The University of Adelaide

THREE ESSAYS IN APPLIED ECONOMETRICS

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A thesis submitted in partial fulfilment
of the requirement for the degree of
Doctor of Philosophy

School of Economics
Faculty of the Professions

February 2018

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Acknowledgements

I am extremely grateful to my supervisor, Dr. Raul Barreto, for his generous support of my PhD studies and related research. His advice, guidance, and all the useful discussions helped me in all the time of research and writing of this thesis, especially during the thesis proposal stage. I am happy to acknowledge my debt to my co-supervisors, Dr. Nicholas Sim for providing insightful discussions and suggestion for developing research framework and Dr. Nicolas Groshenny for invaluable insights and suggestions regarding the topics. Without supports from my supervisors, this dissertation could not be completed.

I have benefited considerably from econometrics courses taught by Dr. Nicholas Sim and Dr. Firmin Doko Tchatoka; and I am grateful to the advice from Dr. Terence Cheng. My appreciation also goes to all the staff, including academic and professional staff, in the School of Economics for their constant support during my whole course in Adelaide. I would like to thank Niranjala Seimon and Augustine Bhaskarraj for all their general support since my first day in Adelaide. I appreciate the feedback from anonymous referee on my dissertation. I also very much appreciate all my PhD colleagues in the same office for useful feedback and sharing their research and experiences. In addition, I thank the Australian government for financial support through the Australia Awards.

Finally, I am forever indebted to my wife, Rathneary. She is an adorable wife and a good mother of my lovely sons, Monireach and Monipong, and has been a constant source of strength and inspiration. More importantly, I would like to express my debt to all my family members for their endless love, support, and encouragement.

Abstract

This dissertation includes three chapters. Chapter 2 focuses on the threshold effect of credit on economic development of 17 developed countries throughout history from the late 1800s. Chapter 3 re-investigates the role of foreign aid in developing countries, emphasising the diminishing returns, and Chapter 4 offers evidence on the interest rate threshold effect on housing prices in 17 advanced economies from 1870 to 2013.

Chapter 2 investigates the impact of bank credit on economic growth using the dynamic threshold panel model on 17 developed countries for the period from the late 1800s to the most recent period (2013). Recent papers suggest that credit ha a non-linear effects on economic growth in the long-run, where the turning points are identified around 80-100% of GDP. This study aims to capture the behaviour of the short-run impact of credit-to-GDP ratio on economic growth, particularly in advanced economies. The results show that there exists credit threshold effects, in which 135% of credit to GDP is the threshold level. An inverted U-shaped relationship between bank credit and economic growth appears to be statistically significant in the sample period after World War II.

Chapter 3 re-examines the impact of foreign aid on economic development using a sample of 71 developing countries for the period from 1967

to 2010. It contributes to the existing literature of the diminishing returns of foreign aid, taking into account the presence of heterogeneity of country's growth process. First, when applying panel data estimation techniques, the results are in-line with previous findings presenting diminishing returns of foreign aid. This is consistent with the concept of absorptive capacity of recipient countries where aid is no longer effective when it reaches a certain threshold. Second, under the Finite Mixture Model in which heterogeneity of a country's growth process is taken into account based on the similarity of the conditional distributions of the growth rates, there exists evidence supporting the existence of two groups of countries, each with its own distinct growth regime. The diminishing returns of foreign aid belong to one group, consisting of 20 countries. There is no statistical evidence to support the diminishing returns for the other group of countries. This implies that the assessment on aid effectiveness should take heterogeneity assumption into account.

Chapter 4 investigates the relationship between interest rates and house prices using data from 17 advanced economies for the period from the late 1800s to 2013, based on the recent argument that the linkage follows non-linear assumptions. This study aims to explore whether there exists an interest rate threshold when following a dynamic threshold panel model. The empirical analyses provide evidence that there exists an interest rate threshold, and these findings reveal that expansionary monetary policy below the threshold level is associated with housing price bubbles; beyond the threshold level, further contractionary monetary policy tends to slow down the housing price bubbles, where the effects have become stronger and statistically significant after World War II.

I dedicate this to my mother.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Background and Motivations

This section provides a brief summary of the background and motivations of the three essays in this dissertation. The details of each essay are discussed below.

1.1.1 Essay One

The first essay investigates the impact of bank credit on economic growth using the panel data of 17 developed countries for the period from 1870 to 2013. Recent papers suggest that credit has non-linear effects on economic growth, where the turning points are identified at around 80-120% of GDP (Cecchetti and Kharroubi, 2012; Law and Singh, 2014; Arcand et al., 2015). Employing the pooled OLS for the dataset of 50 developed and emerging countries, Cecchetti and Kharroubi (2012) find that 90% of credit to GDP is the turning point. Arcand et al. (2015) apply a semi-parametric estimation technique and identify a credit threshold at around 80-120% of GDP. Law and Singh (2014), using the dynamic threshold panel model on 87 countries from 1980 to 2010, estimate a credit threshold of 88% of GDP. These findings imply that there is a positive correlation between credit and economic growth in countries with credit below a threshold level, above which credit starts having a negative effect on economic growth. However, non-linear estimates in these papers focus on the long run impact of credit on economic growth, while less is known about the short-run impact of credit on economic growth.[1] The long run path is different from the process of economic development which is far from smooth. Therefore, capturing the short-run turning points of bank credit is crucial as surges in credit could be the best predictor of crises and their related economic downturns (Loayza and Ranciere, 2006).

This essay is motivated by the lack of understanding of short-run non-linear impact of credit-to-GDP ratio on economic growth. This study contributes to the literature, first, by examining the short-run impact of credit rather than the long run, and by applying the recent method of dynamic threshold panel model proposed as by Baum et al. (2013) and Kremer et al. (2013).[2] Second, the annual data of credit-to-GDP ratio are used in order to capture the near contemporaneous effects of credit. Third, the study focuses on 17 advanced economies with a dataset spanning more than a century from 1870 to 2013 borrowed from Jordà et al. (2016b).

[1]Loayza and Ranciere (2006) find that a positive long run relationship between credit and output growth co-exists with a mostly negative short-run relationship.

[2]There are very few studies which have considered the short-run relationship; exceptions are Loayza and Ranciere (2006) and Narayan and Narayan (2013). Indeed, undertaking a short-run investigation in this study provides three advantages: (a) it prevents the loss of information when averaging data, (b) it allows the estimation of a more flexible model capable of capturing parameter heterogeneity across countries, and (c) the short-run analysis is capable of capturing the dynamic relationship between credit and economic activity, particularly the presence of opposite effects at different time frequencies (Loayza and Ranciere, 2006).

1.1.2 Essay Two

The second essay re-examines the impact of foreign aid on economic development using a sample of 71 developing countries over the period from 1967 to 2010. Over the last two decades, researchers tend to agree upon the diminishing returns of foreign aid (see, e.g. Hadjimichael et al., 1995; Hansen and Tarp, 2000, 2001; Dalgaard and Hansen, 2001; Lensink and White, 2001; Roodman, 2007; Feeny and McGillivray, 2010; Clemens et al., 2012; Feeny and de Silva, 2012; Bandyopadhyay et al., 2015). This is largely concerned with the limited absorptive capacity of typical developing countries to effectively use foreign aid.[3] In most empirical literature in this area, the studies of the diminishing returns of foreign aid typically employ the ratio of aid to GDP and its squared values as independent variables in the pooled cross sectional and panel data estimation techniques. These findings show an inverted U-shaped relationship between foreign aid and economic growth. However, these empirical investigations could have limitations as they fail to address heterogeneity issues. Previous studies employed standard statistical models with the assumption that a sample of observations coming from the same distribution may not be able to capture the true parameters.

Given this motivation, this essay contributes to the literature by employing Finite Mixture Model (FMM) proposed by Deb and Trivedi (2013) in order to observe the diminishing returns of foreign aid. The FMM, due to its convenience in semi-parametric model, is capable of capturing the unknown distributional shapes (Alfò et al., 2008). The model provides a flexible framework to estimate both parameters and posterior probability of the com-

[3]Feeny and de Silva (2012) classify the absorptive capacity constraints (ACCs) into five types: "(i) human and physical capital constraints; (ii) policy and institutional constraints; (iii) macroeconomic constraints; (iv) deficiencies in the manner in which the international donor community delivers its foreign assistance; and (v) social and cultural constraints."

ponent membership for each observation. It estimates data with a mixture of distributions, allowing for the underlying heterogeneity of the growth processes.

1.1.3 Essay Three

The third essay provides new evidence that sheds light on the impact of monetary policy on house prices in advanced countries. Since monetary policy shocks impact the real economy and is one of the most intensively investigated topics in macroeconomics, researchers have attempted to link house price movements to monetary conditions (Adam and Woodford, 2013; Allen and Rogoff, 2011; Del Negro and Otrok, 2007; Glaeser et al., 2010; Goodhart and Hofmann, 2008; Jarocinski and Smets, 2008; Kuttner, 2012; Williams, 2011; Jordà et al., 2015). There is evidence of a significant relationship between interest rates and house prices. In other words, the macroeconomic consequences of house price bubbles are mainly driven by an overly expansionary monetary policy. Recently, Jordà et al. (2015) using the historical dataset spanning over 140 years of modern economic history in 17 advanced economies find that loose monetary conditions are causal for mortgage and house price booms. By and large, the majority of empirical studies on the relationship between interest rates and house prices follow a linear framework. However, the linear assumption may not be appropriate if the house prices follow non-linear properties.

The study is motivated by the study of Kuttner (2012) who argues that the house prices tend to over-react to interest rates below the over-reaction point. This study contributes to the literature by presenting comprehensive empirical investigation on the non-linear relationship between interest rates and house prices. Specifically, this research aims at exploring whether there exists threshold level for interest rate, namely the 'overreaction' point coined by Kuttner (2012). In addition, unlike the previous studies, this empirical work employs a long historical data set of 17 developed countries over the period from the late 1800s to 2013. To the best of the candidate's knowledge, there are no empirical papers which estimate the threshold levels using the dynamic panel threshold model.

1.2 Dissertation Objectives

The three main questions of this dissertation are:

1. Does credit have a non-linear effect on economic growth in the short-run?
2. Does foreign aid have diminishing returns?
3. Do interest rates have a non-linear effect on house prices?

1.3 Structure of the Dissertation

The structure of this dissertation is as follows. Essay 2 focuses on the threshold effect of credit on economic development in 17 developed countries from 1870 to 2013. Essay 3 re-investigates the role of foreign aid in developing countries, emphasising diminishing returns, and Essay 4 offers evidence on the interest rate threshold effect on housing prices in 17 advanced economies from 1870 to 2013.

Chapter 2

Bank Credit and Economic Growth: Short-run Evidence from a Dynamic Threshold Panel Model

2.1 Introduction

Recent papers suggest that credit has non-linear effects on economic growth, where the turning points are identified around 80-120% of GDP (Cecchetti and Kharroubi, 2012; Law and Singh, 2014; Arcand et al., 2015). Employing pooled OLS for the dataset of 50 developed and emerging countries, Cecchetti and Kharroubi (2012) find 90% of credit to GDP as the turning point, while Law and Singh (2014) using the dynamic threshold panel model on 87 countries from 1980 to 2010, estimate credit threshold of 88% of GDP. In recent study, Arcand et al. (2015) apply semi-parametric estimation techniques and identify credit threshold at around 80-120% of GDP. These findings are based on the stylised fact that the marginal effects of bank credit to the private sector of the economy have diminishing returns; implying that there is a positive correlation between credit and economic growth in countries with credit below a threshold level, above which credit starts having a negative effect on economic growth.

The non-linear estimates in these papers, however, focus on the long run impact of credit on growth, while less is known about the short-run impact of credit on growth. Loayza and Ranciere (2006) find that a positive long run relationship between credit and output growth co-exists with a mostly negative short-run relationship. Different from the long run path, the process of economic development is far from smooth along the way. Therefore, capturing the short-run turning points of bank credit is crucial as surges in credit could be the best predictor of related economic downturns (Loayza and Ranciere, 2006).

This study extends existing research by identifying the threshold levels of bank credit to the private sector in advanced economies throughout history from the late 1800s to 2013. The primary objective of this study is to capture the behaviour of the short-run impact of credit-to-GDP ratio on the economic growth following the most recent method of dynamic threshold panel model proposed by Baum et al. (2013) and Kremer et al. (2013). The investigation focuses the short-run impact of bank credit on economic growth using the dataset of Jordà et al. (2016b) for 17 advanced economies from 1870 to 2013. By analysing the impact of a one-year lagged credit-to-GDP ratio on the annual real GDP growth rate, the contemporaneous effect of credit on growth could be captured and interpreted as a stimulating effect of additional bank credit (Baum et al., 2013).[1]

This study contributes to the literature by examining the short-run relationship between credit and economic growth. The study is different from the extant literature in two ways. First, the study focuses only on developed countries using a unique dataset of Jordà et al. (2016b). Second, the paper use a dynamic panel threshold method taking the short-run relationship between credit and economic growth into account. There are very few studies which have considered the short-run relationship; exceptions are Loayza and Ranciere (2006) and Narayan and Narayan (2013). Indeed, undertaking a short-run investigation in this study provides three advantages: (a) it prevents the loss of information when averaging data, (b) it allows the estimation of a more flexible model capable of capturing parameter heterogeneity across countries, and (c) the short-run analysis is capable of capturing the dynamic relationship between credit and economic activity, particularly the presence of opposite effects at different time frequencies (Loayza and Ranciere, 2006).

Given the limitation of the data due to the most significant events of the world, e.g. the World Wars, this empirical analysis cannot use the whole sample in a single analysis. Instead, the whole dataset is divided into different sub-sample periods, i.e. Pre-World War I, Interwar, and Post-World War II. The empirical findings suggest that there exists a credit threshold effect in advanced economies, in which around 135% of credit to GDP is the threshold level. The findings clearly imply that too much credit could not always potentially enhance economic growth, and could be interpreted that the level of credit growth is beneficial to economic growth only up to a certain threshold; beyond this level, further growth in bank credit to the private sector tends to adversely affect economic growth. The findings are

[1] For long-run analysis, the annual data may not be applicable; thus, most studies use the average of a couple of years.

significant only in the sub-sample of Post-World War II; however, there is no statistical evidence to prove the effect of bank credit on economic growth for the period prior to the World War II.

The remainder of the chapter is organized as follows: Section 2 reviews the relevant literature, while Sections 3 and 4 lay out the econometric model and data, respectively. The derived results and related discussion are presented in Section 5, and Section 6 presents the conclusion.

2.2 Literature Review

The relationship between bank credit to the private sector and economic growth has long been observed in the literature of the finance-growth nexus. It has been extensively examined in both theoretical and empirical frameworks for firm-level, industry-level, individual country and cross country studies (King and Levine, 1993; Levine, 1997; Rajan and Zingales, 1998; Levine et al., 2000; Beck et al., 2000; Khan, 2001; Levine, 2003; Beck and Levine, 2004). Most of these studies use the ratio of bank credit to GDP as a proxy for financial development or financial deepening in order to relate them with other macroeconomic indicators, and the findings support the role of credit in stimulating the economy. Among those, King and Levine (1993) employ a simple cross-country regression in order to observe the relationship between financial development and economic growth. Using the dataset of 80 countries for the period from 1960 to 1989, King and Levine (1993) introduce different indicators as proxies for financial development. Those proxies include credit issued to nonfinancial private firms divided by total credit, and credit issued to nonfinancial private firms divided by GDP. The authors find that financial development has positive correlation with economic growth and financial development indicators help to predict long run growth over the next 10 to 30 years.

Beck et al. (2000) examine the causal relationship between financial development and economic growth using the dataset of 63 countries for the period 1960-1995. To control for simultaneity bias, the authors use legal origin of each country as an instrument variable because legal origin can be exogenous compnent as many countries can be classified as having English, French, German or Sacandinavian legal origins. Employing both pure cross-sectional and Generalized Mehtod of Moments (GMM) dynamic panel techniques, Beck et al. (2000) confirm that their findings are consistent with King and Levine (1993) and Schumpeter's argument, and conclude the causal relationship between finance and economic growth. Apart from empirical observation, Khan (2001) develops a theoretical framework of financial development based on the cost associated with asymmetric information between borrowers and lenders. The author emphasises the role of the credit channel in raising borrowers' net worth relative to their debts. This in turn tends to increase the return on investment and thus the rate of economic growth.

However, the most recent literature tends to reject previous claims and argues that credit has a non-linear relationship with economic growth, in which too much credit expansion is associated with negative economic growth (Shen and Lee, 2006; Cecchetti and Kharroubi, 2012; Law and Singh, 2014; Arcand et al., 2015). Analyses in this branch of literature have involved in the idea of diminishing returns of credit, suggesting an inverted U-shape relationship. Shen and Lee (2006) re-examine how credit affects the growth rate of real GDP per capita in 48 countries from 1976 to 2001.[2] The authors employ different econometric techniques from simple linear regression

[2]Shen and Lee (2006) use the ratio of claims on private sector by banks to GDP in measuring financial depth of the banking sector.

to quadratic regression models and include other controlled variables, such as financial liberalization, country income status, banking and currency crises. Using the linear method, the results show that the relationship between the credit-to-GDP ratio and economic growth has a weak relationship; however, the inverted U-shape becomes stronger and they conclude that the non-linear form could be better explained.

Moreover, Arcand et al. (2015) employ both country-level data from 1960 to 2010 and industry-level data from 1990 to 2000 to capture credit threshold. They find that credit has a positive correlation with economic growth only up to a certain credit threshold which is estimated to be at around 80-120% of GDP. Beyond this threshold, credit growth starts having a negative effect on output growth. Their results are similar to those of Cecchetti and Kharroubi (2012) who show that fast growing private sector credit reduce economic growth at the turning point of about 90% of GDP. The threshold effect estimated by Arcand et al. (2015) and Cecchetti and Kharroubi (2012) has been recently confirmed by Law and Singh (2014) who conclude a private sector credit threshold level of 88% of GDP. Law and Singh (2014) observe the relationship between finance and economic growth using the dynamic threshold panel techniques on the dataset consisting of 87 developed and developing countries from 1980 to 2010. Through these empirical observations, the findings tend to emphasise that credit initially has a positive impact growth, but induces negative growth when reaching a certain level.

As stated in the paper of Arcand et al. (2015), there are several ways to explain the economic intuition that high levels of bank credit to private sector is associated with less economic growth. First, domestic financial systems tend to become more market-based as economies developed. Demirgüç-Kunt et al. (2013) claim a declining correlation between bank credit and economic growth in the level of economic development implying that the services provided by banks become less important. This is consistent with the theories highlighting the credit to the private sector is no longer an important positive factor, not necessarily a negative factor, in explaining economic growth. Next, high level of credit could be related to risk-taking and volatility (Minsky, 1974; Kindleberger, 1978). Rajan (2005) argues that the presence of a large and complicated financial system has increased the likelihood of catastrophic meltdown. In addition, Easterly et al. (2000) empirically find that financial depth and the volatility of output growth has convex and non-monotonic relationship.

