than these percentile values are calculated as 166, 83 and 33.

Chapter 3

THE ECONOMETRIC MODEL

3.1 Markov Mixture Model

The fundamental part of model implemented in this study can be described as "regime switching" due to the existence of distinct business cycle phases. As in previous studies at which regime switching had been used as main framework (such as [Hamilton, 1989] and [Albert and Chib, 1993]), structural changes(switching) on observations are represented with latent state variables depending on Markov process. To make these concepts concrete, the main equation can be defined as below:

$$y_t = \mu_{S_t} + \epsilon_t \ , \qquad \epsilon_t \sim N(0, \sigma^2) \tag{3.1}$$

where y_t is real output growth (observation) and μ_{S_t} denotes regime-dependent mean value. Since there are two phases (expansion and recession), the mean value is determined by unobserved state variable, S_t, in binary form. In other words, when $S_t = 1$, it can be said that y_t belongs to the "recession" regime whereas y_t is considered as a sample in "expansion", if S_t takes the value 0. As emphasized above, a shift in S_t depends on first-order two-state Markov process with following transition (or, shift) probabilities:

$$P(S_t = 0|S_{t-1} = 0) = p_{00} \qquad \text{and} \qquad P(S_t = 1|S_{t-1} = 1) = p_{11} \tag{3.2}$$

On the contrary to [Hamilton, 1989] who had employed regime-switching model for business cycle dating, there is no auto-regressive dynamics in this equation, that is, past observations of real output growth(y_{t-i}) are not included in the equation 3.1 as explanatory variable.

The model represented with equations 3.1 and 3.2 can be thought as a Markov mixture model in which components (for each state, S_t) are normally distributed. However, as stated in Chapter 2, both expansion and recession phases have a large number of tail elements which can be understood from positive or negative skewness values for each phase. Hence, hierarchical Markov mixture model, that might be considered as the "restricted" version of Markov mixture model [Geweke and Amisano, 2011], should also be implemented in this study for obtaining reasonable empirical results.

Resulting from the existence of tail elements in both distributions, it can be better if additional states are included in the model to capture these tail elements separately. Following this claim, both expansion and recession phases are divided into two sub-levels: recovery and growth states for expansionary periods and mild and deep states for recessionary periods. This modification seems to be quite reasonable if the real output growth data is constructed for pre-pandemic era. Nevertheless, as discussed in Chapter 2, Covid-19 caused considerable fluctuations in real output levels(therefore, in growth data) which increased the number of tail elements for both business cycle phases (see figures 2.4, 2.5 and 2.6). Thus, two more states are added in the model, at which full sample is employed, to represent exceptionally huge growth rates (in both directions), named pandemic expansion and pandemic recession. As a result, we construct two different "Markov-switching model" with constant transition probabilities ([Kim and Nelson, 1999]) for two distinct data set: four-state for pre-pandemic era and six-state for full sample, including pandemic.

Beyond these models stated above, the core econometric model in this study is hierarchical Markov mixture model in which additional states such as growth and mild recession are not examined as separate regime. In "hierarchical" approach, unobserved state variables, S_t, are determined by two distinct processes. In this type of mixture model, there exist two main regimes: expansion and recession. State variables (denoted as $S_{1,t}$) belong to these main regimes follow two-state first-order Markov chain same as in the expression 3.2

Because of the reason emphasized before, there are three sub-regimes for each main regime(or, business cycle phase) when the pandemic data is included in the data set. To make the structure clear, we can start with "expansion" phase. If full set of observations are deployed, expansion regime(that is, $S_{1,t} = 0$) can be divided into following sub-regimes: recovery, growth and pandemic expansion represented by $S_{2,t} \in \{0, 1, 2\}$. In other words, for instance, when latent state variables $(S_{1,t}, S_{2,t})$ becomes $(0, 0)$, it can be understood that the observation y_t is considered as an element of "growth" sub-regime of "expansion" phase. From the same manner, "recession" regime (denoted as $S_{1,t} = 1$) can be partitioned into these sub-regimes: mild recession, deep(severe) recession and pandemic decline, represented again by $S_{2,t} \in \{0, 1, 2\}$. Let, as an example, state variables $(S_{1,t}, S_{2,t})$ be $(1, 0)$, then it can be said that this observation is included in "mild recession" sub-state of recession phase. Lastly, it should be emphasized that pandemic expansion and pandemic decline sub-regimes are not valid for the model in which pre-pandemic data is employed.

In hierarchical model, the probability of being in specific sub-state is defined conditionally on the main state, and it does not follow any Markov process. If the related probability is represented by q_{ij}, then it can be expressed as below:

$$P(S_{2,t} = j | S_{1,t} = i) = q_{ij} \tag{3.3}$$

For instance, the notation q_{10} denotes the probability of being in "mild recession" sub-state of "recession" phase ($S_{2,t} = 0$ when $S_{1,t} = 1$). Hence, if the hierarchical model with full sample (that is, including pandemic) is taken into consideration, we can construct transition matrix ,which contains corresponding probability values of transition from the former state to current state, as in the following form:

To show the matrix in simple way, let vectors C_1 and C_2 be defined as

$$C_1 = \begin{bmatrix} p_{00}q_{00} \\ p_{00}q_{01} \\ p_{00}(1 - q_{00} - q_{01}) \\ (1 - p_{00})q_{10} \\ (1 - p_{00})q_{11} \\ (1 - p_{00})(1 - q_{10} - q_{11}) \end{bmatrix} \quad \text{and} \quad C_2 = \begin{bmatrix} (1 - p_{11})q_{00} \\ (1 - p_{11})q_{01} \\ (1 - p_{11})(1 - q_{00} - q_{01}) \\ p_{11}q_{10} \\ p_{11}q_{11} \\ p_{11}(1 - q_{10} - q_{11}) \end{bmatrix} \tag{3.4}$$

Then, by using vectors defined before as columns, the transition matrix that defines probability of transition for each possible case, can be expressed as:

$$A_1 = \Big[C_1 \ \vdots \ C_1 \ \vdots \ C_1 \ \vdots \ C_2 \ \vdots \ C_2 \ \vdots \ C_2\Big] \tag{3.5}$$

The reason behind the use of specific matrix form in 3.4 and 3.5 is making transition probabilities suitable for the Bayesian inference. In the simulation, the "basic filter" proposed by [Hamilton, 1989] utilizes the transition matrix in given form via vec operator.

The transition matrix should be updated when the pre-pandemic data is used, because there are only two sub-states for each business cycle phase in stated model. Since extreme values resulted from Covid-19 do not exist anymore, "pandemic expansion" and "pandemic decline" sub-regimes can be neglected. Therefore, for hierarchical Markov mixture model with four sub-states, the transition matrix can be represented in the similar column format as:

$$A_2 = \begin{bmatrix} p_{00}q_0 & p_{00}q_0 & (1-p_{11})q_0 & (1-p_{11})q_0 \\ p_{00}(1-q_0) & p_{00}(1-q_0) & (1-p_{11})(1-q_0) & (1-p_{11})(1-q_0) \\ (1-p_{00})(1-q_1) & (1-p_{00})(1-q_1) & p_{11}(1-q_1) & p_{11}(1-q_1) \\ (1-p_{00})q_1 & (1-p_{00})q_1 & p_{11}q_1 & p_{11}q_1 \end{bmatrix} \tag{3.6}$$

in which the sum of each row shows the total probability of shift to the current state, that is:

$$A_2 = \begin{bmatrix} P\big[S_t = (0,0)\big] \\ P\big[S_t = (0,1)\big] \\ P\big[S_t = (1,0)\big] \\ P\big[S_t = (1,1)\big] \end{bmatrix} \tag{3.7}$$

After the explanation of hierarchical Markov mixture model with constant transition probabilities(i.e. time-independent transition matrix), we can modify the model by introducing time-varying transition probabilities which enables us to examine distinct expansionary and recessionary periods in terms of duration. Moreover, the main reason for including time-varying transition matrix can be stated as investigating the effect credit-related variables on business cycle phases (and, shifts in transition probabilities as a response to observations) during different periods. To determine time-varying transition probabilities, binary and ordered probit model (for detailed description, please refer to [Wooldridge, 2010a]) is constructed as follows:

$$\begin{aligned} p_{ii,t} &= \Phi(p_{ii} + \beta_i x_{t-1}) \\ q_{i0,t} &= \Phi(\alpha_{1,i} - q_i - \theta_i x_{t-1}) \\ q_{i1,t} &= \Phi(\alpha_{2,i} - q_i - \theta_i x_{t-1}) - \Phi(\alpha_{1,i} - q_i - \theta_i x_{t-1}) \\ q_{i2,t} &= 1 - \Phi(\alpha_{2,i} - q_i - \theta_i x_{t-1}) \end{aligned} \tag{3.8}$$

where Φ is the symbol for cumulative distribution function of standard normal distribution, β_i and θ_i are coefficients that describe the effect of credit-related explanatory variables (x_{t-1}) on the transition probabilities $p_{ii,t}$ and $q_{ij,t}$, respectively. Since there are three sub-states for each phase in the model that employs the complete data set, ordered probit model should be used for probabilities which belong to these sub-states. Unlike the binary probit model, "threshold parameters" ([Wooldridge, 2010b]) should be added in the ordered probit model to properly cluster latent variables according to the predetermined sub-states. From the set of equations in 3.8, $\alpha_{1,i}$ and $\alpha_{2,i}$ for $i = 0, 1$ stand for these parameters. For the hierarchical model which takes only pre-pandemic observations into consideration(that is, with two sub-states for each phase), the binary probit model is employed for defining both probabilities $p_{ii,t}$ and $q_{ij,t}$.

3.2 Bayesian Approach

There are two main approach in order to estimate parameters of regime-switching model with Markov chain: classical and Bayesian method. The former is based on maximum likelihood estimation, that is, estimating model parameters which maximizes the likelihood function with respect to given observations. After obtaining estimated parameters, latent state variables(S_t) are estimated conditional on these parameters. In Bayesian approach, unlike the classical one, both model parameters and latent state variables are considered as "random variables" which implies that regime-switching variables are estimated from "joint" distribution. (as stated in [Kim and Nelson, 1999])

As understood from its name, Bayesian approach (or, inference) is originated from the well-known probability concept, Bayes' Rule, that can be formulated as below:

$$p(\beta|y) = \frac{p(y|\beta)p(\beta)}{p(y)} \tag{3.9}$$

where y and β are data and model parameters, respectively. The main point of this method is accepting β as random variable in contrast to the case in maximum likelihood estimation.([Koop, 2003]) Using the equation 3.9, we can write:

$$p(\beta|y) \propto p(y|\beta)p(\beta) \tag{3.10}$$

at which $p(\beta|y)$, $p(y|\beta)$ and $p(\beta)$ represent the posterior, the likelihood and the prior, respectively. This expression means that the posterior probability density function is proportional to the multiplication of the likelihood and prior which constitutes the Bayesian framework.([Koop, 2003]) From this relationship, it can be said that the posterior $p(\beta|y)$ is the focal point of the Bayesian method. In other words, an econometrician who investigates the special function of model parameters (i.e. $f(\beta)$) given observations should use the posterior density as follows:

$$E\big[f(\beta)|y\big] = \int f(\beta)p(\beta|y)d\beta \tag{3.11}$$

In Bayesian approach, depending on the functional form and density, it might be tough to solve integrals like 3.10 without any computational tool. Therefore, as in this study, "Monte Carlo Integration" can be employed to obtain an approximation of given integral. This computational method consists of sampling from the posterior density (i.e., obtaining random draws of parameters from $p(\beta|y)$)([Koop, 2003]). However, it may not be simple (or, not be feasible) everytime to take random draws from the posterior density to continue with Monte Carlo approximation. In such cases, we can continue with Gibbs sampling which is based on sampling from "conditional posterior" densities instead the posterior itself.([Koop, 2003]) For instance, let model parameter vector β be defined as $(\theta_1, \theta_2)'$. For the model at which there is no possible way to take random draws from $p(\theta_1, \theta_2|y)$, but it is feasible to make sampling from conditional distributions $p(\theta_1|\theta_2, y)$ and $p(\theta_2|\theta_1, y)$, then we can proceed with Gibbs sampling. In the generalized form, the algorithm can be expressed as below:

Let the model parameter β be $K \times 1$ vector given as $(\theta_1,\ \theta_2, \ldots, \theta_K)'$ where the posterior density function is defined as $p(\theta_1,\ \theta_2, \ldots, \theta_K|y)$. Then, "the full conditional posterior distributions" ([Koop, 2003]) from which random draws are obtained, are expressed as $p(\theta_j \mid \theta_1,\ \theta_2, \ldots, \theta_{j-1},\ \theta_{j+1}, \ldots, \theta_K,\ y)$. Let D be iteration number (that is, number of draws) and d represents the index of draw. Then, for $d = 1, 2, \ldots, D$, using the initial values $(\theta_j^{(0)})$ for all elements of parameter vector β, the following steps should be applied:

1. Obtain a random draw for the element $\theta_1^{(d)}$ using $p(\theta_1 \mid \theta_2^{(d-1)},\ \ldots\ , \theta_K^{(d-1)}, y)$
2. Obtain a random draw for the element $\theta_2^{(d)}$ using $p(\theta_2 \mid \theta_1^{(d)},\ \ldots\ , \theta_K^{(d-1)}, y)$

   $\vdots$

K. Obtain a random draw for the element $\theta_K^{(d)}$ using $p(\theta_K \mid \theta_1^{(d)},\ \theta_2^{(d)},\ \ldots\ , \theta_{K-1}^{(d)}, y)$

At the end, we have vector of draws $\beta^{(d)} = (\theta_1^{(d)}, \theta_2^{(d)}, \ldots, \theta_K^{(d)})'$, for each iteration $d = 1, 2, \ldots, D$. Using these stored elements, the approximation of the special function $(f(\beta))$ can be obtained as in Monte Carlo integration.

It should be emphasized that the current draw for model parameters contained in $\beta^{(d)}$ is dependent on the former random draws $\beta^{(d-i)}$ similar to the Markov process as seen from the algorithm above. Thus, Gibbs sampling is included in the family of posterior simulation named "Markov Chain Monte Carlo" method. The chain-like structure can be observed clearly. Due to this structure and dependence between successive random draws, the first D_0 stored elements, called burn-in iterations, should be neglected during the Monte Carlo approximation.

