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Southampton Business School

Bank Size, Locality, SME Lending and Local Economies

by

Achraf Mkhaiber

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy in the

Thesis for the degree of Doctor of Philosophy

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ABSTRACT

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Achraf Mkhaiber

This thesis contains both macro- and microeconomic analyses of banking organisational structure, Small and Medium Sized Enterprises (SMEs) lending and local economic development. The first examination is based on a bank-level analysis to investigate the impact of bank size on bank propensity to small and micro business lending. Secondly, I review the regional banking-growth literature and highlight the need for original investigations of the effects of local small business lending, as a measure of local banking development, on local economic development, emphasising the importance of distributional heterogeneity and spatial effects across regions within a one-country framework. Thirdly, I empirically investigate whether small and micro business lending, provided by small local banks, has an impact on the performance of local economies, taking into consideration the distributional heterogeneity among regions. Finally, I examine whether spatial spillover effects of local banks on local economies are significant.

Using an econometric approach and data on over 14,000 U.S banks of all sizes, from 1994 to 2013, the results indicate an inverse relationship between bank size and the propensity of banks to lend to small and micro businesses. The relationship is robust and survives a number of rigorous specification checks. The subsequent review of the literature of regional banking-growth studies reveals that previously employed econometric methodologies do not account for distributional heterogeneity and spatial spillover effects in the examination of the regional banking-growth relationship. I also offer the small business lending channel as a proxy measure for local banking development. Furthermore, the subsequent analyses of the local banking-growth nexus indicate a boosting impact of local banks on the local economies through the small business lending channel. Besides, such impact varies in accordance to the regions' level of economic development and the magnitude of the spillovers of SME loans from one region to another.

Important policy implications can be drawn from my empirical findings. The inverse association of bank size with propensity to small business lending indicates that small banks are superior in SME lending through their form of relationship lending. Accordingly, small banks can be the optimal financial machinery to facilitate credit to and support the growth of SMEs. Moreover, the results emphasise the importance of small locally-operating banks to development of the local economies through small business lending, as well as confirm the existence of heterogeneous effects and significant spatial spillover effects of small local banks on the growth of the regions. The policy implication is that policy-makers need to ensure that localisation effects are sustained, because of the comparatively minimal cost required to minimize individual (in relation to aggregate) uncertainties and local stability can be relied upon to achieve global stability. Both can be done by supporting the creation and continued viability of small local banks. For this, a positive yield curve is required – which currently central banks in many countries are not delivering.

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Achraf Mkhaiber

Chapter 1

Introduction to the Thesis

Chapter 1: Overview

This thesis aims to offer new insights into banking structure, small business lending and economic development. To this end, the research in the following chapter reviews the literature on the regional banking-growth relationship to help in presenting a conceptual framework concerning the optimal financial machinery for regional growth. A subsequent chapter provides a unique analysis of the relationship between the size of the bank and the lending propensities to small and micro business loans. Followed by two distinctive analyses of the importance of local banks in stimulating local economies through small business lending channel.

The small and medium-sized enterprises (SMEs) are the main employer in most economies, they account for 65% in the UK and 80% in Japan of total employment, while they account for almost half of SME share of private sector employment in the United States. There has been mounting concern about barriers that may hamper the growth of SMEs, causing slowdowns in economic growth and employment. In particular, such barriers are not due to internal factors as ideas, know-how, or external factors such as demand. A significant external factor appears to be the availability of finance (e.g. Cook, 1999; Pissarides, 1999; Hessels and Parker, 2013; Kent and Dacin, 2013). It is recognised in the literature that SMEs are likely to be credit-rationed and unable to access capital markets as lending to SMEs has substantially declined since the Great Depression. To this end, a conventional wisdom has been developed, which states that small locally-operating banks are superior in lending to SMEs through relationship lending (e.g. Berger and Udell, 1995; Keeton, 1995; Berger *et al.*, 1998; Strahan and Weston, 1998; Haynes *et al.*, 1999; Berger and Udell, 2002; Berger *et al.*, 2005).

Motivated by the lack of financing to a critical sector in the economy, the rapid increase in M&A activities among financial institutions, the decline in the number of small local banks as a major provider of SME financing and increased public policy interest in ensuring a stable decentralised banking system, this research aims to empirically examine the linkages between bank size, locality, SME lending and local economic development.

The objectives of this research are achieved through several contributions to the literature of banking structure, SME lending and economic development. The first of those contributions is to gain a deeper insight into the macro and microeconomics of healthy banking structures to help SMEs' growth. They are achieved by using a large representative dataset over 20 years from the largest economy and most diversified banking system on the globe, as well as employing a variety of advanced econometric techniques. Secondly, at the microeconomic level, this thesis extends previous research on the link between the organisational structure of the financial institutions and the SME lending. It introduces new measures of bank lending propensities based on lending to small and micro business loans. These measures help in determining more precisely which bank size is more prone to lending to SMEs. Thirdly, this thesis not only highlights the exclusivity of small banks in providing credits to SMEs, but also extends this examination by adding a new dimension to the regional banking-growth literature and directly quantifying the impact of small local banks on the local economies through the small business lending channel. Fourthly, using a quantile technique based on a newly construct instrumental variable, the thesis examines whether local banks differently stimulate local economies at different levels of development. Fifthly, this thesis takes into consideration the geographical dispersion of local banks and the spatial spillover effects of those banks on local development across regions.

In achieving such goals, this thesis not only delivers insights regarding the policy debates for reforming the banking structure, it also suggests a further critical assessment of the banking structure and the level of centralisation in the banking system. From the findings, the need is recognised for banking systems that are not concentrated and instead characterised by a large number of small locally-operating banks.

Chapter 2 Regional Banking-Growth Nexus: Review of the Literature

Chapter 2 reveals further gaps in the extant literature of banking structure and regional growth. It also attempts to highlight the importance of small local banks as a healthier contributor to the local economies through their exclusivity in providing credits to small and micro businesses. To this end, this chapter contains a review of the literature on whether regional banking factors have or have not been major determinants in the success or otherwise of the regional economies. That is, it establishes the theoretical framework and shapes the hypotheses of this thesis. This chapter introduces a number of contributions. For instance, it introduces the local SME lending channel as measure of local banking development. Secondly, it highlights the need for a distributional examination of the regional banking-growth nexus based on different quantiles of local income and employment. Finally, it justifies the need for an original study that takes into account the geographical dispersion of local banks and spatial spillover effects among regions.

In terms of its structure, this chapter begins with contrasting the theoretical arguments on distributional heterogeneity. It subsequently reviews three strands of the empirical regional banking-growth literature. The prior regional banking-growth studies are first discussed, which indicate that regional financial factors are important determinants of regional economic success. Secondly, the studies on banking regulatory changes and their impact on local economic activities are reviewed. Finally, studies on how regional banking distress may heterogeneously affect local economies are examined. Throughout this chapter, the author refers to a number of key methodologies and key findings by previous researchers. A number of contributions to the regional banking-growth nexus are shaped by the work in Chapter 2 and Chapter 3, followed by an important extension presented in Chapters 5 and Chapter 6.

Chapter 3 Conceptual Framework and Methodologies

Chapter 3 presents a conceptual framework that leads to four main hypotheses examined in the following chapters. Firstly, bank size has a negative impact on lending propensities to SMEs. Secondly, local banking development spurs local growth through SME lending channel. Thirdly, the impact of local banks may vary in relation to the level of regional development. Finally, a spatial spillover effect of local SME lending on local economic development may be present across regions and overlooked by previous research. This chapter additionally demonstrates and justifies the adoption of various methodologies which examine the aforementioned hypotheses. The methodology of Chapter 4 is based on a panel fixed-effects model. Chapter 5's methodology, which examines the second and the third hypotheses, consists of two panel data approaches, that is, a conventional dynamic panel data technique (in my case the Generalised Method of Moments GMM), and an instrumental variable quantile panel data technique. The third methodology consists of a theoretical model and a dynamic spatial panel data approach (i.e. dynamic spatial Durbin model, SDM). Those methedolgies are implemented throughtout Chapter 4, Chapter 5, and Chapter 6.

Chapter 4 Bank Lending to SMEs: Does Bank Size Matter?

Chapter 4 contains an empirical analysis of the relationship between the size of the bank and the lending propensities to small and micro business loans. Following a review of the large body of literature on bank size and its association to SME lending, and a number of studies that examine the effect of banking competition and mergers & acquisitions on the SME sector, this chapter empirically investigates the hypothesis that as banks become larger, their propensities to lend to micro and small businesses decrease. Chapter 4 introduces new measures of lending propensities i.e. small and micro business lending propensities. Using a large representative dataset of more than 14,000 banks in the U.S over 20 years from 1994 to 2013, the panel fixed-effects models reveal an inverse relationship between bank size and lending to small and micro businesses. In other words, small banks are more interested in lending to SMEs, while SMEs are more neglected by larger banks. This finding is robust to a broad array of sensitivity tests using different subsamples and alternative sampling periods. In addition, this result is also confirmed when additional variables that shape the propensity to competitive and institutional environment are controlled. Moreover, the findings indicate that the negative effect of bank size on lending propensity is stronger for micro business than small business measures. These findings not only provide evidence that bank size describes different characteristics of bank organisational structure but also question the policy implications regarding the need of a diverse banking sector in order to help overcome growth constraints on small and micro businesses.

Chapter 5 Local Banks and Regional Growth: A Distributional Analysis

Chapter 5 extends the extant literature on regional banking development and regional economic growth. Specifically, it considers the distributional analysis of the link between local banks and regional economic growth. This chapter tests for two hypotheses; firstly, a greater contribution of locally-operating banks to small and micro business lending stimulates regional economic growth. Secondly, the magnitude of effects of these banks may vary measurably across the distribution of regional/local economic growth. This chapter draws upon the reviewed literature in Chapter 2 and builds econometric models that examine the distributional effects of local banks on local economies. The analyses are based on a large representative county-level dataset from the U.S over the period from 1994 to 2013. While previous studies in this area rely heavily on different measures of regional banking, e.g. regulatory changes, bank performance, loans and deposits, this chapter utilises the supply channel of loans to SMEs as proxy measures for local banking development. The empirical investigation consists of two types of regressions, firstly, a 'mean' based panel regression that accounts for endogeneity bias and, secondly, a 'quantile' based instrumental variable panel regression that exploits full distributional heterogeneity in the impact of SME lending on local economic growth. The results confirm the chapter's main hypothesis, that is, a greater share of local banks in SME lending has a significant positive effect on local income and total employment. Additionally, the results of the quantile regressions confirm the hypothesis that the magnitude of the effects of local banking development on local economic development varies according to the regions' level of economic development.

Chapter 6 A Spatial Econometric Analysis of Local Banking-Growth Nexus

Chapter 6 marks a further important contribution to the literature of local banking-growth nexus. This chapter adds a new dimension to the analysis of the relationship between local banks, SME lending, and local growth. It tests the hypothesis whether local banking development, as measured by small and micro business lending, has a positive impact on local economic growth taking into account the spatial frictions among regions. This chapter hypothesises that results from OLS regressions, in the absence of spatial spillover effects, can be overestimated due to spatial externalities. To this end, this chapter extends the convergence-theoretic model and builds an econometric model with a spatial weight matrix in order to isolate the spatial spillover effects that may bias the estimation of the effects of local banking development on local economic growth. The findings of this chapter reiterate those in Chapter 5 and suggest that local banks exert a significant impact on local economies. However, the results from the spatial Durbin model confirms the presence of spatial spillover effects of local banking development on local economic growth. A robust test utilises the micro business lending as an alternative measure of local banking development approves the main findings.

Chapter 7 Conclusions, Policy Implications and Future Research

Chapter 7 delivers a summary of the findings in this thesis and the overall conclusions. This is followed by the formulation of a number of policy implications. This chapter also identifies the limitations of the work in this thesis and finally recommends complementary or further avenues for future research.

Chapter 2

Regional Banking-Growth Nexus: Review of the Literature

Chapter 2: Regional Banking-Growth Nexus: Review of the Literature

2.1 Introduction

The link between financial development and economic growth as first advocated by Schumpeter (1934) has generated a significant empirical literature (e.g. King and Levine, 1993; Arestis and Demetriades, 1997; Levine and Zervos, 1998; Rajan and Zingales, 1998; Claessens and Laeven. 2003; Bekaert *et al.*, 2005; Beck *et al.*, 2008). Before the 1980s, many finance-growth studies, especially cross-country, have neglected interdependencies and disparities across regions within a single-country framework. These studies regard all regions as homogenous, thus amounting to biased and inconsistent predictions of net growth effects. Since the early 1980s, a large body of theoretical and empirical literature has been devoted to scrutiny of the regional finance-growth nexus. Regarding the *negative theory*, Robert and Fishkind (1979), Greenwald *et al.*, (1993), and Samolyk (1994) argue that a country's particular banking system is not an important determinant for its economic growth, because a country's financial system is fully integrated, has no market imperfections and zero financial constraints, with perfect interregional capital flows. Robert and Fishkind (1979), however, posit information asymmetries and dissimilarities in liquidity preferences across regions. Furthermore, Moore and Hill (1982) believe that small borrowers are most affected by the lack of information in some regions, especially peripheral ones, when their local small lenders fail to satisfy their excess credit demands from local deposits, which are their only source of credit supply, while outside non-local lenders are uninterested in lending to those informationally opaque regional businesses and individuals.

Researchers who expounded a *positive theory* of the finance-growth nexus have argued that if we accept that regional factors are important, the above conclusions would have to be revised. In fact, local banks, with their exclusivity in local market information (i.e. potential projects and investment opportunities), can reduce the cost of information gathering and monitoring. The work of Greenwald *et al.*, (1993), and Samolyk (1994), amongst many others, suggests that, under this scenario, local banks can be vital to regional economic stability, by providing funding more efficiently to financially constrained borrowers than non-local lenders. In what follows, I present the main arguments of the Post-Keynesian and the New-Keynesian theories on how regional banking systems are important for local economic growth.

Post-Keynesians argue that regional banking systems are important regarding such matters as the integration between money and economic activities, both at national and regional levels (e.g. Chick and Dow 1988; Dow 1988, 1990, 1992; and Chick 1993). Some of the Post-Keynesian literature is concerned with the role of banks as liquidity providers, also among regions, while allowing for the possibility that markets may not always be perfect. In that case, regional banking may be important, as it may affect the relationships at the centre of their models. Thus, this literature motivates empirical research on the extent to which regional banking factors have an impact on local economic development.

According to the Post-Keynesian theory, both the supply and demand sides of credit are interdependently endogenous to regional liquidity preferences (e.g. Dow 1987). For instance, lower confidence in a regional economy is reflected in higher liquidity preference, which, in turn, translates into: 1) lower borrowing by investors (decrease in credit demand), 2) savers are more willing to invest in safer portfolios and hold more liquid assets (shrinkage in credit supply), and, 3) higher tendency of lenders to reduce their lending within the region, due to higher risk perception or more costly risk assessment (shrinkage in credit supply). Also, regional demographic variations in savings behaviour may affect local loan supply and economic activity, as Becker (2007) finds that cities with a large fraction of seniors have higher volumes of bank deposits.

Because the Post-Keynesian framework is so central to this chapter, there are a number of other salient points. For example, some Post-Keynesians also argue that the supply of credit is influenced by the level of banking development in a region. The latter determines the ability of banks to extend their credit. For instance, banks in a region with a lower level of banking development have limited access to savings and deposits – especially in the case of local banks. Consequently, there is less than optimal finance to fund businesses, thereby generating variabilities across regional economies (see Dow and Rodriguez-Fuentes, 1997; Rodriguez-Fuentes, 1998, for further analysis). That being so, regional banking factors could be expected to be important factors in the determination of local economic activity, justifying further empirical research in this area.

Furthermore, there is a substantial amount of literature on credit rationing, which also affects the supply of credit, by banks (Keeton, 1979; Stiglitz and Weiss, 1981) on the one hand, and the bank lending channel of monetary policy transmission on the other (see Bernanke and Blinder, 1992; Gertler and Gilchrist, 1994; Bernanke and Gertler, 1995). While many researchers within this field of analysis do not consider regional disparities, including income distribution, both strands of literature provide ample motivation to conduct an empirical examination of the extent to which different income and employment quantiles are affected by loan provision by local banks (examined in Chapter 5). Credit rationing is a phenomenon that is based on information imperfection and incentive effects. Thus, it is plausible that the ‘softer’, information-intensive, lending approach the literature has identified in local banks exhibits credit rationing effects to a larger extent than is the case for the more transaction-based credit demand and credit supply common amongst the larger players (note that Chapter 4 reveals that bank size and borrower size are closely related). Thus the credit rationing argument, supported by theory and empirical evidence, provides a reasonable rational for also expecting spatial effects among regions (examined in Chapter 6).