Furthermore, economists worry that a large financial sector may absorb more labour force from other productive sector, creating inefficient allocation of human capital. Philippon and Reshef (2013) provide evidence which is consistent with this view. However, the relationship between credit and economic growth could depend upon whether the credit is provided to non-financial corporations for financial investment in productive assets or to domestic households for consumption purposes. Beck et al. (2012), while employing data for 45 countries for the period from 1994 to 2005, find that enterprise credit is highly associated with economic growth, but there is no statistical evidence of correlation between household credit and economic growth.

The above discussion has highlighted that more credit is definitely not always better and tends to harm economic growth when it reaches a certain level. However, non-linear estimates in these papers focus on the long run impact of credit on growth, while less is known about the short-run impact of credit on growth. An investigation into the short-run impact of credit on growth is crucial as surges in credit could be the best predictor of related economic downturns and the economic development is far from smooth along the way in the short-run (Loayza and Ranciere, 2006). Furthermore, there are very few studies examining the short-run relationship of credit on economic growth; exceptions are Loayza and Ranciere (2006) and Narayan and Narayan (2013). Therefore, it is worth observing the threshold effects in the short-run.

2.3 Methodology

Commencing with the quantitative analysis of the finance-growth nexus, the empirical model follows the basic growth model suggested by Barro (1991) and Sala-i Martin (1997) with the following specification

$$Y = X\beta + \varepsilon \tag{2.1}$$

where Y is the real output, X is a vector of explanatory variables, and ε is the error term.

Empirical estimation of the determinants of growth mentioned in equation (2.1) could have two potential constraints. First, some explanatory variables could not be consistently measured in a single way. For example, the level of technology, human capital, or efficient government could be measured in different ways.[3] Second, it may be difficult to determine what

[3] In almost all economic theory, technology is recognized as one of the determinants of growth. However, the level of technology could be proxied by different measures. Sala-i Martin (1997) mentions that market distortions, discretionary taxes, maintenance of property rights and degrees of monopoly could be potential candidates for the 'level of technology'.

particular variables to use when starting to run regression. Incorporating about different 60 variables, Sala-i Martin (1997) argues that the variable x_1 will be found to be significant when variables x_2 and x_3 are included in the regression; however, it becomes insignificant when another variable is included. Therefore, true parameters may be biased and choosing explanatory variables requires a theoretical framework.

There are different explanatory variables found to significantly affect growth in both theoretical and empirical analyses. In the neoclassical growth model developed by Cass (1965) and Koopmans (1965), variables such as investment and population growth are essential for the growth of the economy. While in trade theory, Helpman et al. (2004) emphasise openness and predict that more trade openness of the economy leads to higher economic growth. In the empirical growth literature, Levine and Renelt (1992) and Sala-i Martin (1997) argue that only a few explanatory variables could be significant among a large set of them, so that they propose a robustness check econometrically.[4] From the regression analyses of about 60 explanatory variables, Sala-i Martin (1997) finds that investment, population growth, inflation rate, openness, and finance appear to affect growth in a significant way. However, inflation and financial variables appear not to matter in a linear model; therefore, Sala-i Martin (1997) argues that these variables could affect growth in non-linear ways.

As the relationship between finance and economic growth, suggested by Sala-i Martin (1997), could potentially be non-linear, this study adopts a dynamic threshold panel regression following the models of Baum et al.

[4]Levine and Renelt (1992) apply extreme bounds test for robustness, but the method may not work well when no variables are robustly correlated with growth. As a result, different methods are applied by Sala-i Martin (1997) through the analysis of the entire distribution of the estimated coefficients by assigning confidence level to each variable.

(2013) and Kremer et al. (2013).[5] The dynamic threshold panel regression was extended from the static panel threshold regression of Hansen (1999) and cross-sectional instrumental variable (IV) threshold model of Caner and Hansen (2004) taking into account endogeneity. In dealing with endogeneity issues, Caner and Hansen (2004) develop an estimator and inference theory where GMM type estimators consist of endogenous variables and an exogenous threshold variable.

The model specification for the threshold analysis begins with the dynamic panel model following Arellano and Bond (1991) as follows:

$$y_{it} = \mu_i + \chi y_{i,t-1} + \alpha X_{it} + u_{it} \tag{2.2}$$

where subscript $i = 1, ..., N$ represent the country, $t = 1, \ldots, T$ index the time period, y_{it} is the economic growth rate of country i at time t, $y_{i,t-1}$ is the lagged dependent variable representing endogenous regressor, X is a vector of control variables, μ_i is a set of country-specific fixed effect, and u_{it} is the error term with independent and identically distributed with mean zero and finite variance.

For dynamic panel threshold analysis, the study adopts a model suggested by Baum et al. (2013) and Kremer et al. (2013) who respectively analyse the non-linear impact of sovereign debt and inflation on growth modifying the model of Caner and Hansen (2004) taking into account of the framework of panel data.[6] The model, based on threshold regression, takes the following form:

[5] In this case, this study uses credit to private sector as proxy for financial development.

[6] The dynamic threshold model of Caner and Hansen (2004) is applicable for only time series data analysis.

$$y_{it} = \mu_i + \chi y_{i,t-1} + \alpha' x_{it} + \beta_1 f_{it} I(q_{it} \leq \gamma) + \beta_2 f_{it} I(q_{it} > \gamma) + u_{it} \qquad (2.3)$$

where x_{it} is a k-dimensional vector of regime independent control variables and f_{it} is a set of variables that are allowed to switch between regimes. $I(\cdot)$ is the indicator function, which takes the value 1 if the argument in parenthesis is valid, and 0 otherwise, indicating the regime defined by the threshold variable q_{it} and the threshold level γ. In this case, if q_{it} is below or above the threshold level γ, the regressor f_{it} has different impacts on the dependent variable y_{it}.

In the dynamic threshold panel regression, removing individual effects μ_i through the standard within transformation or first differencing methods can lead to inconsistent estimates (Kremer et al., 2013). This is due to the fact that the mean of individual errors will always be correlated with a lagged dependent variable; consequently, the distribution assumptions underlying Hansen (1999) and Caner and Hansen (2004) are violated. In order to remove fixed effects in a dynamic threshold panel model, this study follows Kremer et al. (2013), who apply forward orthogonal deviations which make it possible to avoid serial correlation of the transformed error terms.[7] Thus, this strategy will transform the error term as follows:

$$\sqrt{\frac{T-t}{T-t+1}}\left[u_{it} - \frac{1}{T-t}(u_{i(t+1)} + \ldots + u_{iT})\right] \qquad (2.4)$$

To estimate the dynamic panel model in equation (2.3), this study

[7]Suggested by Arellano and Bover (1995), the forward orthogonal deviation transformation subtracts the average of all future available observations of a variable.

first estimates a reduced form of regression of the endogenous variable $y_{i,t-1}$ on a set of instruments.[8] In the next step, the predicted values of $\hat{y}_{i,t-1}$ is substituted into equation (2.3) where the least squares are used to estimate the threshold parameter γ. At this stage, the threshold value $\hat{\gamma}$ is selected, which minimizes the sum of square residuals $S(\gamma)$ and tested for the significance of the selected $\hat{\gamma}$. The threshold value $\hat{\gamma}$ is chosen based on the smallest sum squared residuals, defined by:

$$\hat{\gamma} = arg \quad min \quad S_n(\gamma) \tag{2.5}$$

The critical values for determining the 95% confidence interval of the threshold values based on Hansen (2000) and Caner and Hansen (2004) are given by:

$$\Gamma = \gamma : LR(\gamma) \leq C(\alpha) \tag{2.6}$$

where $C(\alpha)$ is the 95% percentile of the asymptotic distribution of the likelihood ratio statistic $LR(\gamma)$. According to Hansen (1999), the underlying likelihood ratio has been adjusted to account for the number of time periods used for each cross section. After the threshold value $\hat{\gamma}$ is determined, GMM is applied to estimate the estimate slope coefficients.

Following Baum et al. (2013) who observe the relationship between public debt and economic growth in Euro area, this investigation uses one-

[8]For the purpose of growth persistence and short-run impact analysis, Baum et al. (2013) refer $y_{(t-1)}$ to the lagged dependent variable following Arellano and Bond (1991). This is in contrast to Kremer et al. (2013) and Law and Singh (2014) who consider initial income as an endogenous variable as they focus on the growth convergence; therefore, requiring the assumption in Arellano and Bover (1995).

year lagged of credit-to-GDP ratios on annual real GDP growth rates. Using this relationship in the dynamic threshold panel regression, the near contemporaneous effect could be captured; thus, obtaining the idea of the short-run impact of credit on economic growth. The benchmark model is estimated in the following specification:

$$
\begin{aligned}
y_{it} = \mu_i + \chi y_{i,t-1} + \alpha_1 INV_{i,t-1} + \alpha_2 X_{i,t-1} + \beta_1 f_{i,t-1} I(f_{i,t-1} \leq \gamma) \\
+ \beta_2 f_{i,t-1} I(f_{i,t-1} > \gamma) + u_{it}
\end{aligned}
\tag{2.7}
$$

where y is the annual GDP growth rate, INV is the annual percentage change of the ratio of investment to GDP, X is the other control variables, and f is the annual percentage change of the share of private sector credit to GDP, while γ is the credit threshold value.[9] In the dynamic sense, $y_{(t-1)}$ is estimated on its lags of $y_{(t-2)}$ to $y_{(t-p)}$ and the predicted values $\hat{y}_{(t-1)}$ is replaced in equation (2.7). Following Kremer et al. (2013), the study first uses all available lags as instruments in order to increase efficiency. Furthermore, the instruments are kept to a minimum of 1 lag in order to avoid over-fitting instrumented variables.[10] Even so, up to 9 lags of instruments are used, and the results do not alter and are quite consistent.

In the most recent studies of finance-growth nexus, the paper that relates most closely to the non-linear dynamic threshold panel methodology includes the work by Law and Singh (2014). In their study, Law and Singh

[9] Control variable (X) includes GOV, the ratio of government expenditure to GDP, TOT, the terms of trade measured by exports divided by imports; $OPEN$, trade openness which is defined by the share total exports plus total imports to GDP; POP, the annual growth rate of population; and the dummy variable $CRISIS$ capturing the financial crisis.

[10] Roodman (2009) argues that too many instruments may lead to an over-fitting of instrumented variables; therefore, failing to remove their endogenous components that may lead to biased coefficient estimates.

(2014) employ the dynamic threshold panel methodology to examine the long run relationship between finance and economic growth for 87 countries from 1980 to 2010.[11] This study is different as it is focuses on the short-run impact of bank credit on economic growth in which the annual data is employed and it uses different dataset that take into account the long historical perspective from 1870 to 2013. The dynamic panel threshold model is superior non-linear model compared to other model, i.e. quadratic regression model. The squared term of credit is used in the study of Cecchetti and Kharroubi (2012) may have limitation given that the level of credit on growth imposes a prior restriction. In contrast, the level of credit has to be attained before impacting growth. In addition, the threshold model can accommodate the negative ranges of the relationship that may differ in absolute impact compared to positive ranges (Law and Singh, 2014).

2.4 Data

To estimate the short-run impact of bank credit to the private sector on economic growth using the dynamic threshold panel model, I borrowed the unique dataset of Jordà et al. (2016b) for 17 advanced economies from 1870 to 2013. These countries included Australia (AUS), Belgium (BEL), Canada (CAN), Denmark (DNK), Finland (FIN), France (FRA), Germany (DEU), Italy (ITA), Japan (JPN), the Netherlands (NLD), Norway (NOR), Portugal (PRT), Spain (ESP), Sweden (SWE), Switzerland (CHE), the United Kingdom (GBR), and the United States of America (USA). From the yearly

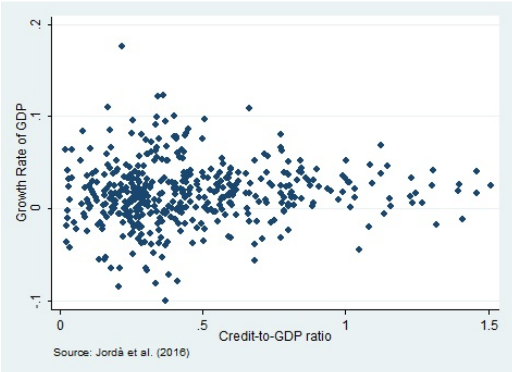
[11] The non-linear relationship between finance and economic growth are observed by several studies using different methodologies including non-dynamic threshold regression, pooled OLS, semi-parametric estimation and so on (see, e.g. Deidda and Fattouh, 2002; Rioja and Valev, 2004a,b; Shen and Lee, 2006; Ergungor, 2008; Huang and Lin, 2009; Cecchetti and Kharroubi, 2012; Arcand et al., 2015).

dataset, I picked out relevant variables for the model specified in the previous section. These included real GDP per capita, nominal GDP, credit (domestic banks' outstanding loans to domestic households and nonfinancial corporations), investment, government expenditure, exports, imports, population, consumer price index, and financial crises dummy variables. Following the previous literature, $CREDIT$ is measured by the ratio of bank credit to GDP.[12] INV and GOV are the ratio of investment and government expenditure to GDP, respectively. Terms of trade (TOT) is measured by exports divided by imports. Trade openness ($OPEN$) is defined by the share total exports plus total imports to GDP, Population (POP) is the annual percentage change of population, and Inflation ($INFL$) is the annual percentage change of the consumer price index.

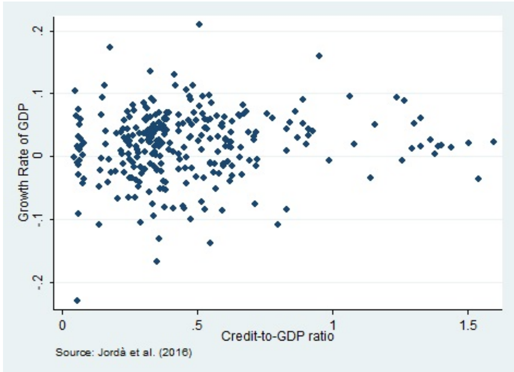
The whole dataset is divided into three main sub-samples: Pre-WWI, Interwar, and Post-WWII. Pre-WWI is the sub-sample period from 1870 to 1913, Interwar is the sub-sample period between the two world wars (1919-1938), and Post-WWII is the sub-sample period from 1948 to 2013. Given the availability of the dataset, the data of sub-sample are unbalanced panel data due to the missing data. The summary statistics of all variables are reported in Table 2.1. The scatter plots of the relationship between bank credit and GDP growth in the three sub-samples are shown in Figure 2.1. The diagrams show that linear relationship between credit and economic growth may hold for the period of Pre-World War I and the Interwar. However, this relationship may be non-linear in the the Post-World War II sample.

[12] Credit to the private sector over GDP was first used by King and Levine (1993) as a measure of financial depth and has now become one of the most commonly used in the literature of financial development.

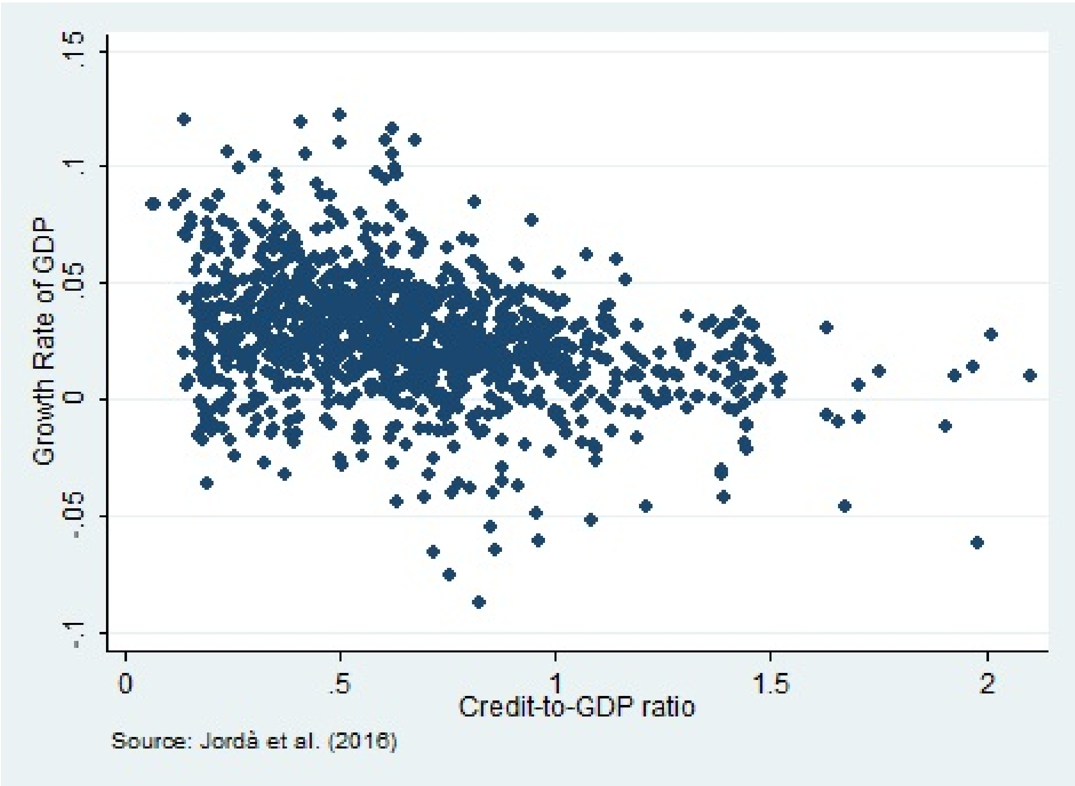
Figure 2.1: Credit and GDP Growth



(a) Pre-World War I



(b) Interwar



(c) Post-World War II

Table 2.1: Summary Statistics

	N. Obs	Mean	SD	Min	Max
Pre-WWI: 1870 - 1913					
GDPGrowth	461	0.0167	0.0332	-0.0996	0.1760
Credit	461	0.4502	0.2948	0.0195	1.5114
INV	461	0.1418	0.0414	0.0612	0.3254
GOV	461	0.0733	0.0357	0.0000	0.1823
POP	461	0.0110	0.0060	-0.0032	0.0500
TOT	461	0.8630	0.2150	0.5129	1.9876
OPEN	461	0.4492	0.4273	0.0768	2.9739
INFL	461	0.0063	0.0396	-0.1455	0.1269
Interwar: 1919 - 1938					
GDPGrowth	284	0.0182	0.0547	-0.2300	0.2106
Credit	284	0.4681	0.3059	0.0449	1.5998
INV	284	0.1507	0.0509	0.0173	0.3580
GOV	284	0.1330	0.0574	0.0296	0.3444
POP	284	0.0088	0.0068	-0.0587	0.0320
TOT	284	0.9094	0.2577	0.3026	2.0433
OPEN	284	0.3389	0.1626	0.0499	0.7964
INFL	284	0.0025	0.0765	-0.1942	0.3305
Post-WWII: 1948 - 2013					
GDPGrowth	1,111	0.0265	0.0273	-0.0863	0.1823
Credit	1,111	0.6683	0.3339	0.0654	2.1059
INV	1,111	0.2296	0.0431	0.0909	0.3889
GOV	1,111	0.2262	0.0871	0.0572	0.4422
POP	1,111	0.0075	0.0098	-0.0110	0.2650
TOT	1,111	0.9641	0.2077	0.3076	1.9015
OPEN	1,111	0.4606	0.2683	0.0406	1.8364
INFL	1,111	0.0473	0.0516	-0.0687	0.7593

2.5 Empirical Results

To formally estimate the threshold level of bank credit, the dynamic threshold panel model is employed. Tables 2.2 - 2.4 show the results for the dynamic threshold panel estimation from different sample periods (Pre-WWI, Interwar, and Post-WWII). In each table, column (a) shows the estimation based on the benchmark model starting with the investment-to-GDP ratio as control variable. Column (b) presents the result of the dynamic threshold panel estimation when more control variables, such as government expenditure, population growth, terms of trade, and openness are included into equation (2.7), and column (c) includes all variables, adding the dummy variable indicating financial crises defined by Schularick and Taylor (2012). In the top rows, the estimated threshold ($\hat{\gamma}$) is presented with its corresponding 95% confidence interval. The following rows show the regime-dependent coefficients ($\hat{\beta}_1$) and ($\hat{\beta}_2$) of credit on growth and their respective standard errors in the parenthesis. The coefficient ($\hat{\beta}_1$) is the marginal effect of credit on growth when credit-to-GDP is below the estimated threshold level; while the coefficient ($\hat{\beta}_2$) denotes the marginal effect of bank credit on economic growth when credit-to-GDP is above the threshold level. The coefficients of the other control variables and standard errors are represented in the rest of each table, except the time dummy variables.