Before the explanation of the posterior simulation, priors can be described. Since there is no former information on model parameters, non-informative priors are mostly employed. The prior related to variance of the model given in 3.1 is determined as:

$$p(\sigma^2) \propto \frac{1}{\sigma^2} \tag{3.12}$$

where the reciprocal of the variance parameter is also called "precision(h)". When time-varying probabilities are included, posterior simulation is made for the parameters that identify coefficients of explanatory variables in probit model, by means of these priors:

$$p(\beta_i) \propto 0 \quad \text{and} \quad p(\theta_j) \propto 0 \;\; \text{for i = 0,1 and j = 0,1} \tag{3.13}$$

To provide accurate structure for regime-switching model, the regime-specific mean values are determined by truncated normal distribution, $p(\mu)$, with the following constraint:

$$p(\mu) \propto \begin{cases} 1, & \text{if } \mu_{02} > \mu_{00} > \mu_{01} > 0 > \mu_{10} > \mu_{11} > \mu_{12} \\ 0, & \text{otherwise} \end{cases} \tag{3.14}$$

The use of truncated normal distribution implies the following fact: The only random draws that satisfy the constraint will be taken into consideration to obtain regime-specific mean values of real output growth rates accurately.

After the brief description of priors, the Gibbs sampling algorithm implemented in this study can be summarized as below:

1. Obtain a random draw of state variables $S_t = (S_{1,t}, S_{2,t})$ conditional on $p_t, q_t, \mu, \sigma^2, \beta, \theta$ and y_T, with the help of filtering

2. Take a random draw of probit model coefficients $\beta = (p_{ii}, \beta_i)$ for $i = 0, 1$ conditional on $S_t, p_t, q_t, \mu, \sigma^2, \theta$ and y_T, then, via binary probit model specifications, transition probabilities $p_t = (p_{00,t}, p_{11,t})$ are constructed.

3. Obtain a random draw of probit model coefficients $\theta = (q_i, \theta_i)$ for $i = 0, 1$, conditional on $S_t, p_t, \mu, \sigma^2, \beta$ and y_T ,then, conditional probabilities of substates $q_t = q_{ij,t}$ for $i = 0, 1$ and $j = 0, 1, 2$ is provided by means of the ordered probit model.

4. Using the structure of truncated normal distribution, regime-specific mean values μ are generated conditional on $S_t, p_t, q_t, \sigma^2, \beta, \theta$ and y_T.

5. The parameter that corresponds to model variance, σ^2, is generated conditional on $S_t, p_t, q_t, \beta, \theta$ and y_T. Then, algorithm turns back to the Step 1.

These steps described above will be iterated many times (N=10,000 in this study) in order to allow the estimated parameters to converge. After completing the iterations, estimation results are extracted by Monte Carlo integration.

Chapter 4

EMPIRICAL APPLICATION

4.1 Data Description

The primary data set named "Gross Domestic Product in Constant Prices" is emphasized in the second chapter. The secondary data employed for estimating time-varying transition probabilities mainly consists of total credit and its derivatives. The source of this data is the database called "Total Credit to Private Non-financial Sector" established by BIS[1] Statistics Warehouse. This database contains total credit to private non-financial sector measured in terms of both percentage of GDP and market value in US dollars. In the related review published by BIS, [Dembiermont et al., 2013] emphasized that the database consists of credit observations obtained from all possible sources. In other words, the mentioned data had been constructed without taking national borders (domestic or foreign lender) and institutional characteristics of lender (e.g. financial and non-financial corporations) into consideration to distinguish observations. At the borrowers' side, the following agents were included in this data: "non-financial corporations" (both public and private), "households" and "non-profit institutions serving households". The term "securitization" had also been stated as a concern by [Dembiermont et al., 2013], especially in credit observations from banks since the "securitized" loan instruments did not have any place on banks' balance sheet(one of the data sources) even though accounting standards has been changed recently. This concern has no longer influence on the data set due to the wide variety of data sources as emphasized above.

[1]Bank of International Settlements

As seen from the empirical application at which time-varying transition probabilities are estimated via latent variable model, required data sets derived from this database can be listed as credit-to-GDP (or, total credit in percentage of GDP), real credit growth (change in the total credit in US dollars adjusted with US consumer price index), annual (accumulated) real credit growth and leverage indicator. Firstly, credit-to-GDP ratio is employed as explanatory variable in the probit model, which determines time-varying probabilities, in order to capture any causal effect. As a second step, both real credit growth (denoted as RCG_t) and annual real credit growth ($ARCG_t$) are included in the matrix of explanatory variables. Finally, leverage indicator ($CR75_t$) is added as a dummy variable in the second form of model.

In order to construct real credit growth data set[2], total credit to private non-financial sector as market value (measured in US dollars) is employed as a raw data. Since the credit growth should be expressed in "real" terms, the quarterly US Consumer Price Index (CPI) data set that takes 2015 as 100 (base) is also used for the related adjustment. Then, the adjusted data elements are transformed into natural logarithm form. The final version, that is, real credit growth data can be defined as follows:

$$RCG_t = \ln\left(\frac{TotalCredit_t}{CPI_t}\right) - \ln\left(\frac{TotalCredit_{t-1}}{CPI_{t-1}}\right) \tag{4.1}$$

After the construction of real credit growth data, annual credit growth rate can be easily established from the sum of four consecutive observations (i.e., annual) for each period. The operation can be expressed in mathematical form:

$$ARCG_t = \sum_{i=0}^{3} RCG_{t-i} \tag{4.2}$$

[2]For all these data modification processes, R libraries and functions that are established for data operations, had been used.

Lastly, the leverage indicator which is formed from credit-to-GDP ratio sample can be expressed as below:

$$CR75_{c,t} = \begin{cases} 1, & \text{if } CR_{c,t} \; > \; 75^{th} \; percentile(\text{Credit-to-GDP}_c) \\ 0, & \text{otherwise} \end{cases} \tag{4.3}$$

which means that the dummy variable trying to represent the leverage status at the period t (i.e. $CR75_{c,t}$) will be equal to 1 if the credit-to-GDP ratio for the period t is greater than the 75^{th} percentile of the credit-to-GDP ratio sample for the specific country c. When the indicator variable takes the value 1, it may be interpreted as a sign of high leverage. It should be additionally noted that the definition of the threshold which determines whether data element belongs to high leverage or low leverage status, can be modified by means of distinct percentiles such as 50^{th} percentile of the credit-to-GDP data, depending on the purpose of study.

Before the interpretation of empirical results, it could be useful to investigate descriptive statistics of aforementioned data sets. Although there does not exist any change in minimum or maximum values after including observations during the Covid-19 pandemic, it can be observed that mean and standard deviations for each data set are slightly different depending on the range of observations.

Table 4.1: Descriptive Statistics

Data Set	**Size(N)**	**Mean**	**Std. Deviation**	**Min**	**Max**
Credit-to-GDP (F)	4282	128.50	58.61	19.10	292.20
Credit-to-GDP (P)	3972	126.12	57.26	19.10	292.20
RCG (F)	4218	9.62×10^{-3}	5.31×10^{-2}	-0.615	0.214
RCG (P)	3908	10.27×10^{-3}	5.33×10^{-2}	-0.615	0.214
ARCG (F)	4218	4.13×10^{-2}	0.118	-0.550	0.5154
ARCG (P)	3908	4.35×10^{-2}	0.121	-0.550	0.5154

Note: The letter F in parenthesis means "Full-sample" which contains observations during the pandemic and afterwards. The letter P in parenthesis represents "Pre-pandemic sample" that only includes observations until the pandemic.

4.2 Posterior Simulation Results

4.2.1 Hierarchical Markov Mixture Model with Fixed Transition Probabilities

As first step through the empirical application, hierarchical Markov mixture model[3] (abbreviated as HMNM) with fixed transition probabilities can be simulated to observe mean real GDP growth rates and smoothed probabilities for each regime. Since economies had experienced sharp fluctuations in real output growth during coronavirus pandemic (see Figure 2.4), it might be better to proceed with the two separate data samples: pre-pandemic sample and full sample (as seen in Table 4.1). From the same reason emphasized in Chapter 3, the main regimes named "expansion" and "recession" are divided into three sub-regimes if the post-pandemic observations are included in the sample.

For justifying the use of hierarchical models with two or three sub-states in this study, the same data set is employed for the various models at which hierarchical structure is not considered. In Table 4.4, empirical results belong to Markov mixture model (MNM) with only two main states are illustrated. As understood from estimated parameters and marginal likelihood values, a model with only two states is incapable of capturing all stages of business cycles. Its counterpart with the time-varying transition probabilities has the same insufficiency as seen from Table 4.9. Different from these models, the MNM model with four main states instead of hierarchical model with two sub-states is simulated. If the pre-pandemic sample is considered, it can be said that hierarchical model with two sub-regimes has slightly greater performance by comparing marginal likelihood values and model variance parameters. (see Tables 4.5 and 4.9)

When the pre-pandemic sample is considered, hierarchical model with two sub-states should be simulated. In this model, the "expansion" regime consists of "growth" and "recovery" as corresponding sub-states, whereas, the "recession" regime contains "mild recession" and "deep(severe) recession" according to magnitude of the change in real ouput level. For the definition of these sub-states, the following

[3] It will be stated as "hierarchical model" in remaining part of this chapter.

inequality of the regime-specific mean values is formed:

$$\mu_{00} > \mu_{01} > 0 > \mu_{10} > \mu_{11} \tag{4.4}$$

where μ_{00}, μ_{01},μ_{10} and μ_{11} represent "growth", "recovery", "mild recession" and "deep recession", respectively. As seen from Table 4.2, these regime-specific mean values are estimated as 3.358, 0.816, -0.512 and -3.147 which is acceptable with respect to the equation 4.4. Also, these estimated mean values (interpreted as percentage change in real output) are consistent with the distribution of standardized real GDP growth rates. The important part is the set of transition probabilities p_{00} and p_{11} that are obtained as 0.946 and 0.743. From the related property of Markov process, the "expected duration" of each regime in this model can be calculated by means of these estimated probabilities[Kim and Nelson, 1999].

With the help the equation $\frac{1}{1-p_{ii}}$ for $i = 0, 1$ which gives the expected duration for the main regime i, it can be said that "expansion" regime ($i = 0$) is expected to last for 18.51 quarters whereas expected duration of "recession" phase ($i = 1$) is computed as 3.89 quarters. Beyond transition probabilities, it can be observed that the probability of being in "recovery" sub-state is far greater than of being in "growth". On the other hand, it is more probable to observe the upper level of "recession" phase named "deep recession". This implies that it is more likely to encounter severe recessions (or, great decline in real output) than expansionary periods with significant rise (e.g. around the mean 3.358 %) in real output.

If the full sample that includes observations during coronavirus pandemic (and, afterwards) is used for posterior simulation, an extra sub-state should be added for each main state due to the reason explained before. Thus, the results shown in the Table 4.3 can be obtained from hierarchical model with three sub-regimes. In this model, the inequality defined in 4.4 has to be modified because of the pandemic-related sub-states:

$$\mu_{02} > \mu_{00} > \mu_{01} > 0 > \mu_{10} > \mu_{11} > \mu_{12} \tag{4.5}$$

at which μ_{02}, μ_{00}, μ_{01}, μ_{10}, μ_{11} and μ_{12} denote the estimated mean values for "pandemic (great) expansion", "growth" , "recovery", "mild recession", "deep recession" and "pandemic (great) decline", respectively. Similar to the previous model, mentioned mean values resulted from hierarchical model with three sub-states seem to be appropriate according to the relationship in 4.5. It can be clearly noticed that the extreme levels in both expansionary and recessionary phases occurred in the pandemic period appeared as mean values μ_{02} and μ_{12} (estimated as 11.130% and −11.347%). By adding an extra sub-state within each main state, sharp fluctuations in real GDP growth (see Figure 2.4) experienced only in coronavirus pandemic era is captured as explained before. Although relatively small increase in terms of absolute values can be observed in both "recovery" and "mild recession" (that is, μ_{01} and μ_{10}) compared to the hierarchical model with pre-pandemic sample, slightly larger shifts in "growth" and "deep recession" sub-states might be noticed. This difference arising from unprecedented fluctuations during coronavirus period implies that an economy has to experience larger rise(or, decline) in real output in order to be included in upper level of expansion (or, recession) phase.

According to the transition probabilities p_{ii} $(i = 0, 1)$ resulted from hierarchical model with three sub-states, expected duration for "expansion" regime is calculated as 17.86 quarters and "recession" regime is expected to last for 3.61 quarters. The probability of being in "mild recession" sub-regime (q_{10}) decreased ,as expected, due to the existence of "pandemic (great) decline" sub-state, whereas there is no considerable change in the conditional probability q_{01} representing "recovery" sub-state. This outcome implies that the coronavirus pandemic had affected the structure of "recession" regime in noticeable way.

The hierarchical Markov mixture models have another important output which enables us to observe(or, compare) regime shifts: filtered probabilities. Using these generated probabilities, the ability of hierarchical model to capture regime shifts (i.e. recessionary and expansionary phases) can be evaluated by means of historical perspective. As an example, graphs that are constructed via filtered probabilities for the United States, Turkey and selected eurozone countries will be investigated for this purpose. It should be emphasized that both hierarchical model with two sub-states and one with three sub-states have almost the same performance on detecting regime shifts, especially in "mild recession" and "deep recession" sub-regimes.

From Figure A.1 and A.6 in Appendix A, periods at which smoothed probabilities rapidly increase to upper levels, coincide with mild and deep recessions in the economic history of the United States. The 1960-1961 Recession can be seen from both mentioned graphs. It should be stated that second stage of the 1970 Recession which was closely related to the strike at General Motors in Fall 1970 (emphasized by [McNees, 1992]) is captured as relatively small peak in "deep recession" probability at the end of 1970 whereas the first stage of this recession is classified as "mild recession". This outcome is consistent with the trough point announced by NBER Business Cycle Dating Committee as November 1970.