Since it is the main concern of this chapter, the debate regarding the role of small local banks in local growth has been intensified over the past decade. A number of studies emphasise the importance of a greater presence of local banks in local economies. For instance, Ashcraft (2005) finds that the closure of healthy banks, as a result of the failures of their mother banks, have detrimental effects on local incomes. Further, a greater presence of community banks helps in reducing the rates of home foreclosures (Fogel *et al.*, 2011), and prevents capital drain from poor to rich regions, where small banks spur regional development in all regions and more prominently in less developed ones (Hakenes *et al.*, 2015). On the other hand, the local ownership of banks does not exhibit a significant effect on local growth, while non-local banks have a negative impact on local economic growth in urban markets and the opposite for rural ones (Collender and Shaffer, 2003). More assertively, Becker (2007) draw conclusions against small local banks and contends that a better geographical reallocation of capital can be fostered by increasing the size and scope of interregional banks, while small local banks are inefficient and aggravate regional segmentation of capital markets. Accordingly, the effect of local deposit supply on local growth was weaker following the introduction of new banking regulations, which led to increased bank size and new formation of large interregional banks in the U.S. Although my hypothesis employs the findings of Ashcraft (2005), Fogel *et al.*, (2011), and Hakenes *et al.*, (2015), their work is not designed to flesh out the distributional aspects and the spatial spillover effects of the local bank impact on local growth across regions. Also, my SME lending-based variables of local banking differ from their bank-performance and local deposit measures.

Moreover, despite the ongoing harmonization of banking regulations in Europe and the United States, the ability of banks to channel funds efficiently is still heterogeneous across regions and not only throughout countries or States (e.g. Bos and Kool, 2006; Burgstaller, 2013; and similarly Huang (2008) for the U.S). What is more, different regions have significantly different growth patterns (e.g. Quah, 1996), are not isolated from their surroundings, and have mutual influence with other regions (e.g. Huang, 2008), thus, the role of small local banks in local growth may vary depending on the level of economic development of the regions and their neighbours. Accordingly, these variations in different frameworks give rise to varied empirical predictions of the regional banking-growth nexus. Motivated by the varied theoretical and empirical predictions, this chapter contributes to the literature of banking structure and regional economic growth in several ways. That is, by contrasting the theoretical arguments and reviewing the varied empirical predictions in the regional banking-growth literature, this chapter reveals further gaps in the extant literature of banking structure and regional growth. The first contribution is to introduce the local SME lending channel as a measure of local banking development. Secondly, it reveals the need for a distributional examination of the regional banking-growth nexus based on different quantiles of local income and employment. Finally, it justifies the need for an original study that takes into account the geographical dispersion of local banks and spatial frictions among regions.

The findings in Chapter 4 also motivate this chapter. That is, Chapter 4 shows that small banks are the optimal financial machinery in serving SMEs which are regarded as a vital source for economic growth. In this chapter, I show that the direct examination of the effect of small local banks on local economic growth, through SME lending channel, is important and has not yet been examined in the banking structure and regional growth literature. Overall, this chapter shapes the conceptual framework and its hypotheses (presented in Chapter 3) concerning the importance of small local banks to local economic growth through their exclusivity in providing credits to small and micro businesses.

The chapter proceeds as follows. The subsequent sections review the empirical studies of the impact of regional banking-growth relationships, banking regulatory changes, regional banking distress, and spatial banking spillovers on regional economic activities, respectively. The final section outlines the conclusions of the chapter.

2.2 Regional Banking-Growth Studies

This section summarises the relevant regional banking-growth studies to show whether regional banking factors have, or have not, been major determinants in the success, or otherwise, of regional economies. This section draws on a large number of prior studies from a number of countries, the U.S in particular. Because these prior studies indicate that regional financial factors are important determinants of regional economic success, this study incorporates them into my models and my analyses throughout Chapter 5 and Chapter 6. The most notable differences in the empirical studies on the subject relate to the way in which the empirical research has treated differences in levels of economic development, mobility of financial capital, competitiveness of banks, the intervention of large banks and, finally, the nature of credit creation alongside the growth of local entrepreneurs and human capital. I now give a short overview of the some of the key relevant academic studies. This is also because the early empirical literature mirrored the aforementioned controversies in the theoretical argument.

Inequalities in regional banking conditions may influence economic performance differently. For instance, Samolyk (1994) concludes that states with healthy banking conditions exhibit a weaker link (or no relationship) to local, real, income than financially distressed U.S states, as they are credit constrained with relatively poorer banking conditions. This emphasises the vital contribution of local banks to regional growth, but only when regional segmentation and information asymmetries exist. Similarly, Rodriguez-Fuentes (1998) finds that banks influence regional economic growth, as they are not geographically neutral in the allocation of funds across regions (see also Dow (1990) and Chick (1993) for applications to the Canadian, and EC cases, respectively). Taking the case of Spain, a recent work by Carbó and Rodríguez (2004) employs panel data techniques that are similar to my approach and other, more recent, studies. They find that the dependence of businesses on lending grants banks a special role in stimulating regional growth. Continuing this line of work, Carbó *et al.*, (2007) conclude that banking development and financial innovation in banking have a positive impact on regional GDP, investment and gross savings growth. Among other European countries, Guiso *et al.*, (2004) consider the case of 103 Italian regions and conclude that local financial development in Italy facilitates the external credit supply to small firms and individuals and, consequently, promotes economic growth. In particular, more financially developed regions are characterised by a higher probability of an individual starting a business at a younger age, larger numbers of start-ups and existing firms, and a higher rate of per capita GDP. This, therefore, suggests that even in a highly integrated market, regional financial development still matters for economic growth. Rather than simply studying the amount of credits channelled to borrowers, Guiso *et al.*, (2004) consider the probability of households or firms being denied loans, or being discouraged from applying for loans, in each region. In the same vein, Vaona (2008) reaches similar conclusions about the regional finance-growth nexus in Italy. However, his study, like many other studies, does not consider indicators of banking development derived from micro data; rather, he considers aggregate ones, directly concerning the size of the banking sector relative to the local economy as a measure of its degree of financial intermediation, an approach which my analysis follows.

The volume of credit provided by banks may not be sufficiently indicative of financial development. Hasan *et al.*, (2009) argue that more efficient banks (i.e. banks with superior ability to channel credit) have significantly more effects on regional growth than banks that only increase their credit amounts. Accordingly, they construct quality measures of financial services offered by banks, based on cost and profit efficiency estimates, in addition to quantity measures, in order to assess the impact of regional financial development on economic growth for 147 regions across 11 European countries. To fill such a gap in representing regional banking development, the current research emphasises the SME lending channel of local banks as an alternative indicator of local banking development, where these measures are derived from bank-level data and are aggregated at county-level.

The above studies and many more like them show, as this chapter tries to show, the importance of regional banking development in evaluating regional economic growth. Although the above evidence validates the methodological and data collection approach of Chapter 5 and Chapter 6, there is some contrary evidence, most notably from newly emerging countries, such as the Peoples' Republic of China. These studies have tended to show that similar measures of financial deepening do not seem to favour local growth for a fast growing economy, such as China's. Hasan *et al.*, (2009a), for example, find that the relationship between banking sector depth and regional economic growth is flat or negative, and they attribute this relationship to the high share of public ownership of banks in China.

In the context of Asian economies, using the data from China, Cheng and Degryse. (2010) find that banking development has a greater impact on local economic growth than the development of non-banking institutions. Similarly, in the Indian context, Kendall (2012) documents strong evidence that less developed local banking systems are associated with slower local growth for 209 Indian districts. Further evidence from BRICS countries is taken from 354 South African regions over 2003-2004. Results reveal that access to finance is one of the most important determinants of new business formation rates (Naudé *et al.*, 2008). That is to say, a larger presence of bank branches provides new businesses with an easier access to finance, and banks with lower monitoring costs, as they serve fewer clients. Moreover, private banks reduce economic disparities among Turkish provinces, as the GDP per capita is motivated by the private credit. On the other hand, state-owned banks stimulate economic growth in the more developed provinces, while they make no contributions to the growth of less developed ones (Önder, and Özyıldırım, 2010).

So far, this literature review chapter has shown that regional banking development is very important both in the developed and emerging economies, and subsequent empirical chapters develop my contribution to this important area. However, I now leave the more general regional banking-growth literature and review studies that examine whether the actual presence of local banks has a significant impact on local economic activities, an issue I very much concentrate on in subsequent chapters.

Much extant literature points to the importance of a network of local banks to economic development. Thus, researchers, such as DeYoung *et al.*, (2004) and Berger and Black (2011), find that community banks have a competitive advantage over larger banks through maintaining long-term personalized relationships with their borrowers, and collecting and utilizing local soft information to make lending decisions. This is because banks that are deeply imbedded in their local communities can, a priori, be expected to have major competitive advantages over their nonlocal competitors regarding such issues as adverse selection and moral hazard problems. That being so, the relevance of this chapter becomes more obvious.

Further, over the past ten years, there have been growing concerns in the empirical literature about the role of local, or local-like, banks, such as rural and savings banks, in regional development. Some empirical studies, such as those by Carbó-Valverde *et al.*, (2009) and Degryse and Ongena (2007), focus on credit availability to SMEs; this is because SMEs' contributions to local employment and income levels are crucial to regional development. Studies such as these suggest that small banks with restricted market power reduce SME credit constraints. Guevara and Maudos (2009) show that businesses in industries with a greater dependence on external finance develop faster in more financially developed regions. Berger *et al.*, (2004) argue that relatively healthier community banks with a larger market share and higher efficiency may have a positive impact on economic performance. This impact may be transmitted through two mechanisms: firstly, through a greater financial support that community banks may channel to SMEs, since community banks specialise in SME lending, and, secondly, through a reduction in the market power by competing more effectively with other banks in the market, causing a higher rate of overall credit flow.

Empirically, Berger *et al.*, (2004) examine these hypotheses using bank-level and industry-level data collected from 49 countries over the period 1993-2000. Their findings validate the aforementioned hypotheses for both developed and developing countries; in particular, a larger market share held by community banks and more efficient community banks enhance SME employment share, as well as overall bank lending in the market, causing the economy to grow faster. However, because I am more focused on regional effects than large, countrywide, effects, I focus the rest of my discussion more on regional measurements and regional results rather than summarising more cross-country results.

There are, in fact, a large number of such finance-growth related studies which employ regional-level data from a single-country in order to investigate the effects of regional financial development and structure on the regional economic growth. For instance, the Usai and Vannini (2005) study looks at the role that each of four types of intermediaries plays in regional economic growth for 20 Italian regions between 1970 and 1993. In their study, a special focus is given to the role of cooperative and rural banks, since they are historically regarded as the major relationship credit providers to SMEs within the Italian local markets. Results suggest that, despite the insignificant impact of overall financial development on economic growth, the cooperative banks and the special credit institutions are found to have a positive impact on regional growth, while large private banks and state-owned banks have either no impact or a negative impact. Their study suggests that smaller banks foster regional economic growth through relationship lending to SMEs, emphasising the notion that smaller and less complex banks play a better role than large hierarchical banks in providing essential finance to SMEs.

Similar conclusions, from a developing country, are reached by Meslier-Crouzille *et al.*, (2012). They perform a panel cointegration analysis of data collected from 16 Philippine regions over the period 1993-2005 to investigate whether a long-run equilibrium relationship exists between the role of rural banks, regional banking development and regional economic growth. Like Usai and Vannini (2005), they find an insignificant impact of overall regional financial development on regional economic growth. Nevertheless, the specific measures of rural banks show a positive impact of a larger presence of rural banks on economic growth for intermediate and less-developed regions; this impact is found to be stronger for intermediate regions. The results indicate a comparative advantage of rural banks over commercial banks in relationship lending.

A study by Fogel *et al.*, (2011) highlights the importance of a greater presence of community banks to local economies. Their U.S county-level research over the three years predating the 2008 financial crisis concludes that counties where community banks are more prevalent show lower rates of home foreclosures. In other words, community banks help in reducing the rates of home foreclosures in U.S local markets. However, this study relies solely on the deposit share of local banks in the market (county) as a measure of local market presence. Most recently, Hakenes *et al.*, (2015) present very strong evidence that emphasises the importance of small local banks in preventing capital drain from poor to rich regions. They theoretically and empirically compare the contributions of small and large banks to regional economic activities for 395 German regions from 1995 to 2004. In short, their findings indicate that small banks, represented by savings banks, spur regional development in all regions and even more prominently in less developed ones. The economic measures used are the new business formation rates and GDP per capita at a regional level. In line with their study, my hypothesis is compatible with the conclusions of Hakenes *et al.*, (2015).

The above section summarises prior empirical studies of the impact of regional banking development on regional growth. When viewed in their entirety, these studies show that regional banking-growth nexus, the focus of this chapter, has generated much valuable research and an ongoing debate concerning the real impact of regional banking sectors on local growth. Consequently, this chapter is an important contribution to such debate which is settled in the following empirical chapters.

2.3 Banking Regulatory Changes and Local Growth

This section examines the relevant literature regarding the role of banking deregulation and the removal of geographical restrictions on local economic growth. I review this literature because such changes in regulations play a critical role in the structure and development of regional banking systems. Depending on the degree of dissimilarities between different regions, the effects of such regulatory changes on local banking markets and, hence, on regional growth, may have varying effects, both in scale and scope, on the respective markets. What is more, depending on the degree of the geographical liberalisation among regions, the spatial spillover effects of local banking development on local growth may vary accordingly (as will be shown in a following section).

Thus, for example, an early study by Jayaratne and Strahan (1996) finds that intrastate branching liberalisation in the U.S improves state-level economic activities. They specifically observe a positive effect on both per capita income and GDP after structural deregulations, which allowed banks and bank holding companies to be involved in in-state M&As and to establish new branches in the same state. Their paper asserts that the resulting economic improvement is not due to increased investment or lending volume, but that it is, rather, due to the results of improved bank efficiency through better bank monitoring and screening measures. That being so, the cost of intermediation is reduced and savings are channelled into superior investments.

Seminal though their paper was, it has an important number of empirical caveats. Interstate banking, for example, was inhomogeneously restricted across states at the time when the sample was taken, indicating that the U.S financial markets were not fully integrated at that time. Thereafter, as a result of various interstate banking deregulatory measures, bank holding companies were allowed to merge with, or acquire, banks located in other states. Banks have gradually become more integrated across states as a consequence and the overall American banking system has become much more integrated and local divergences have become less pronounced.

One important result of this has been that increased bank integration with more linkages between banks across states, plays a direct pivotal role in smoothing state economic fluctuations (Morgan *et al.*, 2004). That is to say, year-to-year state business cycles converge and diminish. Similar mitigating effects have been observed by Demyanyk *et al.,* (2007) over the period 1970-2001. They document improvements in state income insurance as a result of the deregulation of both interstate and intrastate banking restrictions. That is, as banks become more financially integrated across states following such banking reforms, state-level personal income becomes more insulated against, and less sensitive to, state economic shocks. In other words, a state is partly sharing the income risk emerging from other state-specific fluctuations in outputs. What is more, the deregulation impact is stronger in states that have a larger presence of small businesses.

Demyanyk *et al.,* (2007) posit that these U.S banking industry reforms have led to greater efficiency in small business lending and to greater efficiency in interbank capital allocation. Building on this, Beck *et al.,* (2010) find that intrastate bank branching reduced income inequality by boosting incomes for those with the lowest incomes, while the highest income class remained relatively unchanged. In particular, wages and working hours were increased among low-skilled workers, suggesting an increase in labour demand following branching liberalisation. Beck *et al.,* (2010) attribute the tightening in income distribution to improved bank performance as branching liberalisation weakens the monopoly power held by local banks. The effect is found to be stronger in states that experienced better bank performance with more diffused populations. However, their analysis does not examine the channels by which improved bank performance may influence income distribution, leaving such investigation for further empirical studies. This question, as to how differences in county-level banking systems impact on local growth, will be addressed in my subsequent analysis sections.

Other research uses different approaches than state-level aggregate data to represent local markets. Collender and Shaffer (2003), for example, adopt a smaller definition for locality by collecting data at the metropolitan and nonmetropolitan area levels. Their study finds that local growth is positively affected by geographical liberalisation and banking deregulation in the U.S; in particular, they find that bank-entry, which is allowed through bank M&As or/and intrastate branching, spurs local per capita income, that the impact is stronger for the metropolitan markets (i.e. urban areas) than nonmetropolitan area markets (i.e. rural areas), and is persistent in the long-run. However, their results exhibit a paradox, since they find that non-local banks have a negative impact on local economic growth in metropolitan markets, while the opposite is true for nonmetropolitan ones. My analyses in the following chapters attempt to settle such a paradox, by employing different methodologies based on quantile and spatial econometric techniques, albeit by using broadly similar macroeconomic level data from the U.S.

Although Becker (2007) uses a similar approach, he finds that the effect of local deposit supply on the local growth, following intrastate deregulations, was up to 33% weaker. He deduced from this that the liberalisation of intrastate branching reduces the restrictive effects of geographical variations on the transfer of funds from regions with high local deposits to regions with high loan demands. Becker goes on to argue that a better geographical reallocation of capital can be fostered by increasing the size and scope of interregional banks, while small local banks are inefficient and aggravate regional segmentation of capital markets. However, Becker does not address the issue of the potential outflow of funds from less-developed regions to richer ones that, in turn, deteriorate the economic conditions of poor regions. However, my analyses in the following empirical chapters consider the spillovers of funds among regions and also the results are markedly different from those of Becker.