2.5.1 Post-War Estimations

In this section, the empirical analyses of the short-run impact of bank credit on economic growth are presented for the sub-sample of Post-World War II (Post-WWII). Table 2.2 reports the estimation results of equation (2.7). First, the credit threshold is estimated at around 135.14% (or 1.3514) of GDP for all estimation models in columns a - c of Table 2.2, with respective 95% confidence interval [1.3301 - 1.3549], [1.3301 - 1.4082], [1.3301 - 1.4082]. The threshold value splits the observations into two regimes, in which 142 observations fall in the lower regime and 969 observations fall in the upper regime. The estimate is a bit higher than that of Arcand et al. (2015). Second, the regime-dependent coefficients ($\hat{\beta}_1$ and $\hat{\beta}_2$) show the marginal effect of credit on economic growth. Both coefficients of credit are significant and expectedly signed, where the coefficient $\hat{\beta}_1$ has a positive sign in the first regime and the coefficient $\hat{\beta}_2$ has a negative sign in the second regime. This suggests that private sector credit is positively correlated with economic growth if it is below the credit threshold (135.14%), while the impact on growth is negative if it is above the credit threshold. In this sample period, the inverted U-shaped relationship between bank credit and economic growth exists. The regime-dependent coefficients do not noticeably change compared to the benchmark results when more control variables are added into the model (columns b and c). The coefficient of y_{t-1} is positive, suggesting that the past economic growth has a positive impact on the current economic growth. It has been noted that financial crises have negative impact on economic growth, as shown in column (c) of Table 2.2. However, there is no statistical evidence to prove that investment, government expenditure, terms of trade, openness and population growth significantly influence economic growth in the short-run.

2.5.2 Pre-War Estimations

To further understand the role of credit in the pre-war periods, the study extends analyses back to the late 1800s. Two sub-sample periods are observed: Pre-WWI (1870-1913) and Interwar (1919-1938). Due to the limitation of the data, the empirical analyses use unbalanced panel data; therefore, leaving some missing observations of some countries in these sub-sample periods. The estimation results from Pre-WWI are shown in Table 2.3 using the same model as shown in equation (2.7). The empirical results indicate that the threshold level of credit is 117.96% (or 1.1796) of the GDP with a corresponding 95% confidence interval [1.1796 - 2.2175], [1.1718 - 2.1966], and [1.1727 - 2.1934]. The credit threshold level is found to be lower than that of the sub-sample Post-WWII. The coefficients of credit below

Table 2.2: Dynamic Threshold Panel Regression Results for Post-WWII: 1948-2013

	Models		
	(a)	(b)	(c)
Threshold estimates	1.3514	1.3514	1.3513
95% confidence interval	[1.3301-1.3549]	[1.3301-1.4082]	[1.3301-1.4082]
Impact of credit			
$\hat{\beta}_1$	0.0292^{*}	0.0279^{*}	0.0285^{*}
	(0.0161)	(0.0162)	(0.0162)
$\hat{\beta}_2$	-0.0174^{***}	-0.0169^{***}	-0.0159^{***}
	(0.0043)	(0.0044)	(0.0044)
Impact of covariates			
y_{t-1}	0.3356^{***}	0.3325^{***}	0.3327^{***}
	(0.0407)	(0.0399)	(0.0398)
INV	0.0281	0.0181	0.0213
	(0.0260)	(0.0274)	(0.0274)
GOV		−0.0264	−0.0265
		(0.0221)	(0.0221)
POP		0.0699	0.0599
		(0.1390)	(0.1350)
TOT		−0.0049	−0.0056
		(0.0045)	(0.0045)
$OPEN$		−0.0006	−0.0005
		(0.0075)	(0.0075)
$CRISIS$			-0.0143^{***}
			(0.0044)
N	17	17	17
Obs.	1,111	1,111	1,111
Obs. below threshold	142	142	142

Notes: The standard errors are reported in the parentheses. Dependent variable: Annual growth rate of GDP per capita. Time trends and time dummies are not reported in this table in order to save space. *** indicates significance level at 1% level. ** indicates significance level at 5% level. * indicates significance level at 10% level.
(a) – benchmark model
(b) – benchmark model including some control variables
(c) – benchmark model including all control variables

the threshold ($\hat{\beta}_1$) has a positive sign and credit above the threshold ($\hat{\beta}_2$) has both positive and negative signs. However, they are statistically insignificant even at 10% level. Therefore, it may be difficult to conclude the role of credit in shaping the economy during the Pre-WWI.

In addition, the study proceeds to investigate the credit threshold in the Interwar period, which is the period between World War I and World War II. The estimation results are presented in Table 2.4. Applying the dynamic threshold panel techniques, the estimation results show that the threshold level of credit is 115.71% (or 1.1571) of the GDP. The threshold estimations of credit to GDP ratio are consistent with those of the Pre-World War I. However, the inverted U-shaped relationship of credit and economic growth could not be identified as the coefficients of $\hat{\beta}_1$ and $\hat{\beta}_2$ are not statistically significant despite positive signs in both regimes. As a result, the role of credit in shaping the economy in this period could not be determined.

For the sub-samples of Pre-World War I and Interwar, the inverted U-shape relationship between credit and economic growth could not be identified using the dynamic threshold panel techniques as the relationship is relatively weak and there is no enough statistical evidence to claim the role of credit in the economy. There could be three main reasons for this. First, bank credit may not be correlated with the economic growth given that the banking system did not play a large role in the pre-WWI and Interwar periods. Second, due to the missing data in the sample, the model specification could not fit the data well. Third, the relationship between bank credit and economic growth could not be captured in the non-linear framework and this can clearly identified in the scatter plots of Figure 2.1.

However, credit plays more important roles in the economy after the

Table 2.3: Dynamic Threshold Panel Regression Results for Pre-WWI: 1870-1913

	Models		
	(a)	(b)	(c)
Threshold estimates	1.1796	1.1796	1.1796
95% confidence interval	[1.1796-2.2175]	[1.1718-2.1966]	[1.1727-2.1934]
Impact of credit			
$\hat{\beta}_1$	0.0340	0.0410	0.0408
	(0.0255)	(0.0261)	(0.0260)
$\hat{\beta}_2$	0.0071	-0.0012	-0.0004
	(0.0139)	(0.0141)	(0.0141)
Impact of covariates			
y_{t-1}	-0.1728^{***}	-0.1901^{***}	-0.1868^{***}
	(0.0619)	(0.0618)	(0.0621)
INV	-0.0324	0.1037	0.0996
	(0.0693)	(0.0830)	(0.0829)
GOV		-0.4384^{***}	-0.4421^{***}
		(0.1297)	(0.1307)
POP		-0.5699	-0.5470
		(0.5108)	(0.5111)
TOT		0.0352^{*}	0.0339
		(0.0196)	(0.0196)
$OPEN$		0.0189	0.0180
		(0.0303)	(0.0301)
$CRISIS$			-0.0047
			(0.0069)
N	16	16	16
Obs.	461	461	284
Obs. below threshold	51	51	51

Notes: The standard errors are reported in the parentheses. Dependent variable: Annual growth rate of GDP per capita. Time trends and time dummies are not reported in this table in order to save space. *** indicates significance level at 1% level. ** indicates significance level at 5% level. * indicates significance level at 10% level.
(a) – benchmark model
(b) – benchmark model including some control variables
(c) – benchmark model including all control variables

Table 2.4: Dynamic Threshold Panel Regression Results for Interwar: 1919-1938

	Models		
	(a)	(b)	(c)
Threshold estimates	1.1571	1.1571	1.1571
95% confidence interval	[1.1571-1.7339]	[1.1571-1.7366]	[1.1571-1.7366]
Impact of credit			
$\hat{\beta}_1$	0.0711	0.0559	0.0515
	(0.0573)	(0.0548)	(0.0590)
$\hat{\beta}_2$	0.0176	0.0333	0.0443
	(0.0412)	(0.0436)	(0.0440)
Impact of covariates			
y_{t-1}	0.2173***	0.2208***	0.2163***
	(0.0803)	(0.0787)	(0.0784)
INV	0.0296	0.0240	0.0303
	(0.1137)	(0.0240)	(0.1122)
GOV		0.0234	0.0132
		(0.0944)	(0.0902)
POP		−0.8289	−0.8256
		(0.6521)	(0.6577)
TOT		−0.0118	−0.0114
		(0.0258)	(0.0251)
$OPEN$		0.0460	0.0346
		(0.0560)	(0.0547)
$CRISIS$			−0.0294**
			(0.0123)
N	15	15	15
Obs.	284	284	284
Obs. below threshold	26	26	26

Notes: The standard errors are reported in the parentheses. Dependent variable: Annual growth rate of GDP per capita. Time trends and time dummies are not reported in this table in order to save space. *** indicates significance level at 1% level. ** indicates significance level at 5% level. * indicates significance level at 10% level.
(a) – benchmark model
(b) – benchmark model including some control variables
(c) – benchmark model including all control variables

World War II. During this period, the empirical results identify the threshold level of credit is around 135.14% of GDP. Credit has both positive and negative effects on economic growth. Credit has a strong positive effect on growth when its threshold level is below 135.14% of GDP. The positive effect of credit on growth has long been argued by several empirical investigations (see, e.g. King and Lavine, 1993; Beck et al., 2000; Levine et al., 2000). This gives a significant role the financial intermediaries in shaping the economy. On the other side, bank credit seems to have a negative effect on economic growth when the level of credit to GDP is beyond its threshold level. The findings are in-line with Arcand et al. (2015) and many others who find that finance is harmful to economic growth when credit to the private sector is higher than the size of the economy (GDP). From the short-run perspective, the results confirm that bank credit has a negative effect on economic growth, which is in line with Loayza and Ranciere (2006) and Narayan and Narayan (2013). The findings support the non-linear relationship between credit and economic growth and are in-line with other studies (Shen and Lee, 2006; Cecchetti and Kharroubi, 2012; Arcand et al., 2015).

2.5.3 Robustness Check

Through the empirical analyses, credit has a non-linear relationship with economic growth in the Post-WWII sub-sample. To assess the robustness of the results, a variety of addition tests were conducted. First, the empirical analyses include additional an explanatory variable, such as inflation, into the model. Managing price stability is the core objective of central banks' monetary policy, as it is a key factor in determining the growth rate of an economy, as too high inflation may distort economic growth. Second, the emprical analyses use longer lags of the GDP growth rate, as instruments, to the endogenous regressor, the first lag of the dependent variable ($y_{i,t-1}$). Last, the United States of America (USA), which suffered from the recent financial crisis due to the credit booms and bursts, were excluded from the benchmark model. The sub-sample period of Post-World War II (1948-2013) is applied in all the robustness tests. The empirical results are reported in Tables 2.5 and 2.6, in which the results are quantitatively similar to those reported in Table 2.2. The findings support the non-linear relationship between credit and economic growth and are in line with Shen and Lee (2006), Cecchetti and Kharroubi (2012), and Arcand et al. (2015), and the threshold level is consistent with the previous estimations as shown in Table 2.2.

Table 2.5 presents the results of robustness check when controlling for inflation and the additional lags of instruments. Column (1) shows the benchmark results, as reported in the column (c) of Table 2.2, and column (2) reports the results when the inflation rate is included into the benchmark model (1 lag instrument). Column (3) is similar to column (2) but the instruments are up to 9 lags. By controlling inflation and lags of instrument, the private sector credit threshold values remain unaltered at around 135.14% of GDP. More specifically, the regime-dependent coefficients ($\hat{\beta}_1$) and ($\hat{\beta}_2$) remain robust and significant with expected signs at the conventional level. This strongly suggests that the relationship between credit and economic growth has an inverted U-shaped relationship. As shown in column (2) and (3), inflation has negative impact on economic growth, but it is not statistically significant even at 10% level.

To conduct further robustness check, the United States of America was excluded from the sample period of the Post-WWII. The empirical results are reported in Table 2.6, where column (1) presents the benchmark model when all countries are included (all coefficients are taken from Table 2.2),

Table 2.5: Robustness Test Results for Post-WWII: 1948-2013

	Models		
	(1)	(2)	(3)
Threshold estimates	1.3513	1.3514	1.3514
95% confidence interval	[1.3301-1.4082]	[1.3300-1.3549]	[1.3300-1.3549]
Impact of credit			
$\hat{\beta}_1$	0.0279^{*}	0.0321^{**}	0.0313^{*}
	(0.0162)	(0.0162)	(0.0162)
$\hat{\beta}_2$	-0.0159^{***}	-0.0148^{***}	-0.0154^{***}
	(0.0044)	(0.0043)	(0.0043)
Impact of covariates			
y_{t-1}	0.3327^{***}	0.3366^{***}	0.3238^{***}
	(0.0398)	(0.0394)	(0.0389)
INV	0.0213	0.0213	0.0236
	(0.0274)	(0.0285)	(0.0274)
GOV	−0.0265	−0.0225	−0.0219
	(0.0221)	(0.0218)	(0.0211)
POP	0.0599	0.0815	0.0797
	(0.1350)	(0.1194)	(0.1182)
TOT	−0.0056	−0.0069	−0.0071
	(0.0045)	(0.0045)	(0.0044)
$OPEN$	−0.0005	0.0011	0.0012
	(0.0075)	(0.0076)	(0.0075)
$CRISIS$	-0.0143^{***}	-0.0135^{***}	-0.0135^{***}
	(0.0044)	(0.0044)	(0.0044)
$INFL$		−0.0522	−0.0516
		(0.0404)	(0.0398)
N	17	17	17
Obs.	1,111	1,111	1,111
Obs. below threshold	142	142	142

Notes: The standard errors are reported in the parentheses. Time trends and time dummies are not reported in this table in order to save space. *** indicates significance level at 1% level. ** indicates significance level at 5% level. * indicates significance level at 10% level.
(1) – benchmark model as reported in column (c) of Table 2.2
(2) – benchmark model including inflation (1 lag instrument)
(3) – benchmark model including inflation (up to 9 lags instrument)

while column (2) shows the results when two countries are excluded from the sample and column (3) presents the estimation up to 9 lags of instruments. When excluding two countries from the sample, there is no significant impact on the results. The private sector credit threshold value is very close to 135% of GDP. The results are robust and the signs of the regime-dependent coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$ remain unchanged although the values of the coefficients change only marginally.

2.6 Conclusion

This chapter investigates the short-run impact of bank credit on economic growth. In this study, the the dynamic threshold panel techniques adopted from Baum et al. (2013) and Kremer et al. (2013) are applied using data from 17 advanced countries covering the late 1800s to 2013. The empirical analyses capture three main periods – Pre-WWI, Interwar, and Post-WWII. The findings show that there exists evidence supporting the existence of a credit threshold of about 135% of GDP for the post-war sample. An inverted U-shaped relationship, which is statistically significant in the sample period after the World War II, suggests that additional credit has a positive impact on economic growth until credit reaches its threshold, followed by declining growth as credit exceeds the threshold. However, there is no evidence of an inverted U-shaped relationship in other sub-sample periods prior to the World War II. The evidence highlights the economic importance of credit in the post-war modern economies as opposed to the limited role of credit prior to the World War II.

The empirical findings show that countries with a very large financial sector is definitely not always better as there is no positive correlation be-

Table 2.6: Robustness Test Results for Post-WWII: 1948-2013 (excluding USA)

	Models		
	(1)	(2)	(3)
Threshold estimates	1.3515	1.3495	1.3495
95% confidence interval	[1.3301-1.4082]	[1.3300-1.3549]	[1.3301-1.3549]
Impact of credit			
$\hat{\beta}_1$	0.0285^{*}	0.0279^{*}	0.0271^{*}
	(0.0162)	(0.0166)	(0.0165)
$\hat{\beta}_2$	-0.0159^{***}	-0.0171^{***}	-0.0175^{***}
	(0.0044)	(0.0046)	(0.0045)
Impact of covariates			
y_{t-1}	0.3327^{***}	0.3470^{***}	0.3341^{***}
	(0.0398)	(0.0416)	(0.0409)
INV	−0.0213	0.0219	0.0242
	(0.0274)	(0.0280)	(0.0271)
GOV	−0.0265	−0.0232	−0.0225
	(0.0221)	(0.0221)	(0.0214)
POP	0.0599	0.0597	0.0582
	(0.1350)	(0.1332)	(0.1317)
TOT	−0.0056	−0.0039	−0.0041
	(0.0045)	(0.0051)	(0.0050)
$OPEN$	−0.0005	−0.0007	−0.0006
	(0.0075)	(0.0077)	(0.0076)
$CRISIS$	-0.0143^{***}	-0.0170^{***}	-0.0170^{***}
	(0.0044)	(0.0044)	(0.0044)
N	16	16	16
Obs.	1,111	1,045	588
Obs. below threshold	142	133	133

Notes: The standard errors are reported in the parentheses. Time trends and time dummies are not reported in this table in order to save space. *** indicates significance level at 1% level. ** indicates significance level at 5% level. * indicates significance level at 10% level.
(1) – benchmark model as reported in column (c) of Table 2.2
(2) – benchmark model excluding USA (1 lag instrument)
(3) – benchmark model excluding USA (up to 9 lags instrument)

tween credit growth and economic growth. Understanding the optimal level of credit is extremely crucial for policy-makers since the growth-enhancing strategies through an increase in size of the financial systems may not foster economic growth when it reaches a certain level. Arcand et al. (2015) describe three possible reasons that large financial systems may have a negative effect on economic growth. First, market-based financial intermediation becomes more important than credit markets as economies develop. Second, excessive financial depth could result in volatility and a banking crisis. Third, a large financial sector hurts industries that need skilled workers, therefore, this could result in a brain drain from the productive sectors of the economy. However, the relationship between credit and economic growth could depend upon whether the credit is provided to non-financial corporations for financing investment in productive assets or to domestic household for consumption purposes.