The subsequent recessionary period had been experienced between 1973-1975. The oil embargo(or, sanction) initiated by Arab oil-producer countries as a reaction to Israel is thought as the main stimulus for this period. This recession was considered as the starting point of long-lasting "stagflation" era (that is, high inflation and sluggish growth rates) on a global scale, stated by [Kose et al., 2020] According to [McNees, 1992], the similar two-stage structure can be observed during the 1973-1975 Recession. Although no severe decline in economic indicators (e.g. industrial production and unemployment rate) had been observed in the first stage (ended in September 1974 according to [McNees, 1992]), there was clear clues about the amplitude of this recession such as drastic rise in unemployment rate. [McNees, 1992] stated that the core inflation had reached its local maximum in February 1975. This partitioned structure can be understood from movements in filtered probabilities in these periods. If the figure related to "deep recession" is examined, it can be noticed that the probability of deep recession gradually increases towards the end of 1973-1975 recession.

Another oil price shock aroused mainly from Iran and contractionary policies such as rise in the federal funds rate led to the series of recessions at the beginning of new decade(1980s). [McNees, 1992] claimed that 1980 and 1981-1982 recessions may be considered as a "single" recessionary period with two successive troughs that had been stated as unprecedented for the post-WWII period. This claim can be clearly seen from the graph for probability of ”deep recession” sub-state in the United States (at the bottom of Figure A.1 and Figure A.6). Both hierarchical models with fixed transition probabilities are able to indicate these consecutive recessions.

Unlike the recessions of early 1980s, the 1990-1991 recession should be included mainly in ”mild recession” sub-regime according to the filtered probabilities resulted from hierarchical models(consistent with the interpretation by [McNees, 1992]). The recession caused by dot-com bubble in 2000 is also counted as ”mild recession” which has negligible probability of being in ”deep recession”.

Unsurprisingly, the Global Financial Crisis (also called Great Recession) occurred between 2007 and 2009 is included in ”deep recession” sub-state with almost certain probability. The important point deduced from filtered probability graph (Figure A.2), is that the probability value denoting ”recovery” gradually turned back to its pre-crisis levels (also stated in [Kose et al., 2020]). This implies that the recovery from the Great Recession had been experienced at slow pace which is consistent with the ”stylized fact” emphasized by [Jordà et al., 2013]. They claimed that severe recessions and sluggish recovery more likely succeed expansionary periods with high levels of credit as in the Great Recession. Following this deep recession, EU member countries had faced with relatively long-lasting sovereign debt crises in early 2010s. As seen from Figure A.5 and Figure A.10, probability values for ”mild recession” sub-regime indicate the mentioned debt crises among EU economies. In accordance with the historical records, Greece has very high probability values corresponding to ”mild recession” for relatively longer periods, compared to other selected countries. Lastly, the only contraction considered as ”pandemic (great) decline” for the United States is the recession triggered by Covid-19 pandemic , because unprecedented real output growth rates had been recorded during the pandemic.

If filtered probabilities for Turkey are investigated within the historical perspective similar to the U.S. economy, it can be said that hierarchical models are able to distinguish well-known expansionary and recessionary periods starting from the first quarter of 1998. When the graph for "deep recession" in Figure A.8 is examined, the accordance with the Turkish economic history can be clearly observed. Turkey had experienced two deep (or, severe) economic crises at the beginning of twenty-first century (excluding coronavirus pandemic): 2001 Financial Crisis and the Global Recession. The financial crisis occurred in February 2001 was considered as an instance of "very severe" economic downturn according to [Cizre and Yeldan, 2005]. They argued that this crisis caused by combined policies became gradually effective such as ill-timed deregulation of financial markets throughout 1990s. With these policies, the Turkish economy was getting vulnerable (and sensitive) to the short-term fluctuations in capital flows from (or, to) abroad ([Cizre and Yeldan, 2005]).

If the graph for "mild recession" that corresponds to the Turkish economy is examined via Figure A.3 and Figure A.8, the first case described as mild recession is the 1998 crisis caused particularly by spread of the 1997 Asian Crises' financial consequences. ([Orhangazi and Yeldan, 2021]) The most interesting point might be stated as the gradual increase in the probability of "mild recession" after the Global Financial Crisis (that is, 2010s). [Orhangazi and Yeldan, 2021] stated the possible reason behind this observation as the shift in the perception on overall economic conditions led by considerable issues. This gradual rise reached its peak in August 2018 when a kind of exchange rate crisis (i.e., sharp depreciation in domestic currency) emerged. In addition, these periods ,at which hikes in the filtered probability of "mild recession" are observed during late 2010s, coincide with the sudden declines in "foreign capital inflows" in US dollars illustrated in the study [Orhangazi and Yeldan, 2021].

Table 4.2: Results for Hierarchical Markov Mixture Model with Fixed Probabilities

	2-Substate HMNM Pre-Pandemic Sample	**2-Substate HMNM** Full Sample
μ_{00}	3.358 (0.107)	10.199 (0.352)
μ_{01}	0.816 (0.022)	0.805 (0.017)
μ_{10}	-0.512 (0.102)	-2.398 (0.135)
μ_{11}	-3.147 (0.187)	-11.261 (0.205)
σ^2	0.533 (0.019)	1.121 (0.027)
p_{00}	0.946 (0.0059)***	0.975 (0.0028)***
p_{01}	0.054 (0.0059)***	0.025 (0.0028)***
p_{10}	0.257 (0.0223)***	0.306 (0.0268)***
p_{11}	0.743 (0.0223)***	0.694 (0.0268)***
q_{00}	0.051 (0.0054)***	0.009 (0.0016)***
q_{01}	0.949 (0.0054)***	0.991 (0.0016)***
q_{10}	0.849 (0.0214)***	0.805 (0.0300)***
q_{11}	0.151 (0.0214)***	0.195 (0.0300)***
Marginal Log-Likelihood	-4585.89	-6405.74

The table above indicates the Bayesian simulation outcome of the hierarchical Markov mixture model which contains two main regimes and two sub-regimes. A fixed probability p_{ij} denotes the probability of transition from the main state i to the main state j. Another fixed probability q_{ij} corresponds to the probability of being in the sub-state j conditional on the main state i. There are four different regimes in total. The state labels 00, 01, 10 and 11 represent regimes "growth","recovery","mild recession" and "deep recession", respectively. It should be emphasized that regime mean values, μ_{ij}, should be interpreted as percentage growth rate in real output.
* within the 90% HPDI(Highest Posterior Density Interval)
** within the 95% HPDI(Highest Posterior Density Interval)
*** within the 99% HPDI(Highest Posterior Density Interval)

Table 4.3: Results for Hierarchical Markov Mixture Model with Fixed Probabilities

	3-Substate HMNM Full Sample
μ_{02}	11.130 (0.227)
μ_{00}	3.845 (0.132)
μ_{01}	0.826 (0.023)
μ_{10}	-0.520 (0.149)
μ_{11}	-3.348 (0.215)
μ_{12}	-11.347 (0.199)
σ^2	0.707 (0.024)
p_{00}	0.944 (0.0064)***
p_{01}	0.056 (0.0064)***
p_{10}	0.277 (0.0248)***
p_{11}	0.723 (0.0248)***
q_{00}	0.040 (0.0046)***
q_{01}	0.951 (0.0048)***
q_{02}	0.009 (0.0015)***
q_{10}	0.818 (0.0205)***
q_{11}	0.127 (0.0176)***
q_{12}	0.055 (0.0102)***
Marginal Log-Likelihood	-5560.35

The table above indicates the Bayesian simulation outcome of the hierarchical Markov mixture model which contains two main regimes and three sub-regimes. A fixed probability p_{ij} denotes the probability of transition from the main state i to the main state j. Another fixed probability q_{ij} corresponds to the probability of being in the sub-state j conditional on the main state i. There are six different regimes in total. The state labels 00, 01, 02, 10, 11 and 12 represent regimes "growth","recovery","pandemic (great) expansion","mild recession","deep recession" and "pandemic (great) decline", respectively. It should be emphasized that regime mean values, μ_{ij}, should be interpreted as percentage growth rate in real output.
* within the 90% HPDI(Highest Posterior Density Interval)
** within the 95% HPDI(Highest Posterior Density Interval)
*** within the 99% HPDI(Highest Posterior Density Interval)

4.2.2 Time-Varying Probability (TVP) Model with Credit-to-GDP Ratio

In the former section, the model output with the assumption that transition probabilities in Markov process are constant for all periods, were investigated. By permitting time-varying transition probabilities, selected factors (or, explanatory variables) will be pursued in order to obtain a meaningful relation. In this study, the main concern is about credit-related variables such as credit-to-GDP ratio and real credit growth. As [Gadea Rivas and Perez-Quiros, 2015] did before, the possible effect of credit-related variables on business cycle fluctuations will be investigated by constructing Markov switching models with fixed regime means and time-varying transition probabilities.

For the specification of time-varying probability, probit model (or, binary response model expressed by [Wooldridge, 2010a]) is employed. In the probit model, the "first lag" of credit-to-GDP ratio (CR_{t-1}) is thought as an explanatory variable with coefficient β_i (and θ_i for conditional probabilities) for each main regime ($i = 0, 1$). In order to be in harmony with the previous section, firstly, empirical results for hierarchical model based on pre-pandemic sample will be interpreted. From results shown in the Table 4.7, it can be said that there are relatively small changes in estimated mean values μ_{ij} compared to the same model (HMNM with two sub-states) with fixed probabilities shown in Table 4.2. Also, there exists a little improvement in the marginal log-likelihood value and decrease in the estimated model variance σ^2 in the hierarchical model with time-varying probabilities. If transition probabilities are considered, following probit model equations can be formed according to the estimation results:

$$p_{00,t} = \Phi\big(\mathbf{1.6231} - 0.0045 \times CR_{t-1}\big) \quad (4.6)$$

$$p_{11,t} = \Phi\big(0.0505 + \mathbf{0.2841} \times CR_{t-1}\big) \quad (4.7)$$

The probability of transition to "recession" from "recession" increases as rise in credit-to-GDP ratio is observed (as seen from the equation 4.7) which also implies that the such rise leads to an increase in expected duration of recessionary period.

Unlike the "recession" regime, the credit-to-GDP ratio does not have significant effect on the probability of transition to "expansion" from "expansion" state (in equation 4.6). However, the estimated intercept of the probit model means that this probability will move approximately around the value 0.948 which is close to the its counterpart on the model with fixed probabilities (0.946).

When the conditional probabilities which correspond to sub-regimes are examined through the probit model that can be described as below:

$$q_{01,t} = \Phi\big(\mathbf{1.0299\ +\ 0.5584} \times CR_{t-1}\big) \tag{4.8}$$

$$q_{11,t} = \Phi\big(\mathbf{\text{-}0.440\ \text{-}\ 0.5127} \times CR_{t-1}\big) \tag{4.9}$$

According to the estimated parameters of probit model in 4.8, given that the current period is included in "expansion" regime, a rise in credit-to-GDP ratio decreases the probability of being in "growth" sub-state (that is, negative effect on observing great levels of real output growth). On the other hand, as understood from 4.9, conditional on being in "recession" regime, credit-to-GDP ratio decreases the probability of being in "deep recession" sub-regime. Hence, it can be claimed that credit-to-GDP ratio makes greater levels of real output growth in both direction less probable to occur which implies a kind of smoothing in business cycles.

If the hierarchical model for full sample (that is, with three sub-states) is investigated, there exist considerable changes in mean values related to "mild recession" and "deep recession" sub-regimes compared to the fixed probabilities model with the same sample (see Table 4.3 and Table 4.6). Also, unlike the HMNM model with two sub-states, the positive effect of credit-to-GDP ratio on the probability of transition to "recession" from "recession" seem to be disappeared (Table 4.6) in this model. These distortions on recession-related results may be caused by the movement of credit-to-GDP ratio during the pandemic which can be observed through Figure A.3 for the United States[4].

[4]Because the U.S. has official business cycle dating procedure led by NBER

The probability of transition from "expansion" to "expansion" is mainly determined by the intercept term in the probit model:

$$p_{00,t} = \Phi\big(\mathbf{1.7223} + 0.0392 \times CR_{t-1}\big) \tag{4.10}$$

which implies that this probability fluctuates around 0.957, slightly higher than its counterpart in the fixed probability model. Since there are three sub-states for each regime in this hierarchical model, threshold parameters should be taken into consideration during the interpretation of estimation results for conditional probabilities (see [Wooldridge, 2010b]). To prevent identification problems, one of the threshold parameters is fixed on the zero value whereas another one is enabled to adjust. In "recession" phase, following equations can be constructed (as stated in set of equations 3.8):

$$q_{10,t} = \Phi(\mathbf{1.1153} - \mathbf{0.3426}CR_{t-1}) \tag{4.11}$$

$$q_{11,t} = \Phi(0.793 + \mathbf{1.1153} - \mathbf{0.3426}CR_{t-1}) - \Phi(\mathbf{1.1153} - \mathbf{0.3426}CR_{t-1}) \tag{4.12}$$

$$q_{12,t} = 1 - \Phi(0.793 + \mathbf{1.1153} - \mathbf{0.3426}CR_{t-1}) \tag{4.13}$$

where the upper threshold moves around the value 0.793 according to the model. According to estimated ordered response model parameters, conditional on being in "recession" regime, high levels of credit-to-GDP ratio decreases only the probability of being in "mild recession" which confronts the corresponding result deduced from the previous model based on pre-pandemic sample. For the "expansion" phase, the equations belong to the ordered probit model is formed as:

$$q_{00,t} = \Phi(\mathbf{\text{-}1.4138} - \mathbf{0.3135}CR_{t-1}) \tag{4.14}$$

$$q_{01,t} = \Phi(4.32\ \mathbf{\text{-}\ 1.4138} - \mathbf{0.3135}CR_{t-1}) - \Phi(\mathbf{\text{-}1.4138} - \mathbf{0.3135}CR_{t-1}) \tag{4.15}$$

$$q_{02,t} = 1 - \Phi(4.32\ \mathbf{\text{-}\ 1.4138} - \mathbf{0.3135}CR_{t-1}) \tag{4.16}$$

where the upper threshold seems to fluctuate around 4.32 in this model. With the help of these estimated parameters, it can be stated that the rise in credit-to-

GDP ratio has negative effect only on the probability of being in "growth" sub-state (denoted as 00). It might be said that the inclusion of pandemic-related observations leads to some serious distortions on the relationship between real output growth and credit-to-GDP ratio, especially for "recession" regime.