Although a number of other research papers rely on measures of firms' growth to represent local economic development, these studies do not reach common consent on the effect of banking deregulation and increased market competition on local growth. In 2002, for example, Black and Strahan additionally include the relaxation of interstate banking in their analysis. Their results indicate that state-level competition is increased following banking deregulations, that is to say, existing banks need to compete with new entrants allowed into their local markets, and that the rate of business creation rises as results of intensified competition and new deregulations, even in markets characterised by higher local bank concentration.

The study by Cetorelli and Strahan (2006) finds that the decrease in the share of small banks after deregulation of interstate consolidation fosters the rates of business creation across states and, what is more, the effect of increased banking competition is not the same across firm sizes in the manufacturing sectors. That is to say, in addition to the growth in the total number of firms, Cetorelli and Strahan observe an increase in the share of the very small ones (i.e. less than five employees), while they observe no effect on the largest firms, which are less dependent on bank financing. Furthermore, this rate shows an inverted-'U' relationship with bank market power in a province-level study from Italy (Di Patti and Dell'Ariccia, 2004). Such relationships are not constant across industries in that bank market power at lower levels is more beneficial to highly informationally opaque businesses and less harmful at more extreme levels. I return to this relationship between SMEs and local banks in subsequent analysis chapters.

Another important relationship that my future chapters examine is how the regional finance-growth relationship may vary with regard to the particulars of each specific country. In this regard, Carbo-Valverde *et al.,* (2003) conclude that, despite the rise in deposit rates and the decrease in lending costs following banking deregulation in Spain, increased market competition does not show any significant effect on regional GDP over the 1986–1998 period. Because, unlike U.S banking data, most EU countries lack deposit data at branch-level, Carbo-Valverde *et al.,* (2003) rely on the 'regional distribution of branch offices' to calculate the Herfindahl-Hirschman Index (HHI), even though this method may inaccurately represent market competition and, hence, draw false conclusions about the impact on regional growth. Therefore, the HHI variable in my analysis is based on deposits held at branch offices. I return to this issue in other chapters.

A more recent paper by Guevara and Maudoa (2009) adopts the growth of firms' sales as an indicator of local economic performance. Their results show no effect of banking market competition on local growth. However, firms that have relationships with banks, which hold moderate market power, are mostly positively affected. Specifically, firms with greater dependence on external finance (e.g. SMEs) benefit more from moderate market power. Their paper points out that perfect competition may not always be a lever for economic growth, but that some levels of bank market power may be necessary to facilitate the benefit accruing from relationship banking. Such imperfections would appeal to small informationally opaque firms, which prefer maintaining their long-term relationship with their banks, so that difficulties in providing required collaterals to obtain sufficient funds for their activities and investments may be lessened. Francis *et al.,* (2008) specifically examine the impact of banking consolidations on new business formation at the smaller geographic scope of local markets (i.e. Labour Metropolitan Area, LMA). Their results vary over time, where, in the short-term, banking consolidations have a negative impact on business creation, mainly driven by M&As involving large banks. However, this effect is compensated for by smaller banks in the markets, as well as by large acquirers in the long-term. On the other hand, they find that M&A activities between small and medium-sized banks tend to almost always boost business creation in local markets.

The mixed results concerning the changes in local banking structure as a result of banking deregulations necessitates the need for further analysis of the impact of local banking structure on regional economic performance. The new measures of local banking contributions and the analysis in subsequent chapters are entirely concerned with this issue.

Policymakers have introduced lending programs and imposed restrictions on banks, aiming at reducing inequalities among income classes and regions to facilitate access to credit by low- and moderate-income communities and minority borrowers, but primarily to encourage lending to small businesses. A number of researchers have examined whether these measures meet their objectives to promote local economic development through credits locally channelled to targeted communities. Two methods have been implemented in the literature to assess the effects of guarantee programmes: a macro approach and a micro approach. In relation to those studies, I have reviewed some of them because my indicators of the contributions of local banks to the local economies are based on small business lending.

To begin with, Craig *et al.,* (2007) apply a macro approach to investigate the regional impact of participation in a loan-guarantee program. Their first paper analyses the effect of the number of Small Business Administration (SBA) guaranteed loans on the growth rate of regional per capita income, while in their second paper, Craig *et al.,* (2008), uses the same technique to examine the impact of the same measure on the annual level of employment. Either way, the authors find that the number of SBA loans has a positive correlation with higher per capita income and higher employment. However, they conclude that it is difficult to tell whether the SBA loans stimulate regional economic development, or whether the regional economic development spurs the demand for SBA loans.

This problem of reverse causality they encountered is typical of the macro approach. A further study by Kobeissi (2009), for example, suggests a stimulative impact of the credits channelled through the Community Reinvestment Act (CRA) on new businesses creation, which, in turn, promotes local employment rates in the U.S local markets. However, Kobeissi's examination only covers loans supplied by banks with an asset size greater than 300 million dollars (i.e. banks beyond this threshold do not have to report CRA loans), thereby disregarding a significant proportion of loans provided by smaller banks that fall into the CRA loan categories, such as small business loans. This study is particularly important, not just in its overall context, but also with regard to my study as well. I return to this chapter in a subsequent section.

This section has overviewed the relevant literature, much of which will be returned to in subsequent chapters. It shows how the variations in the empirical predictions of regional banking-growth persist, and also none of these studies have examined the direct effect of local SME lending on local growth as this chapter proposes. The next section examines the links between banking distress and local economic performance, and will be also referred to in my methodologies and other subsequent chapters.

2.4 Banking Distress and Local Economic Performance

This section reviews previous studies which are concerned about the channels through which regional banking distress may slow regional economic growth. In particular, this section reveals that the distress of local healthy banks harms the regional economies through decreased SME lending. Lending support to my conceptual framework in the next chapter, this review highlights the exclusivity of small local banks in SME lending and, in turn, stresses the importance of the SME lending channel to local development. It also shows how the effect of regional banking shocks may vary at different times, as well as in both the scale and scope of the respective regions.

Since at least the time of the Great Depression, there has been a large body of literature about the causality links between banking distress and economic growth, with particular emphasis on the channels through which these effects are transmitted. Two such channels are, firstly, the reduction in the wealth of bank shareholders and, secondly, the contraction in money supply. Friedman and Schwartz (1963), for example, find a decline in aggregate available funds caused by bankrupt banks and a contraction in the money multiplier, because depositors tend to withdraw their deposits from distressed banks and the money multiplier decreases when banking reserves increase.

Bernanke (1983) builds on this result. He introduces a third linkage that played an important role in exacerbating the Great Depression. He finds that, in addition to the decline in credit supply – resulting from bank failures, deposit withdrawals and suspended deposits, that banks become less effective in performing intermediation services (e.g. costly monitoring and gathering information about borrowers) and that obtaining credits becomes more expensive for borrowers relative to their income, causing firms to have weak balance sheets or a degradation in a firm's creditworthiness. He then found that financial distress of both banks and firms leads to additional contraction in aggregate lending and, hence, prolongs the depressing effects on output.

However, a number of studies have questioned Bernanke's claims, and have criticised him for overestimating the impact on economic performance and not distinguishing between credit demand and credit supply sides (e.g. Peek and Rosengren, 2000; Calomiris and Mason, 2003). In addition, Rockoff (1993) claims that the nonmonetary variables adopted by Bernanke become less influential relative to the inclusion of a quality-adjusted measure of credit supply. For instance, Rockoff finds that the decline in the liquidation velocity of suspended deposits of failed banks has a larger impact on deepening and protracting economic depression than other nonmonetary factors, such as the contraction in the quantity of credit supply. In the long-term, for periods of 10 years or more, both credit contraction and the slow liquidation of suspended deposits are found to have significant effects on industrial production (Anari *et al.*, 2005). In 2003, Calomiris and Mason examine Bernanke's view, taking into consideration this criticism. They exploit variations across states and counties by performing a panel data analysis rather than merely relying on time-series regressions at the national level, as used by Bernanke and others. To address the issue of credit supply-demand identification, they use instrumental variables[1] to identify credit supply shocks and to capture their impact on local economic activities during the Great Depression between 1930 and 1932. Their results indicate a strong effect of credit supply shocks, caused by banking distress, on state income growth, as well as real state income at county-level.

Consistent with my hypothesis, the credit supply channel is regarded as an important factor to explain local growth. The current chapter utilises two indicators of credit supply channels, that is to say, loans supplied by local banks to small and micro businesses.

Despite the evident effects of banking distress on the propagation of economic downturns, the results of the aforementioned studies may only be valid during the Great Depression, which took place in early 1930s. One may argue that, ever since, many regulatory changes (e.g. aforementioned branching deregulations) have been introduced and precautionary measures (e.g. the creation of deposit insurance) taken to mitigate against the potential consequences of banking shocks. Such changes may influence the mechanism, and the extent to which local economies absorb banking shocks.

Hancock and Wilcox (1998) examine the Texas counties during a period of crisis characterised by a series of bank failures over the period 1981-1991. Their analysis of banking structure and economic growth reveals that the decline in bank capital forced banks, especially small banks, to considerably tighten their loan portfolios. This decline caused shocks to credit supply, reflected in local economic performance. The shrinkage in lending share by small banks is found to be more harmful to the local

[1] Real estate owned relative to loans, average bank size and the ratio of net worth to total assets.

economy than the harm that would be caused by a decline in large banks. That is to say, depressing effects are observed on several state-level economic measures, such as GDP and the number of firms. Interestingly, economic activities in small businesses are more negatively affected than those in large businesses. Consistent with my hypothesis, this pattern implies a strong linkage between small banks and small businesses (i.e. small bank-dependent businesses), as well as the superiority of larger businesses in changing financial sources.

In an attempt to resolve the identification problem of credit demand-supply shocks, Peek and Rosengren (2000) reveal that the banking crisis in Japan in the early 1990s has a negative impact on construction activities in U.S commercial real estate markets. The external event allows them to attribute such a deteriorating impact to the strongly exogenous credit supply shock. The impact is transmitted through contraction in commercial real estate loans, supplied in the U.S by branches and subsidiaries of the distressed parent banks in Japan. Their study only covers three states that have the highest presence of Japanese banks in local commercial real estate markets, signifying the considerable influence of Japanese banks on those markets. On the other hand, Driscoll (2004) documents weakly negative and statistically insignificant effects of state-specific credit supply shocks on the same state personal income in a study covering 48 U.S states. Since it is difficult to identify strongly independent credit supply shocks, Driscoll relies on state-specific money demand shocks as instruments to endogenise changes in the quantity of the loans supplied – a strong causation running from the former to the latter is proved before instrumentation. Likewise, in this research I provide evidence of a strong unidirectional relationship between my proposed instrument (i.e. Yield Curve) and the loan supply, also running from the former to the latter. More specifically, Driscoll uses a deposit-based instrument to measure shocks to loan supply. Similarly, Kendall (2012) employs the same for a district-level study from India. In contrast, the total domestic deposits variable from my dataset seems to be highly correlated with both the SME loan supply and local economic variables. Therefore, using a deposit-based instrument to measure my loan supply variable violates a fundamental condition of the IV approach – i.e. no correlation between the instrument and the dependent variable.

In a seminal empirical study, Ashcraft (2005) exploits two remarkable events of the Texas banking network in 1988 and 1992, when the FDIC decided to close 56 healthy bank subsidiaries because of the failure of their mother banks. That is to say, the reasons for their closures are independent from pre-existing local economic conditions, implying strong exogeneity of such events. He examines the impact of the closing of those healthy banks on local real income for all Texan counties. The results indicate significant detrimental, and apparently permanent, effects on local economic activity following the healthy bank closures. The depressed performance of local economies emerges from a shrinkage in the loans supplied by the closed healthy banks. In the subsequent empirical chapters, I adopt similar measures of both county-level per capita income and of the importance of small healthy banks to local per capita income. However, my dataset consists of almost all the U.S counties and I adopt specific measures of local bank credit supply (i.e. local SME loans).

In this context, Chodorow-Reich (2014) asserts that bank health has a significant impact on employment of SMEs during financial crises. Using the period prior to the failure of Lehman Brothers, he shows that businesses that borrow from less healthy banks face a lower probability of obtaining a loan, incurring a higher interest rate, and having a sharper reduction in employment when compared to borrowers from healthier banks. Also using data from the 2008-9 crisis, Goetz and Gozzi (2010) document that banks, small local banks in particular, that are more dependent on wholesale funding, are more vulnerable to market shocks following the Lehman Brothers bankruptcy in 2008. Subsequent liquidity shocks at such banks are adversely transmitted to local economies through reduction in the credit supply to firms with a greater dependence on bank financing. Goetz and Gozzi further find that in urban areas, where banks relied more heavily on wholesale funding, the decreases in employment and business establishments were more pronounced during the recent financial crisis. This pattern emphasises the substantial role of local banks in transmitting liquidity shocks to the local economy.

2.5 Spatial Externalities in Regional Banking-Growth Nexus

This section reviews the extant literature of spatial regional banking-growth relationship. Specifically, it emphasises on the space as an indirect key factor in determining the real effect of regional banking development on regional economic growth. Complementing previous sections, this section justifies the necessity for an original examination, which quantifies the spatial spillover effect of local SME lending on local growth.

The modern Neoclasical theory still expects economic convergence through diffusion processes and spatial spillovers across regions (e.g. Barro and Sala-i-Martin, 1991, 1992). However, such convergence is subject to persistent interregional disparities and other region-specific factors (Camagni and Capello, 2010). Thus, location factor is important, motivating the role of economic geography for spatial planning and regional policy evaluation (Clinch and O’neill, 2009; Potter, 2009; Martin and Sunley, 2011). Also, the local banking development factor is one of those key regional factors for regional growth (as shown in previous sections). The existence of location factors added to the mixed findings in the banking-growth literature confirm that the presence of interregional disparities are persistent in the long-term, hindering diffusion processes and hence economic convergence. According to such mixed findings, the development of the banking sector cannot be considered to be equally important, despite the re-equilibrating processes, that due to interregional disparities and spatial heterogeneity.

Furthermore, Quah (1996) asserts that different regions have significantly different growth patterns. Also, the ability of banks to efficiently intermediate credits are still regionally heterogeneous despite ongoing harmonization of banking regulation, such those in Europe and the United States (e.g. Bos and Kool, 2006; Burgstaller, 2013; and similarly Huang, 2008, for the U.S). That is to say, even in a single-country framework, a region is not isolated from its surroundings and has mutual influence with other regions, especially the neighbouring ones. Such interactions between regions can, for example, be caused by small differences in banking regulations, leading to unidirectional flows of cross-border credits (Fidrmuc and Hainz, 2013). Therefore, the growth rates of regions are differently affected by the developments of their banking sectors, due to their heterogeneous geographical dispersion.

The reviewed literature, in previous sections, have shown conflicting findings for the effect of regional banking development on regional growth. The mixed findings can be partially attributed to neglecting an important factor, which is the spatial organisation of regions within a single-country framework. This neglect may raise concerns of unobserved spatial effects (spatial externalities), creating spurious correlation between local banking development and local growth. The analysis of regional banking-growth should allow for the possibility that economic growth in a region may depend systematically on banking development in neighbouring regions (Anselin, 1988b).

Over the past decade, the role of space as a determinant of growth in regional finance-growth literature has received growing attention. However, the number of attempts is scarce, specifically for regional banking-growth link. Most of these studies examine the EU regions, for instance, Pereira and Roca-Sagales (2003) use Spanish data to investigate the impact of public capital on regional outputs, also Dall'erba (2005), Dall'erba and Le Gallo (2007, 2008), and Mohl and Hagen (2010) on structural funds and economic activities for EU regions.

More specifically on regional banking-growth relationship, Hasan *et al.*, (2009) utilise spatial statistical techniques that allow banks' quantity and quality measures to affect growth in the geographical vicinity of the regions in which they are headquartered. They use regional data from 147 regions in 11 EU countries between 1996 and 2004. Their approach permits banking development in neighbouring regions to affect the growth rate in region r to study whether financial economic activity are spatially independent. In particular, they specify a spatial-lag model that captures whether banking development of the neighbouring regions spill overs to region r. Hasan *et al.*, (2009) find that the direct effect of banking development measures on regional growth remains positive and significant after the inclusion of the spatial weights, i.e. the inclusion of spatial effects does not alter their main conclusions. Besides, the spatial lags of the profit efficiency (i.e. banking quality measure) in neighbouring regions are insignificant, while they are negatively significant for the aggregate lending volume (i.e. banking quantity measure). This suggests that deeper credit markets in the geographic vicinity exert a pull effect, perhaps by attracting some of the local investors. However, these centrifugal forces of economic activity are clearly compensated by economically (and statistically) significant direct effects through all identified channels of financial development on growth (Hasan *et al.*, 2009). A more recent study by Belke *et al.*, (2016) questions the validity of Hasan *et al.,* (2009)'s findings by extending their dataset to include the financial crisis and more EU regions. Their spatial-lag approach reveals contrasting findings to Hasan *et al.,* (2009). That is, growth in a region is stimulated by the banking quality of the neighbouring regions, while there is no evidence for spatial spillovers of bank lending volume. Also from EU regions, Burgstaller *et al.,* (2013) reveal that none of the banking development indicators, which are used in their spatial-lag model, exhibits a significant impact on regional growth in Austria. Therefore, the findings of Hakenes *et al.,* (2009) that German savings banks stimulate regional growth are not applicable for Austria. Although these studies are based on EU regional data, they exhibit contradicting findings of the role of space in determining the effect of regional banking development on regional growth.