The empirical findings in this study have strong policy implications. First, the size of bank credit to private sector matters for the economic growth. Given that too much credit may harm economic growth, policy-makers, especially for central banks, should strengthen the quality of credit, and loans to the productive sectors should be enhanced. Second, central banks should be very cautious with the macro-prudential policy as too tight credit may distort growth, while too much credit could bring negative effect. However, as the study focuses on bank credit to private sector as an indicator to financial sector development, other indicators such credit to enterprises, credit to household, and the size of stock market should be worth exploring in the non-linear framework.

Chapter 3

Foreign Aid and Economic Growth: Evidence from Finite Mixture Model

3.1 Introduction

Over the last two decades, researchers tend to agree upon the diminishing returns of foreign aid (see, e.g. Hadjimichael et al., 1995; Hansen and Tarp, 2000, 2001; Dalgaard and Hansen, 2001; Lensink and White, 2001; Roodman, 2007; Feeny and McGillivray, 2010; Clemens et al., 2012; Feeny and de Silva, 2012; Bandyopadhyay et al., 2015).[1] The relationship between

[1] Given the importance of foreign aid in rebuilding post-conflict societies, reducing poverty, and spurring economic development in less-developed countries, some economists criticise the role of foreign aid for not being able to fulfil the ambitions of economic growth in less-developed countries. Among those, one of the greatest development economists in history, Peter Bauer, claims that foreign aid fails to speed up the economy and hurts economic development (Shleifer, 2009). Since then, there have been critiques of foreign aid from a number of well-known economists, including the 2015 Nobel Laureate Angus Deaton. The reason behind this is that aid effectiveness may be measured and analysed differently using tools or analytical methods, which may have flaws and thus, leading to

foreign aid and economic growth takes the form of an inverted U-shaped, meaning that that there are diminishing and eventually negative returns to foreign aid. This could be largely concerned with the limited absorptive capacity of typical developing countries to effectively use foreign aid.[2] Indeed, the concepts of diminishing returns to aid has been recognized over 50 years ago when the problem of absorptive capacity was first introduced by Chenery and Strout (1966). Virtually, the existence of the diminishing returns to foreign aid with respect to economic growth have been empirically tested, where the ratio of aid to GDP and its squared values are used as independent variables in the pooled cross-sectional and panel data estimation techniques. One common issue is that these empirical investigations follow the homogeneous assumptions of the standard growth model.

While most growth economists agree that heterogeneity is an important consideration in the study of economic growth, dealing with the issue may not be satisfactorily addressed in the studies mentioned above (Alfò et al., 2008).[3] Although dummy variables or country fixed effects are applied in panel data estimation techniques, as Owen et al. (2009) argue, the differences in the marginal effects of the regressors could not be captured. Furthermore, despite being grouped based on prior income threshold (i.e. lower income or lower middle income), countries within each group may still follow different growth processes (Owen et al., 2009). Therefore, these standard statistical methods may not satisfactorily address heterogeneity issues

contrasting conclusions.

[2]Feeny and de Silva (2012) classify the absorptive capacity constraints (ACCs) into five types: "(i) human and physical capital constraints; (ii) policy and institutional constraints; (iii) macroeconomic constraints; (iv) deficiencies in the manner in which the international donor community delivers its foreign assistance; and (v) social and cultural constraints."

[3]The cross-country models usually based on the paper of Mankiw et al. (1992) do not allow for heterogeneity among countries. Basically, several papers identify strong parameter heterogeneity in cross-country or panel type growth regressions (see, e.g. Brock and Durlauf, 2001; Masanjala and Papageorgiou, 2004; Alfò et al., 2008). In the aid-groth nexus, the empirical results may be biased due to unobserved country heterogeneity stemming from different country policies or capacity to allocate foreign aid.

as they, with the assumption that a sample of observations coming from the same distribution, could not capture the true parameters. Basically, standard models do not help to identify which observation goes with which distribution if the data are actually from more than one distribution with no information.

This study fills these gaps by applying Finite Mixture Model (FMM) proposed by Deb and Trivedi (2013) taking fixed effects into account. The primary objective of this study is to examine the differential impacts of foreign aid on economic growth using an economic technique to decompose the distributions of the growth rates. More importantly, this study aims at re-investigating the diminishing returns of foreign aid. The FMM, due to its convenience in semi-parametric model, is capable of capturing the unknown distributional shapes (Alfò et al., 2008). The model provides a flexible framework to estimate both parameters and posterior probability of component membership for each observation. It estimates data with a mixture of distributions, allowing for the underlying heterogeneity of the growth processes. Furthermore, applying the FMM to the multiple growth processes can deal with varying parameters across countries, omitted variables, and non-linearities in the growth model (Alfò et al., 2008). The FMM sorts countries into different groups on the basis of the posterior probabilities estimates based on the similarity of the conditional distribution of the growth rates determined by other control variables.

The findings are as follows. Firstly, by applying the panel data estimation techniques to the dataset of 71 developing countries over the period from 1967 to 2010, the results show an inverted U-shaped relationship between foreign aid and economic growth. The findings are consistent with existing empirical literature. Next, by applying the FMM to the same dataset, the results show that there are two groups of countries in the growth regimes. Unlike the standard panel data estimation techniques under the homogeneous assumptions, the results from the FMM do not support the diminishing returns of foreign aid in general. The inverted U-shaped relationship between foreign aid and economic growth significantly appears only in one group, consisting of 20 countries. However, there is no statistical evidence to support the diminishing returns for the other group of countries in the sample (51 countries). Furthermore, when the interaction terms of aid and economic policy are included following Burnside and Dollar (2000) into the FMM model, the results do not significantly alter. The diminishing returns relationship appears to be statistically significant only in one group of countries, but not the other. The coefficient of the interactive terms of foreign aid and economic policy statistically significant different from zero, which is consistent with the argument that aid is effective only for countries with a good economic policy environment. However, it is noticed that the numbers of countries belonging to this group are fewer.

The rest of the chapter is organized as follow. Section 2 reviews the relevant literature. Sections 3 and 4 lay out the econometric model and data, respectively, while the derived results and related discussion are presented in Section 5. Section 6 concludes.

3.2 Literature Review

The early empirical research on foreign aid received first attention in the 1960s (McGillivray et al., 2006). After World War II, the purposes of aid provision to poor countries were to supplement domestic savings or foreign exchange reserves. This is because of the low level of investment in these countries given insufficient domestic savings that can add to the investible resources for domestic investment, and thus, foreign aid is believed the only way to augment capital stocks. While aid has been playing an important role in economies of developing countries, its effectiveness is still under debate throughout generations of research (Easterly et al., 2004; Roodman, 2007; Rajan and Subramanian, 2008). The first batch of research raises a question of whether aid works. McGillivray et al. (2006) survey 50 years of empirical research on aid effectiveness, and conclude that the relationship between aid and economic growth or other related variables remain ambiguous. Some studies find a positive relationship, while others find a negative or no relationship of foreign aid and economic growth. Following similar reasoning, a second batch of research on aid effectiveness is based on the seminal work of Burnside and Dollar (2000). Basically, Burnside and Dollar (2000) argue that aid works only if the recipient country's economic policy is good enough. However, the policy recommendation that aid should be mainly allocated only to countries with good policies receives a big criticism essentially due to the lack of robustness. (see, e.g. Easterly et al., 2004; Roodman, 2007; Rajan and Subramanian, 2008). The third batch of research argues that aid is subject to diminishing returns due to the absorptive capacity of developing economies (Feeny and de Silva, 2012).

A large number of studies have confirmed the hypothesis of diminishing returns of foreign aid, which implies an inverted U-shaped relationship between aid and growth. The concept is about the absorptive capacity constraints of recipient countries. Furthermore, too much aid inflows may induce Dutch disease, which could create exchange rate volatility in the recipient's economy (Rajan and Subramanian, 2005). Thus, this suggests that foreign aid spurs economic growth only up to a certain level and beyond a certain threshold, additional aid could harm economic growth. This hypothesis has been proved by a large number of empirical literature (see, e.g. Hadjimichael et al., 1995; Hansen and Tarp, 2000, 2001; Dalgaard and Hansen, 2001; Lensink and White, 2001; Roodman, 2007; Feeny and McGillivray, 2010; Clemens et al., 2012; Feeny and de Silva, 2012; Bandyopadhyay et al., 2015). Table 3.1 summarizes some of these non-linear studies between foreign aid and economic growth.

Table 3.1: Summary of the non-linear studies between foreign aid and economic growth

Authors	**Sample**	**Data/period**	**Methods**	**Findings**
Hadjimichael et al. (1995)	41 Sub-Saharan African countries	Data (1986 - 1992)	Pooled time series and cross section data	There exists non-linear relationship between foreign aid and growth.
Hansen and Tarp (2000)	56 countries	Panel data (1970 - 1993): averaged over 4-year interval	Panel data techniques and IV methods	There is a robust aid-growth link even in countries hampered by an unfavourable policy environment, and aid squared term is statistically significant and robust.
Dalgaard and Hansen (2001)	Sample data from Burnside and Dollar (2000)	Sample data from Burnside and Dollar (2000)	Theoretical model, OLS and IV methods	No robust result on the positive impact of aid on growth in good policy environments. There is a non-linear relationship between aid and growth, in which there is a diminishing returns to aid, confirming their theoretical model.

Table 3.1 – continued from previous page

Authors	Sample	Data/period	Methods	Findings
Hansen and Tarp (2001)	56 countries	Panel data (1974 - 1993): averaged over 5-year interval	OLS, GMM with IV mothods	Aid promotes growth unconditional on the policy index established by Burnside and Dollar (2000). The decreasing returns to aid depends on the choice of estimator and the set of control variables.
Lensink and White (2001)	111 countries	Panel data (1975 - 1992): averaged over 5-year and 3-year intervals	OLS and IV methods	Aid is more effective for countries with good economic policy, but subject to negative returns at high levels of aid inflows.
Roodman (2007)	Sample data from Easterly et al. (2004) and extension	Panel data (1970 - 2001)	OLS, 2SLS, GMM, IV methods	Aid raises growth but with diminishing returns.
Feeny and McGillivray (2010)	29 small island developing states	Panel data (1980 - 2004): annual and averaged over 4-year interval	OLS, Fixed Effects, GMM with IV methods	Foreign aid is effective at spurring economic growth but with diminishing returns.
Clemens et al. (2012)	Dataset from Burnside and Dollar (2000) and Rajan and Subramanian (2008)	Panel data (1961 - 2000): averaged 5-year interval	OLS, 2SLS, GMM, IV methods	Aid promotes economic growth in recipient countries and diminishes at high levels of aid.

Table 3.1 – continued from previous page

Authors	Sample	Data/period	Methods	Findings
Feeny and de Silva (2012)	140 countries	Panel data (1990 - 2005): averaged 3-year interval	OLS, FE, GMM	Various dimensions of absorptive captivity are identified.
Bandyopadhyay et al. (2015)	131 developing countries	Panel data (1996 - 2010): annual and averaged over 3-year interval	OLS, FGLS, Diff-GMM, Sys-GMM	Non-linear inverted U-shaped relationship between aid and growth, but U-shaped relationship between loans and growth.

Typically, most of these studies introduce the ratio of aid to GDP and its squared values on the right-hand side of the model by applying a range of econometric techniques. This includes cross-sectional or panel data estimation techniques such as OLS, fixed effects, instrumental variables, and GMM. Although these studies find robust results confirming the diminishing returns of foreign aid, Hansen and Tarp (2001) argue that the decreasing returns of aid depends on the choice of estimator and the set of control variables. Therefore, its robustness is worth observing with a new dataset that offers a longer time horizon. Given the limitation of the common statistical methods with the homogeneous assumptions, using an econometrics technique such as the FMM to the multiple growth processes could be more advantageous in dealing with varying parameters across countries, omitted variables, and non-linearities in the growth model (Alfò et al., 2008).

The FMM approach is preferable to the previously used rolling regression models as it is capable of sorting variables endogenously (Owen and Temesvary, 2014). Unlike previous models in which researchers impose the sorting variables (i.e. developed and developing countries group) a priori, the FMM classifies country into groups based on the conditional distribution of growth rates. The approach allows classification of countries on the basis of the posterior probabilities estimates. In other words, the model picks out countries belonging to the same groups or the same coefficients in the estimated regression.

3.3 Methodology

The aim of this study is to examine the non-linear relationship between foreign aid and economic growth using the finite mixture model proposed by Deb and Trivedi (2013). The model specification begins with a simple panel method using the ratio of aid-to-GDP with the squared value on the right-hand side of the model. This quadratic equation is adopted from the empirical literature. The model specification is written as follows.

$$y_{it} = \alpha_i + \beta_0 + \beta_1 AID_{it} + \beta_2 AID_{it}^2 + \beta_3 X_{it} + \varepsilon_{it} \tag{3.1}$$

where, y_{it} is growth rate of country i at time t, α_i is a set of country-specific fixed effects, AID_{it} is the ratio of foreign aid to GDP, X_{it} represents other control variables, and ε_{it} is the error term which is assumed to be independent and identically distributed with mean zero and finite variance. For simplicity, the equation (3.1) is rewritten into matrix format.

$$y_{it} = \alpha_i + X_{it}^{'}\beta + \varepsilon_{it} \tag{3.2}$$

where the sub-index i denotes country and t denotes time period. X_{it} is a vector of observations on k explanatory variables, and β is a k-vector of unknown coefficients to be estimated. The time-invariant regressors in equation (3.2) are country-specific characteristics that may or may not influence the predictor variables, which need to be controlled for. The fixed effects model can deal with this issue. The country-specific fixed effect parameters α_i can be eliminated through using the 'within' or 'first-differencing' transformations. In this study, the within transformation is used to omit the country-specific effects. Denote $\bar{y}_i$ and $\bar{x}_i$ the sample means of $T^{-1}\sum y_{it}$ and $T^{-1}\sum x_{it}$ respectively, and assume $\varepsilon_{it} \sim N[0, \sigma^2]$, the within transformation yields:

$$y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)^{'}\beta + (\varepsilon_{it} - \bar{\varepsilon}_i) \tag{3.3}$$

where again the fixed effects do not appear in the transformed model. The next consideration is the conditional likelihood. The sufficient statistic for α_i is $\sum_{i,t} y_{it}$ or $T\bar{y}_i$. Then, under normality assumption for ε_{it}, the maximum likelihood estimator (MLE) of β, ignoring σ^2, is based on the conditional likelihood:

$$\begin{aligned} L_{COND}(\beta, \sigma^2, \alpha) &= \prod_{i=1}^{N} f(y_{i1}, ..., y_{iT}|\bar{y}_i) \\ &= \prod_{i=1}^{N} \frac{f(y_{i1}, ..., y_{iT}, \bar{y}_i)}{f(\bar{y}_i)} \\ &= \prod_{i=1}^{N} \frac{(2\pi\sigma^2)^{-T/2}}{(\frac{2\pi\sigma^2}{T})^{1/2}} \\ & exp\left\{\sum_{t=1}^{T} -\frac{1}{2\sigma^2}[(y_{it} - X_{it}^{'}\beta)^2 + (\bar{y}_i - \bar{X}_i\beta)^2]\right\} \end{aligned} \tag{3.4}$$

Next, the conditional maximum likelihood (CML) estimator $\hat{\beta}_{CML}$ or the within estimator is obtained by solving the first-order condition:

$$\sum_{t=1}^{T}\sum_{i=1}^{N}[(y_{it}-\bar{y_i})-(x_{it}-\bar{x_i})'\beta](x_{it}-\bar{x_i})=0 \tag{3.5}$$

where the solution coincides with the first-order conditions from least squares regression of $(y_{it}-\bar{y_i})$ on $(x_{it}-\bar{x_i})$. This suggests that the within estimator is equal to $\hat{\beta}_{CML}$ in this case, where the country-specific fixed effects α_i are eliminated. Therefore, the conditional log-likelihood function can be maximized with respect to the common parameters. Although the estimator $\hat{\beta}_{CML}$ is consistent in this case, the estimator $\hat{\sigma}^2 = \sum \hat{\varepsilon}_t^2/NT$ is biased to $0(T^{-1})$, where the bias adjustment needs to be replaced by the estimator $\sum \hat{\varepsilon}_t^2/(N(T-1)-K)$.

The FMM with fixed effects is adopted from Deb and Trivedi (2013) in order to take heterogeneity into account. It is assumed that GDP growth rate, y_{it}, could be clustered into C latent classes (C-component mixture). The standard definition of a C-component mixture of an arbitrary density with $f(y_{it}|x_{it},\theta_j)$, $j=1,2,...,C$ is

$$\sum_{j=1}^{C}\pi_j f(y_{it}|X_{it},\theta_j) \tag{3.6}$$

where, $0<\pi_j<1 \forall j=1,2,...,C$, $\sum_j \pi_j = 1$; and $y_{it} \sim f(y_{it}|X_{it},\theta_j)$ with probability π_j.

With the mixing proportions having been set up; where a pooled data mixture model is specified, and the above likelihood function (equations (3.5) and (3.6)) is referred to as mixture likelihood. However, no country-specific effects, α_i, are included into the mixture model. It is noticed that the above conditioning approach works for the Normal regression, but not for the mixture of the Normal finite mixture models. In order to extend the CML approach to Normal finite mixture model, a sufficient statistic for the α_i must hold, where fixed effects are first removed and then a mixture of concentrated marginals is formed.

Let s_i be a sufficient statistic for α_i; then equation (3.6) is written as follows:

$$\sum_{j=1}^{C} \pi_j f(y_{it}|X_{it}, \theta_j, s_i) \tag{3.7}$$

The estimation objective is to obtain consistent estimates of $(\pi_j, \theta_j),\ j = 1, \ldots, C$.

Following the component-wise conditional density, the mixture was constructed using the conditional likelihood for each component Normal regression.

$$f_j(\beta_j, \sigma_j^2|\alpha) = \frac{(2\pi\sigma^2)^{-T/2}}{(\frac{2\pi\sigma^2}{T})^{1/2}} exp\left\{\sum_{t=1}^{T} -\frac{1}{2\sigma^2}[(y_{it} - \bar{y}_i) - (x_{it}^{'} - \bar{x}_i^{'})\beta_j)^2]\right\} \tag{3.8}$$

for $i = 1, \ldots, N$, and the mixture distribution is

$$\sum_{j=1}^{C} \pi_j f_j(\beta_j, \sigma_j^2|\bar{y}_i, x_i) \tag{3.9}$$

and $0 < \pi_j < 1, \forall j = 1, 2, \ldots, C,\ \sum_j \pi_j = 1$.