4.2.3 TVP Model with Real Credit Growth and Annual Real Credit Growth

Other credit-related variables are listed as real credit growth(its first lag) and annual real credit growth (which is the sum of real credit growth occurred through four consecutive quarters) that are required to observe whether the credit growth(expansion) has significant effect on "amplitude" and "duration" of business cycles. (examined in [Jordà et al., 2013] and [Claessens et al., 2012]). If simulation results for the hierarchical model based on pre-pandemic sample (thus, with two sub-states) are investigated (given in Table 4.10), it can be claimed that rise in annual real credit growth (as a representative for "past credit accumulation" ([Jordà et al., 2013])) decreases the probability of two successive "expansion" regimes ($p_{00,t}$) whereas it increases the probability of transition to "recession" from "recession" as seen from equations below. Therefore, annual real credit growth ($ARCG_{t-2}$) has a positive effect on the expected duration of recessionary period, contrary to expansionary period.

$$p_{00,t} = \Phi\big(\mathbf{1.7093\ \text{-}\ 0.8332} \times ARCG_{t-2} - 1.1504 \times RCG_{t-1}\big) \tag{4.17}$$

$$p_{11,t} = \Phi\big(\mathbf{0.3123 + 1.7828} \times ARCG_{t-2} - 1.5720 \times RCG_{t-1}\big) \tag{4.18}$$

The reason why the annual real credit growth decreases the duration of "expansion" regime may be stated by the perception that the credit expansion may stimulate financial fragility(or, vulnerability) during expansionary times.

When the conditional probabilities related to "expansion" regime which may give some clues about the "amplitude" of expansion phase are examined via estimated parameters:

$$q_{01,t} = \Phi\big(\mathbf{1.8101 \text{ - } 1.4609} \times ARCG_{t-2} - 0.6628 \times RCG_{t-1}\big) \tag{4.19}$$

which implies that the probability of being in "recovery" sub-state decreases as annual real credit growth increases. This result is consistent with the findings of [Claessens et al., 2012]. For pre-pandemic period, it can be claimed that, conditional on "expansion" state, cumulative real credit growth magnifies the expansionary period(i.e. high levels of real output growth). Similar to the "expansion" regime, an increase in annual real credit growth makes "deep recession" (or, severe recession) more probable seen from the following equation:

$$q_{11,t} = \Phi\big(\mathbf{\text{- } 1.3654 + 2.0664} \times ARCG_{t-2} \mathbf{\text{ - } 4.648} \times RCG_{t-1}\big) \tag{4.20}$$

In other words, given that the economy is in "recession" phase, cumulative real credit growth has positive effect on the "amplitude" of recessionary period. However, in "recession" regime, positive real credit growth at the previous quarter decreases the probability of being in "deep recession". This result may be meaningful if rise in real credit growth at the former period is interpreted as a signal for recovery within recessionary period.

The empirical results obtained from the hierarchical model based on full sample (that is, with three sub-states) are shown in Table 4.11. Like in the previous model, rise in annual real credit growth can lead to a decrease in the probability of staying in "expansion" (thus, decrease in expected duration of expansionary period) whereas such rise can cause an increase in the probability of staying in "recession" regime (i.e., increase in expected duration of recessionary period) shown from following equations.

$$p_{00,t} = \Phi\big(\mathbf{1.7696 \text{ - } 0.7680} \times ARCG_{t-2} + 0.2007 \times RCG_{t-1}\big) \tag{4.21}$$

$$p_{11,t} = \Phi\big(0.0748 \mathbf{+ 1.8090} \times ARCG_{t-2} + 0.6145 \times RCG_{t-1}\big) \tag{4.22}$$

For the full sample, the effect of annual real credit growth on sub-states related to "recession" seems to be disappeared, compared to the hierarchical model based on pre-pandemic sample. Within the scope of conditional probabilities, real credit growth of the previous quarter has positive effect on the probability of being in "mild recession" as in the former model(shown at the equation 4.26). Given that the economy is in "expansion" regime, cumulative real credit growth may lead to an increase in the probability of being in "growth" sub-state (or, higher real output growth rates) which can be deduced from the equation 4.23. Lastly, it should be emphasized that there are improvements in marginal log-likelihood values for both models aforementioned, compared to model at which only the credit-to-GDP ratio is used as explanatory variable to estimate model parameters.

$$q_{00,t} = \Phi(-\mathbf{1.8850} + \mathbf{1.3419} \times ARCG_{t-2} - 0.5489 \times RCG_{t-1}) \tag{4.23}$$

$$\begin{aligned} q_{01,t} &= \Phi(4.346 - \mathbf{1.8850} + \mathbf{1.3419} \times ARCG_{t-2} - 0.5489 \times RCG_{t-1}) \\ &\quad - \Phi(-\mathbf{1.8850} + \mathbf{1.3419} \times ARCG_{t-2} - 0.5489 \times RCG_{t-1}) \end{aligned} \tag{4.24}$$

$$q_{02,t} = 1 - \Phi(4.346 - \mathbf{1.8850} + \mathbf{1.3419} \times ARCG_{t-2} - 0.5489 \times RCG_{t-1}) \tag{4.25}$$

$$q_{10,t} = \Phi(\mathbf{0.7211} + 0.5314 \times ARCG_{t-2} + \mathbf{4.7034} \times RCG_{t-1}) \tag{4.26}$$

$$\begin{aligned} q_{11,t} &= \Phi(0.699 + \mathbf{0.7211} + 0.5314 \times ARCG_{t-2} + \mathbf{4.7034} \times RCG_{t-1} \\ &\quad - \Phi(\mathbf{0.7211} + 0.5314 \times ARCG_{t-2} + \mathbf{4.7034} \times RCG_{t-1}) \end{aligned} \tag{4.27}$$

$$q_{12,t} = 1 - \Phi(0.699 + \mathbf{0.7211} + 0.5314 \times ARCG_{t-2} + \mathbf{4.7034} \times RCG_{t-1}) \tag{4.28}$$

4.2.4 TVP Model with Real Credit Growth and Leverage Indicator

As explained in the *Data Description* section, the variable denoted as $CR75_t$ is constructed in order to detect periods at which the credit-to-GDP ratio exceeds the threshold determined by 75^{th} percentile of the same sample. In order words, this dummy variable that takes 0 or 1, can be used as representative for high leverage.

From the estimated parameters for the transition probability $p_{11,t}$ in Table 4.12, it is said that experiencing a recession during the high leverage period might be more long-lasting. Thus, being in the high leverage status considerably increases the expected duration of "recession" regime. Similar to the model in Table 4.10, annual real credit growth can also increase the expected duration of "recession" (or, increase the transition probability $p_{11,t}$) On the other hand, leverage indicator does not have any significant effect on the probability of transition from "expansion" to "expansion" for pre-pandemic periods.

Conditional on the "expansion" regime, although cumulative real credit growth increases the probability of being in "growth" sub-regime, there is a fall in the same probability under the high leverage conditions (The related parameter in Table 4.12 is positive). This might be explained by the financial instability(or, fragility) concept. But, this relation could not be seen in the "recession" phase. It seems that the leverage indicator does not have considerable effect on sub-regimes of "recession". However, both $ARCG_{t-2}$ and RCG_{t-1} have the same influence on "mild recession" and "deep recession" as these variables have in the model that excludes the leverage indicator (see Table 4.10).

When the hierarchical model for full sample (thus, with three sub-states for each main state) is taken into consideration, it can be noticed that the leverage indicator has no longer effect on the probability of transition to "recession" from "recession". This might be resulted from the fact that large number of countries had been recorded as highly leveraged during the Covid-19 pandemic. For the main regime "expansion", none of explanatory variables, except the intercept p_0, has no meaning for the transition probability of staying in "expansion" state. This probability varies around the value $\Phi(1.7952) \sim 0.964$, almost independent of the other credit-related variables. On the contrary, annual real credit growth preserves its effect on the transition probability of staying in "recession" regime. It increases the expected duration of recessionary period. Given that the economy is in "expansion" phase, it is clear that high leverage increases the probability of being in "recovery" sub-state. In other words, the economy currently in expansionary period is less likely to experience great levels of real output growth under high leverage conditions. The interesting result is that leverage indicator mitigates the effect of annual real credit growth conditional on ”expansion” regime. It might be said that unless the credit-to-GDP ratio exceed the high leverage threshold, ”past credit accumulation” ([Jordà et al., 2013]) behaves like a kind of stimulus for real output. Conditional on ”recession” phase, it is noticed that empirical results implies the same relation as in the model of which results are given at Table 4.11

Table 4.4: Results for 2-State Markov Mixture Model with Fixed Probabilities

	2-State MNM Pre-Pandemic Sample	**2-State MNM** Full Sample
μ_0	0.799 (0.094)	0.755 (0.015)
μ_1	-2.226 (0.165)	-10.835 (0.232)
σ^2	0.970 (0.039)	2.047 (0.044)
p_{00}	0.981 (0.0055)	0.992 (0.0013)
p_{01}	0.019 (0.0055)	0.008 (0.0013)
p_{10}	0.387 (0.0393)	0.455 (0.0514)
p_{11}	0.613 (0.0393)	0.545 (0.0514)
Marginal Log-Likelihood	-Inf	-7694.38

The table above indicates the Bayesian simulation outcome of the Markov mixture model which contains two regimes: "expansion" and "recession". A fixed probability p_{ij} denotes the probability of transition from the main state i to the main state j. The state labels 0 and 1 represent regimes "expansion" and "recession", respectively. It should be emphasized that regime mean values, μ_{ij}, should be interpreted as percentage growth rate in real output.

Table 4.5: Results for 4-State Markov Mixture Model with Fixed Probabilities

	4-State MNM Pre-Pandemic Sample	**4-State MNM** Full Sample
μ_0	3.039 (0.104)	9.330 (0.456)
μ_1	0.683 (0.019)	0.762 (0.016)
μ_2	-1.880 (0.234)	-3.079 (0.140)
μ_3	-4.772 (0.730)	-11.305 (0.192)
σ^2	0.601 (0.022)	1.165 (0.028)
p_{00}	0.302 (0.0299)	0.041 (0.0148)
p_{01}	0.509 (0.0361)	0.880 (0.0239)
p_{02}	0.183 (0.0237)	0.053 (0.0194)
p_{03}	0.006 (0.0038)	0.026 (0.0083)
p_{10}	0.032 (0.0028)	0.003 (0.0004)
p_{11}	0.934 (0.0040)	0.970 (0.0016)
p_{12}	0.029 (0.0028)	0.022 (0.0016)
p_{13}	0.005 (0.0012)	0.005 (0.0005)
p_{20}	0.260 (0.0241)	0.093 (0.0166)
p_{21}	0.507 (0.0302)	0.598 (0.0287)
p_{22}	0.143 (0.0390)	0.104 (0.0176)
p_{23}	0.090 (0.0314)	0.205 (0.0179)
p_{30}	0.199 (0.0508)	0.759 (0.0393)
p_{31}	0.385 (0.0676)	0.154 (0.0376)
p_{32}	0.356 (0.0624)	0.058 (0.0130)
p_{33}	0.060 (0.0260)	0.029 (0.0089)
Marginal Log-Likelihood	-4798.85	-6531.98

In this table, posterior simulation results related to 4-state Markov mixture model can be observed. Mean values and standard deviations (in parenthesis) obtained via Monte Carlo integration, are listed above. A fixed probability p_{ij} denotes the probability of transition from the state i to the state j. The state labels 0,1,2 and 3 represent the regimes "growth", "recovery", "mild recession" and "deep(severe) recession", respectively. The first two regimes are included in *expansion* phase. Regime mean values, μ_i, should be interpreted as percentage growth rate in real output.

Table 4.6: Results for Hierarchical MNM Model with Time-Varying Probabilities according to Credit-to-GDP Ratio

	3-Substate HMNM-TVP
	Full Sample
μ_{02}	11.109 (0.222)
μ_{00}	3.779 (0.121)
μ_{01}	0.753 (0.020)
μ_{10}	-1.528 (0.210)
μ_{11}	-4.163 (0.403)
μ_{12}	-11.491 (0.209)
σ^2	0.721 (0.023)
p_0	1.7223 (0.1040)***
β_0	0.0392 (0.0760)
p_1	-0.0763 (0.2339)
β_1	0.0609 (0.1540)
q_0	1.4138 (0.0909)***
θ_0	0.3135 (0.0622)***
q_1	-1.1153 (0.2638)***
θ_1	0.3426 (0.1736)*
Marginal Log-Likelihood	-5523.66

The table above indicates the Bayesian simulation outcome of the hierarchical Markov mixture model which contains two main regimes and three sub-regimes. There are six different regimes in total. The state labels 00, 01, 02, 10, 11 and 12 represent regimes ”growth”,”recovery”,”pandemic expansion”,”mild recession”,”deep recession” and ”pandemic decline”, respectively. It should be emphasized that regime mean values, μ_{ij}, should be interpreted as percentage growth rate in real output.
* within the 90% HPDI(Highest Posterior Density Interval)
** within the 95% HPDI(Highest Posterior Density Interval)
*** within the 99% HPDI(Highest Posterior Density Interval)

Table 4.7: Results for Hierarchical MNM Model with Time-Varying Probabilities according to Credit-to-GDP Ratio

	2-Substate HMNM-TVP Pre-Pandemic Sample
μ_{00}	3.321 (0.105)
μ_{01}	0.808 (0.023)
μ_{10}	-0.602 (0.118)
μ_{11}	-3.226 (0.194)
σ^2	0.525 (0.019)
p_0	1.6231 (0.1124)**
β_0	-0.0045 (0.0808)
p_1	0.0505 (0.1896)
β_1	0.2841 (0.1278)**
q_0	1.0299 (0.0992)***
θ_0	0.5584 (0.0822)***
q_1	-0.4440 (0.2240)**
θ_1	-0.5127 (0.1498)***
Marginal Log-Likelihood	-4537.28