As for studies based on U.S data and also test for spatial dependence on bank regulatory decisions, Garrett *et al*., (2005) incorporate spatial spillover effects directly into an empirical model to investigate spatial dependence on bank regulatory decisions. In particular, they estimate probit models for the decision between permitting intrastate bank branching or not, and for permitting interstate bank branching or not. They conclude that banking deregulations in some states are induced by expectations of future local growth. In other words, some states announced new banking deregulations after witnessing a positive effect of such deregulations in other states, expecting similar future local growth. Such expectations are unobservable to econometricians. Therefore, the findings of Jayaratne and Strahan (1996) might be spurious, despite controlling for all cross-sectional and time-dependent omitted variables. The episodes of growth accelerations documented by previous studies may indicate heterogeneity in different regions' growth paths (Garrett *et al.,* 2005), or difference of expected future growth opportunities across states, independent of and not caused by, changes in state-level banking regulations. What is more, Garrett *et al.,* (2007) provide evidence that spatial correlation is present in state-level income growth. Specifically, they find that a 1% point increase in the income growth of neighbouring states causes between a 0.22 and 0.29 point increase in the income growth of state r, depending on the specification. That is to say, policies and shocks in neighbouring regions are also likely to stimulate or deteriorate economic growth in state r. Such transmitted effect (exogenous effect or spatial externalities) between regions comes in the form of spatial spillover effects. In 2008, Huang takes a different approach to analysing banking deregulation and economic growth. Huang compares the growth rates of 285 pairs of neighbouring counties. Each pair of counties are separated by state borders and witnessed banking deregulation at different times. Taking Garrett's criticisms into account, Huang argues that since the timing of banking deregulation is decided at a state-level, "it is unlikely that economic conditions and the financial sector's structure in a county can influence regulatory decisions made by the state legislature". The findings of a difference-in-difference analysis does not indicate a significant effect of banking deregulation on local growth. Besides, Huang considers "hinterland counties'' of states with no deregulation, but are distant from the state borders. However, the findings do not change and, hence, he rejects previous claims which invalidate the empirical design due to cross-county spillover of deregulation effects.

It can be noticed that the aforementioned U.S studies, which take the spatial spillovers into account, have merely focused on the effects of banking regulatory changes on regional growth. Consequently, the spatial spillover effects of banking development indicators remain an empirical question and has not yet been sufficiently investigated in the empirical literature (especially in the U.S context). To this end, Chapter 6 contributes to and expand the extant literature on spatial banking-growth models by introducing macroeconomic lending variables, and develop an analytical framework that captures spatial spillover effects among U.S counties.

2.6 Conclusions

The theoretical and empirical literature has been growingly more concerned about the effect of changes in regional banking development on regional economic growth and related local banking issues, such as regulatory changes, structure, market competition, and distress; in particular, the role of local, or local-like, banks, such as rural and savings banks in regional development. This chapter presents a synoptic review of the literature about regional banking-growth to show whether local banking factors have, or have not, been major determinants in the success or otherwise of the local economies. It draws on a large number of prior studies from a number of countries, the U.S in particular. This review of the literature primarily focuses on: (i) discussing the relative merits/demerits of various lines of arguments following economic and financial theory, and, (ii) discussing the validity of observed effects from an empirical point of view. In particular, this chapter summarises prior theoretical work about whether heterogeneity in banking across regions within a single-country framework. Additionally, it critically reviews empirical contributions concerning the impact of regional banking structure, banking regulatory changes, regional banking distress, and spatial externalities on regional economic performance. When these studies are viewed in their entirety, they show that regional banking structure, the focus of this chapter, has generated much valuable research and, consequently, indicates that this chapter is an important contribution to the regional banking-growth literature. This literature review chapter shows that regional banking development is very important, both in the developed and emerging economies and, hence, subsequent empirical chapters develop my contribution to this important area. This chapter identifies a number of gaps in the existing literature and the possible direction of further work, motivating my present contribution. Thus, this literature motivates the conceptual framework and the empirical research of this thesis, and also justifies the methodological approaches used in Chapter 5 and Chapter 6 in order to examine the extent to which local banking factors have an impact on local economic development. This chapter stresses the local SME lending channel as an alternative measure of local banking development. It also highlights the need for a distributional examination of the regional banking-growth nexus based on different quantiles of local income and employment. Finally, it justifies the need for a local banking-growth investigation that takes into consideration the geographical dispersion of local banks and spatial spillover effects among regions.

Chapter 3

Conceptual Framework and Methodologies

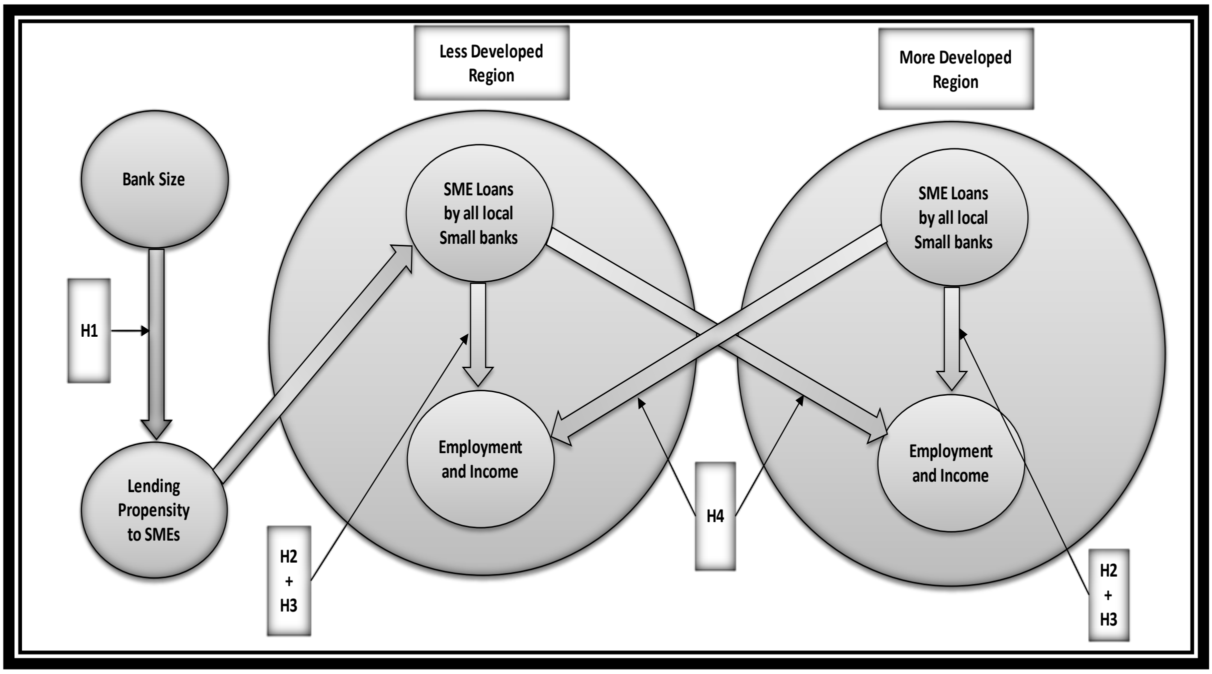
Chapter 3: Conceptual Framework and Methodologies

This chapter presents a conceptual framework that leads to various hypotheses to be examined in the subsequent empirical chapters. The various methodologies which are used to examine such hypotheses are also presented in different sections throughout this chapter.

3.1 Conceptual Framework

The aggregate economy is the macro environment. The aggregate (in this case, the national) economic growth is accelerated by local economic development. The latter is operationally efficient under a developed financial system. The bank-size effects are the envisaged instruments in establishing the role of local banking in local economic growth. The conceptual framework of this thesis consists of four main hypotheses as shown in Figure 3.1, below:

Figure 3.1 Conceptual Framework with Four Main Hypotheses



Note: This figure illustrates the conceptual framework of the thesis. It shows the four main hypothesis underpinning the three empirical chapters and the process by which these hypotheses are connected. The first hypothesis (H1) is examined in Chapter 4. The second and the third hypotheses (H2 & H3) are examined in Chapter 5. The fourth hypothesis (H4) is examined in Chapter 6.

Hypothesis 1 (H1): *Bank size negatively affects lending propensity to SMEs*

The H1 in Figure 1, above, is the establishing hypothesis of the conceptual framework of this thesis. It assumes that bank size is an important determinant of SME lending and has a negative impact on a bank's propensity to lend to SMEs. That is, small banks are more interested in lending to small businesses than large ones. The main variables used to test this hypothesis are the lending propensity to lend to small businesses and bank size. The former is calculated, at bank-level, as the share of small business loans to total business loans while the latter is the bank's total assets. This hypothesis is examined in Chapter 4, i.e. the first empirical chapter.

Hypothesis 2: *Local banks promote regional growth through SME lending channel*

The second hypothesis in Figure 1, above, builds on H1 and assumes a positive impact of local banks on regional economic growth. That is, it assumes that a greater amount of SME loans (aggregated at region-level) provided by small local banks stimulates regional economic growth (i.e. regional income and employment growth). This hypothesis introduces local SME lending channel as a measure of regional banking development. This hypothesis is tested in Chapter 5, i.e. the second empirical chapter.

Hypothesis 3: *The impact of local banks on regional growth varies depending on the region's level of development*

The third hypothesis emphasises the stimulating effect of small local banks on local economic growth. However, it assumes the presence of distributional heterogeneity in the impact of local small business lending on regional economic growth. In other words, the magnitude of the effect of local banks varies measurably across the distribution of regional economic growth. This hypothesis is also examined in Chapter 5, i.e. the second empirical chapter.

Hypothesis 4: *Spatial spillover effect of local banks is an important determinant of regional growt*

The final hypothesis also stresses the importance of small local banks in promoting local economic development. However, this hypothesis assumes that spatial externalities across regions are important determinants of regional economic development. More specifically, a region's economic growth is affected by local banks in other regions. This hypothesis is examined in Chapter 6, i.e. the third empirical chapter.

Overall, the aforementioned sequence of hypotheses forms this thesis' conceptual framework which establishes the empirical examinations in the following chapters. The examination of such hypotheses is an important contribution to the literature of banking structure and economic development.

3.2 Methodology for Chapter 4

The empirical examination of Hypothesis 1, in Chapter 4, models the effect of bank size on lending propensity to SMEs for a large number of banks (cross-sections) over 20 years (time series). Accordingly, my bank-level panel dataset is based on a combination of cross-sectional and stationary time series data. That is, additional degrees of freedoms can be gained, and hence helping to examine cross-section variations through time (Verbeek, 2010, p.365). Based on such panel data characteristics and statistical tests, a static fixed-effects panel data approach suits the empirical analysis of Chapter 4, and hence, used to test the relationship between bank size and SME lending propensity.

The fixed-effects model is used when the intercepts of the model are not the same for different sections or different time series. In this case, dummy variables can be added to the model to estimate the regression coefficients (e.g. Stock and Watson, 2011, p.401). The decision on using the fixed-effects model among other static models is taken after the computation of the F-statistic and Hausman test. The former test is applied to select between a pooled model and a fixed-effects model, whereas the latter is implemented to choose between a random-effects model and a fixed-effects model.

The general fixed-effects model takes the following form (e.g. Stock and Watson, 2011, p.402):

$$Y_{it} = \beta X_{it} + \theta_i + \nu_t + \varepsilon_{it} \tag{3.1}$$

Where,

- Y_{it} : the dependent variable,
- X_{it} : a set of explanatory variables,
- θ_i : unobserved region-specific effects,
- ν_t : unobserved time-specific effects,
- ε_{it} : error term,
- *i* and *t* are entity and yearly time period, respectively.

In Chapter 4, I employ a similar fixed-effects panel data approach to the model above. Thus, my model specification takes the following form:

$$\begin{aligned} PROPNS_{it} &= \beta_1 SIZE_{it} + \beta_2 NPL_{it} + \beta_3 ROA_{it} + \beta_4 LEV_{it} + \beta_5 MBHC_{it} + \\ &\beta_6 MDS_{it} + \beta_7 GDP_{it} + \beta_8 IIEA_{it} + \beta_9 MSA_{it} + \beta_{10} BLTL_{it} + \beta_{11} AGE_{it} + \\ &\beta_{12} YD_i + \beta_{13} RD_t + \varepsilon_{it} \end{aligned} \tag{3.2}$$

where, i represents the bank and t the year, $PROPNS_{it}$ represents the lending propensity ratios. $SIZE_{it}$ is my main explanatory variable which represents the bank size. The rest of the variables control for regional bank-market characteristics, regional economic characteristics, and bank specific characteristics. YD_t is the set of yearly dummy variables. RD_i is the set of bank dummy variables, and ε_{it} is the error term. The standard errors are robust, whereas I account for serial correlation by allowing for clustering of the error term at the bank level (See Petersen (2009) for a detailed explanation for why the correction for clustering is essential). The included variables and the model specification are further defined, justified, and detailed in Chapter 4.

3.3 Methodology for Chapter 5

The empirical examination of Chapter 5 models the effect of local banking development on local economic growth for many regions/counties over 20 years. The dataset in this chapter is also a panel dataset which consists of many regions (cross-sections) over 20 years (time series). Owing to the economic characteristics of the panel dataset employed in Chapter 5, I examine the Hypotheses 2 & 3 and estimate the proposed relationship between local SME lending and local economic growth by employing: (i) conventional panel data technique (in my case dynamic panel data) and, (ii) quantile panel data regression. The latter models the effects of local banks on the entire distribution of the local economic growth path. In what follows, I present the panel approaches respectively.

3.3.1 Dynamic Panel Estimation with Endogeneity Bias

The examination of Hypothesis 2 of Chapter 5 relies primarily on a dynamic panel data approach. I adopt a dynamic panel approach because the analysis of a macro-based dataset requires the inclusion of the feedback effects, due to the fact that an economy does not grow simply by depending on all other factors; yet it also depends on how it performed in the past. Therefore, I use a dynamic panel estimation to control for the spillover effects over time and, hence, I begin with presenting a general dynamic panel regression equation, as follows (see Nickell, 1986; Arellano and Bond, 1991):

$$Y_{it} = \alpha X'_{it-k} + \beta X''_{it} + \theta_i + v_t + \varepsilon_{it} \tag{3.3}$$

where,

- Y_{it} : dependent variable,
- X'_{it-k} : a set of lagged explanatory variables and lagged dependent variable,
- X''_{it} : a set of current values of explanatory variables,
- θ_i : unobserved region-specific effects,

- v_t : unobserved time-specific effects,
- ε_{it} : error term,
- k : number of lags,
- *i* and *t* are region and yearly time period, respectively.

As for my regression model used in Chapter 5, I estimate the following equation by invoking the properties of dynamic panel data regressions presented in Equation (3.3):

$$
\begin{aligned}
Ygr_{it} &= \alpha Ygr_{it-k} + \beta_1 LOAN_{it} + \beta_2 \{LOAN_i * Y_{1994}\} + \beta_3 Y_{it} + \beta_4 ROA_{it} + \\
&\beta_5 EQV_{it} + \beta_6 INT_{it} + \beta_7 HHI_{it} + \beta_8 LABF_{it} + \beta_9 INF_t + \beta_{10} BDEN_{it} + \\
&\beta_{11} YD_t + \beta_{12} RD_i + \varepsilon_{it}
\end{aligned}
\tag{3.4}
$$

where *i* represents the county and *t* the year. Ygr_{it} represents the growth in economic activities, that is to say, I interchangeably use the per capita income growth and the total employment growth. Ygr_{it-k} represents the lags of the dependent variable. $LOAN_{it}$ represents each of the two local banking indicators, firstly, the LSBL and, secondly, the LMBL. The rest is a set of control variables. YD_t is the set of yearly dummy variables. RD_i is the set of region dummy variables, and ε_{it} is the error term. More details on my model specification and variables are shown in Chapter 5.

My underlying economic model is a convergence-pattern framework, where the growth of per capita income is regressed on the initial level of income, its interaction with other controls, the main explanatory variable (in my case, local SME lending), and a set of (region specific/economy-wide) controls. The underlying idea of using a convergence-pattern framework is that I allow regional economic growth to be dependent on the initial level of income (an inverse empirical relationship means that poor regions converge with richer regions growth paths over time).