For the convenience of estimation with the *full-data likelihood*, define d_{it} an indicator variable identifying individual i's latent class at time t, with the indicator function $1(d_{ji})$.

$$d_{ji} = \begin{cases} 1 & \text{if } i \text{ belongs to the component } j, \\ 0 & \text{otherwise} \end{cases} \tag{3.10}$$

Then the full-data likelihood for this model, under the assumption that the observations are conditionally independent across individuals and over time is

$$L_{COND}(\beta, \sigma^2|\alpha) = \prod_{i=1}^{N} \prod_{t=1}^{T} \sum_{j=1}^{C} (\pi_j f(\beta_j, \sigma_j^2|\bar{y}_{it}, X_{it}))^{1(d_{jt}=1)} \tag{3.11}$$

The maximization of equation (3.11) could be based on the expectation-maximization algorithm. The EM algorithm is an iterative method for finding maximum likelihood or maximum a posterior (MAP) estimates in a model that depends on unobserved latent variables. Each iteration of the EM algorithm consists of two processes: (1) the E (expectation) step computes the expectation of the complete likelihood, and (2) the M (maximization) step computes parameters maximizing the expected log-likelihood found on the E step. Each step increases the log-likelihood and iterates until convergence. McLachlan and Peel (2004) and Frühwirth-Schnatter (2006) provide a detailed discussion of the EM algorithm.

When considering the panel data, where observation y_{it} can be drawn from one of the C latent classes, each of which has a density $f(y_{it};\theta_j)$. Here $f(y_{it};\theta_j)$ is shorthand for the jth component of concentrated likelihood and θ_j is a generic notation for common parameters in component j. Let $y_i = (y_{i1}, y_{i2}, ..., y_{iT})$ be the vector of observed values for unit i. Let $d_i = (d_{i1}, d_{i2}, ..., d_{Ci})$ define a set of indicator variables such that $d_{ji} = 1$ if the unit i was drawn from the latent class j, $d_{ji} = 0$ otherwise; and $\sum_j d_{ji} = 1$. Then, the panel finite mixture model specifies that $(y_i|d_i, \theta, \pi)$ are independently distributed with densities:

$$\prod_{j=1}^{C} (f(y_{i1};\theta_j) \times (f(y_{i2};\theta_j) \times ... \times (f(y_{iT};\theta_j))^{d_{ji}} = \prod_{j=1}^{C} \left(\prod_{t}^{T} (f_j(y_{it};\theta_j)) \right)^{d_{ji}} \tag{3.12}$$

and $(d_{ji}|\theta, \pi)$ are i.i.d. with multinomial distribution $\prod_{j=1}^{C} \pi_j^{d_{ji}}$, $0 < \pi_j < 1$, $\sum_{j=1}^{C} \pi_j = 1$.

Thus,

$(y_{i1}, y_{i2}, ..., y_{iT}|\theta, \pi) \sim \sum_{j=1}^{C} \left(\pi_j \prod_{t=1}^{T} f_j(y_{it};\theta_j) \right)^{d_{ij}}$, where $\theta = (\theta_1, ..., \theta_C)$

The likelihood function is then

$$L(\theta, \pi|y) = \prod_{i=1}^{N} \sum_{j=1}^{C} \left(\pi_j \prod_{t=1}^{T} f_j(y_{it};\theta_j) \right)^{d_{ji}} \tag{3.13}$$

and the log-likelihood function is

$$lnL(\theta,\pi|y)=\sum_{i=1}^{N}\sum_{j=1}^{C}d_{ji}\left(\ln(\pi_j)+\sum_{t=1}^{T}ln(f_j(y_{it};\theta_j))\right) \tag{3.14}$$

Replacing d_{ji} by its expected value, $E[d_{ji}]=\hat{z}_{ji}$, yields the expected log-likelihood (EL),

$$EL(\theta,\pi|y)=\sum_{i=1}^{N}\sum_{j=1}^{C}\hat{z}_{ji}\left[lnf_j(y_i;\theta_j)+\ln\pi_j\right] \tag{3.15}$$

The M-step of the EM procedure maximizes equation (3.15) by solving the first order conditions

$$\bar{\pi}_j-\frac{\sum_{i=1}^{N}\hat{z}_{ji}}{N}=0 \tag{3.16}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{C}\hat{z}_{ji}\frac{\partial lnf_j(u_i;\theta_j)}{\partial\theta_j}=0 \tag{3.17}$$

The M-step of the EM procedure obtains the new values of $E[d_{ji}]$ using the equation (3.16). The marginal probability that an observation comes from the class j is the average of all individual observation probabilities coming from the jth population. The posterior probability that unit i belongs to population $j, j=1,2,...C$, denote z_{it} is defined as

$$z_{ji}=\frac{\pi_j\prod_{t=1}^{T}f_j(y_{it};\theta_j)}{\sum_{j=1}^{C}\pi_j\prod_{t=1}^{T}f_j(y_{it};\theta_j)} \tag{3.18}$$

In estimating the latent class, firstly, the E-step calculates z_{ji} to define the set of posterior probabilities of classification for each unit given a set of parameters $\{\theta_j, \pi_j\}_{j=1,2,\ldots,C}$. Secondly, the values of $\{\pi_j\}_{j=1,2,\ldots,C}$ are obtained for the next M-step, where the equation (3.15) is maximized. Both E- and M-steps are alternated repeatedly until the expected log-likelihood changes by an arbitrarily small amount. Estimating the latent class starts with a one-class model ($C = 1$), and then proceed to estimate subsequent models assuming ($C = C + 1$) until the finite value of the number of components is reached. After that, the penalised likelihood criterion, the Bayesian Information Criterion (BIC), is used to select the model that best fits the data. The model is chosen with the lowest BIC, because BIC decreases in value of the log-likelihood and increase in the number of parameters estimated. By obtaining the latent class, the parameters can be estimated accordingly.

3.4 Data

The empirical application of the finite mixture model to the aid-growth nexus is based on a panel-dataset of 71 developing countries for the period from 1967 to 2010. All variables are averaged over non-overlapping four-year periods (1967-1970, 1971-1974, 1975-1978, 1979-1982, 1983-1986, 1987-1990, 1991-1994, 1995-1998, 1999-2002, 2003-2006, 2007-2010). For each country, the annual growth rates of real GDP per capita in constant 2005 prices ($GDPGrowth$) are obtained from Penn World Table 7.1. Data on foreign aid is collected from the World Development Indicator of the World Bank database. The other control variables that could be correlated with economic growth are included following the aid-growth literature (see, e.g. Hadjimichael et al., 1995; Burnside and Dollar, 2000; Hansen and Tarp, 2000, 2001; Dalgaard and Hansen, 2001; Lensink and White, 2001; Roodman, 2007; Feeny and McGillivray, 2010; Clemens et al., 2012; Feeny and de Silva, 2012; Bandyopadhyay et al., 2015). Those variables include: investment/GDP as commonly proxied for fixed capital formation, M2/GDP as financial deepening, population growth, human capital, and economic policy. Moreover, as political regimes play key roles in economic development, variables such as democracy and autocracy are included in the model. For instance, Rachdi and Saidi (2015) while employing the data of 17 Middle East and North Africa countries over the period 1983-2012 find that democracy have a robust and negative impact on growth. Carden and James (2013) use the data of 155 countries from 1920 to 2000 find that the longer a country was within an autocracy, the lower is the country's economic performance.

More information about the control variables is contained in the Appendix A. The descriptive statistics are reported in Table 3.2.

Table 3.2: Summary Statistics

	N. Obs	Mean	SD	Min	Max
$GDPGrowth$	775	1.6661	4.0942	-24.1316	20.4806
AID/GDP	738	6.4093	7.5938	-0.2079	57.7240
KI	781	2.9315	0.5994	0.3682	4.5820
$M2/GDP$	719	3.3028	0.6213	0.0300	5.4773
POP	781	2.2996	1.1009	-4.7064	17.6882
HAI	773	3.6278	0.6951	-0.1754	4.5736
$DEMOC$	751	3.2143	3.4988	0	10
$AUTOC$	751	3.6357	3.2255	0	10
$POLICY$	485	2.3926	0.8771	-0.01480	5.9025

3.5 Empirical Results

This study first estimates the equation (3.1) using the panel data methods. Table 3.3 shows the results obtained by using different estimation methods including the ordinary least squares (OLS), fixed effects (FE), and the dynamic panel data model, using the difference-generalized method of moments (Diff-GMM), and system-GMM (Sys-GMM). The results from all estimation models indicate that almost all variables included are statistically significant and show, in general, the expected signs. Interestingly, the findings present the patterns of non-linearities between foreign aid and economic growth, which are consistent with the literature. Like most previous papers, the ratio of foreign aid-to-GDP and its squared value present an inverted U-shaped relationship, implying the diminishing returns of foreign aid on economic growth.

The results obtained from the OLS estimation is shown in the OLS column of Table 3.3. The signs of the aid-to-GDP and its square term show the expected signs although the aid-to-GDP is not statistically significant. However, as OLS estimates could be biased given individual heterogeneity (unobserved country-specific effects), a re-estimation of equation (3.1) was undertaken, taking into account fixed effects, and the results are presented in the FE column. Compared to the OLS, the signs of the variables of interest do not change, but are highly significant at the 1% level. The inverted U-shaped relationship between foreign aid and economic growth suggests that foreign aid becomes more intensified initially and then peaks out to decline at the higher level of foreign aid.[4] Moreover, the findings show that human capital and good economic policy are associated with economic growth while the population growth tend to adversely affect growth in developing countries.

To confirm the results from the FE estimation, the equation (3.1) is estimated by introducing the first lag of the dependent variable $y_{i,t-1}$. Equation (3.1) becomes a dynamic panel data model.[5] In the dynamic panel data

[4]The estimated threshold of foreign aid is equivalent to 13% of GDP.
[5]Appendix C provides further detail on the dynamic panel data model.

model, a serious difficulty arises when dealing with unobserved heterogeneity by applying the within or demeaning transformation (Nickell, 1981). This is because of the presence of the correlation between regressor and error term in the demeaning process when the individual's mean value of the dependent variable and each independent variable is subtracted from the respective variable. In order to solve this problem, this study adopts the GMM estimators developed for the dynamic panel data model introduced by Arellano and Bond (1991). First, it is necessary to take the first differences of the original model in order to remove the constant term and the individual effect. Second, it is necessary to construct the instruments for the lagged dependent variable from their lags, i.e., the second lag of the dependent variable, in order to deal with the correlation between the differenced lagged dependent variable. The column Diff-GMM presents the results of the dynamic panel model following Arellano and Bond (1991).[6] The findings are relatively robust indicating that all the variables included are statistically significant, and show in general, the expected signs.

In order to improve the efficiency of instrumenting, it is necessary to apply the system GMM proposed by Arellano and Bover (1995) and Blundell and Bond (1998). Extended from the difference-GMM, Arellano and Bover (1995) and Blundell and Bond (1998) make an additional assumption that the first differences of instrumenting variables are uncorrelated with fixed effects. The system GMM, built from the original equation and the transformed one, allows the introduction of more instruments. In this case, this empirical investigation include the first lags of investment, money supply, population, and human asset index as instruments. The estimation results

[6] In this study, I use the minimum of 1 lag of instrument in order to avoid overfitting instrumented variables. Too many instruments could fail to remove their endogenous components which may lead to biased coefficient estimates (Roodman, 2009). Furthermore, I conduct a standard test for the validity for the instrument using Sargan test. The p-value of the Sargan test suggests that the moment condition for the Diff-GMM are valid.

are shown in the Sys-GMM column of Table 3.3. The results from system-GMM do not significantly alter from the fixed effects and difference-GMM estimations. The coefficients for aid-to-GDP and its square values from the fixed effects and system-GMM are almost equal, giving the robustness of the results when applying alternative methods of the panel data techniques. As discussed above, the results hold for all the models using the panel data estimation techniques, which clearly suggest that aid has diminishing impact on economic growth. The findings are robust and consistent with the literature (Hadjimichael et al., 1995; Hansen and Tarp, 2000, 2001; Dalgaard and Hansen, 2001; Lensink and White, 2001; Roodman, 2007; Feeny and McGillivray, 2010; Clemens et al., 2012; Feeny and de Silva, 2012; Bandyopadhyay et al., 2015).

To explore further the possibility of heterogeneous effects of foreign aid on economic growth, I apply the finite mixture model to the same data set. As mentioned in the previous section, the FMM is convenient in decomposing the distributions of the growth rate, and is capable of capturing the unknown distributional shapes, so that it can endogenously classify countries into homogeneous groups. In the first step of the estimation procedure, one has to decide the number of the mixture components. The main challenge is to use the appropriate penalised likelihood criteria in a way that provides strong consistency and efficiency. The penalised likelihood criteria, such as the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) have been used to estimate the number of mixture components. In this study, BIC is used as it picks the components with the highest probability (Keribin, 2000). BIC performs better than AIC because AIC is not strongly consistent, though it is efficient (Claeskens and Hjort, 2008).

As shown in Table 3.4 presenting the component membership for the

Table 3.3: Estimates from Panel Data Methods

Variables	OLS	FE	Models Diff-GMM	Sys-GMM
$GRGDP(-1)$			-0.0801	-0.2358^{***}
			(0.0551)	0.0515
AID/GDP	0.1188	0.3342^{***}	0.5253^{***}	0.3091^{*}
	(0.0791)	(0.1150)	(0.1779)	(0.1678)
$(AID/GDP)^2$	$-.0072^{**}$	-0.0126^{***}	-0.0222^{***}	-0.0159^{***}
	(0.0034)	(0.0037)	(0.0053)	(0.0049)
KI	0.5148	-0.4570	-0.1722	-0.9071
	(0.4922)	(0.6738)	(0.9334)	(0.8735)
$M2/GDP$	0.4157	-0.8574	-0.6668	-0.5831
	(0.3278)	0.6206	(0.8884)	(0.8056)
POP	-0.5939^{*}	-0.5481^{***}	-0.3773^{**}	-0.5444^{***}
	(0.3211)	0.1610	(0.1913)	(0.1769)
HAI	0.1360	2.8091^{***}	2.4255	4.5849^{***}
	(0.3536)	0.9135	(1.5593)	(1.1691)
$DEMOC$	-0.0890	-0.0725	0.2304	-0.0950
	(0.0942)	0.1252	(0.2080)	(0.2276)
$AUTOC$	-0.0847	-0.0546	0.2562	0.1047
	(0.1329)	0.1494	(0.2258)	(0.2227)
$POLICY$	0.2455	0.7396^{**}	1.5374^{***}	1.3382^{***}
	(0.1902)	0.3345	(0.5104)	(0.4826)
$Constant$	0.9651	-6.2986	-6.6972	-12.5387^{**}
	(2.3651)	4.5479	(6.1785)	(5.4697)
R^2	0.2033			
$Within R^2$		0.2346		
$Overall R^2$		0.1203		
Sargan test (p-value)			0.2870	0.0000
AR(1) Prob.				0.0000
AR(2) Prob.				0.1680
Obs.	474	474	377	456
Countries	71	71	70	71
Year dummy	YES	YES	YES	YES

Notes: The standard errors are reported in the parentheses. Time dummies and country dummies are not reported in this table in order to save space. The symbols ***, **, * mean that the coefficient is statistically different from zero, respectively, at the 1%, 5%, and 10% level.

models, BIC suggests that two mixture components best fits the data. The mixture components provided by AIC cannot be determined as the values keep decreasing when the number of components increase. As a result, BIC is considered as model selection criterion. The two mixture components provide a clue that countries follow different growth processes. By using panel data, the model specification restricts countries to belong to the same class in each time period.

Table 3.4: Fit Statistics for Growth Mixture Model

C	*LogLikelihood*	*AIC*	BIC
2	**-1164.922**	**2375.843**	**2471.551**
3	-1131.704	2333.408	2479.051
4	-1111.350	2316.701	2512.278
5	-1075.129	2268.257	2513.769

Table 3.5 presents the results from the Finite Mixture Model with fixed effects proposed by Deb and Trivedi (2013). The sample is divided into two groups of countries based on the obtained posterior probabilities.[7] The first group contains 51 countries and the second one contains 20 countries. In the first group of countries, there is no statistical evidence to support the inverted U-shaped relationship between foreign aid and economic growth. The majority of countries in the sample period consisting of 51 countries belong to this group, where foreign aid plays no role in explaining the response variable. On the other hand, in the second group, the sign of aid-to-GDP ratio is positive and its squared value is negative at the 1% significance level. This presents an inverted U-shaped relationship between foreign aid and economic growth.

Table 3.6 displays the group for the individual countries in the sample belonging to the second group. Countries in this group do not all share the same observable characteristics such as region or income that researchers

[7]In order to obtain the posterior probabilities of class membership, I first estimate the FMM model to get the posterior probability of class membership for each country at each point in time. Next, I classify the group of countries based on the mean posterior probabilities for each country which is greater than 0.5.

typically use to group countries. This group contains countries belonging to all stages of development including lower income, lower middle income and upper middle income countries from different regions around the world. There is no clear-cut pattern showing the diminishing returns of foreign aid as it presents in different categories of income level.

Table 3.5: Estimates from Finite Mixture

	FMM	
Variable	Component1	Component2
AID/GDP	-0.0206	0.5011^{***}
	(0.1114)	(0.0657)
$(AID/GDP)^2$	-0.0008	-0.0080^{***}
	(0.0032)	(0.0017)
KI	-0.0893	-0.2862
	(0.3494)	(0.2420)
$M2/GDP$	-2.3678^{*}	-0.4861
	(0.9442)	(0.5125)
POP	-0.9027^{***}	-0.1527
	(0.2101)	(0.1903)
HAI	1.6806	-0.5036
	(1.1602)	(0.5554)
$DEMOC$	0.0588	-0.2060
	(0.2051)	(0.1159)
$AUTOC$	-0.0208	0.0493
	(0.2316)	(0.1351)
$POLICY$	0.8969^{*}	1.1962^{***}
	(0.5240)	(0.3536)
$Constant$	0.0820	1.1601^{***}
	(0.4087)	(0.2587)

Notes: The standard errors are reported in the parentheses. *** indicates significance level at 1% level. The symbols ***, **, * mean that the coefficient is statistically different from zero, respectively, at the 1%, 5%, and 10% level.

In addition to the main results, further testing was conducted, as to whether the impact of foreign aid and economic policy jointly affect growth. The interaction terms of aid and economic policy following Burnside and Dollar (2000) are included into the Finite Mixture Model. Similar to the estimation above, first by estimating the model in order to decide the mixture components based on the Bayesian Information Criterion (BIC) and then

Table 3.6: Class Membership - Component 2

No.	Country	No.	Country
1	Bolivia	11	Mongolia
2	Brazil	12	Nepal
3	Colombia	13	Nicaragua
4	Egypt, Arab Rep.	14	Pakistan
5	El Salvador	15	Philippines
6	Guinea-Bissau	16	Sri Lanka
7	Honduras	17	Sudan
8	Lao PDR	18	Tunisia
9	Mali	19	Uganda
10	Mexico	20	Vietnam

estimate the coefficients in each group of countries. These estimates are presented in Tables 3.7 and 3.8. Table 3.7 presents the fit statistics for mixture components, which best fits the data. According to the BIC, the fit statistics with the lowest value (2,278.284) suggest that three components best fit the data. However, the results from the FMM model with the three components do not show any country in the third group. Therefore, the two components are chosen instead.[8] Table 3.8 reports the results estimates using the FMM model by including the interaction term of aid and economic policy. The results do not significantly alter as the diminishing returns appear to be statistically significant only in one class of membership, but not the other. The results are consistent with the findings above. The interactive terms of aid and economic policy are statistically significant different from zero, which is consistent with the argument that aid is effective only for countries with a good economic environment. However, it is noticed that the numbers of countries belonging to this class membership are fewer. In short, the impact of foreign aid on economic growth seems to be heterogeneous across countries regardless of different levels of income.