The table above indicates the Bayesian simulation outcome of the hierarchical Markov mixture model which contains two main regimes and two sub-regimes.There are four different regimes in total. The time-varying transition probability $p_{ii,t}$ is defined by the equation $p_{ii,t} = \Phi(p_i + \beta_i CR_{t-1})$ where CR_{t-1} represents the credit-to-GDP ratio. The time-varying probability that belongs to the sub-states $q_{i,t}$ is expressed by $q_{i,t} = \Phi(q_i + \theta_i CR_{t-1})$ The state labels 00, 01, 10 and 11 represent regimes "growth","recovery","mild recession" and "deep recession", respectively. The value $q_{0,t}$ denotes the probability of being in "recovery" (when the main regime is *expansion*) whereas $q_{1,t}$ indicates the probability of "deep recession"(when the main state is *recession*).It should be emphasized that regime mean values, μ_{ij}, should be interpreted as percentage growth rate in real output.
* within the 90% HPDI(Highest Posterior Density Interval)
** within the 95% HPDI(Highest Posterior Density Interval)
*** within the 99% HPDI(Highest Posterior Density Interval)

Table 4.8: Results for Hierarchical MNM Model with Time-Varying Probabilities according to Credit-to-GDP Ratio

	2-Substate HMNM-TVP
	Full Sample
μ_{00}	10.388 (0.318)
μ_{01}	0.807 (0.017)
μ_{10}	-2.498 (0.129)
μ_{11}	-11.276 (0.197)
σ^2	1.112 (0.027)
p_0	1.9102 (0.1137)***
β_0	0.0372 (0.0790)
p_1	-0.2897 (0.2605)
β_1	0.1033 (0.1768)
q_0	2.8024 (0.1953)***
θ_0	-0.2299 (0.1182)**
q_1	-1.5457 (0.2944)***
θ_1	0.4122 (0.1919)**
Marginal Log-Likelihood	-6383.05

The table above indicates the Bayesian simulation outcome of the hierarchical Markov mixture model which contains two main regimes and two sub-regimes.There are four different regimes in total. The time-varying transition probability $p_{ii,t}$ is defined by the equation $p_{ii,t} = \Phi(p_i + \beta_i CR_{t-1})$ where CR_{t-1} represents the credit-to-GDP ratio. The time-varying probability that belongs to the sub-states $q_{i,t}$ is expressed by $q_{i,t} = \Phi(q_i + \theta_i CR_{t-1})$ The state labels 00, 01, 10 and 11 represent regimes "growth","recovery","mild recession" and "deep recession", respectively. The value $q_{0,t}$ denotes the probability of being in "recovery" (when the main regime is *expansion*) whereas $q_{1,t}$ indicates the probability of "deep recession"(when the main state is *recession*).It should be emphasized that regime mean values, μ_{ij}, should be interpreted as percentage growth rate in real output.
* within the 90% HPDI(Highest Posterior Density Interval)
** within the 95% HPDI(Highest Posterior Density Interval)
*** within the 99% HPDI(Highest Posterior Density Interval)

Table 4.9: Results for 2-state MNM Model with Time-Varying Probabilities according to Credit-to-GDP Ratio

	2-State MNM Pre-Pandemic Sample	**2-State MNM** Full Sample
μ_0	0.797 (0.017)	0.758 (0.017)
μ_1	-2.295 (0.127)	-10.652 (0.964)
σ^2	0.961 (0.024)	2.060 (0.112)
p_0	1.7762 (0.1248)***	2.7457 (0.1760)***
β_0	0.2395 (0.0998)**	-0.2299 (0.1113)**
p_1	-0.4472 (0.2883)	NaN (NaN)
β_1	0.3391 (0.2186)	NaN (NaN)
Marginal Log-Likelihood	-5627.03	-Inf

The table above indicates the Bayesian simulation outcome of the Markov mixture model which contains two regimes: "expansion" and "recession". The time-varying transition probability $p_{ii,t}$ is defined by the equation $p_{ii,t} = \Phi(p_i + \beta_i CR_{t-1})$ where CR_{t-1} represents the credit-to-GDP ratio used as explanatory variable in probit model. The state labels 0 and 1 represent regimes "expansion" and "recession", respectively. It should be emphasized that regime mean values, μ_{ij}, should be interpreted as percentage growth rate in real output.

Table 4.10: Results for Hierarchical MNM Model with Time-Varying Probabilities according to Real Credit Growth and Annual Real Credit Growth

		2-Substate HMNM-TVP Pre-Pandemic Sample
	μ_{00}	3.289 (0.114)
	μ_{01}	0.802 (0.024)
	μ_{10}	-0.678 (0.127)
	μ_{11}	-3.417 (0.201)
	σ^2	0.517 (0.018)
	p_0	1.7093 (0.0663)***
$ARCG_{t-2}$	$\beta_{0,1}$	-0.8332 (0.3854)**
RCG_{t-1}	$\beta_{0,2}$	-1.1504 (0.8023)
	p_1	0.3123 (0.1258)**
$ARCG_{t-2}$	$\beta_{1,1}$	1.7828 (0.6136)***
RCG_{t-1}	$\beta_{1,2}$	-1.5720 (1.0572)
	q_0	1.8101 (0.0660)***
$ARCG_{t-2}$	$\theta_{0,1}$	-1.4609 (0.4092)***
RCG_{t-1}	$\theta_{0,2}$	-0.6628 (0.7661)
	q_1	-1.3654 (0.1231)***
$ARCG_{t-2}$	$\theta_{1,1}$	2.0664 (0.7591)***
RCG_{t-1}	$\theta_{1,2}$	-4.6489 (1.1451)***
	Marginal Log-Likelihood	-4446.02

The table above indicates the Bayesian simulation outcome of the hierarchical Markov mixture model which contains two main regimes and two sub-regimes. There are four different regimes in total.
* within the 90% HPDI(Highest Posterior Density Interval)
** within the 95% HPDI(Highest Posterior Density Interval)
*** within the 99% HPDI(Highest Posterior Density Interval)

Table 4.11: Results for Hierarchical MNM Model with Time-Varying Probabilities according to Real Credit Growth and Annual Real Credit Growth

		3-Substate HMNM-TVP Full Sample
	μ_{02}	11.116 (0.229)
	μ_{00}	3.783 (0.127)
	μ_{01}	0.774 (0.027)
	μ_{10}	-1.110 (0.294)
	μ_{11}	-3.759 (0.291)
	μ_{12}	-11.430 (0.213)
	σ^2	0.701 (0.022)
	p_0	1.7696 (0.0720)***
$ARCG_{t-2}$	$\beta_{0,1}$	-0.7680 (0.3995)*
RCG_{t-1}	$\beta_{0,2}$	0.2007 (0.8031)
	p_1	0.0748 (0.1841)
$ARCG_{t-2}$	$\beta_{1,1}$	1.8090 (0.7114)***
RCG_{t-1}	$\beta_{1,2}$	0.6145 (1.0884)
	q_0	1.8850 (0.0456)***
$ARCG_{t-2}$	$\theta_{0,1}$	-1.3419 (0.3141)***
RCG_{t-1}	$\theta_{0,2}$	0.5489 (0.6795)
	q_1	-0.7211 (0.1364)***
$ARCG_{t-2}$	$\theta_{1,1}$	-0.5314 (0.7964)
RCG_{t-1}	$\theta_{1,2}$	-4.7034 (1.0012)***
	Marginal Log-Likelihood	-5400.25

The table above indicates the Bayesian simulation outcome of the hierarchical Markov mixture model which contains two main regimes and three sub-regimes. There are six different regimes in total.
* within the 90% HPDI(Highest Posterior Density Interval)
** within the 95% HPDI(Highest Posterior Density Interval)
*** within the 99% HPDI(Highest Posterior Density Interval)

Table 4.12: Results for Hierarchical MNM Model with Time-Varying Probabilities according to Real Credit Growth and Leverage Indicator

		2-Substate HMNM-TVP
		Pre-Pandemic Sample
	μ_{00}	3.176 (0.111)
	μ_{01}	0.793 (0.023)
	μ_{10}	-0.654 (0.117)
	μ_{11}	-3.356 (0.199)
	σ^2	0.514 (0.019)
	p_0	1.6976 (0.0698)***
$ARCG_{t-2}$	$\beta_{0,1}$	-0.6734 (0.4089)*
$CR75_{t-1}$	$\beta_{0,2}$	0.1449 (0.1440)
$ARCG_{t-2} * CR75_{t-1}$	$\beta_{0,3}$	-1.3694 (1.1022)
RCG_{t-1}	$\beta_{0,4}$	-1.2534 (0.8256)
	p_1	0.2360 (0.1253)*
$ARCG_{t-2}$	$\beta_{1,1}$	1.6588 (0.6824)**
$CR75_{t-1}$	$\beta_{1,2}$	0.3943 (0.1992)**
$ARCG_{t-2} * CR75_{t-1}$	$\beta_{1,3}$	2.3307 (1.4474)
RCG_{t-1}	$\beta_{1,4}$	-0.9474 (1.0695)
	q_0	1.5926 (0.0674)***
$ARCG_{t-2}$	$\theta_{0,1}$	-0.9769 (0.4124)**
$CR75_{t-1}$	$\theta_{0,2}$	1.7346 (0.7367)***
$ARCG_{t-2} * CR75_{t-1}$	$\theta_{0,3}$	-1.0333 (3.0877)
RCG_{t-1}	$\theta_{0,4}$	-0.2756 (0.8106)
	q_1	-1.2340 (0.1520)***
$ARCG_{t-2}$	$\theta_{1,1}$	1.8031 (0.8603)**
$CR75_{t-1}$	$\theta_{1,2}$	-0.3335 (0.2397)
$ARCG_{t-2} * CR75_{t-1}$	$\theta_{1,3}$	-0.6413 (1.5499)
RCG_{t-1}	$\theta_{1,4}$	-5.1885 (1.1793)***
	Marginal Log-Likelihood	-4417.34

The table above indicates the Bayesian simulation outcome of the hierarchical Markov mixture model which contains two main regimes and three sub-regimes. There are six different regimes in total.
* within the 90% HPDI(Highest Posterior Density Interval)
** within the 95% HPDI(Highest Posterior Density Interval)
*** within the 99% HPDI(Highest Posterior Density Interval)

Table 4.13: Results for Hierarchical MNM Model with Time-Varying Probabilities according to Real Credit Growth and Leverage Indicator

		3-Substate HMNM-TVP Full Sample
	μ_{02}	11.115 (0.230)
	μ_{00}	3.723 (0.131)
	μ_{01}	0.764 (0.024)
	μ_{10}	-1.210 (0.232)
	μ_{11}	-3.836 (0.265)
	μ_{12}	-11.445 (0.211)
	σ^2	0.697 (0.022)
	p_0	1.7952 (0.0656)***
$ARCG_{t-2}$	$\beta_{0,1}$	-0.6323 (0.4412)
$CR75_{t-1}$	$\beta_{0,2}$	-0.0593 (0.1196)
$ARCG_{t-2} * CR75_{t-1}$	$\beta_{0,3}$	-0.7324 (0.9344)
RCG_{t-1}	$\beta_{0,4}$	0.1315 (0.7855)
	p_1	0.0527 (0.1588)
$ARCG_{t-2}$	$\beta_{1,1}$	1.8566 (0.7872)**
$CR75_{t-1}$	$\beta_{1,2}$	-0.1201 (0.2157)
$ARCG_{t-2} * CR75_{t-1}$	$\beta_{1,3}$	-0.4773 (1.6961)
RCG_{t-1}	$\beta_{1,4}$	0.4708 (1.0861)
	q_0	1.8017 (0.0560)***
$ARCG_{t-2}$	$\theta_{0,1}$	-1.2266 (0.3524)***
$CR75_{t-1}$	$\theta_{0,2}$	0.2558 (0.0926)***
$ARCG_{t-2} * CR75_{t-1}$	$\theta_{0,3}$	0.2696 (0.8227)*
RCG_{t-1}	$\theta_{0,4}$	0.6259 (0.7035)
	q_1	-0.8080 (0.1308)***
$ARCG_{t-2}$	$\theta_{1,1}$	-0.6766 (0.8558)
$CR75_{t-1}$	$\theta_{1,2}$	0.3797 (0.2384)
$ARCG_{t-2} * CR75_{t-1}$	$\theta_{1,3}$	2.1025 (1.7010)
RCG_{t-1}	$\theta_{1,4}$	-4.2237 (1.0355)***
	Marginal Log-Likelihood	-5396.75

The table above indicates the Bayesian simulation outcome of the hierarchical Markov mixture model which contains two main regimes and three sub-regimes. There are six different regimes in total.
* within the 90% HPDI(Highest Posterior Density Interval)
** within the 95% HPDI(Highest Posterior Density Interval)
*** within the 99% HPDI(Highest Posterior Density Interval)

Chapter 5

CONCLUSION

This research seeks for any evidence that there exists statistically significant and reasonable interaction between credit measures and business cycles, by means of HMNM model with time-varying transition probabilities. Following the findings that indicate a kind of relationship mentioned just before, possible effects of credit-related variables on business cycles are investigated in terms of their direction (i.e., positive or negative impact). Hence, simulation results seem to be consistent with the former studies in the literature. Main findings can be stated as follows: (a) high credit-to-GDP ratio (CR_{t-1}), causes an increase in the duration of recession phases for pre-pandemic era, (b) credit-to-GDP ratio is more likely to decrease magnitude of the current phase for both expansionary and recessionary periods which implies increased probabilities of "recovery" and "mild recession". However, if data elements from Covid-19 period are included in the sample, this relationship is reversed for the recession phase. (c) For both pre-pandemic sample and full sample, a rise in annual real credit growth ($ARCG_{t-2}$) probably leads to an increase in the expected duration of recession phase while it affects the expected duration of expansion phase in opposite way. The adverse effect of annual real credit growth on expansionary period can be thought as the sign of increased financial fragility during expansion phase. (d) Another finding related to this adverse impact states that annual real credit growth acts as a stimulus for real output unless the leverage indicator ($CR75_{t-1}$) takes value of 1 which implies high credit-to-GDP ratio. (e) Lastly, real credit growth (RCG_{t-1}) has tendency to mitigate downward effect of the recessionary period. In other words, rise in real credit growth makes mild recession sub-state more probable rather than deep recession. This outcome can be thought as the justification of credit expansion programs implemented by monetary and fiscal authorities during the coronavirus pandemic.