Moreover, such an economic growth model specification also allows me to look at the impact of different factors on local economic growth and control important parameters, such as population growth, human capital, and the index of competition prevalent in the local economy. Thus, the examination has to be based on a growth accounting framework, where one can use any defined growth theoretic approach, either endogenous or exogenous growth models, and expand the settings. That is to say, an extended Solow Swan model can be used for the exogenous growth model or an extended Romer type model for the endogenous theoretic growth model. In the empirical framework of this chapter, I extend an endogenous growth model as it accounts for the presence of human capital, externalities, policy interventions etc. Since this chapter is centred upon the economic growth of different regions within a single-country framework, I adopt a growth accounting framework. Thus, estimating a growth model based on convergence theoretic framework can explain whether an endogenous or exogenous growth theoretic framework is evident in these types of settings. That is to say, because of different types of loan structure and other variables, some regions are converging to the same statistical level.

Problems may arise in the panel estimation, as the estimation of a fixed-effects or pooled OLS regression may be spurious, indicating a false causal relationship between the local banking presence and local growth. In this context, unobserved region-specific effects that directly affect both local growth and local SME lending may also recall the endogeneity problem. The unobserved factors or omitted variables are absorbed by the error term causing the local SME lending variable to become a weak exogenous to explain local growth, that is to say, my key local banking presence variables become endogenous and correlated with the error terms. As a result, the OLS regression is inconsistent and leads to biased estimation in the presence of dynamic effects and endogeneity, even in a large dataset. Therefore, an instrumental variable (IV) approach, is needed to endogenise the key explanatory variables, that is to say, each of the LSBL and the LMBL.

Endogeneity Concern

To address the potential endogeneity problem in my data and to overcome its effects on parameter estimates, many recent studies on local finance-growth have used instrumental regressions, such as the Two-Stage Least Squares (2SLS) approach (e.g. Driscoll, 2004; Fogel *et al.*, 2011). Other researchers, such as Levine *et al.*, (2000), and Beck *et al.*, (2000) use the Generalised Method of Moments (GMM) techniques proposed and developed by Arellano and Bond (1995) and Blundell and Bond (1998) for dynamic panel estimation. In this research, I employ the two-step system GMM, thus assuring robust conclusions concerning the real effect of local SME lending on local economic growth. The two-step system GMM combines the regression in differences with the regression in levels (see Bond, 2002). According to Blundell and Bond (1998), the instruments used in the level regression of the GMM estimator are the lagged differences in their original variables, and the lagged levels are used to instrument the difference regression. More specifically, I adopt the two-step system GMM because it is asymptotically more efficient than the one-step GMM.

A large number of recent empirical studies, in particular in macroeconomics and finance, have employed the GMM estimator (Greene, 2008, p.441). In a panel context, the GMM is designed mainly to deal with econometric problems caused by unobserved region-specific effects, as well as joint endogeneity of the regressors in lagged-dependent-variable models (e.g. growth regressions).

The GMM, as a system dynamic panel estimator, involves instruments known as internal instruments, based on past observations of the explanatory variables, to address the joint endogeneity of all the explanatory variables involved. However, this estimator only controls for weak endogeneity[2]. In other words, the GMM estimator assumes that the regressors are only weakly

[2] "The weak exogeneity assumption implies that future innovations of the growth rate do not affect current financial development. This assumption is not particularly stringent conceptually, and its validity can be statistically examined" (Beck *et al.*, 2000)

exogenous and, hence, these regressors can be affected by current and past observations of the growth rate, while there must not exist a correlation with future values of the error term, ε, (Wooldridge, 2002).

The GMM approach is proposed and developed by Chamberlain (1984), Holtz-Eakin *et al.,* (1990), Arellano and Bond (1991), and Arellano and Bover (1995). In order to eliminate bias and inconsistency arising from region-specific effects, Arellano and Bond (1991) suggest taking the first difference of the regression equation, as follows:

$$Ygr_{it} - Ygr_{it-1} = \alpha(X'_{it-1} - X'_{it-2}) + \beta(X''_{it} - X''_{it-1}) + (\varepsilon_{it} - \varepsilon_{it-1}) \qquad (3.5)$$

However, this procedure could only eliminate the region-specific effect problem, and may cause the new error term $(\varepsilon_{it} - \varepsilon_{it-1})$ to be correlated with the lagged dependent variables $(Ygr_{it} - Ygr_{it-1})$ when these are included in $(X'_{it-1} - X'_{it-2})$. Therefore, Arellano and Bond (1991) advocate a solution to solve this problem, by suggesting using the lags of the regressors in levels as instruments based on two imposed assumptions: that the error term (ε_{it}) is stationary, and that the regressors (X_{it}), where $X_{it} = \{X'_{it}\ X''_{it}\}$, are weakly exogenous. Arellano and Bond (1991) use the following moment conditions:

$$E[X_{it-s}.(\varepsilon_{it} - \varepsilon_{it-1})] = 0 \quad \text{where, } s \geq 2; t = 3,....,T \qquad (3.6)$$

Under these moment conditions, the model can be estimated using a two-step GMM method, known as the difference estimator (Arellano and Bond, 1991). The first step assumes that the regression has independent and homoskedastic error terms across regions and through time. Secondly, the assumptions of independence and homoskedasticity are relaxed as the residuals from the first step are used to build a consistent estimate of the variance-covariance matrix. However, this version of the GMM estimator suffers from several drawbacks. For instance, Griliches and Hausman (1986) argue that differencing may decrease “signal-to-ratio”, which exacerbates measurement error biases. Moreover, if the involved regressors are persistent over time, then their lagged levels are weak instruments for the regression in differences (Alonso-Borrego and Arellano, 1999). Simulation studies show that the GMM difference estimator suffers from a potentially large finite-sample bias and poor precision.

Arellano and Bover (1995) present an alternative estimator to overcome the weaknesses associated with the differencing estimator. This method estimates regression in differences together with the regression in levels. Unlike the differencing estimator, this method, by the inclusion of the regression in levels, acknowledges cross-region variations and does not intensify the strength of the measurement error. What is more, based on Monte Carlo experiments, Blundell and Bond (1997) reveal that the improved estimator reduces the potential finite-sample bias and poor precision accompanying the difference estimator.

Since the regression in levels does not directly eliminate problems emanating from region-specific effects, Blundell and Bond (1997) assert that valid instruments must be utilised to control for such effects. In this estimator, lagged differences of the regressors are used as instruments which, however, are only valid based on the assumption that region-specific effects (θ_i) and regressors' levels are correlated constantly over time, as follows:

$$E[X_{it-p}.\theta_i] = E[X_{it-q}.\theta_i] \qquad \text{for all } p \text{ and } q \tag{3.7}$$

According to this assumption, the differences in the regressors and region-specific effects are not correlated. This means, for instance, that banking development may have a time-invariant correlation with the region-specific effect (Beck *et al.,* 2000). Therefore, lagged differences can be valid instruments for the regression in levels which follows the moment conditions in Equation (3.8), below:

$$E[(X_{it-s} - X_{it-s-1}).(\varepsilon_{it} - \theta_i)] = 0 \quad \text{where, } s \geq 1; t = 3,...., T \tag{3.8}$$

Overall, the model is estimated using a two-step GMM system, as follows. Firstly, the regression in differences is estimated in accordance with the moment conditions in (3.7). Subsequently, the regression in levels is estimated in accordance with the moment conditions in (3.8). As a result, these procedures generate consistent and efficient coefficient estimates.

Prior to estimating the Equation (3.4), it is essential to ensure that all the included variables in the regression are stationary. This helps me to avoid the risk of estimating spurious GMM regressions in the data (e.g. Mur and Trivez, 2003; Baltagi *et al.,* 2007). To do so, I perform an IPS test (Im *et al.,* 2003). As for the post-estimation tests to ensure robust and valid estimations, Arellano and Bond (1991), and Arellano and Bover (1995) introduce two specification tests to verify the consistency of the GMM estimator. That is to say, in order for the estimated model to be consistent, the instruments involved and the assumption of no serial-correlation of ε must be valid. Accordingly, I report the Hansen test of over-identifying restrictions, which tests the overall validity of the instruments used in the regressions. Additionally, I employ the autoregressive (AR) test to examine the assumption that there is no serial correlation between the error term and both the difference regression and the system difference-level regressions. Serial correlation must not exist at the second order of the differenced error term or at a higher order. Accepting the null hypotheses of both tests grants support to the validity of the instruments and the no serial correlation assumption. Consequently, the estimated model is consistent.

3.3.2 Estimating Distributional Heterogeneity

The third hypothesis (H3) of this thesis is tested in Chapter 5 using Instrumental Variable quantile panel approach. I adopt such technique in order to examine whether the magnitude of the effect of local banks varies measurably across the distribution of regional economic growth. Empirical studies assessing the growth effects of banking development commonly use the following econometric framework:

$$Y_{it} = \alpha\ BD_{it} + \beta\ X_{it} + \varepsilon_{it} \tag{3.9}$$

where Y_{it} is the dependent variable (i.e. economic activities), BD_{it} is the measure of banking development (i.e. the LSBL or the LMBL in my model), X_{it} represents a set of control variables, ε_{it} is the unobserved disturbance. One important concern in this estimation procedure is the possibility of endogeneity, which could bias the BD's estimated coefficient and standard error. Thus, I need to construct instruments for BD:

$$BD_{it} = \lambda\ Z_{it} + \gamma\ X_{it} + \nu_{it} \tag{3.10}$$

where Z_{it} is a set of instrumental variables and ν_{it} is the unobserved disturbance of BD_{it} estimation. After controlling for endogeneity, Hakens *et al.*, (2015) find that bank performance exerts a positive impact on local economic growth. However, the growth effect of bank performance may vary across regions (poor and rich), according to their state of development. The rationale is that regions with lower per capita and human capital are able to obtain greater benefits from the expansion of SME lending.

Quantile Regression (QR) is a useful method for estimating the impact of regressors on the conditional distribution of the outcome (see Koenker and Bassett, 1978; Buchinsky, 1998b; Koenker, 2005). The linear quantile regression can be written as:

$$Y_{it} = \alpha(q)BD_{it} + \beta(q)X_{it} + o\mathrm{i}(\mathrm{q}), \tag{3.11}$$

where $\alpha(q)$ and $\beta(q)$ represent the unknown parameters associated with the qth quantile, $q \in (0,1)$. $o\mathrm{i}(q)$ represents the error term at each quantile. Suppose that the conditional qth quantile of the error term is equal to zero, ϱ(q|F,X) = 0, but the distribution of $oi(q)$ is unspecified, as q increases from 0 to 1, I can identify the influence of regressors on the entire conditional distribution of Y_{it}.

Since solving (3.11) can be formulated as a linear programming problem, I can estimate the parameter vector efficiently with some form of the simplex algorithm.

In order to control for the potential endogeneity of regional banking development (i.e. the LSBL or the LMBL), I apply the instrumental variable quantile regression method. In my work, I employ Powell (2015)'s unconditional quantile panel IV method. Powell (2015)'s method solves a fundamental problem posed by alternative fixed-effects quantile estimators, namely, that the inclusion of individual fixed effects alters the interpretation of the estimated coefficient on the treatment variable.

Letting D_{it} represent policy variables, X_{it} represent control variables, Z_{it} represent instruments, and Y_{it} represent the dependent variable, then equations (3.9) and (3.11) can be generalized to the following unconditional panel quantile IV regression equation, as in Powell (2016):

$$Y_{it} = d'_{it}\beta(u^*_{it}) \ , \tag{3.12}$$

In Equation (3.11), $u^*_{it}|Z_{it}, X_{it} \sim u^*_{it}|X_{it}, \qquad u^*_{it} \sim U(0,1)$.

Moreover, $P(Y_{it} \leq D'_{it}\beta(\tau)|Z_{it}, X_{it}) = P(Y_{it} \leq D'_{it}\beta(\tau)|\ X_{it}) = \tau X_{it}$, where τ denotes the quantile of the distribution. Powell (2016) maintains the non-separable disturbance property implicit in conditional quantile regression. The exogeneity assumption is that, within-individual changes in the policy variables, they do not provide information about changes in the disturbance term, u^*_{it}. (See Powell, 2016) for a detailed description of the properties and the estimation issues). As mentioned previously, the quantile panel regression I intend to perform also employs an instrumental variable technique. However, the instrument in this case is different from the one typically assumed in a dynamic panel model, where distant lags of the dependent variable are used as a potential instrument. Contrarily, I create an instrument based on a Yield Curve (details are in section 5.4.3), which is unique to this stream of literature and performs well in my estimation.

As for the regression model used in Chapter 5, I estimate the following equation by invoking the properties of quantile panel data regressions shown in Equation (3.11):

$$\begin{aligned} Y_{it} = \alpha\ (q) + \delta_1(q)LOAN_{it} + \delta_2(q)ROA_{it} + \delta_3(q)EQV_{it} + \delta_4(q)INT_{it} + \\ \delta_5(q)HHI_{it} + \delta_6(q)LABF_{it} + \delta_7(q)INF_t + \delta_8(q)BDEN_{it} + o\mathrm{i}(q) \end{aligned} \tag{3.13}$$

where i represents the county and t the year. Y_{it} represents the economic activities, that is to say, I interchangeably use the total income and the total employment, both in logarithm. $LOAN_{it}$ represents each of the two local banking variables, firstly, the LSBL and, secondly, the LMBL. The rest is a set of control variables. $o\mathrm{i}(q)$ represents the error term at each quantile. Also, $\alpha(q)$ and $\beta(q)$ represent the unknown parameters associated with the qth quantile, $q \in (0,1)$. More details on my model specification and variables are shown in Chapter 5.

3.4 Methodology for Chapter 6

The empirical examination of Chapter 6, as in Chapter 5, models the effect of local banking development on local economic growth for many regions/counties over 20 years. The dataset in this chapter is also a panel dataset which consists of many regions (cross-sections) over 20 years (time series). However, this chapter takes a different approach to analysing the regional banking-growth relationship. The empirical analysis of this chapter takes into account the spatial frictions (i.e. spatial interactions among regions) that emanates from the spatial organisation of regions within a single-country framework such as those of the United States. Therefore, this chapter examines the fourth hypothesis of this thesis, that is, regional economic development is affected by spatial spillover effects of local banks in other regions. In what follows, I present the theoretical and the empirical panel approaches to test Hypothesis 4.

3.4.1 Theoretical Justification

In chapter 6, I extend the convergence-theoretic model to accommodate spatial frictions. To achieve this, I present the following framework. Assume that there are N regions, indexed by $i = 1 \ldots N$. Each region's income growth is assumed to be characterized by three factors: (i) M_i (local small business lending), (ii) X_i (other control variables), and (iii) D_{ij} (spatial attributes). To begin with, I present the income function as follows.

$$Income_i(t) = A_i(t)\left(M_i(t)^{\alpha} X_i D_i(t)^{1-\alpha}\right)^{\gamma} \tag{3.14}$$

where $A_i(t)$ is technology (or residual productivity, the growth of which is the net of the growth of both M and HD). γ measures the extent of returns to scale, whereas α delineates the importance of small business lending in local income growth. I impose two conditions: (i) A_i is contaminated by small business lending through productivity transmission effects, and (ii) X_i as various other control variables, such as population growth, inflation, etc., exert constant effect in each region. The latter can allow me to use M_i/X_i (denoted as mx as a ratio) indicating the proportion of small business lending variations with respect to changes in control variables. I can then express:

$$A_i(t) = \Gamma(t) mx_i(t)^{\delta} \prod_{j \neq i}^{N} A_j(t)^{\beta D_{ij}} \tag{3.15}$$

Externalities from small business lending variations, transmission and learning by doing are captured by $0 < \delta < 1$ in Equation (3.15). Income growth interdependence (across regions) is represented by the parameter $0 < \beta < 1$, where it is assumed that the interdependence is not perfect because of the presence of possible frictions between the region i and other regions $j \neq i, j = 1,, N$. This is represented by D_{ij}. Elements of D_{ij} are assumed to be positive, such that $\sum_{j \neq i}^{N} D_{ij} = 1$. Values of D_{ij}, i.e., higher (the limit being 1) or lower (the limit being 0) imply the strength of relationship or distance among regions. The greater is the strength the higher is the spillover.