[8]Indeed, the fit statistics based on the BIC for the two and three components is not significantly different; therefore, the two components could be the option for this analysis. When applying three components in the FMM, the results, which were not reported here, do not significantly alter, and countries still belong to the two components.

Table 3.7: Fit Statistics for Growth Mixture Model (2)

C	*LogLik*	*AIC*	BIC
2	**-1164.391**	**2378.782**	**2482.813**
3	**-1122.079**	**2320.158**	**2478.284**
4	-1091.228	2284.457	2496.678
5	-1066.206	2260.413	2526.730

Table 3.8: Robustness Check: Policy Interaction

	FMM(2)	
Variable	Component1	Component2
AID/GDP	0.0461	0.5060***
	(0.0971)	(0.0879)
$(AID/GDP)^2$	−0.0002	−0.0252***
	(0.0023)	(0.0024)
$AID * POLICY$	0.0077	0.1066***
	(0.0375)	(0.0361)
KI	0.2183	−0.7729***
	(0.3203)	(0.2556)
$M2/GDP$	−1.7145**	−0.3868
	(0.8620)	(0.5504)
POP	−0.0908	−0.5253***
	(0.3048)	(0.1214)
HAI	1.3806	−0.6345
	(1.0357)	(0.8749)
$DEMOC$	−0.0634	−0.0855
	(0.1968)	(0.1608)
$AUTOC$	−0.0497	0.0846
	(0.2141)	0.1475
$POLICY$	1.3014*	0.1280
	(0.7023)	(0.5589)
$Constant$	0.0627	1.4585***
	(0.3753)	(0.2867)

Notes: The standard errors are reported in the parentheses. The symbols ***, **, * mean that the coefficient is statistically different from zero, respectively, at the 1%, 5%, and 10% level.

3.6 Conclusion

This chapter re-investigate the concept of diminishing returns of foreign aid on economic growth using a sample of 71 developing countries for the period from 1967 to 2010. Beginning with the panel data methods following the existing literature using the aid-to-GDP ratio and its squared value on the right-hand side of the model, the results are consistent with previous findings, which present the diminishing returns to foreign aid. The findings also support the recent empirical research suggesting an inverted U-shaped relationship between foreign aid and economic growth in developing countries. This is due to absorptive capacity of the recipient countries, meaning that an inflow of foreign aid has a positive effect when it is below a certain level, above which, aid starts to have a negative effect on economic growth.

However, the estimations using the panel data techniques above could have limitations, as they fail to address heterogeneity issues. This is due to the assumption that aid affects growth homogeneously. Basically, the standard statistical methods may not satisfactorily address heterogeneity issues and they mostly assume that a sample of observations comes from the same distribution; and if the data are actually from more than one distribution with no information, the true parameters could not be captured. Therefore, to capture the true impact of foreign aid on economic growth, statistical model such as the Finite Mixture Model proposed by Deb and Trivedi (2013) is worth considering. Under the FMM, heterogeneity of a country's growth process is taken into account based on the similarity of the conditional distributions of their growth rates. Different from the panel data techniques, the results from the FMM do not support the diminishing returns of foreign aid in general because there are two groups of countries in the growth regimes. The diminishing returns of foreign aid belong to only one group, consisting of 20 countries. There is no statistical evidence to support the diminishing returns for the other group, where the inverted U-shaped relationship between foreign aid and economic growth is statistically insignificant.

The findings do not intend to argue that the previous results of diminishing returns of foreign aid, using the panel data estimation techniques under the homogeneous assumption, are incorrect. However, the main point is that the homogeneous assumption could be very sensitive to the results as countries may not follow homogeneous growth processes. While it can be argued that the conclusion of aid effectiveness from cross-country studies under the homogeneous assumption could not be well-captured, the FMM provides more reliable results given that the heterogeneity issues are taken into account. Therefore, further research is needed in order to observe the aid effectiveness as a basis for policy decisions.

Appendix A: Variable Description

Table 3.9: List of Variables

Variable	Variable Description	Source
GDP Growth	Annual growth rate of PPP real per capita GDP	Penn World Table 7.1
AID/GDP	Net ODA/GDP	World Development Indicator
KI	Investment share of PPP converted GDP per capita at 2005 constant prices	Penn World Table 7.1
M2/GDP	M2 to GDP ratio	World Development Indicator
POP	Growth rate of population	World Development Indicator
HAI	Human asset index is a composite index of education and health used as an identification criteria of the Less-developed countries by the UNCDP	FERDI (Foundation pour les Etudes et Recherches sur le Developpment International)
DEMOC	Institutionalized Democracy scaled from 0 to 10.	Polity IV Project, Political Regime Characteristics and Transitions, 1800-2015
AUTOC	Institutionalized Autocracy scaled from 0 to 10.	Polity IV Project, Political Regime Characteristics and Transitions, 1800-2015
POLICY	Policy index adopted from the methods by Burnside and Dollar	Burnside and Dollar (2000)

Appendix B: List of Countries

Table 3.10: List of Countries

No.	Country	ISO	Region	Income
1	Algeria	DZA	MENA	UMI
2	Bangladesh	BGD	SA	LMI
3	Benin	BEN	SSA	LI
4	Bolivia	BOL	LAC	LMI
5	Botswana	BWA	SSA	UMI
6	Brazil	BRA	LAC	UMI
7	Burkina Faso	BFA	SSA	LI
8	Burundi	BDI	SSA	LI
9	Cambodia	KHM	EAP	LI
10	Cameroon	CMR	SSA	LMI
11	Central African Republic	CAF	SSA	LI
12	Chad	TCD	SSA	LI
13	Chile	CHL	LAC	UMI
14	China	CHN	EAP	UMI
15	Colombia	COL	LAC	UMI
16	Congo, Dem. Rep.	ZAR	SSA	LI
17	Congo, Rep.	COG	SSA	LMI
18	Costa Rica	CRI	LAC	UMI
19	Dominican Republic	DOM	LAC	UMI
20	Ecuador	ECU	LAC	UMI
21	Egypt, Arab Rep.	EGY	MENA	LMI
22	El Salvador	SLV	LAC	LMI
23	Ethiopia	ETH	SSA	LI
24	Gabon	GAB	SSA	UMI
25	Gambia, The	GMB	SSA	LI
26	Ghana	GHA	SSA	LMI
27	Guatemala	GM	LAC	LMI
28	Guinea	GIN	SSA	LI
29	Guinea-Bissau	GNB	SSA	LI
30	Honduras	HND	LAC	LMI
31	India	IND	SA	LMI
32	Indonesia	IDN	EAP	LMI
33	Iran, Islamic Rep.	IRN	MENA	UMI
34	Jamaica	JAM	LAC	UMI
35	Kenya	KEN	SSA	LI
36	Lao PDR	LAO	EAP	LMI
37	Lebanon	LBN	MENA	UMI
38	Madagascar	MDG	SSA	LI
39	Malawi	MWI	SSA	LI
40	Malaysia	MYS	EAP	UMI
41	Mali	MLI	SSA	LI

Table 3.10 – continued from previous page

No.	Country	ISO	Region	Income
42	Mauritania	MRT	SSA	LMI
43	Mauritius	MUS	SSA	UMI
44	Mexico	MEX	LAC	UMI
45	Mongolia	MNG	EAP	UMI
46	Morocco	MAC	MENA	LMI
47	Namibia	NAM	SSA	UMI
48	Nepal	NPL	SA	LI
49	Nicaragua	NIC	LAC	LMI
50	Niger	NER	SSA	LI
51	Nigeria	NGA	SSA	LMI
52	Pakistan	PAK	SA	LMI
53	Panama	PAN	LAC	UMI
54	Papua New Guinea	PNG	EAP	UMI
55	Paraguay	PRY	LAC	LMI
56	Peru	PER	LAC	UMI
57	Philippines	PHL	EAP	LMI
58	Rwanda	RWA	SSA	LI
59	Senegal	SEN	SSA	LMI
60	Sierra Leone	SLE	SSA	LI
61	Sri Lanka	LKA	SA	LMI
62	Sudan	SDN	SSA	LMI
63	Tanzania	TZA	SSA	LI
64	Thailand	THA	EAP	UMI
65	Togo	TGO	SSA	LI
66	Tunisia	TUN	MENA	UMI
67	Turkey	TUR	ECA	UMI
68	Uganda	UGA	SSA	LI
69	Vietnam	VNM	EAP	LMI
70	Zambia	ZMB	SSA	LMI
71	Zimbabwe	ZWE	SSA	LMI

Note: EAP: East Asia & Pacific, ECA: Europe & Central Asia, LAC: Latin America & Caribbean, MENA: Middle East & North Africa, SA: South Asia, SSA: Sub-Saharan Africa; LI: Low income, LMI: Lower middle income, UMI: Upper middle income.

Appendix C: Dynamic Panel Data Model

This appendix describes the econometric method of dynamic panel data model extended from equation (3.1). The lagged dependent variable is introduced into equation (3.1), and the new model specification begins can be written as follows.

$$y_{it} = \alpha_i + \rho y_{i,t-1} + \beta_0 + \beta_1 AID_{it} + \beta_2 AID_{it}^2 + \beta_3 X_{it} + \varepsilon_{it} \tag{3.19}$$

Estimating equation (3.19) using one-way fixed effects models (within or demeaning transformation) to remove unobserved heterogeneity are not appropriate. This is because the error term is correlated with the regressor although the individual mean value of the dependent variable and each independent variable are subtracted from the respective variable in the demeaning process. Therefore, one solution to this problem is to take the first differences, where the constant term and the country-specific effect are removed:

$$\Delta y_{it} = \rho \Delta y_{i,t-1} + \beta_1 \Delta AID_{it} + \beta_2 \Delta AID_{it}^2 + \beta_3 \Delta X_{it} + \Delta\varepsilon_{it} \tag{3.20}$$

To simplify, equation (3.20) is re-written as follows:

$$\Delta y_{it} = \rho \Delta y_{i,t-1} + \Delta x_{it}\beta + \Delta\epsilon_{it} \tag{3.21}$$

The dynamic structure of equation (3.21) suffers from an endogeneity problem even if the country-specific effects are removed. There exists a correlation between the new error term $\Delta\epsilon_{it}$ and the differenced lagged dependent variable $\Delta y_{i,t-1}$. To solve the endogeneity issues, Anderson and

Hsiao (1981) proposes instrumenting for $\Delta y_{i,t-1}$ with either $\Delta y_{i,t-2}$ or $y_{i,t-p}$ because these instruments are uncorrelated with the disturbance in equation (3.21). This is consistent with Holtz-Eakin et al. (1988) who argue that the lagged levels of the endogenous variable, three or more time periods before, can solve for unknown parameters. Arellano and Bond (1991) propose a Difference-GMM estimator, which could exploit all possible instruments and obtain estimators using the moment conditions generated by the lagged levels of the dependent variables. The advantage of GMM is that the estimators are unbiased compared to other estimators. Moreover, the Arellano and Bond approach is extended to the System GMM. Arellano and Bover (1995) and Blundell and Bond (1998) argue that first differences of instrumenting variables are uncorrelated with fixed effects. Therefore, introducing more instruments can dramatically improve efficiency. The system GMM consists of two equations, the original equation and the transformed one. The system GMM is appropriate for a situation with small T and large N panels.

Chapter 4

Monetary Policy and House Prices: The Threshold Effect of Interest Rates

4.1 Introduction

There is a considerable amount of interest in understanding the interactions between real estate prices and monetary policy (Taylor, 2007; Bernanke, 2010; Adam et al., 2011; Leamer, 2015). Observing the current status quo of record low interest rates, the impact of central bank's interest-rate policy decisions on house prices has been much debated, especially after the recent real estate booms and busts in the United States and in other developed countries.[1]. Given that the impact of monetary policy shocks on the real economy is one of the most intensively investigated topics in macroeconomics, researchers have attempted to link house price move-

[1]Since the second half of the 20th century, there has been a threefold increase in real house prices in industrial countries (Knoll et al., 2014)

ments to monetary conditions (Del Negro and Otrok, 2007; Goodhart and Hofmann, 2008; Jarocinski and Smets, 2008; Glaeser et al., 2010; Allen and Rogoff, 2011; Williams, 2011; Kuttner, 2012; Adam and Woodford, 2013; Jordà et al., 2015). While some studies find that monetary policy plays less important roles on house prices (Del Negro and Otrok, 2007; Goodhart and Hofmann, 2008; Glaeser et al., 2010), other studies provide evidence of a significant relationship between interest rates and house prices (Taylor, 2007, 2009; Jordà et al., 2015).

The findings regarding the importance of interest rates for house prices remain competing. Indeed, monetary policy affects house prices through both direct and indirect channels (Maclennan et al., 1998). The direct channel refers to Keynesian interest rates, while the indirect one refers to the credit channel. Based on these channels, a large amount of literature has examined the effect of interest rate on real estate prices using an array of econometric techniques including district level, time series, cross-country, and panel data. By and large, the majority of empirical studies on the relationship between interest rates and house prices follows a linear framework. However, Himmelberg et al. (2005) theoretically contend that house prices are more sensitive to changes in real interest rates when rates are already low. This is due to the fact that home-ownership is more attractive than alternative investment when the real interest rates are low. In addition, Kuttner (2012) points out that house prices tend to over-react to interest rate deductions that are not in-line with the fundamentals in the standard theory. Thus, the linear assumption may not be appropriate if the house prices follow non-linear properties. From these theoretical arguments, it would be worth observing the over-reaction point of the house prices due to the interest rate reduction.

Such relationship between monetary policy and house prices is an important topic from the perspective of monetary policy-makers. The monetary policy's influence on house prices could be a key source of risk to financial stability (Williams, 2015). Given the sharp rise in real estate finance in many countries (Jordà et al., 2016a), the transmission of monetary policy comes through the influence of short-term interest rates on house prices, and the movements increase the cost of owning a house. Thus, having accurate estimates of the relationship between interest rates and house prices is crucial for monetary authorities. Furthermore, understanding the response of house prices to changes in monetary policy is important as the development in the housing market signficantly affect credit markets, which in turn influence real economic activity. As pointed out by Mishkin (2007), the delinquencies of mortgage-backed securities in the United States have led to sharp increases in credit spreads and substantial losses to holders of securities. As a consequent, it is crucial to have accurate estimates of the responsiveness of real estate prices to monetary policy, as it could assess the credit risk of some financial institutions.

This chapter provides new evidence that sheds light on the impact of monetary policy on house prices in advanced countries. Specifically, this study aims at exploring whether there exists threshold levels of interest rates in history over the periods from the late 1800s to 2013. To the best of the researcher's knowledge, there are no empirical papers which estimate the threshold levels using the dynamic panel threshold model proposed by Kremer et al. (2013). The method was extended from the original static setup to endogenous regrssors by Hansen (1999). Given that housing price model is a dynamic process in nature, using a dynamic panel threshold method is more appropriate rather than a static threshold specification to capture the nonlinear relationship between interest rates and house prices, especially with a panel data set. This relationship may be contingent on central banks' monetary policy, monetary policy below or above the threshold level could trigger fluctuation of house prices. The empirical analyses provide evidence that there exists interest rate thresholds, and these findings reveal that expansionary monetary policy below the threshold level is associated with housing price bubbles; beyond the threshold level further contractionary monetary policy tends to slow down the housing price bubbles, where the effects have become stronger and statistically significant after World War II.

The remainder of the chapter is organised as follows: section 2 reviews the relevant literature on house price modelling, while sections 3 and 4 present the applied methodology and data, respectively. In section 5, a detailed description of the results of the empirical analysis are presented, and Section 6 concludes.

4.2 Literature Review

The impact of monetary policy on real estate prices has been a topic of interest for monetary policymakers. The current status quo of record low interest rates and the hike of real estate prices suffuse the debate on their relationship. The housing market sensitivities to the short-term interest rates has gone through both direct and indirect monetary transmission channels (Maclennan et al., 1998). By either raising or lowering short-term interest rates, changes in the central banks' policy rates could affect the housing market, and in turn the overall economy. Mishkin (2007, p. 5) describes the mechanism that monetary policy affects housing markets through six channels "(1) the user cost of capital, (2) expectations of future house-price movements, and (3) housing supply; and indirectly through (4) standard wealth effects from house prices, (5) balance sheet, credit-channel effects on consumer spending, and (6) balance sheet, credit-channel effects on housing demand." According to the direct channel, policy rate influences user cost of capital, expectations of future house price movements, and housing supply; and for the indirect channel, interest rates affect house prices through wealth effects from house prices, balance sheet and credit effects on consumer spending, and balance sheet and credit channel effects on housing demand.

Figure 4.1: Monetary policy transmission channels and the housing market based on Wadud et al. (2012)

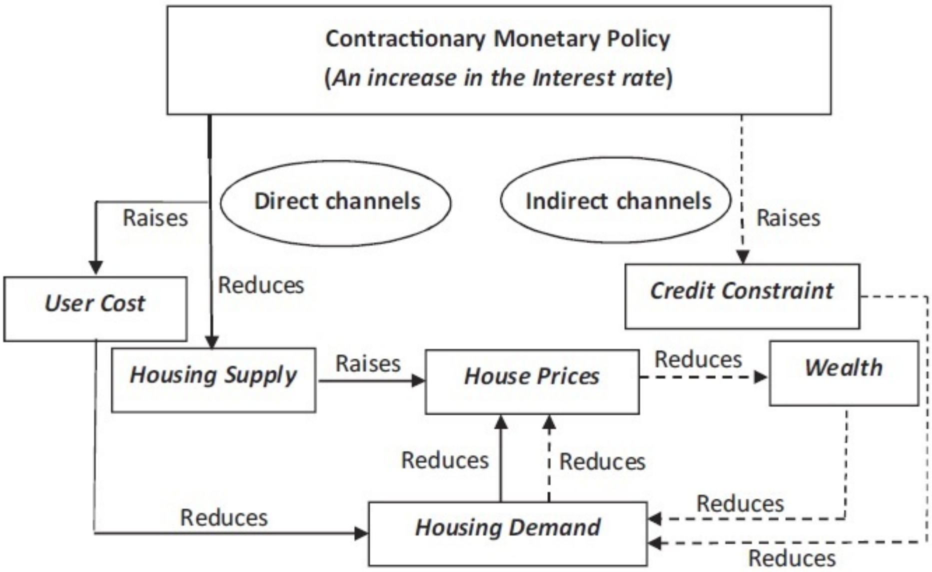


Figure 4.1 shows the monetary policy transmission channels to housing prices based on Wadud et al. (2012), who examine the effect of monetary transmission in the Australian housing market. The diagrammatic representation on the left side presents direct channels while the right hand-side (dotted lines) presents the indirect ones. Through the direct effect, change in policy rate influences real interest rates which in turn affect the cost of capital. As illustrated by Wadud et al. (2012), contractionary monetary policy raises the short-term interest rates and the long-term interest rates driven by expectations of future short-term interest rates. These ultimately increase

the cost of capital, thereby leading to a decline in housing demand and house prices. Meanwhile, Case and Shiller (2003) argue that a decline in expected inflation resulted from contractionary monetary policy lead an increase in the after-tax user cost of housing, which in turn raises the user cost of housing and thus lowers (real) home prices. While contractionary monetary policy has an impact on the demand side, it may have an immediate impact on the supply side when housing construction costs increase, as emphasised by Wadud et al. (2012), causing a fall in housing output.