After summarizing all these findings of this research, it should be noted that there exists an inflationary period at global scale when this research has been just completed. Thus, it may lead interesting deductions if data sets employed here are expanded with incoming observations from these inflationary (with monetary contraction, as a response) periods. The scope of study can be modified according to pre-specified country groups(e.g., emerging markets and the European Union) in order to investigate whether these findings can vary (or, disappear) with different samples employed as input or not. From all results emphasized above, it can be said that the research is able to find an evidence for the interaction between credit-related variables and business cycles. Moreover, the hierarchical model with time-varying probabilities model may lead to original findings in future researches.

BIBLIOGRAPHY

[Albert and Chib, 1993] Albert, J. H. and Chib, S. (1993). Bayes inference via gibbs sampling of autoregressive time series subject to markov mean and variance shifts. *Journal of Business & Economic Statistics*, 11(1):1–15.

[Bry and Boschan, 1971] Bry, G. and Boschan, C. (1971). *Cyclical Analysis of Time Series: Selected Procedures and Computer Programs.* National Bureau of Economic Research New York, NY: Technical paper. National Bureau of Economic Research.

[Cizre and Yeldan, 2005] Cizre, m. and Yeldan, A. E. (2005). The turkish encounter with neo-liberalism: Economics and politics in the 2000/2001 crises. *Review of International Political Economy*, 12:387–408.

[Claessens et al., 2012] Claessens, S., Kose, M. A., and Terrones, M. E. (2012). How do business and financial cycles interact? *Journal of International Economics*, 87(1):178–190.

[Dembiermont et al., 2013] Dembiermont, C., Drehmann, M., and Muksakunratana, S. (2013). How much does the private sector really borrow? a new database for total credit to the private non-financial sector. *BIS Quarterly Review.*

[Gadea Rivas and Perez-Quiros, 2015] Gadea Rivas, M. D. and Perez-Quiros, G. (2015). The failure to predict the great recession—a view through the role of credit. *Journal of the European Economic Association*, 13.

[Geweke and Amisano, 2011] Geweke, J. and Amisano, G. (2011). Hierarchical markov normal mixture models with applications to financial asset returns. *Journal of Applied Econometrics*, 26(1):1–29.

[Gourinchas and Obstfeld, 2012] Gourinchas, P.-O. and Obstfeld, M. (2012). Stories of the twentieth century for the twenty-first. *American Economic Journal: Macroeconomics*, 4(1):226–65.

[Hamilton, 1989] Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57.

[Harding and Pagan, 2003] Harding, D. and Pagan, A. (2003). A comparison of two business cycle dating methods. *Journal of Economic Dynamics and Control*, 27.

[Jordà et al., 2013] Jordà, O., Schularick, M., and Taylor, A. M. (2013). When credit bites back. *Journal of Money, Credit and Banking*, 45.

[Kaminsky and Reinhart, 1999] Kaminsky, G. L. and Reinhart, C. M. (1999). The twin crises: The causes of banking and balance-of-payments problems. *American Economic Review*, 89(3):473–500.

[Kim and Nelson, 1999] Kim, C.-J. and Nelson, C. R. (1999). *State-Space Models with Regime Switching: Classical and Gibbs-Sampling Approaches with Applications*. The MIT Press.

[Koop, 2003] Koop, G. (2003). *Bayesian Econometrics*. Wiley.

[Kose et al., 2021] Kose, M. A., Ohnsorge, F., and Sugawara, N. (2021). A mountain of debt: Navigating the legacy of the pandemic. *Journal of Globalization and Development*, 13(2):233–268.

[Kose et al., 2020] Kose, M. A., Sugawara, N., and Terrones, M. E. (2020). Global recessions. *World Bank Prospects Group*.

[McNees, 1992] McNees, S. K. (1992). The 1990-91 recession in historical perspective. *New England Economic Review*.

[Orhangazi and Yeldan, 2021] Orhangazi, O. and Yeldan, A. E. (2021). The remaking of the turkish crisis. *Development and Change*, 52(3):460–503.

[Wooldridge, 2010a] Wooldridge, J. M. (2010a). *Binary Response Models*, pages 561–642. The MIT Press.

[Wooldridge, 2010b] Wooldridge, J. M. (2010b). *Multinomial and Ordered Response Models*, pages 643–666. The MIT Press.

Appendix A

FIGURES

A.1 Hierarchical Markov Mixture Model with Three Sub-Regimes

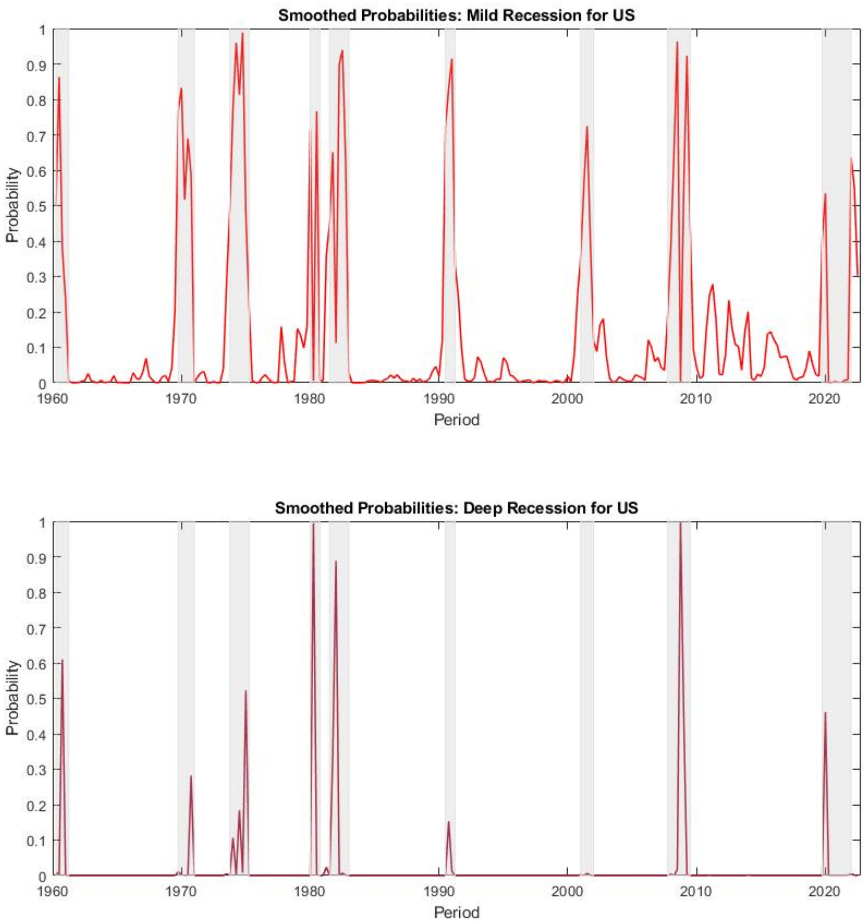


Figure A.1: Smoothed regime probabilities resulted from the model with three sub-states and fixed transition probabilities: Mild & Deep Recession in the U.S
Shaded areas represent recessionary periods announced by NBER Business Cycle Dating Committee.

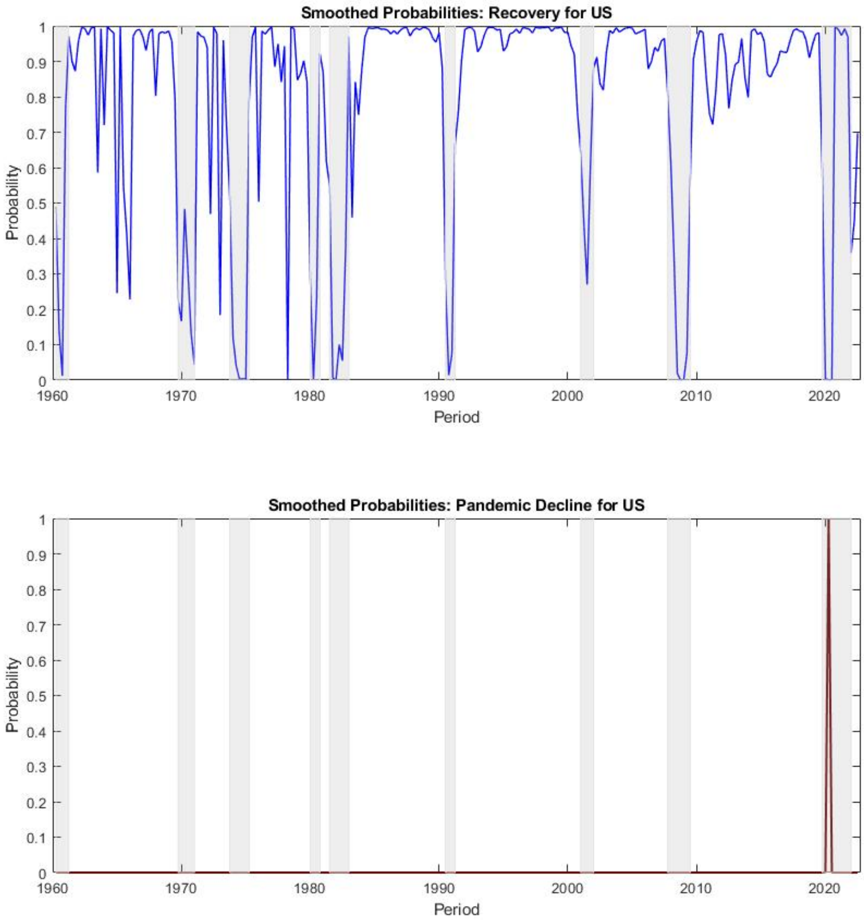


Figure A.2: Smoothed regime probabilities resulted from the model with three sub-states and fixed transition probabilities: Recovery & Pandemic Decline in the U.S. Shaded areas represent recessionary periods announced by NBER Business Cycle Dating Committee.

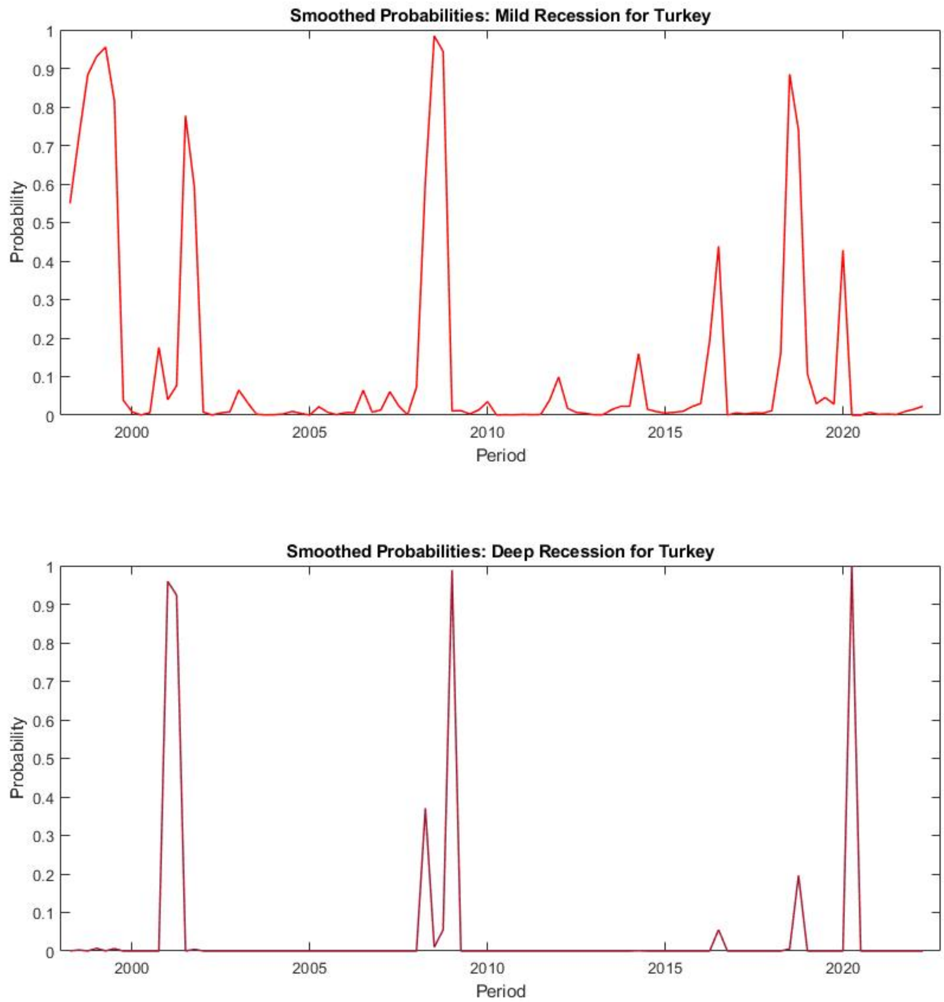


Figure A.3: Smoothed regime probabilities resulted from the model with three sub-states and fixed transition probabilities: Mild & Deep Recession in Turkey