Equation (3.15) can be re-written by taking the natural logarithm on both sides:

$$A = \Gamma + \delta mx + \beta DA \tag{3.16}$$

where A, γ, mx and D without i subscripts refer to vectorial representation of the counties.[3] Mathematically, $(I - \beta D)^{-1}$ exists if and only if $| I - \beta D | \neq 0$.

$$A = (I - \beta D)^{-1} \Gamma + \delta (I - \beta D)^{-1} mx \tag{3.17}$$

If $| \beta | < 1$, then regrouping terms gives,

$$A = \frac{1}{(1 - \beta)} \Gamma + \delta mx + \delta \sum_{r=1}^{\infty} \beta D^{(r)} mx \tag{3.18}$$

where $D^{(r)}$ is the matrix D to the power r. For county i, then I have,

$$A_i(t) = \Gamma^{\frac{1}{(1-\beta)}}(t) mx_i^{\alpha}(t) \prod_{j=1}^{N} mx_j^{\delta} \sum_{r=1}^{\infty} D_{ij}^{(r)}(t) \tag{3.19}$$

Replacing this term in income function I obtain the following:

$$Income_i(t) = \Gamma^{\frac{1}{(1-\beta)}}(t) mx_i^{u_{ii}}(t) + \prod_{j \neq i}^{N} mx_j^{u_{ij}}(t) \tag{3.20}$$

where $u_{ij} = \alpha + \delta (1 + \sum_{r=1}^{\infty} \beta^r D_{ij}^{(r)}$ and $u_{ij} = \delta \sum_{r=1}^{\infty} \beta^r D_{ij}^{(r)})$

Based on the properties described above, I can then present the following proposition.

[3] In (6) describes a linear system that can be solved for A, if $\beta \neq 0$ and if $1/\beta$ is not an eigenvalue of D.

Defining by $Income_{i,t} = G(Income_{i,t-1}; M_{i,t}; X_{i,t}; f_i(D_t(i, j))$, spatial frictions determine the extent to which small business lending affects income variations across counties.

The proof of this proposition is straightforward and follows from the analytical equations, above. In particular, based on the assumption that spatial frictions affect income dynamics among regions (i, j), the effect of small business lending variations will depend upon the strength of β. Simply because, higher β represents greater interdependence, the latter would ensure faster movements of small business lending shocks across borders. Hence, interdependent economies will experience greater and similar effects of shocks than would have been under atomistic environment. The analytical model presented above needs to be estimated. Recalling that mine is a spatio-temporal case, I will discuss about relevant methods in spatial panel estimation.

3.4.2 Estimation

My estimation will involve a spatio-temporal method, which combines instrumentality of 'space' with the dynamics of income growth. Based on the idea from LeSage and Pace (2009, p.190-191), the extended spatiotemporal partial adjustment model can be presented as follows.[4]

$$Income_t^* = a\iota_N + \gamma W Income_t^* + \sum_{k=1}^{K} X_{kt}\zeta_k + \sum_{k=1}^{K} WX_{kt}\eta_k + \rho W \pi_t \tag{3.21}$$

I can re-write the above as:

$$Income_t^* = (1-\gamma W)^{-1}\left(a\iota_N + \sum_{k=1}^{K} X_{kt}\zeta_k + \sum_{k=1}^{K} WX_{kt}\eta_k + \rho W \pi_t \right) \tag{3.22}$$

$$Income_t = (1-\theta) Income_t^* + \theta(PIncome_{t-1}) + \varepsilon_t \tag{3.23}$$

$$P = \beta I_N + \psi W \tag{3.24}$$

The above three equations present specification for basic spatiotemporal partial adjustment model: where t is an index for the time dimension (years), with t = 1. . . T; and k is the number of exaplanotry varibales, with k = 1. . . K.; and N is the number of regions/counties. $Income_t^*$ represents the total

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[4] In this case, the subscript of cross-section has been ignored as I mainly focus on the effect offered by time dimension.

income. ι_N is an N×1 vector of ones associated with the constant parameter a. X_{kt} denotes an N×K matrix of exogenous explanatory variables. W is an N×N matrix of known constants describing the spatial arrangement of the regions in the sample. The parameter θ in Equation (3.23) describes the degree of spatiotemporal adjustment between equilibrium variable ($Income_t^*$) and lagged values for both temporal and spatially temporal ($PIncome_{t-1}$). Error terms (ε_t) are identically and independently distributed by $N(0,\sigma^2 I_N)$. P is the parameter that captures both spatial and temporal dependencies of the dependent variable. Specifically, as shown in Equation (3.21), the equilibrium status of dependent variable, $Income_t^*$, can be explained as the intercept ($a\iota_N$), spatial dependence from endogenous variable ($\gamma WIncome_t^*$), the independent variables both within spatial boundaries ($\sum_{k=1}^{K} X_{kt}\zeta_k$) and across spatial adjacent locations ($\sum_{k=1}^{K} WX_{kt}\eta_k$), and spatial dependence among the error term ($\rho W\pi_t$), respectively. Moreover, the dependent variable, $Income_t$, can be interpreted by its equilibrium level ($Income_t^*$) and both its temporal and spatially temporal lagged values $(PIncome_{t-1})$. After some algebraic manipulation, I arrive at the following equation:

$$Income_t = (1-\theta)(1-\gamma W)^{-1}\left(a\iota_N + \sum_{k=1}^{K} X_{kt}\zeta_k + \sum_{k=1}^{K} WX_{kt}\eta_k + \rho W\pi_t\right) + \theta PIncome_{t-1} + \varepsilon_t \qquad (3.25)$$

To summarize, I showed that the dependent variable, $Income_t$, is determined by its equilibrium level and both lagged temporal and spatially temporal dependencies. In other words, spatiotemporal partial adjustment model enables me to explain the disequilibrium shock of $Income_t$ through its spatial and temporal lagged values, respectively. The dynamic spatial Durbin model (that I adopt for the purpose and discussed below) also enables me to recognize and interpret the disequilibrium shocks for the dependent variable via its dynamic components (both temporal and spatially temporal). In other words, it provides me a mechanism to free the strict limitation of fully competitive equilibrium by admitting the existence of disequilibrium variations.

3.4.3 Specification of Panel Data Characteristics

Given that my study involves panel data, the general specification of dynamic spatial panel model follows:

$$\begin{aligned} Income_{it} &= \alpha + \beta Income_{i\,t-1} + \gamma \sum_{j=1}^{N} W_{ij} Income_{it} + \psi \sum_{j=1}^{N} W_{ij} Income_{it-1} \\ &+ \sum_{k=1}^{K} X_{it}\zeta_k + \sum_{k=1}^{K}\sum_{j=1}^{N} W_{ij} X_{jkt}\eta_k + \theta_i + \nu_t + \pi_{it} \end{aligned} \qquad (3.26)$$

$$\pi_{it} = \rho \sum_{j=1}^{N} W_{ij} \pi_{it} + \varepsilon_{it} \tag{3.27}$$

$$i = 1, \ldots, N; t = 1, \ldots, T; k = 1, \ldots, K; i \neq j .$$

where *i* is an index for the cross-sectional dimension (regions/counties), with *i* = 1, . . . , *N*; and *t* is an index for the time dimension (years), with *t* = 1, . . . , *T*; and k is the number of exaplanotry varibales, with k = 1, . . . , *K*. In addition, $Income_{it}$ denotes an observation on the dependent variable (total income) at *i* and *t*. Whereas, X_{it} represents a 1 × K vector of observations on the explanotry variables at *i* and *t*. Also, W_{ij} is an element of a spatial weight matrix *W* that describes the spatial arrangement of the regions in the sample. It can be seen that the following three different spatial dependencies are considered in the above model, namely, endogenous interactions ($\sum_{j=1}^{N} W_{ij} Income_{it}$), exogenous interactions ($\sum_{k=1}^{K} \sum_{j=1}^{N} W_{ij} X_{jkt}$) and residual interaction ($\sum_{j=1}^{N} W_{ij} \pi_{it}$). Besides, α is the constant parameter vector. $\gamma, \psi, \zeta, \eta$ and ρ are coefficients for these above spatial dependencies separately. θ_i and v_t refer to the region fixed and the time fixed effects with respect to the panel dataset. The above model can be called as a dynamic spatial panel model by controlling the coefficients of time lags ($Income_{it-1}$) and spatial time lags ($W_{ij} Income_{it-1}$) of endogenous variable to be non-zero (Debarsy *et al.*, 2012). ε_{it} indicates a vector of identically independently distributed error terms with a zero mean and constant variance σ^2.

Most importantly, it has been shown that the temporal lag terms for both X_{it} and $W_{ij} X_{jkt}$, and for both π_{it} and $W_{ij} \pi_{it}$ cannot be incorporated into the above model simultaneously, otherwise it will cause the non-identification problems for parameter (Anselin *et al.*, 2008; Elhorst, 2014).[5] Hence, the three different types of spatial panel model are mainly derived by considering different types of spatial dependencies (Elhorst, 2014), which are the spatial autoregressive model (SAR) including spatial endogenous dependence, the spatial Durbin model (SDM) including spatial endogenous dependence and spatial exogenous dependencies, and the spatial error model (SEM) allowing spatial residual dependence, respectively. Besides, whether the model is dynamic or not should be further determined by examining whether both $Income_{i\,t-1}$ and $W_{ij} Income_{it-1}$ are jointly equal to zero. The

[5] Moreover, the three types of spatial dependencies described above have been shown not appear simultaneously so as to ensure identifiability of parameter (Manski, 1993).

appropriate specification of spatial panel model in this chapter will be selected from the SAR, the SDM and the SEM.

SAR

$$Income_{it} = \alpha + \beta Income_{i\,t-1} + \gamma \sum_{j=1}^{N} W_{ij} Income_{it} + \psi \sum_{j=1}^{N} W_{ij} Income_{it-1} + \sum_{k=1}^{K} X_{it} \zeta_k + \theta_i + \nu_t + \pi_{it} \tag{3.28}$$

$$\pi_{it} = \varepsilon_{it} \tag{3.29}$$

SDM

$$Income_{it} = \alpha + \beta Income_{i\,t-1} + \gamma \sum_{j=1}^{N} W_{ij} Income_{it} + \psi \sum_{j=1}^{N} W_{ij} Income_{it-1} + \sum_{k=1}^{K} X_{it} \zeta_k + \sum_{k=1}^{K} \sum_{j=1}^{N} W_{ij} X_{jkt} \eta_k + \theta_i + \nu_t + \pi_{it} \tag{3.30}$$

$$\pi_{it} = \varepsilon_{it} \tag{3.31}$$

SEM

$$Income_{it} = \alpha + \beta Income_{i\,t-1} + \psi \sum_{j=1}^{N} W_{ij} Income_{it-1} + \sum_{k=1}^{K} X_{it} \zeta_k + \theta_i + \nu_t + \pi_{it} \tag{3.32}$$

$$\pi_{it} = \rho \sum_{j=1}^{N} W_{ij} \pi_{it} + \varepsilon_{it} \tag{3.33}$$

As for my regression model used in Chapter 6, I invoke the properties of the dynamic SDM, which is represented in Equation (3.30), above, to examine the Hypothesis 4 of this thesis.

3.4.4 Model Selection

In order to achieve the convergence requirement of the ML estimation, I only add the spatial fixed effects and remove the time fixed effects. Furthermore, the function of the time fixed effects to account for the effects of unobserved spatial autocorrelated variables in the residuals has already been well-considered by the SDM specification through adding both the spatial endogenous and exogenous dependencies (Fingleton and Le Gallo, 2010).

I employ the Hausman specification test in Chapter 6 to decide whether the fixed effects estimation are better than the random effects estimation in the case of the SDM. Using the fixed effects model in my analysis is consistent to the idea proposed by Elhorst (2012) that the fixed effects model is more appropriate than the random effects model in the spatio-temporal analysis. Besides, two difficulties pointed out by him can be also solved in my research. Firstly, I have a sufficiently long time period (T equals to 20), secondly, I apply the SDM as the spatial panel specification, which has been proved to cover the endogeneity problem in regard to the variable omissions (Fingleton and Le Gallo, 2010).

Besides, although the SDM has been proved to be superior to other spatial panel specifications (SAR and SEM), based on the estimation result of the SDM by the ML, I propose two likelihood ratio (LR) tests to prove whether the SDM is the most appropriate specification to explain my empirical data in Chapter 6 (see Elhorst, 2010b). That is, on the basis of both (3.24) and (3.26)[6], firstly, the null hypothesis $H_0 : \eta = 0$ tests whether the SDM can be simplified to the SAR. The second null hypothesis $H_0 : \eta + \rho\zeta = 0$ examines whether the SDM can be simplified to SEM.

In addition, I perform another LR test to examine whether the static SDM can be extended to be dynamic by the hypothesis $H_0 : \beta = \gamma = 0$. Overall, after the model selection process, the dynamic SDM with spatial fixed effects has been selected as the spatial panel specification in my empirical research (as shown in section 6.3).

[6] All parameters mentioned below are the coefficients of different variables on the right hand side of (3.26).

Bank Lending to SMEs: Does Bank Size Matter?

Chapter 4: Bank Lending to SMEs: Does Bank Size Matter?

4.1 Introduction

The issue of raising finance is usually very high on the agenda of entrepreneurs. “Acquiring resources is a crucial task for the survival and success of entrepreneurial ventures” (Chua *et al.,* 2011). In particular, small and medium-sized enterprises (SMEs) are known to face barriers to growth that are not due to such internal factors as ideas, know-how, or external factors, such as demand. A significant external factor appears to be the availability of finance (Cook, 1999; Pissarides, 1999; Hessels and Parker, 2013; Kent and Dacin, 2013). Pissarides (1999) finds, in a large empirical study on Eastern European SMEs, that "credit constraints constitute one of the main obstacles to growth of SMEs".

At the same time, since the 2008 banking crisis, many SMEs have been quoted in the financial press to the effect that the big banks have not been helpful to them and, specifically, are failing to provide funding to entrepreneurs. Many policy-makers have since emphasised the need to increase bank lending to SMEs.

Government interventions in the credit markets, to facilitate credit to entrepreneurial start-ups, expansion of existing SMEs, and SME survival, are important for economic development and job creation, argue Riding and Haines (2001). An example for such interventions is the loan guarantee programmes in Canada and the United States; also, similar schemes have been implemented in Japan, Korea, the United Kingdom, and Germany. In recent years in the U.K, in addition to the grant, loan and government guarantee schemes (operated by the Department for Business, Innovation and Skills), a number of other government initiatives have been launched to stimulate bank lending to SMEs. These include Project Merlin (HM Treasury), and the Funding for Lending Scheme (FLS, operated by the Bank of England). Meanwhile, the Federation of Small Businesses (FSB) has been flagging up the unmet demand for borrowing by SMEs.

Thus, it can be said that policy-makers and business representatives recognise the problems with the funding of small businesses and entrepreneurs. Meanwhile, some SMEs, such as German ones, seem to face fewer such constraints than others, even during times of financial crisis. This is surprising, since export growth is usually thought to depend on foreign demand.

In the United Kingdom, the Department for Business, Innovation and Skills had tasked an entrepreneur (as 'Serial Entrepreneur in Residence' in 2013-14, Mr Lawrence Tomlinson) with looking into the practices of the big banks, in order to see whether they discriminate against small firms.[7] His report was highly critical of big banks, but has been criticised itself for its focus on case studies and lack of quantitative analysis. It is well established that SMEs are more dependent on bank lending than other sources of external funding (e.g. Beck and Demirguc-Kunt, 2006). While recent developments in financial markets have widened the spectrum of entrepreneurial funding opportunities, with peer-to-peer lending and crowdfunding (Belleflamme *et al.*, 2014) becoming important sources, this trend may provide support for the hypothesis that the size of the lender needs to be proportionate to the size of the borrower (the entrepreneur) for funding to be likely. In this chapter, the role of SME bank financing is examined, in particular, the role of bank size and its link to borrower size. The question is asked whether big banks are less prone to support small firms, and whether small banks are more likely to lend to small firms.

Many studies have investigated the link between the organisational structure of financial institutions and lending to small businesses. These studies developed a conventional wisdom that larger banks devote a smaller proportion of their lending portfolios to small businesses than smaller banks (e.g. Berger and Udell, 1995; Keeton, 1995; Berger *et al.*, 1998; Strahan and Weston, 1998; Haynes *et al.*, 1999; Berger and Udell, 2002; Berger *et al.*, 2005). Others have explicitly examined the role of bank size (Bertay *et al*., 2013), though without considering customer size.

The theoretical argument of the aforementioned studies is based on the differing lending technologies adopted by banks of different size: large banks are said to enjoy comparative advantages in 'hard information' lending (or transactions lending), thus, targeting more transparent and large firms, while small banks have comparative advantages in 'soft information' lending (or relationship lending) and, thus, are more interested in lending to small, opaque firms. Because of the informational opaqueness associated with small businesses, relationship lending is regarded as one of the most important technologies through which banks provide credit to small businesses (e.g. Berger and Udell, 2002). Thus, large banks may be disadvantaged in relationship lending to small firms. This is said to be due to difficulties in processing 'soft information', which is problematic to quantify, verify and transmit through the communication channels of organisationally complex large banks, causing additional expenses and problems (e.g. agency problems), due to Williamson-type (1988) managerial diseconomies, which may also occur in transactions lending (e.g. Stein, 2002). On the other hand, the comparative advantages of small banks in lending to informationally opaque small businesses may be attributed to the superior ability of small banks to avoid managerial diseconomies. Additionally, small banks are more often located closer to their potential relationship clients, offering smoother communications, which enable the bank management to collect and transmit more easily 'soft information' about the local market and the firm characteristics. Small banks with fewer layers of management hierarchy may mitigate contracting problems between the bank managers and the loan officers (e.g. Berger and Udell, 2002).