On the right-hand side of Figure 4.1, the indirect channels of monetary policy on house prices consist of wealth and credit channels. When monetary policy is tightened, the value of individual housing wealth decreases due to the decline in house prices, this in turn further reduces the housing demand given the decline in individual wealth. In addition, contractionary monetary policy usually raises credit constraints for households as interest rates increase, nominal rates also rise, thus reducing cash flows. This causes mortgages for households to become less available, which causes housing demand to decline and ultimately lowers house prices.

The existence of these channels has been empirically modelled within a linear framework. McQuinn and O'Reilly (2008) propose a simple model of housing demand and empirically examine its determinants using quarterly data of the Irish Property Market for the period from 1980Q1 to 2005Q4. The findings suggest that interest rates have a direct and significant impact on Irish house prices. Meanwhile, Jordà et al. (2015) analyse the link between monetary policy and house prices using the data set from 17 economies from 1870 to 2012. The findings suggest that loose monetary conditions lead to booms in real estate lending and house price bubbles.

On the other hand, Del Negro and Otrok (2007), while applying VAR on quarterly state-level data of the United States from 1986 to 2005 find that the impact of monetary policy shocks on house prices appears to be small. Goodhart and Hofmann (2008) employ a Panel VAR on a dataset of 17 industrial countries spanning for the period from 1970 to 2006, and reach similar conclusion when no immediate impact of interest rates on house prices is identified. Different from Del Negro and Otrok (2007) and Goodhart and Hofmann (2008) who employ VAR in their studies, Glaeser et al. (2010) apply a simple regression on the dataset of the United State from 1996 to 2006, and reach similar results, where changes in interest rates have little impact on house prices.

The findings from the relationship between monetary policy and house prices, usually examined in the linear frameworks of vector autoregression, error correction, time series, or panel data methods as shown in the above discussed studies, remain contradictory and inconclusive. The linear framework may be inappropriate if the impact of monetary policy shocks on house prices have varying effects, which are embedded with the non-linear properties. Given this, researchers have been theoretically or empirically trying to model house prices allowing for non-linear properties. Constructing measures of the annual cost of housing for 46 metropolitan areas in the United States for the period from 1995 to 2004, Himmelberg et al. (2005) argue that house prices are more sensitive to fundamentals when interest rates are already low. Meanwhile, Abelson et al. (2005) develop and estimate a long-run equilibrium model and a short-run asymmetric error correction model with the Heaviside indicator function to represent house price changes in Australia from 1970 to 2003. The results show that real house prices are determined significantly and negatively by real mortgage rates.

Furthermore, Kuttner (2012) reviews empirical literature for the relationship between interest rates and property prices and examine the linkage. The findings suggest that the effect of interest rates on house prices appears to be modest, and that house prices tend to over-react to interest rates below the over-reaction point. Applying the Smooth Transition Autoregressive (STAR) model based on non-linear properties for the entire United States and four regions, Kim and Bhattacharya (2009) confirm the non-linearity of housing prices for the entire United States and all regions, except for the Midwest. Similarly, Lim and Tsiaplias (2016) apply a non-linear smooth transition VAR model to the Australian dataset of five major capital cities for the period from December 1995 to June 2015. The empirical results confirm the non-linear relationship between house prices and interest rates, and the interest rates threshold of 6.1256% is computed.

From these studies on the relationship between the interest rates and house prices, it was noticed that the findings regarding the importance of interest rates for house prices are competing. A common issue is that the estimation methods used in these studies, including VAR or Panel VAR, follow linear assumptions. The assumption of the linear relationship may be over-simplified. As argued by Himmelberg et al. (2005), house prices are theoretically more sensitive to fundamentals when rates are already low. Furthermore, Kuttner (2012) contends that house prices tend to over-react to interest rate reductions below the over-reaction point, while Kim and Bhattacharya (2009) confirm the non-linearity of housing prices. Given that the relationship between interest rates and house prices could possibly follow non-linearity, this study adopt a dynamic panel threshold method developed by Kremer et al. (2013) taking endogenous regressors into account. The model is extended from the original static one of Hansen (1999). Given that the house prices follow a dynamic process, using a dynamic panel method is more appropriate rather than a static threshold specification such as Hansen (1999). Furthermore, as the relationship between house prices and interest rates follow non-linear relationship, especially when the interest rates are low (Himmelberg et al., 2005; Kuttner, 2012), a dynamic panel method is suitable in capturing the interest rate threshold. In addition, the methodology has not been applied in analysing the non-linear relationship between interest rates and house prices.

4.3 Methodology

Following the theoretical framework and the empirical works of Goodhart and Hofmann (2008) and Jordà et al. (2015), the basic house price model can be written in the following specification

$$hp_{it} = \beta r_{it} + \gamma X_{it} + \varepsilon_{it} \tag{4.1}$$

where the sub-index $i = 1, \ldots, N$ denotes country, $t = 1, \ldots, T$ denotes time period, hp_{it} is the house price to income ratios, r_{it} is the interest rate, X_{it} is a vector of control variables (initial house price to income ratios, income per capita, population growth, mortgage loans to non-financial private sector, broad money, inflation, financial crises) and ε_{it} is the error term.

In order to explore the non-linear behaviour of interest rate in relation to house prices, the empirical model is based on the dynamic panel threshold regression approach suggested by Kremer et al. (2013). Extended from the original static panel threshold model of Hansen (1999) and the instrumental variable (IV) estimation of the cross-sectional threshold model of Caner and Hansen (2004), Kremer et al. (2013) apply the generalised method of moments (GMM) type estimators in order to deal with endogeneity. The model, based on the threshold regression, takes the following form:

$$hp_{it} = \mu_i + \theta_t + \chi hp_{i,t-1} + \beta_1 r_{it} I(r_{it} \leq \gamma) + \beta_2 r_{it} I(r_{it} > \gamma) + \alpha X_{it} + u_{it} \quad (4.2)$$

where μ_i is a set of country-specific fixed effect, θ_t is the time effect, $hp_{i,t-1}$ is the lag of the dependent variable, X_{it} is a k-dimensional vector of regime independent control variables and u_{it} is the error term. r_{it} is the level of interest rates representing the threshold variable for splitting the sample into regimes or groups. $I(\cdot)$ is the indicator function, which takes the value 1 if the argument in parenthesis is valid, and 0 otherwise, indicating the regime defined by the threshold variable r_{it} and the threshold level γ. In this case, if r_{it} is below or above the threshold level γ, the regressor r_{it} has different impacts on the dependent variable hp_{it}. Therefore, the coefficients β_1 and β_2 show the impact of interest rates on house prices for countries with a low and high level of interest rates, respectively.

One of the main challenges of the dynamic threshold panel regression is to deal with individual effects μ_i. The standard within transformation or first differencing methods can lead to inconsistent estimates because the mean of individual errors will always be correlated with lagged dependent variable; consequently, the assumptions underlying Hansen (1999) and Caner and Hansen (2004) are violated. To overcome this issue, (Kremer et al., 2013) propose the forward orthogonal deviations transformation suggested by Arellano and Bover (1995). The forward orthogonal deviation transformation subtracts the average of all future available observations of a variable, making it possible to avoid a serial correlation of the transformed error terms. This strategy will transform the error term in the following

$$\sqrt{\frac{T-t}{T-t+1}}\left[u_{it}-\frac{1}{T-t}(u_{i(t+1)}+\ldots+u_{iT})\right] \tag{4.3}$$

There are three steps to estimate the dynamic panel model in equation (4.2). Firstly, a reduced form regression of the endogenous variable $hp_{i,t-1}$ is estimated on a set of instruments. Secondly, once the predicted values of $\hat{hp}_{i,t-1}$ is obtained from the first step, it will be plugged into the equation (4.2), where the least squares are used to estimate the threshold parameter γ that will be chosen based on the smallest sum of squared residuals $S_n(\gamma)$. The significance of the selected γ is tested based on

$$\hat{\gamma} = arg \quad min \quad S_n(\gamma) \tag{4.4}$$

The critical values for determining the 95% confidence interval of the threshold values based on Hansen (2000) and Caner and Hansen (2004) are given by

$$\Gamma = \gamma : LR(\gamma) \leq C(\alpha) \tag{4.5}$$

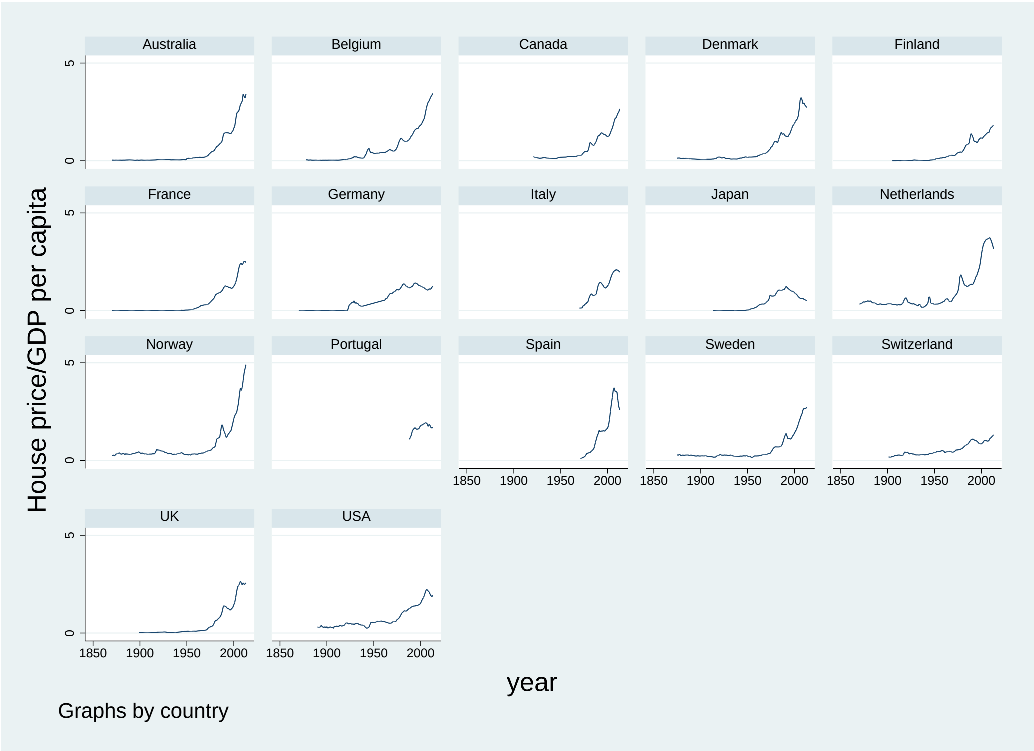
where $C(\alpha)$ is the 95% percentile of the asymptotic distribution of the likelihood ratio statistic $LR(\gamma)$. According to Hansen (1999), the underlying likelihood ratio has been adjusted to account for the number of time periods used for each cross section. Thirdly, after the threshold value $\hat{\gamma}$ is determined, GMM is applied to estimate the slope coefficients.

4.4 Data

To estimate the non-linear relationship of interest rates on house prices, using the dynamic threshold panel model, this study employs the unique dataset of Jordà et al. (2016b) and Knoll et al. (2014). The Jordà-Schularick-Taylor Macrohistory Database provides an extensive data collection of macroeconomic data on annual basis across a variety of sources over a century. The database comprises 25 real and nominal variables for 17 developed countries from 1870. These countries include Australia (AUS), Belgium (BEL), Canada (CAN), Denmark (DNK), Finland (FIN), France (FRA), Germany (DEU), Italy (ITA), Japan (JPN), the Netherlands (NLD), Norway (NOR), Portugal (PRT), Spain (ESP), Sweden (SWE), Switzerland (CHE), the United Kingdom (GBR), and the United States of America (USA). The relevant variables picked out from the database include the house price index, nominal short-term interest rate, population, Real GDP per capita (PPP) and its index, mortgage loans to non-financial private sector, broad money, consumer price index, and the systemic financial crises dummy. The dependent variable, the house prices, are measured by the ratio of the house prices to household disposable income. This measure of house prices is adopted from Jordà et al. (2015).

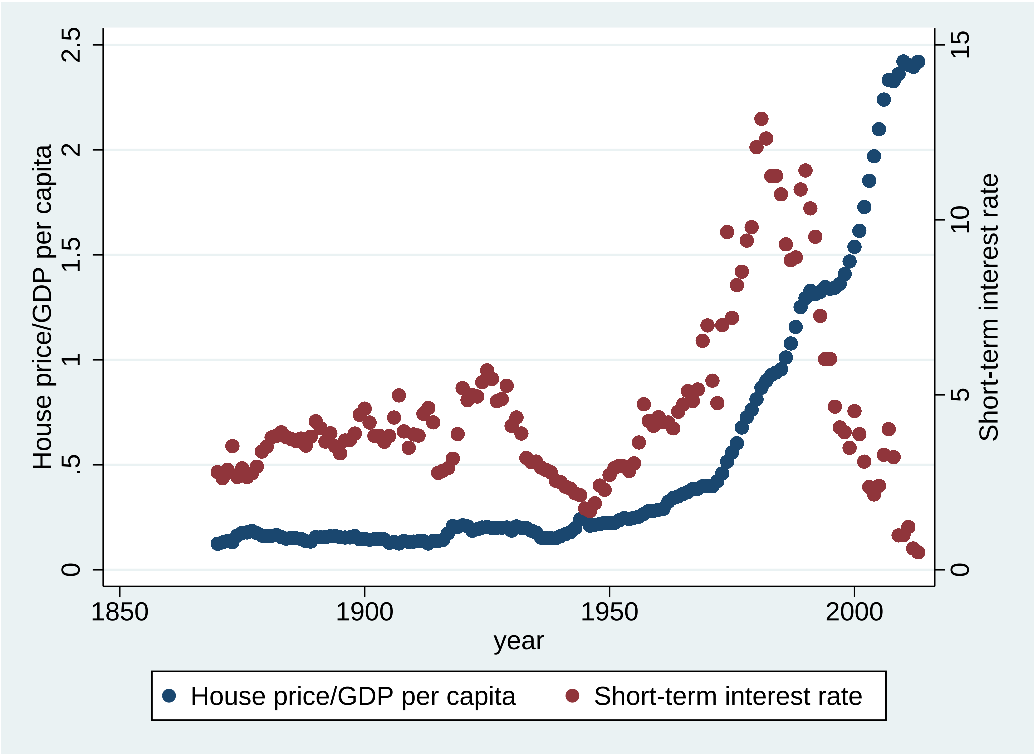
Figure 4.2 shows the ratio of house price to GDP per capita for all countries from 1870 to 2013. From the diagram, relative house prices to GDP per capita for all countries were stable before the World War II, but it is noticed that the house prices increased sharply for most of the countries after the World War II. Figure 4.3 displays the average trend in house prices relative to GDP per capita and short-term interest rates for the 17 countries. From the figure, the house prices and interest rates were roughly stable from the period 1870 to the World War II, but the house prices embarked on a strong uptrend relative to GDP per capita. The average short-term interest became more intensified after the World War II, and peaked out to decline in the mid-1980s. Figure 4.4 shows scatter plots of the house prices and short-term interest rates from 1870 to 2013. The relationship does indeed appear to exist but in a non-linear form.

Figure 4.2: Aggregate House Price to Income (By Country)



Similar to Chapter 3, the dataset is split into three main eras, Pre-WWI, Interwar, and Post-WWII. However, given some missing data, the panel data is unbalanced for all sub-sample periods. Pre-WWI is a sub-sample of the Pre-World War I covering the period from 1870 to 1913. The Interwar is the period between the two world wars, covering the period form 1919 to 1938, while Post-WWII is a sub-sample of the Post-World War II, covering the period from 1946 to 2013. Furthermore, this investigation employs the full dataset from 1870 to 2013 in order to compare the results from

Figure 4.3: Aggregate House Price to Income



the sub-sample periods. The summary statistics of all variables are reported in Table 4.1.