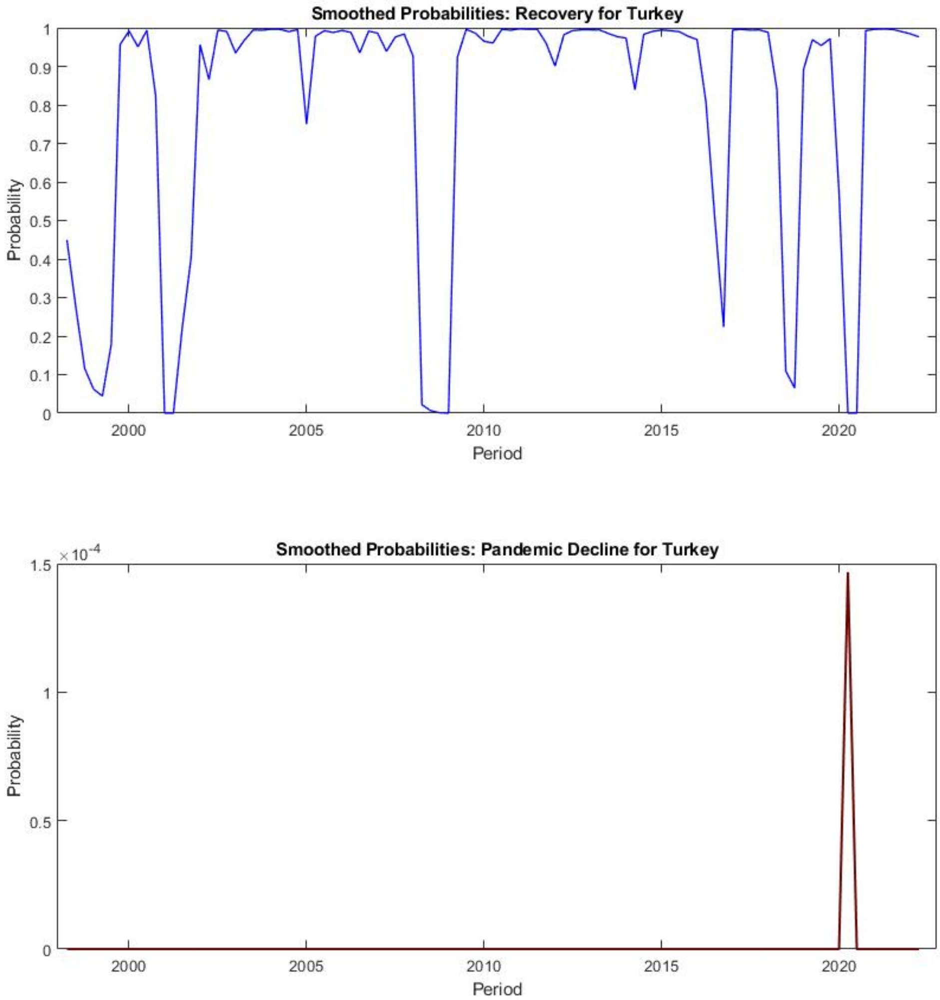


Figure A.4: Smoothed regime probabilities resulted from the model with three sub-states and fixed transition probabilities: Recovery & Pandemic Decline in Turkey

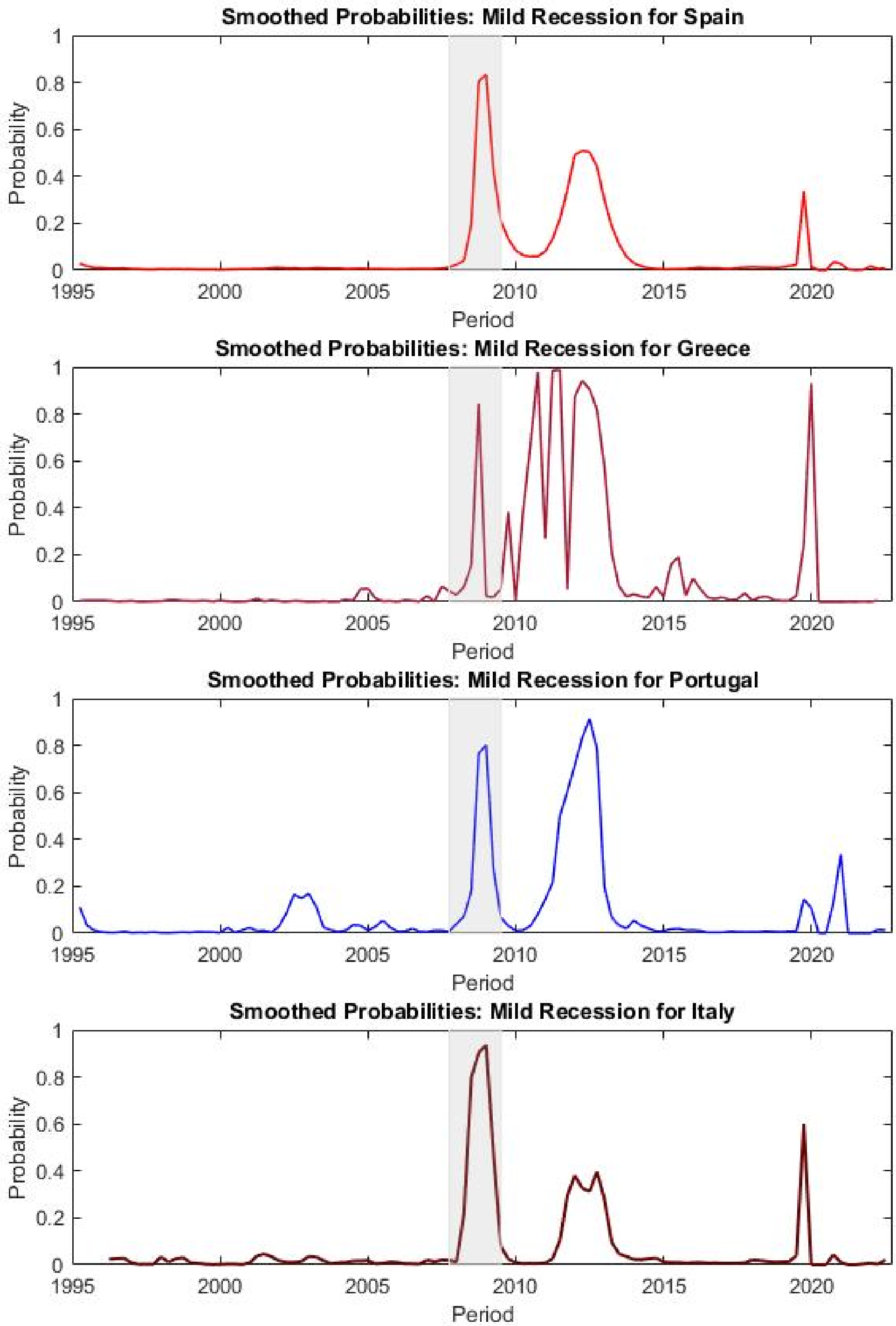


Figure A.5: Smoothed "Mild Recession" probabilities for four EU member states that had experienced sovereign debt crises after the global financial crisis.

A.2 Hierarchical Markov Mixture Model with Two Sub-Regimes

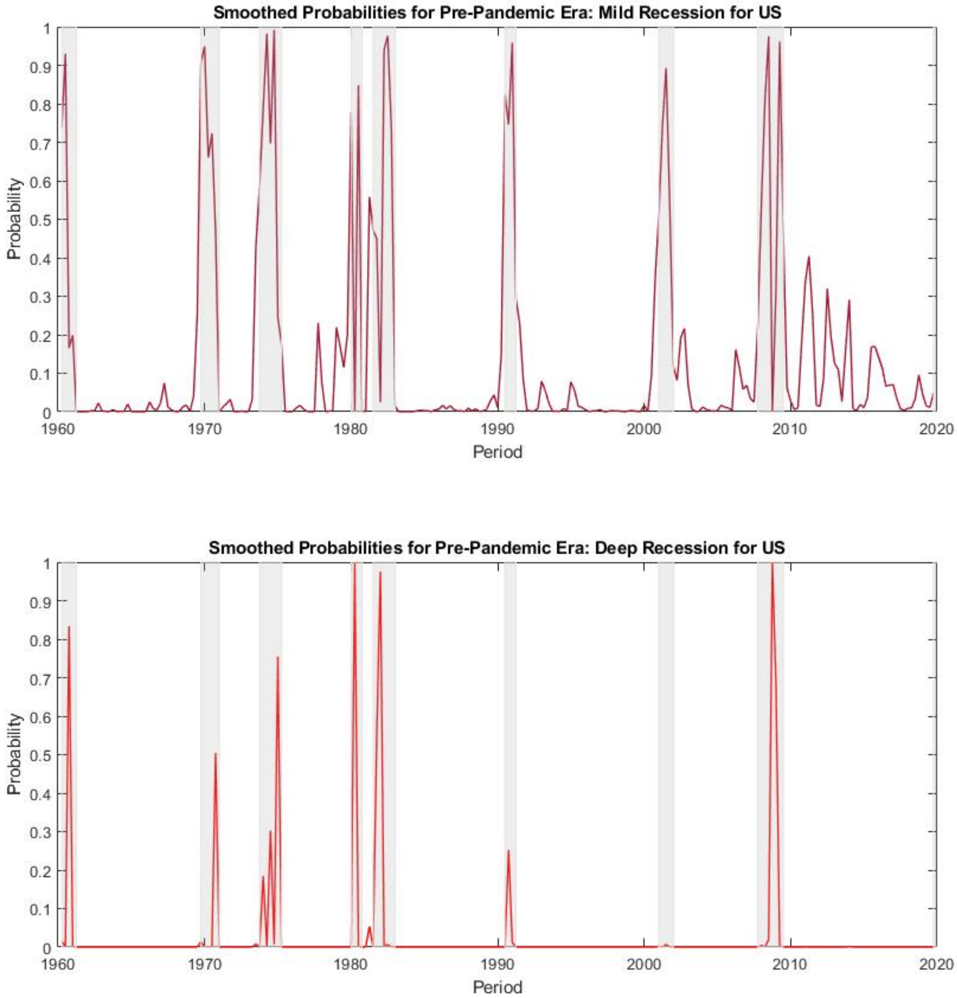


Figure A.6: Smoothed regime probabilities resulted from the model with two sub-states and fixed transition probabilities: Mild & Deep Recession in the U.S.
Shaded areas represent recessionary periods announced by NBER Business Cycle Dating Committee.

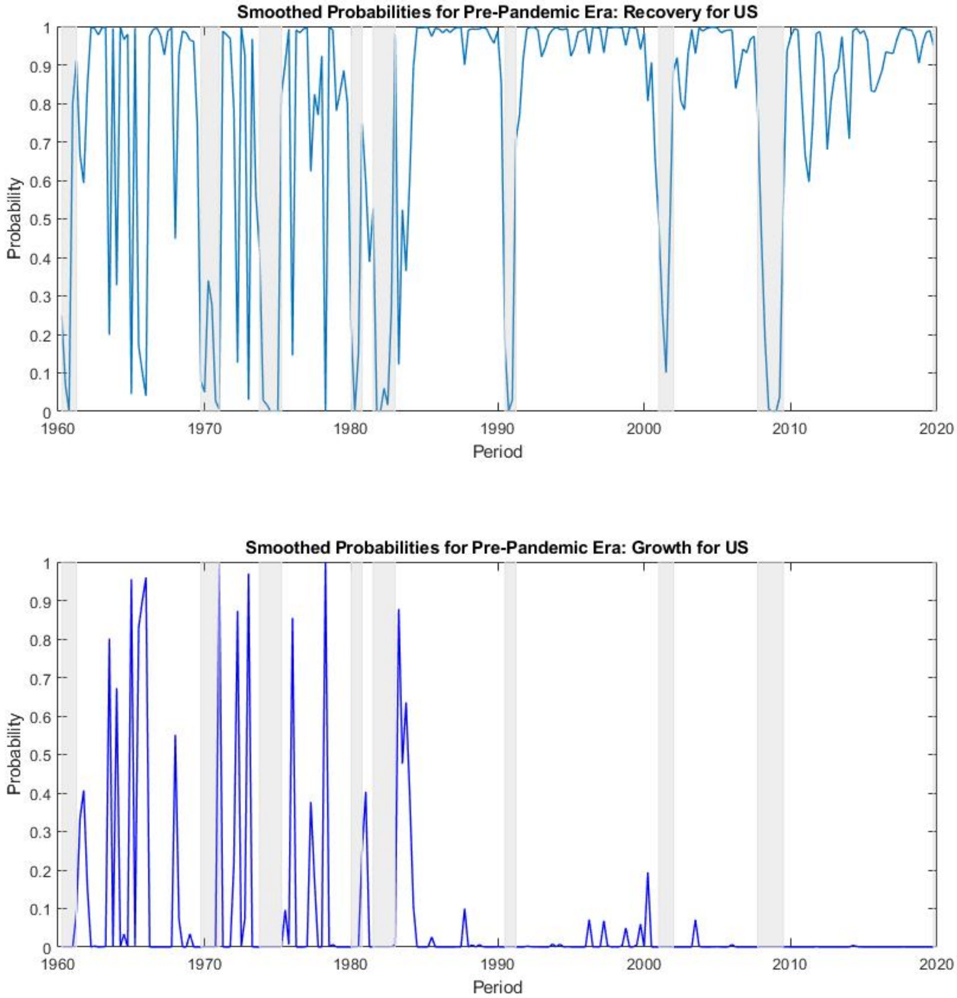


Figure A.7: Smoothed regime probabilities resulted from the model with two substates and fixed transition probabilities: Recovery & Growth in the U.S.

Shaded areas represent recessionary periods announced by NBER Business Cycle Dating Committee.