[7] see https://www.gov.uk/government/news/you-re-hired-entrepreneurs-in-residence-to-advise-government

However, Berger and Udell (2006) question this conventional wisdom as being “oversimplified”, by failing to distinguish between transactions lending technologies, and viewing them as a single homogenous lending technology used mainly by large banks dealing with informationally transparent firms. Therefore, they develop a theoretical framework postulating how financial structures affect the feasibility and profitability of the different lending technologies, and the effects of these technologies on small business credit availability. According to this framework, only the financial statement lending technology satisfies such characteristics, while the rest of transactions lending technologies (e.g. small business credit scoring, fixed-asset lending, leasing, asset-based lending, and factoring) may be used to target informationally opaque borrowers. It also argues against drawing a conclusive answer to the question of whether a large market presence of small banks is essential for small businesses to obtain credit. Further, such effects may differ in accordance with countries’ financial structures. Similarly, Petersen and Rajan (2002) claim that the use of information and communication technologies (e.g. credit scoring) have made local information, exclusively possessed by small banks, less valuable in assessing small business loans. Accordingly, the technological improvements have reduced the advantage that small banks may have enjoyed in small business lending.

Nevertheless, Brickley (2003) asserts that small, locally owned banks will continue to concentrate their offices in small urban or/and rural markets because, 1) many clients prefer to deal directly with local banks, rather than distant ones, 2) office managers of small local banks are granted greater authority, thus, bank headquarters do not need to pay for recruiting extra staff to monitor distant office managers as is the case at large banks, and, 3) information held by local office managers is still important despite the technological improvements. Also, Alessandrini *et al.,* (2008) highlight the importance of functional distance between bank branches and their headquarters as a critical organisational factor to hinder innovations by SMEs. In markets where local banking is more dispersed and functionally distant, SMEs become less innovative. On the other hand, the impact of a large bank presence on SMEs introducing innovations is insignificant.

Due to such counter-arguments and contradictory or ambiguous empirical results (e.g. Berger and Udell, 2002; Petersen and Rajan, 2002), it can be said that the question of whether SME lending is best, or most often, done by small banks, or whether large banks are doing the job just as well, remains open. In order to contribute to this debate and deliver an answer that could contribute towards settling the dispute in the existing literature, I analyse the empirical evidence from the world’s largest and most diverse banking system, namely, that of the USA. I analyse the relationship between bank size and improve measures of SME lending propensity for more than 14,000 banks, over twenty years from 1994 to 2013, utilising over 173,000 observations.

Since other studies may be questioned with respect to the degree to which their findings can be generalised, or their methodology to gauge the bank propensities to small business lending, this chapter additionally contributes to the empirical literature in two ways. Unlike most of the studies that have employed survey data, my bank-level dataset consists of 14,453 domestic U.S depositary institutions insured by the FDIC, that is to say, approximately all U.S depositary institutions over two decades. Accordingly, the results can be generalised across the USA. The second contribution is the improvements of two measures of bank propensities to lend to small and micro businesses, which address the weakness in prior work of potential biases due to the "denominator effect" and an imprecision in the calculations of propensity ratios, as identified by Berger et al., (2007) and will be shown in the literature review (see section 4.3).

Does bank size affect the propensity by banks to lend to small businesses? The new evidence from the largest banking system over the past twenty years is a resounding 'Yes' – smaller banks are more willing to lend to small businesses than larger banks. In contrast to Berger and Black (2007), Erel (2009), and Berger and Black (2011), I conclude that the conventional wisdom has been correct on this issue. This means that a key barrier to growth by SMEs - including growth in their exports - can be overcome by ensuring a diverse banking system which includes many small, local banks, such as is the case in the U.S and Germany, but distinctly not so in the United Kingdom.

The chapter proceeds as follows. In the following section a review is presented of the literature on bank size, bank consolidation, propensity measures and small business lending. The next two sections describe the data and the methodology utilised in this study. After this, results are discussed and further subjected to robustness tests. The final section presents the study's conclusions.

4.2 Literature Review

Two strands can be distinguished from the extant literature about bank size and small business lending. Firstly, a number of studies have investigated the extent to which banks of different sizes approach and lend to small businesses. Secondly, another strand of research has examined the extent to which bank size, resulting from bank mergers and acquisitions (M&As), affect small business lending.

4.2.1 Bank Size and Small Business Lending

Concerning the first strand of literature, it has been argued that small banks allocate a higher proportion of their loan portfolio to small businesses than large banks do (e.g. Berger *et al.*, 1995), whereas larger banks charge small businesses lower loan interest rates and less frequently require collateral from them (e.g. Berger and Udell, 1996; Carter *et al*., 2004). Here, it is argued that a lower loan rate implies less opaque borrowers. Haynes *et al.*, (1999) find that large banks are more likely to lend to larger and older small businesses and, hence, ones which are more secured.

On the other hand, small banks are more willing to serve micro businesses, mainly through relationship lending as an advantageous technology that is inherent in small banks' lending to small businesses (Berger and Udell, 1995). A central interest of the literature is the process by which banks of different sizes approach small businesses. For instance, a study by Cole *et al.*, (2004), (see also 1999) lends support to the conventional wisdom that large banks are more tied to transactions lending, to control for agency problems, while small banks rely more on relationship lending. Further, Berger *et al.,* (2005) assert that small banks have longer and more exclusive relationships, deal more personally with borrowers, and are more effective in alleviating credit constraints than large banks and, therefore, small banks tend predominantly to lend to smaller, financially distressed firms. Uchida (2011) observes a partial shift from collateral/guarantee lending to relationship lending following the banking crisis in Japan. In this context, Shimizu (2012) contends that in the local credit market in Japan a greater amount of non-performing loans (NPL) is held by small banks than large banks, and that such NPLs at small banks are associated with a lower number of bankrupt unincorporated firms or small businesses with a very small number of employees.

Unlike other studies, Berger *et al.*, (2007) explore the impact of market size structure (i.e. the shares of different bank sizes in the local market) on credit supply to small businesses. Their findings contradict conventional wisdom and advocate the conceptual framework developed by Berger and Udell (2006), suggesting that large banks are not disadvantaged in lending to small or informationally opaque businesses; rather, they may have alternative transactions lending technologies to approach small and opaque businesses. Berger *et al.*, (2007) also find that small business loan prices (borrowing rates) are significantly negatively affected by a larger market presence of large banks, but not by the bank's size itself. More recently, Berger and Black (2011) assert that, 1) the comparative advantages of large banks in transactions lending vary across technologies, lending support to Berger and Udell (2006)'s framework against grouping transactions lending technologies, 2) not all of those advantages appear to be monotonically increasing as firm size increases, and, 3) small banks may have a comparative advantage in relationship lending; however, the strongest advantage is found for lending to the largest firms. Accordingly, small banks may not be superior in serving small businesses. Further evidence to contradict the conventional wisdom is presented by Ongena *et al.,* (2011), from Turkey. They report that small firms are more interested in dealing with large, domestic, private banks than small banks. They speculate that this may be due to the extensive influence of loan officers in large banks in Turkey (Benvenuti *et al.,* 2009).

An important aspect in relationship lending is the role that loan officers can play in producing soft information about their small business clients. This role may differ according to bank type and size. Uchida *et al.,* (2012) stress that loan officers do play a critical role in relationship lending; in particular, loan officers in small banks produce more soft information than those in large banks. However, the superiority of small banks in relationship lending is not due to the inability of large banks to produce soft information; rather, it is due to greater efforts exerted by loan officers in small banks to produce soft information, the greater incentives granted by less organisationally complex banks (Stein, 2002), and a tendency by large banks to focus on transactions lending instead.

A small number of cross-country studies exist in the empirical literature. De La Torre *et al.,* (2010) consider 12 developed and developing countries. They conclude that all types of private banks are essentially interested in lending to small businesses and view them as a profitable market segment. However, banks do not rely solely on relationship lending when serving small businesses. In contrast, Mudd (2012) uses data from 71 countries to emphasise the importance of small banks in lending to small businesses through the implementation of relationship lending technology, suggesting that a greater market presence of small banks in total lending increases the credit access for SMEs.

4.2.2 Mergers & Acquisitions and Small Business Lending

The effect of bank consolidation on small business lending is an important subject that has been intensively investigated over the past two decades. To start with, Peek and Rosengren (1996) conclude that most banks that are involved in M&A activities reduced credits to small businesses in New England. This reduction occurs when most large and distant acquirers recast the targets' business strategies according to the acquirers' and consider them as junior partners (Keeton, 1996), such as modifications in the loan terms and reassessment of the lending portfolios (Bonaccorsi di Patti and Gobbi, 2007). The negative impact on small business lending is stronger with out-of-state urban acquirers (Keeton, 1995), and when many of pre-merger relationships with small borrowers are terminated (Bonaccorsi di Patti and Gobbi, 2007). Since most small businesses are single-relationship borrowers, Degryse *et al.,* (2009) argue that, in Belgium, borrowing firms which hold single-relationships with target banks are more likely to be dropped, and, consequently, being deprived of credits. To confirm, these dropped firms show a deteriorating performance and a higher rate of bankruptcy compared to others that do not face discontinuation of relationships or those that switch to other banks. In view of this, large borrowers, which build multiple-relationships with lenders, are more likely to survive the consequences of bank mergers.

Moreover, Berger *et al.,* (1998) employ a large sample of approximately all U.S M&As (i.e. 6000 M&As) that took place between 1977 and 1992. The static analysis suggests a decrease in small business loans, whereas the dynamic investigation shows that such decline is mostly offset by other lenders in the same market and partially by recasting post-consolidation policies toward small business lending. In a later study in Italy, Sapienza (2002) reports that small borrowers tend to seek financial alternatives to satisfy their credit demands following the mergers of their banks. Together, large acquirers tend more to reduce their lending to small borrowers subsequent to the acquisition of small banks. Nevertheless, such decline is offset in the market after three years of M&A events (Bonaccorsi di Patti and Gobbi, 2007), while Craig and Hardee (2007) claim that it is partially offset by non-bank institutions.

A number of studies have been less negatively, or even positively, viewing M&A impact on small business lending. To begin with, Strahan and Wetson (1996) document no evidence of effects of bank M&As on lending to small businesses. However, in a subsequent study, Strahan and Wetson

(1998) find an increase in such lending following small bank consolidations. Along the same line of argument, Peek and Rosengren (1998) argue that small business lending increases when the acquirer is small or when the acquirer has a greater share of small business loans than that of its target. On the other hand, small business lending decreases when the acquirer is large and not specialised in small business lending. Jayaratne and Wolken (1999) do not observe a significant decrease in the probability of a small business obtaining a line of credit as the result of a reduced presence of small banks in the market. In a recent and deeper attempt to examine the changes in post-consolidation lending policies, Erel (2009) concludes that banks, after mergers, charge lower interest rates, especially for small loans. The reduction in spreads can be attributed to scale and/or scope efficiencies in the long-run, as well as efficiency gains in the short term, thanks to technological improvements in lending and changes in risk diversification following mergers. Accordingly, larger acquirers do not significantly reduce small business lending by setting smaller targets; rather, they grant greater amounts of loans to small businesses, implying a positive effect of mergers on small business lending.

Another angle to investigate the effect of M&As on small businesses is by analysing their effect on the rate of new business formations. For instance, Black and Strahan (2002) find that the decline in the share of small banks, as a result of bank consolidations, helps entrepreneurs and positively impacts the formation of new businesses in the United States. This may occur, as previously stressed by Strahan and Wetson (1998), as a result of size-related diversification, which reduces delegated monitoring costs incurred by small banks to build long-term relationships with their borrowers. In contrast, Francis *et al.*, (2008) conclude that both in-market and out-of-market consolidations by large acquirers hamper the formation of new businesses. However, the adverse effects become positive in the long-term. However, consolidations by small or medium-sized acquirers are found to have a positive impact on small business formation and local entrepreneurial activities.

4.2.3 Lending Propensity and Sampling

Controversies in the above reviewed literature can be attributed to many factors, such as the sample size and data source, in addition to the proxy measures employed and the model adopted. The empirical literature relies primarily on data taken from surveys (e.g. NSSBF survey for the U.S) of small business borrowing activities (e.g. Cole, 1998) or the Management Survey of Corporate Finance Issues for Japan (e.g. Uchida, 2011). Others, such as Berger *et al.*, (1995), Peek and Rosengren (1998) and McNulty *et al.*, (2013), take samples of bank lending activities, such as the so-called Call Reports. Moreover, a number of researchers form samples by matching small business borrowers with their lenders, such as matching data from the National Survey of Small Business Finances (NSSBF) survey and the Call Reports (e.g. Haynes *et al.*, 1999; Berger and Black, 2011). It is possible that, for instance, the Survey of Small Firm Finance used by Berger and Black (2007) is not fully representative of the population of all small businesses with commercial bank loans found in the call report data, due to possible survivorship bias and probable exclusion of very small businesses. In my call report data, I consider all small business loans made by all commercial banks, which almost certainly explains the difference between their interpretation of the data and mine.

Moreover, results from these studies may be questioned for the degree to which their results can be generalised and whether there are any inherent biases. An important example is the widely used NSSBF survey, which is conducted only once every five years and may neglect many of the micro firms. By relying on it, many researchers do not account for the changes in lending propensity over time and may face questions concerning sampling bias. As I aim to examine small business lending patterns from the banks' perspective, I collect a representative sample of virtually all depositary institutions in the U.S over 20 years.

As for the proxy measures employed, Uchida (2011), for instance, criticises other studies (e.g. Berger *et al*., 2005; Uchida *et al*., 2008; Berger and Black, 2011) for merely relying on measures of contract terms and the relationship strength between banks and firms to identify lending technologies, rather than focusing on factors that drive such terms and strength. He collects data on loan screening from Japan and conducts a factor analysis in order to study the impact of small business characteristics on loan underwriting decisions. However, his data on the loan screening and the bank process of credit evaluation are merely taken from borrowers' perceptions. Further, Shen *et al.*, (2009) reach contradictory results when using different measures of the bank size. That is to say, bank size does not have an effect on lending when measured by total assets, whereas it does have an effect when it is measured by the number of levels in the decision-making hierarchy.

A number of studies examine the propensity of banks to lend to small businesses and rely on the ratio of small business loans to total assets as an indicator of bank propensity to lend to small businesses (e.g. Berger and Udell, 1996; Berger *et al*., 1998; Peek and Rosengren, 1998; Strahan and Weston 1998; Akhavein *et al*., 2005; Frame *et al*., 2004; Laderman, 2008). For instance, Berger *et al.*, (1998) employ this lending propensity indicator to find a negative impact of M&As on small business lending in the U.S. Besides, Peek and Rosengren (1998) assert that small business lending propensities at target banks follow the same pattern as the acquirers following the M&As, but those propensities do not change when the acquirers are also small banks. In other words, they find that an acquiring bank tends to impose its business model on the target, in effect reconstructing the target bank in its own image. Their results show that the ratio of small business loans to total assets for the consolidated institution converges toward the pre-merger ratio of the acquirer (see also Karceski *et al.*, 2005 on Norway). These findings, of imposing a new small business lending pattern, provide a strong evidence that the reduced lending to small businesses is mainly due to changing in bank policy or, in other words, changing in propensity to lend to small businesses.

On the other hand, Berger *et al.*, (2007) question the importance of lending propensities. They suggest that perhaps large banks have lower ratios because the denominator is expanded (i.e. growth opportunities) and not because the numerator is contracted. Their results are based on matching firm data from the National Survey of Small Business Finance and bank data from the call reports and the Summary of Deposits. There are 648 matched bank-firm observations. In contrast, I look at virtually all small business loans made by banks by considering all usable call report data reported by the FDIC. Clearly, lending propensities are important because they are a reflection of major differences in the business models of large and small banks. These differences determine the effect of specific mergers on individual small business borrowers at individual banks. Berger *et al.*, (2007) claim that large banks are more capable, and less legally constrained than small banks, of expanding their assets by making large business loans or other investments. Such asset expansion shrinks the ratio of small business loans to total assets, as a result of a larger denominator rather than a smaller numerator. To correct this problem, a few studies alternatively use the ratio of small business loans to total loans (e.g. Shen *et al*., 2009; McNulty *et al*., 2013). The latter ratio ameliorates the effect of the denominator that is inherent in the former ratio by excluding other specific large bank assets, (i.e. investment assets, trading account assets and other assets that would be a more significant portion of large bank balance sheets than small bank balance sheets), which are more likely to amount to a substantial portion of large bank assets. The ratio of small business loans to total loans is calculated by Shen *et al*., (2009) and McNulty *et al*., (2013) as follows:

$$Propensity\ Ratio = \frac{Small\ Business\ Loans}{\substack{Total\ Loans \\ (i.e. Total\ Assets - Investments\ assets + \\ Trading\ account\ assets + \\ other\ large\ bank\ specific\ assets)}}$$

However, this correction may not be sufficient, as this ratio may include loans which are provided by banks that are more specialised in other types of lending (e.g. real estate lending) or more capable to provide sizable loans to other depository institutions. As a result, the inclusion of these loans is translated in the ratio of small business loans to total loans as low propensity (i.e. due to larger denominator resulted from larger total loans or smaller numerator resulted from smaller amount of small business loans), erroneously showing them as being unwilling to lend to small businesses. Therefore, it is necessary to further ameliorate this problem by considering the ratio of small business loans to total business loans. My improved ratio excludes other non-business loans (i.e. personal loans, property loans, agricultural loans, credit card loans, loans to depository institutions and other non-commercial and industrial loans) as follows:

$$Propensity\ Ratio = \frac{Small\ Business\ Loans}{\substack{Business\ loans \\ (i.e. Total\ Assets - Investments\ assets + \\ Trading\ account\ assets + \\ Non\ business\ loans + \\ other\ large\ bank\ specific\ assets)}}$$

As argued by Berger *et al.,* (2007) concerning the denominator problem, large banks are also more capable to expand and diversify their lending portfolios. For example, large banks are more capable to provide large loans to other financial institutions that small banks cannot provide. Thus, including those types of loans in the denominator may also shrink the propensity ratio for large banks, showing them unwilling to lend to small businesses. Accordingly, I take the concern of Berger *et al.,* (2007) further, regarding the denominator effect, and eliminate assets that may cause biases in lending propensities between large and small banks. This is the approach used for the empirical work presented below.