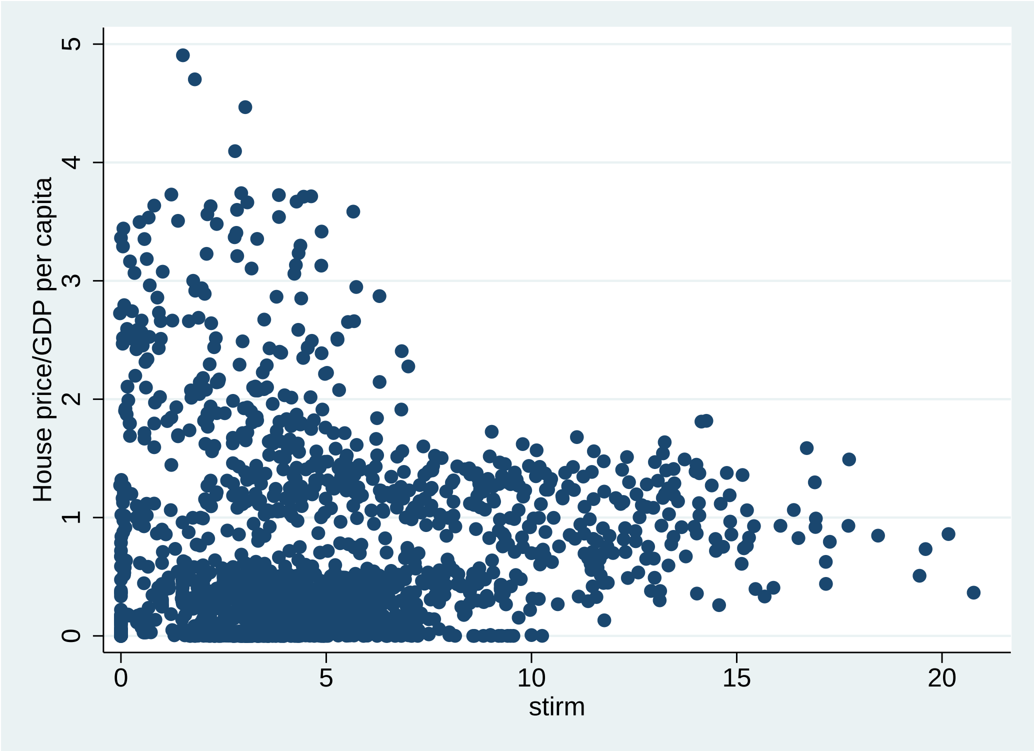
4.5 Empirical Results

The results for the empirical relationship between interest rates and house prices are presented in Tables 4.2 - 4.5. The empirical analyses are divided into two main parts based on the sub-samples of Pre-WWI, Interwar, and Post-WWII, and the full sample of the dataset covering the period from 1870 to 2013. In each table, column (a) shows the benchmark results based on equation (4.2) for the dynamic panel threshold estimation with 1 lag instrument. Additional lags of the instrument to the maximum are included into the benchmark model and the results are presented in column (b). In each table, the estimated threshold ($\hat{\gamma}$) is presented with its corresponding

Table 4.1: Summary Statistics

	N	N. Obs	Mean	SD	Min	Max
Pre-WWI: 1870 - 1913						
hp	11	294	0.1514	0.1361	3.46e-13	0.4413
r	11	294	4.0062	1.0810	1.0700	7.0100
$GDPPC$	11	294	0.0153	0.0333	-0.1438	0.1378
POP	11	294	0.8654	0.5689	0.2240	1.9895
$MORTG$	11	294	0.0085	0.0696	-0.2078	0.5269
$MONEY$	11	294	0.0501	0.0492	-0.0948	0.5267
$INFL$	11	294	0.0050	0.0369	-0.1243	0.1266
Interwar: 1919 - 1938						
hp	14	245	0.2012	0.1596	8.84e-13	0.5497
r	14	245	3.9150	2.2348	0.0000	11.5830
$GDPPC$	14	245	0.0188	0.0547	-0.1677	0.1743
POP	14	245	1.0861	0.5415	0.4155	2.1155
$MORTG$	14	245	0.0441	0.1304	-0.4350	0.7888
$MONEY$	14	245	0.0385	0.0934	-0.1589	0.8610
$INFL$	14	245	-0.0016	0.0750	-0.1845	0.3305
Post-WWII: 1946 - 2013						
hp	17	1013	1.0543	0.8401	0.0098	4.9055
r	17	1013	5.7178	4.0376	-0.0231	20.7721
$GDPPC$	17	1013	0.0245	0.0334	-0.2146	0.6590
POP	17	1013	1.3106	0.5341	0.5004	2.5000
$MORTG$	17	1013	0.0136	0.0554	-0.3592	0.5124
$MONEY$	17	1013	0.0893	0.0951	-0.0882	2.0181
$INFL$	17	1013	0.0472	0.0637	-0.0687	1.2533
Full Sample: 1870 - 2013						
hp	17	1552	0.7486	0.8025	3.46e-13	4.9055
r	17	1552	5.1090	3.5130	-0.0231	20.7721
$GDPPC$	17	1552	0.0218	0.0377	-0.2146	0.6590
POP	17	1552	1.1908	0.5697	0.2240	2.5000
$MORTG$	17	1552	0.0175	0.0757	-0.4350	0.7888
$MONEY$	17	1552	0.0738	0.0905	-0.1589	2.0181
$INFL$	17	1552	0.0315	0.0653	-0.1845	1.2533

Figure 4.4: House Prices vs Short-term Interest Rates



95% confidence interval in the upper part of the table. In the middle part, the regime-dependent coefficients ($\hat{\beta}_1$) and ($\hat{\beta}_2$) of interest rates on house prices are presented. The coefficient $\hat{\beta}_1$ is the marginal effect of interest rates on house prices when the interest rates are below the estimated threshold level and $\hat{\beta}_2$ is the marginal effect of interest rates on house prices when the interest rates are above the threshold level. The coefficients of the other control variables are presented in the lower part of each table, except the time trend and time dummy variables. I begin the empirical analysis with Post-WWII, followed by the estimations from the sub-samples Interwar and Pre-WWI, and the estimations from the full sample.

The column (a) of Table 4.2 shows the interest rate threshold value of 5.1039% with respective 95% confidence interval [4.4817 - 6.1054]. The threshold value is close to the recent estimate by Lim and Tsiaplias (2016), who compute the interest rate threshold of 6.1256% for Australia. This threshold value of 5.1039% splits the observations into two regimes, in which 142 observations fall in the lower regime and 871 observations fall in the upper regime. Both coefficients of interest rate are expectedly signed and highly significant. The first coefficient ($\hat{\beta}_1$=0.6479) suggests that interest rates are positively correlated with house prices if it is less than the interest rate threshold (5.1039%), while the impact on house prices is negative if the interest rate is above the threshold level. Furthermore, the lagged dependent variable, income per capita, money growth, and inflation have positive impact on the house prices. However, there is no statistical evidence that population, mortgage loans and crisis significantly influence house prices. Meanwhile, the regime-dependent coefficients do not noticeably change compared to the benchmark results when more lags of instrument are added into the model. The impacts of covariates are not much different except the income per capita and population.

Presented in Table 4.3, the estimation results of the Interwar period from 1919 to 1938 suggest an interest rate threshold level of 4.4817% with a corresponding 95% confidence interval [4.4371 - 4.7469]. The threshold level for the Interwar period is found to be lower than that of the Post-WWII. Despite highly significant at 1% level, the regime-dependent coefficients ($\hat{\beta}_1$ and $\hat{\beta}_2$) have positive signs for both regimes. This suggests that the interest rates have positive impact on house prices even it is below or above the threshold level. However, the coefficients of interest rate in the first regime ($r \leqslant$4.4817) is higher than that of the second regime ($r >$4.4817). It can still be implied that lower interest rates are highly associated with housing price bubbles. Furthermore, the lagged dependent variable and income have significantly positive and negative impacts on house prices, respectively. However, there is no statistical evidence to prove the relationship of other variables and house prices. When more lags of instrument are added into the benchmark

Table 4.2: Results of Dynamic Panel Threshold Estimations for Post-WWII: 1946-2013

	Models (a)	(b)
Threshold estimates	5.1039	5.1039
95% confidence interval	[4.4817-6.1054]	[4.4817-6.1054]
Impact of interest rate		
$\hat{\beta}_1$	0.6479***	0.6292***
	(0.0359)	(0.0320)
$\hat{\beta}_2$	−0.0207***	−0.0209***
	(0.0019)	(0.0019)
Impact of covariates		
hp_{t-1}	1.0298***	0.7026***
	(0.0566)	(0.0441)
$GDPPC$	0.2004***	0.0567
	(0.0996)	(0.0998)
POP	−0.0692	−0.3439***
	(0.0781)	(0.1092)
$MORTG$	0.0858	0.0830
	(0.0509)	(0.0798)
$MONEY$	0.1457***	0.1639***
	(0.0606)	(0.0678)
$INFL$	0.6689***	0.5345***
	(0.0501)	(0.0625)
$CRISIS$	−0.0290	0.0293
	(0.0234)	(0.0287)
N	17	17
Obs.	1013	1013
Obs. below threshold	142	142

Notes: The standard errors are reported in the parentheses. Dependent variable: house price-to-income ratio. Time trends and time dummies are not reported in this table in order to save space. *** indicates significance level at 1% level. ** indicates significance level at 5% level. * indicates significance level at 10% level.
(a) – model with 1 lag instrument
(b) – model with 9 lags instrument

model, the results as shown in column (b) of Table 4.3, do not significantly alter.

Table 4.4 reports the estimation results of the dynamic threshold panel model for the relationship between interest rates and house prices in the sub-sample of Pre-World War I. The interest rate threshold level of 33.7844% with a corresponding 95% confidence interval [21.693 - 106.693] is far different from those of the Interwar period and Post-WWII. The confidence interval is too large for the sub-sample period suggesting that the estimate could be less precise. There could be a number of reasons that have caused the confidence interval to be too large. Firstly, this could be the fact that the number of countries have been reduced to 11 due to some missing data, making the sample size relatively small. Secondly, the data may not fit the model as the interest rates may not be the key determinant of the house prices prior to the World War I. This can be seen from the evidence of the regime-dependent coefficients ($\hat{\beta}_1$ and $\hat{\beta}_2$) shown in Table 4.4 as they are statistically insignificant even at the 10% level.

Table 4.5 presents threshold estimates using the full sample consisting of 17 countries over the period from 1870 to 2013. The estimated interest rate threshold is identified at 9.7332% with the 95% confidence interval [8.2181 - 11.8224]. The threshold value of the full sample is higher than those in the Interwar and Post-WWII periods, but much lower compared to the sub-sample period of Pre-WWI. Both regime-dependent coefficients of interest rate are significant and plausibly signed, which are consistent with those in the Post-WWII. It is noticed that only 265 observations fall in the lower regime, but 1287 observations fall in the upper regime, meaning that interest rates are below the interest rate threshold. The findings clearly suggests that interest rates are positively correlated with housing price bubbles if it is less

Table 4.3: Results of Dynamic Panel Threshold Estimations for Interwar Period: 1919-1938

	Models (a)	(b)
Threshold estimates	4.4817	4.4817
95% confidence interval	[4.4371-4.7469]	[4.4371-4.7469]
Impact of interest rate		
$\hat{\beta}_1$	0.0384^{***}	0.0387^{***}
	(0.0063)	(0.0061)
$\hat{\beta}_2$	0.0048^{***}	0.0036^{***}
	(0.0015)	(0.001438)
Impact of covariates		
hp_{t-1}	0.9793^{***}	0.9768^{***}
	(0.0769)	(0.0761)
$GDPPC$	-0.1507^{***}	-0.1536^{***}
	(0.0363)	(0.0357)
POP	-0.0917	-0.1097
	(0.0819)	(0.0721)
$MORTG$	-0.0098	-0.0085
	(0.0098)	(0.0097)
$MONEY$	0.0195	0.0209
	(0.0183)	(0.0182)
$INFL$	0.0273	0.0304
	(0.0301)	(0.0299)
$CRISIS$	-0.0069	-0.0062
	(0.0060)	(0.0060)
N	17	17
Obs.	245	245
Obs. below threshold	39	39

Notes: The standard errors are reported in the parentheses. Dependent variable: house price-to-income ratio. Time trends and time dummies are not reported in this table in order to save space. *** indicates significance level at 1% level. ** indicates significance level at 5% level. * indicates significance level at 10% level.
(a) – model with 1 lag instrument
(b) – model with 3 lags instrument

Table 4.4: Results of Dynamic Panel Threshold Estimations Pre-WWI: 1870-1913

	Models (a)	(b)
Threshold estimates	33.7844	33.7844
95% confidence interval	[21.693-106.343]	[21.693-106.343]
Impact of interest rate		
$\hat{\beta}_1$	-0.0025	-0.0024
	(0.0059)	(0.0045)
$\hat{\beta}_2$	0.0011	0.0009
	(0.0029)	(0.0030)
Impact of covariates		
hp_{t-1}	0.3547	0.1810
	(0.5317)	(0.2099)
$GDPPC$	-0.1393^{***}	-0.1354
	(0.0367)	(0.0362)
POP	-0.0201	-0.0150^{***}
	(0.0254)	(0.0255)
$MORTG$	0.0162	0.0216
	(0.0226)	(0.0156)
$MONEY$	-0.0279	-0.0285
	(0.0213)	(0.0234)
$INFL$	-0.0218	-0.0426
	(0.0730)	(0.0454)
$CRISIS$	0.0017	0.0046
	(0.0093)	(0.0067)
N	14	14
Obs.	294	294
Obs. below threshold	104	104

Notes: The standard errors are reported in the parentheses. Dependent variable: house price-to-income ratio. Time trends and time dummies are not reported in this table in order to save space. *** indicates significance level at 1% level. ** indicates significance level at 5% level. * indicates significance level at 10% level.
(a) – model with 1 lag instrument
(b) – model with 7 lags instrument

than the threshold level, while the opposite is true when the interest rate goes beyond the threshold level. In addition, the lagged dependent variable, population, and money supply have a positive impact on house prices, while the income per capita has a negative impact. However, there is no statistical evidence to prove that mortgage loans, inflation, and crisis have a significant impact on house prices.

From the empirical analyses, it is worth noting the relationship between interest rates and house prices broadly confirms non-linear assumptions. Using the dynamic threshold panel model, the empirical analyses provide evidence that there exists an interest rate threshold at different periods. Overall, interest rates below threshold level are highly associated with housing price bubbles, while interest rates have an opposite relationship with house prices when the interest rate is beyond the threshold level. When the dataset is divided into sub-sample, the findings clearly reveal that interest rates play a key role in the post-war era with the interest rate threshold of 5.1039%. The threshold value is close to that of Lim and Tsiaplias (2016) who estimate the interest rate threshold of 6.1256% for Australia.

The findings above could provide policy implications for monetary economists. Understanding the optimal level of monetary policy is important in ensuring asset price booms and bursts given that that monetary policy shocks are highly associated with house price instability (Adam and Woodford, 2013; Allen and Rogoff, 2011; Del Negro and Otrok, 2007; Glaeser et al., 2010; Goodhart and Hofmann, 2008; Jarocinski and Smets, 2008; Kuttner, 2012; Williams, 2011; Jordà et al., 2015). Adopting the dynamic panel model based on the concept of the threshold effect proposed by Kremer et al. (2013), the findings suggest that the response of house prices to changes in interest rates depends on whether the interest rate is below or above its threshold

Table 4.5: Results of Dynamic Panel Threshold Estimations for Full Sample: 1870-2013

	Models (a)	(b)
Threshold estimates	9.7332	9.7332
95% confidence interval	[8.2181-11.8224]	[8.2181-11.8224]
Impact of interest rate		
$\hat{\beta}_1$	0.1664***	0.1783***
	(0.0069)	(0.0069)
$\hat{\beta}_2$	−0.0048***	−0.0066***
	(0.0010)	(0.0009)
Impact of covariates		
hp_{t-1}	0.9207***	0.9191***
	(0.0190)	(0.0140)
$GDPPC$	−0.2055***	−0.2206***
	(0.0658)	(0.0635)
POP	0.3121***	0.3214***
	(0.0513)	(0.0389)
$MORTG$	−0.0274	−0.0280
	(0.0241)	(0.0263)
$MONEY$	0.1204***	0.1199***
	(0.0468)	(0.0479)
$INFL$	0.0410	0.0580
	(0.0412)	(0.0394)
$CRISIS$	0.0145	0.0148
	(0.0099)	(0.0103)
N	17	17
Obs.	1552	1552
Obs. below	265	265

Notes: The standard errors are reported in the parentheses. Dependent variable: house price-to-income ratio. Time trends and time dummies are not reported in this table in order to save space. *** indicates significance level at 1% level. ** indicates significance level at 5% level. * indicates significance level at 10% level.
(a) – model with 1 lag instrument
(b) – model with 7 lags instrument

level. This means that expansionary monetary policy below the interest rate threshold of 5.1039% is highly associated with significant increases in house prices, while the contractionary monetary policy above the threshold level reduces house price bubbles. These findings become significant, especially in the post-war era.

4.6 Conclusion

This study provides new evidence on the non-linear relationship between interest rates and house prices for 17 advanced economies using the unique dataset of Jordà et al. (2016b) and Knoll et al. (2014) for the period from 1870 to 2013. Given the long historical dataset for more than a century, the stuy extended the analyses into different eras, Pre-World War I, Interwar, and Post-World War II, in addition to the full-sample dataset. The main objective is to test whether the relationship between interest rates and house prices follow the non-linear properties, and whether there exists a threshold level of interest rate throughout history. Applying the dynamic panel threshold model proposed by Kremer et al. (2013), the results confirm the general consensus among economists. (1) The results confirm the non-linear relationship between interest rates and house prices. (2) The results reveal that interest rates below the certain critical value (5.1039%) are highly associated with house price bubbles. On the other hand, if the interest rates exceed the threshold level, it is likely that house prices decrease. The results are robust, especially during the period after World War II.

The empirical findings imply that loose monetary policy is definitely associated with housing price bubbles, as confirmed by Jordà et al. (2015). The non-linear relationship between interest rates and house prices with the dynamic threshold panel frameworks is in-line with Kuttner (2012) who argue that house prices tend to over-react to interest rate reductions when the threshold is breached. Therefore, understanding the optimal level of interest rates provides an important implication for monetary policy. Policy makers usually face challenges whether the interest rate is sufficiently low that could lead to house price instability. The empirical analysis suggests that an interest rate target at or around the critical threshold level could maintain housing price stability.

What policy implications can be drawn form this study? The findings have substantial implications for monetary policy strategy if the goal were to smooth the housing cycle or stabilize the financial stability risks. The current status quo of record low interest rates is associated with the strong growth in the real estate lending and accounts for the dominant share of bank lending in many countries (Jordà et al., 2015). Central bank should be very careful in in pursuing macroeconomic stabilization policy and financial stability as interest rates impact financial stability through the credit markets. This in turn is an obstacle to monetary policy strategy; therefore, the trade-off between macroeconomic stabilization and financial stability could be managed through the use of macro-prudential tools.

Chapter 5

Concluding Remarks

The main findings of this dissertation are listed in the order of the chapters as follows:

Chapter 2 aims at examining the impact of bank credit on economic growth using the dynamic threshold panel model of 17 advanced economies for the period from 1870 to 2013. The empirical results suggest that there exists evidence supporting the existence of threshold equal to 135% of credit to GDP. Moreover, an inverted U-shaped relationship between credit and economic growth is statistically significant in the sample period after World War II. These findings imply that credit is beneficial to economic growth only up to a certain threshold, and that too much credit may not necessarily enhance economic growth. Beyond the threshold, further growth in bank credit tends to adversely affect growth. However, there is no statistical evidence of the effect of bank credit on economic growth for the period before World War II. The evidence highlights the economic importance of credit in the post-war modern economies as opposed to the limited role of credit prior to the World War II.

Chapter 3 re-examines the role of foreign aid on economic growth in 71 developing countries for the period from 1967 to 2010. The primary objective of this study is to examine the differential impact of foreign aid on economic growth using an econometric technique to decompose the distributions of the growth rates. First, when applying the standard panel data techniques, the results show an inverted U-shaped relationship between foreign aid and economic growth. Next, when applying Finite Mixture Model to the same dataset, the results show that there are two groups of countries in the growth regimes. Unlike the standard panel data estimation techniques with the homogeneous assumptions, the results from the FMM do not support the diminishing returns of foreign aid in general. The inverted U-shaped relationship between foreign aid and economic growth significantly appears only in a group of countries, consisting of 20 countries. However, there is no statistical evidence to support the diminishing returns for the rest of the other countries in the sample (51 countries).

Chapter 4 investigates the relationship between interest rates and house prices using data from 17 developed countries for the period from 1870 to 2013. Based on the recent argument that the linkage follows non-linear assumptions, this study explores whether there exists an interest rate threshold following a dynamic threshold panel model. The empirical analyses provide evidence that there exists an interest rate threshold, and these findings reveal that expansionary monetary policy below the threshold level is associated with housing price bubbles; beyond the threshold level further contractionary monetary policy tends to slow down the housing price bubbles, where the effects have become stronger and statistically significant after World War II.

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