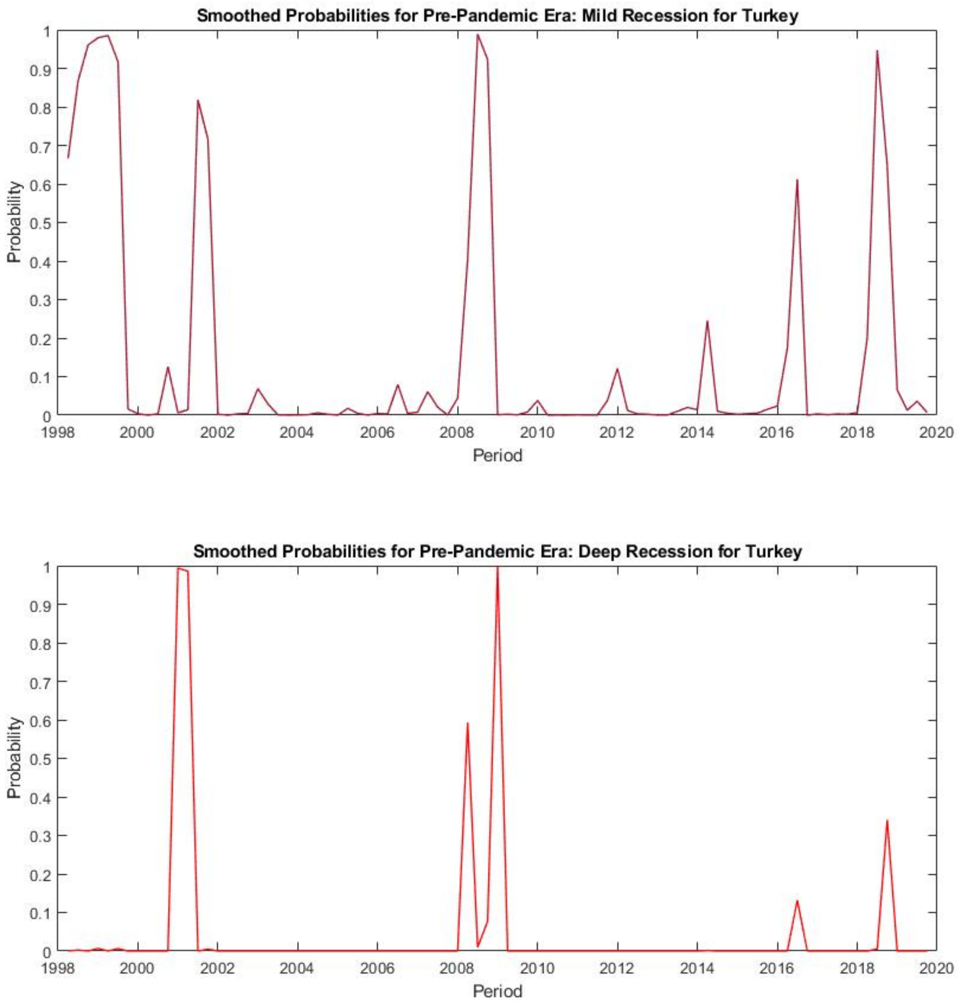


Figure A.8: Smoothed regime probabilities resulted from the model with two sub-states and fixed transition probabilities: Mild & Deep Recession in Turkey

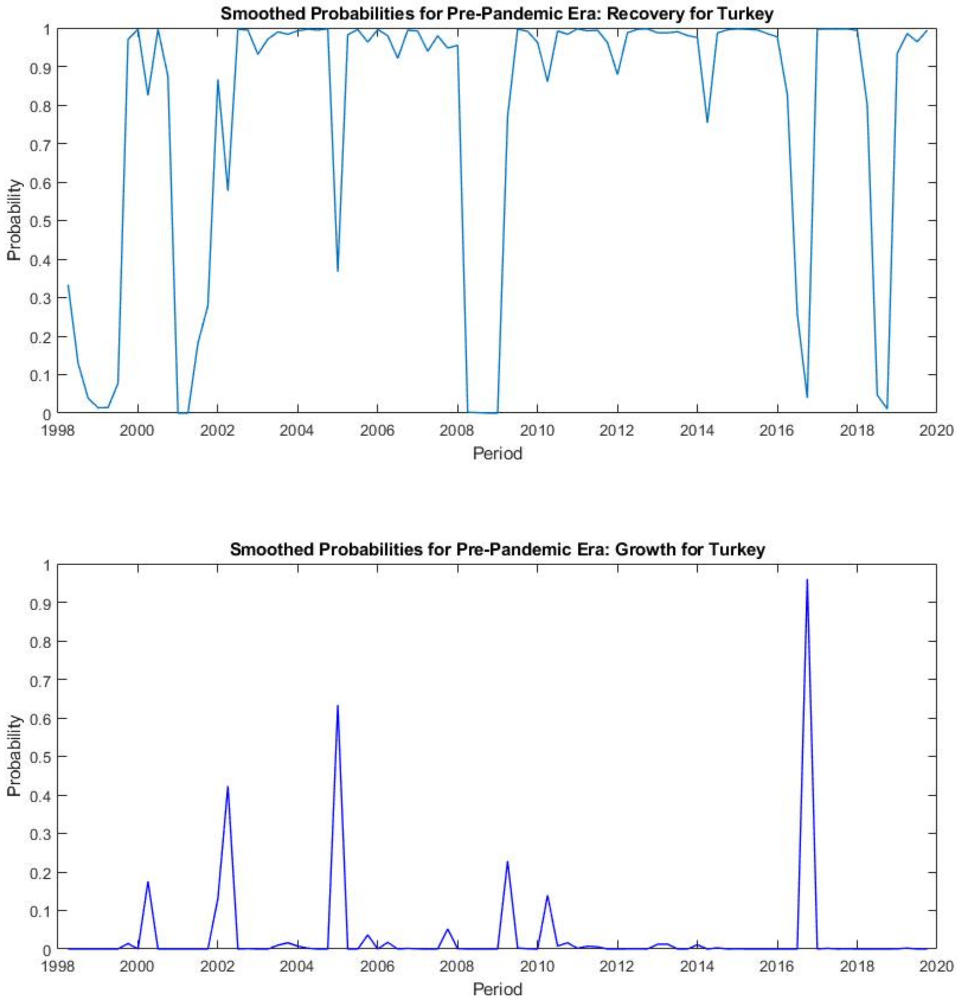


Figure A.9: Smoothed regime probabilities resulted from the model with two sub-states and fixed transition probabilities: Recovery & Growth in Turkey

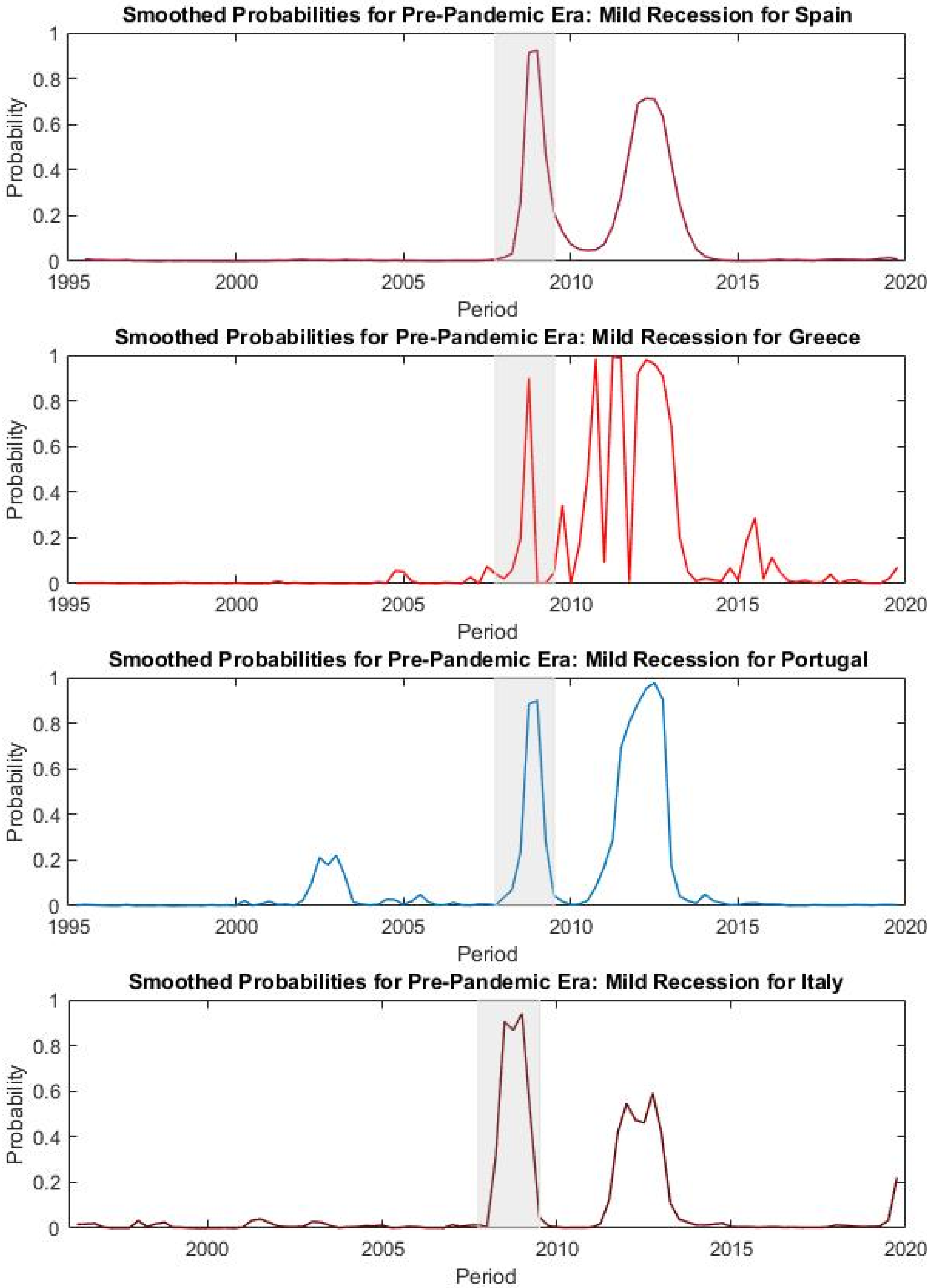


Figure A.10: Smoothed "Mild Recession" probabilities resulted from the hierarchical model with two sub-regimes for four EU member states that had experienced sovereign debt crises after the global financial crisis.
The global financial crisis, named Great Recession, is denoted with the shaded area at each figure above.

A.3 Credit-Related Variables

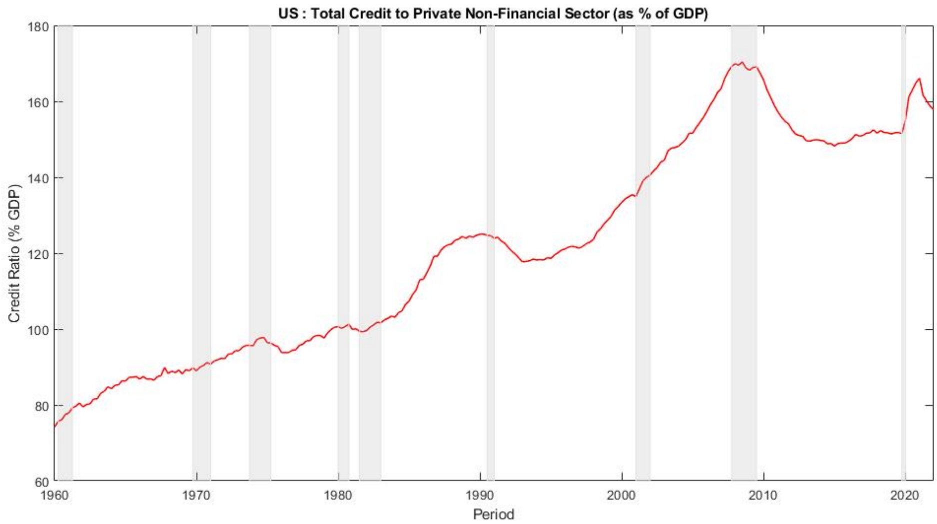


Figure A.11: Total credit to private non-financial sector measured as percentage of output (used as credit-to-GDP ratio): Data for the United States
Shaded areas represent recessionary periods declared by NBER Business Cycle Dating Committee.

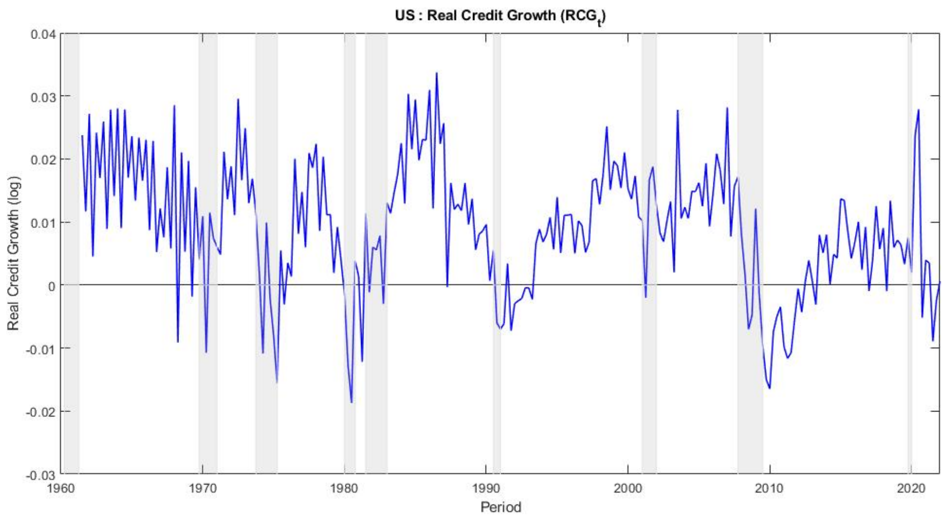


Figure A.12: Real credit growth in natural logarithmic scale (adjusted with the U.S. CPI): Data for the United States
Shaded areas represent recessionary periods declared by NBER Business Cycle Dating Committee.

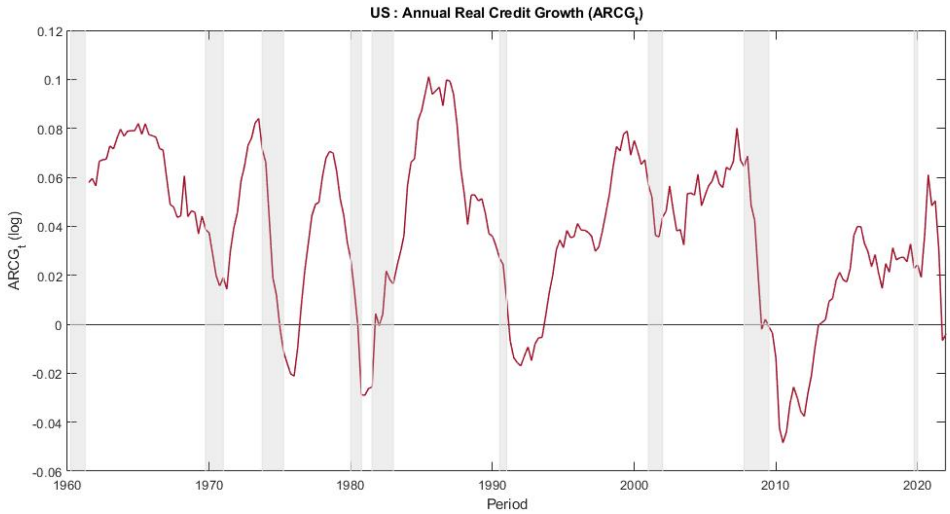


Figure A.13: Annual real credit growth in natural logarithmic scale (adjusted with the U.S. CPI): Data for the United States

Shaded areas represent recessionary periods declared by NBER Business Cycle Dating Committee.