This chapter, as also asserted by McNulty *et al*., (2013), does not say that a higher propensity ratio at small banks necessarily implies that small banks provide a larger volume of small business loans than large banks. However, it shows that small banks are more specialised in delivering loans to small businesses. In other words, a few independent small banks can be better for small and micro businesses than a single bank. The dataset employed in this chapter reveals that small banks with assets less than $1 billion channel more small business loans, relative to their deposits, than medium and large banks with assets over $1 billion (8.5% and 4.03%, respectively). This pattern is precisely what I expect from looking at lending propensities.

4.3 Data

4.3.1 Data Source

My primary source of data is the Federal Deposit Insurance Corporation (FDIC). "The FDIC collects, corrects, updates and stores Reports of Condition and Income data submitted to the FDIC by all insured national and state non-member commercial banks and state-chartered savings banks on a quarterly basis. Reports of Condition and Income data are a widely used source of timely and accurate financial data regarding a bank's condition and the results of its operations" (FDIC, 2014). My dataset includes all domestically active and inactive U.S depositary institutions that have reported to the FDIC over the past 20 years from 1994 to 2013, those institutions report the amount of their business loans. This gives me a dataset of 14,453 depositary institutions in an unbalanced panel dataset of 173,719 observations. Arguably, it is the largest, the longest and, hence, the most representative dataset in the extant empirical literature. Unlike other variables, loans to small businesses are only reported as of June 30; thus, I have to use yearly data for all variables. For simplicity, I use the term "bank" for all types of depositary institutions. I calculate the ratio of small business loans to total business loans and the ratio of micro business loans to total business loans (SBLTBL and MBLTBL), respectively.

As a robustness check, I seek to control for potentially large variations in the competitive environment and specialisation of banks. I thus construct a subsample of banks that specialise in commercial lending only and which operate in the largest U.S cities (those with a population of more than 500,000). This leaves me with 912 banks headquartered in 34 cities, which operate in a more homogeneous environment with respect to market and economic conditions. This eliminates any unobserved regional or market effects, which are not captured by the control variables in the main regressions.

4.3.2 Variable Definitions

As noted in the literature review, and taking into consideration the argument of Berger and Udell (2007) concerning the ratio of small business loans to total assets, my key dependent variables to measure the propensity of bank lending to small micro businesses are:

1) the ratio of Small Business Loans to Total Business Loans (SBLTBL), and

2) the ratio of Micro Business Loans to Total Business Loans (MBLTBL).

Small business loans are defined by the FDIC as the amount of currently outstanding commercial and industrial loans with original amounts less than $1,000,000 held at domestic bank offices. In addition, I consider loans with original amounts of less than $100,000 to be micro business loans. Since a small business definition is based on the size of the loan (Call Report definition), I name small business loans with original amounts of less than $100,000 as ‘micro business loans’ (i.e. loans granted to the smallest of the small businesses).

Several researchers have adopted the FDIC definition of small business loans, such as Keeton (1995), Strahan and Wetson (1998), Peek and Rosengren (1998), Carter and McNulty (2005), Carter *et al*., (2004), and Berger *et al*., (2011). Although, in theory, the data is based on the loan size and not the company size, it is reasonable to interpret the way that the FDIC and authors have done it. Because of the due-diligence and transactions costs, it is unlikely for large companies to take out very small loans, while small companies cannot take out large loans. Therefore, this approximation is reasonable and has become the standard in the literature. According to the Community Reinvestment Act (CRA), on average, 93% of small business loans have an amount of less than $100,000. The CRA requires banks with asset size greater than $300 million to report their small business loans. In addition, primary surveys have established a close correspondence between loan size and the size of the borrower. For instance, according to the 1989 National Survey of Small Business Finance, 80 percent of loans to businesses with less than $1 million in annual sales amounted to less than $100,000 each (Board of Governors). Additionally, earlier surveys have yielded similar results (Keeton, 1995).

My key explanatory variable is the logarithm of total bank assets. It is defined as the sum of all assets owned by the institution, including cash, loans, securities, bank premises and other assets. This total does not include off-balance-sheet items. Since my study is based solely on data about banks’ activities, I include a number of explanatory variables to control for other factors which may affect the credit supply to small businesses. These control variables are consistent with previous studies (e.g. Peek and Rosengren, 1998; DeYoung *et al*., 1999; Carter and McNulty, 2005) and are discussed below.

Regional Bank-Market Characteristics (RBMC): firstly, I use a variable for regional banking market concentration that is represented by a bank's share in the market for deposits (it indicates a bank presence in the local market). This is computed as the share of deposits that is domestically held by a bank in the state where it is headquartered, as a percentage of all domestically held deposits in the state. Peterson and Rajan (1995) suggest that small banks in less competitive markets have a greater incentive to invest in loan relationships because there is less chance that the borrower will switch to a competing lender. Prior research shows that local market share of large banks is a powerful predictor of the lending bank size (e.g., Berger et al., 2007; Berger and Black, 2011), which suggests that firms may generally choose an institution based on convenience. The effect of market concentration may be either favourable or unfavourable for small business borrowers (e.g., see Scott and Dunkelberg, 2010). (Source: Summary of Deposits by FDIC, 2014). Secondly, a dummy variable takes the value of '1' if a banks' headquarters is located in an MSA and '0' if bank is not headquartered in the MSA. This variable indicates the level of market competition where banks are active (i.e. urbanised areas, as in MSA, show higher market competition than rural Non-MSA ones). Carter and McNulty (2005) argue that relative to small banks, large banks are more likely to operate in more competitive metropolitan markets, are more likely to be affiliated with a bank holding company, make relatively fewer small business loans but more credit card loans. Moreover, Akhigbe and McNulty (2003) report that 57% of small U.S banks are in non-metropolitan areas, so the typical small bank should have greater investment in small-firm relationships, which could give them an advantage in their lending activities. Accordingly, I expect a negative effect of MSA variable on SME lending propensities. (Source: Summary of Deposits by FDIC, 2014).

Regional Economic Characteristics (REC); the logarithm of GDP per capita (the Gross Domestic Product per capita) is added to account for the effect of local economic activities and business cycles on credit demand. Unlike Black and Starhan (2002) that use the personal income growth, I use the GDP per capita of the state in which the bank is headquartered. The use of state-level GDP per capita and state-level deposit share may not be sufficiently representative of the actual bank local market. However, using county-level or MSA-level data (for Non-MSA areas, a county has to be considered instead) is too small, particularly for those multi-county banks (they form over 50% of the banks included in my dataset). Banks in more developed markets seek large deals with large firms and tend to invest in less costly loans to finically safer firms, while banks are more inclined to issue small business loans in less developed markets, especially, through relationship lending. It is expected that large banks would more often lend to firms with high ROE relative to small banks (e.g. Rice and Strahan, 2009; Berger and Black, 2011). Therefore, bank lending propensities to micro and small businesses are expected to be lower in states with higher GDP per capita. (Source: Bureau of Economic Analysis, BEA)

Bank Specific Characteristics (BSC); I firstly add a dummy variable that takes the value of '1' if a bank is regulated by a multibank holding company, and takes '0' otherwise. This identifies a bank's autonomy in lending policies, since many holding companies may impose their policies on their smaller subsidiaries. Keeton (1995) argues that small banks affiliated with bank holding companies may act more like large banks, suggesting a lower propensity to lend to micro and small businesses (as this chapter hypothesises).

In addition, I include the following five variables to control for bank health, performance, and fundamental risk characteristics (all variables are collected from the FDIC, 2014):

1) The ratio of nonperforming loans to total loans, defined as loans and leases 90 days or more past due plus loans in nonaccrual status, as a percent of gross loans and leases (e.g. Peterson and Rodengren, 1998). A greater share of nonperforming loans is expected to have a negative impact on the bank lending policy to small, informationally opaque firms.

2) The leverage ratio, defined as the Tier 1 (core) capital as a percent of average total assets minus ineligible intangibles. A bank that relies more on debt-based capital is less likely to be engaged in risky lending (e.g. SME lending), and the bank is more willing to approve loans to large, transparent companies (e.g. Peterson and Rodengren, 1998). Thus, the bank propensity to lend to micro and small businesses is expected to decrease as a result of a higher leverage ratio.

3) Bank profitability, I use the return on assets (ROA) ratio as a measure of bank profitability (e.g. Peterson and Rodengren, 1998). This variable is defined as net income after taxes and extraordinary items as a percent of average total assets. Bank profitability is typically used as a control variable to capture any link between bank performance and the local supply of credit (Carter *et al.*, 2004).

4) The ratio of interest income to earning assets, defined as total interest income as a percent of average earning assets. This ratio is used to control for lending performance (e.g. Carter and McNulty, 2005). Improved lending performance is expected to have a positive impact on the share of small and micro business loans.

5) The logarithm of the bank age, which is calculated by subtracting the year of bank establishment from the current year of observation plus one year i.e. logarithm (age +1). To be compatible with the lending date, the first four bank specific control variables are annualised over the past four quarters prior to 30th of June of each year. This measure captures whether a bank changes its small business lending behaviour as it becomes older. This variable allows me to test the extent to which bank age has a negative effect on small business lending (as found by DeYoung, 1998), or whether age is simply a proxy for other influences on the bank. I expect a negative relationship between bank age and small business lending (as also found by DeYoung *et al.*, 1999).

4.3.3 Descriptive Statistics

Table 4.1, below, provides summary statistics for all variables. The median of total assets ($100 million) indicates that half of the banks in the sample are small, with total assets of less than $100 million. It is worth noting that there are significant gaps between the mean and median for the SBLTBL ratio (i.e. 85.97 and 99.98) and those for the MBLTBL ratio (i.e. 49.02 and 37.66), respectively. This may be attributed to a general lack of interest by banks in lending to the very small or micro businesses.

Table 4.1 Summary Statistics

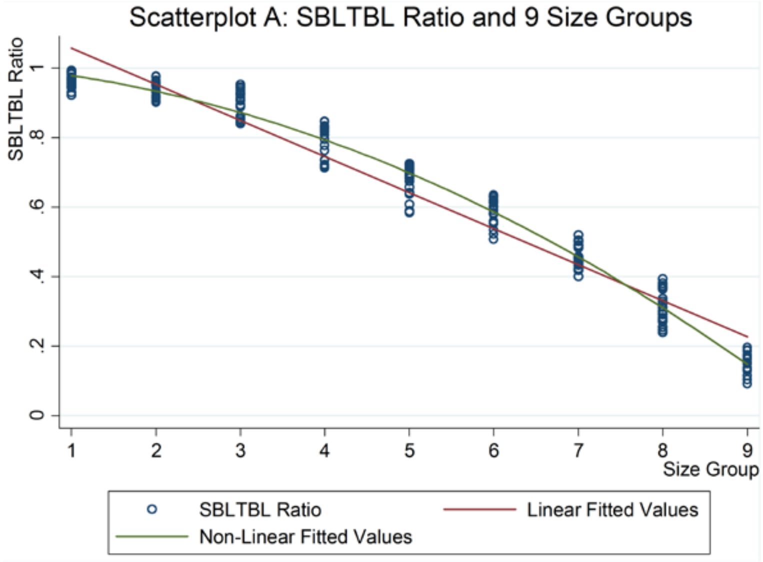
Variable	Description	Mean	Min	Max	Median	St. Deviation
Loan Ratios						
SBLTBL % (SBL < $1000,000)	Ratio of Small Business Loans to Total Business Loans (SBLTBL)	85.967	0 .0004	100	99.979	21.577
MBLTBL % (MBL < $100,000)	Ratio of Micro Business Loans to Total Business Loans (MBLTBL)	49.015	0	100	37.657	35.274
Bank Size						
Total Assets*	Total bank assets in billions	1	0.002	1,950	0.996	19.9
Regional bank-market characteristics						
Market Deposit Share	Bank deposit share in the local market	0.3812	0	79.909	0.0893	1.7415
MSA Dummy	= 1 if bank's headquarters in MSA, = 0 for non-MSA	0.5493	0	1	1	0.4976
Regional economic characteristics						
Log. GDP Per Capita	Logarithm of gross domestic product per capita by state where bank is headquartered	10.575	9.8318	12.089	10.642	0.2542
Bank Characteristics						
Multi-Bank Holding Company	= 1 if the bank owned by a Multi-Bank Holding Company, = 0 otherwise	0.2311	0	1	0	0.4215
Non-Performing Loan Ratio %	Ratio of non-performing loans to total loans	1.4111	0	89.339	0.7172	2.3408
Leverage %		10.600	-9.7883	294.14	9.3587	6.2890
ROA %	Return on assets	0.8952	-68.610	44.414	1.0350	1.4199
Interest Income/Earning Assets %	Ratio of total interest income as a percent of average earning assets	6.8253	0	69.065	6.9618	1.7214
Business Loans/Total Assets	Ratio of total business loans as a percent of total assets	9.4009	0.00002	97.750	7.7606	7.4539
Bank Age*	Year of establishment – year of observation.	68.801	1	221	78	41.942
Time Dummies	Twenty dummy variables for the years 1994 – 2013	20	20	20	20	20
No. of Observations		173,719	173,719	173,719	173,719	173,719

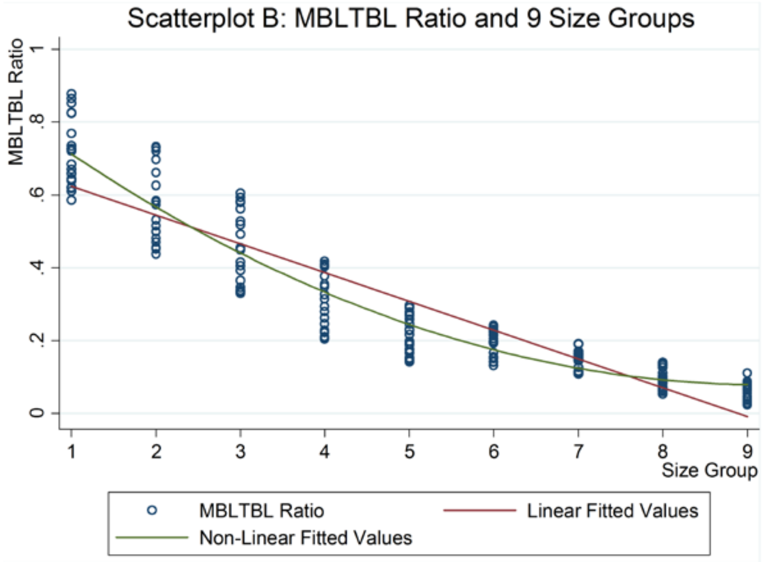
Note: * The total assets variable in this table is displayed in thousands, while it is converted to a logarithm when included in the regressions.
* The bank age variable in this table is displayed by the number of years plus one, while it is converted to a logarithm when included in the regressions.

To conduct a preliminary descriptive analysis for my dataset, I draw two scatter plots illustrating the correlation between bank size and each of the SBLTBL and MBLTBL ratios. I categorise banks into 9 peer groups based on bank asset size. Next, small business loans and micro business loans are summed up for all banks in each peer group and the ratios of SBLTBL and MBLTBL for each peer group over the period 1994-2013 are computed.

The scatter plots (A) and (B) displayed in Figure 4.1, below, illustrate a downward slope of the best-fitted line across the plotted points that represent the correlation between the ratio of SBLTBL and bank size. Notably, the nonlinear function (displayed in green) is, to a large degree, compatible with a linear one. Consistent with my hypothesis, this is indicative of a strong negative correlation between bank size and each of the SBLTBL and MBLTBL ratios.

Figure 4.1 Correlation between SBLTBL and MBLTBL Ratios and Bank Size for 9 Groups

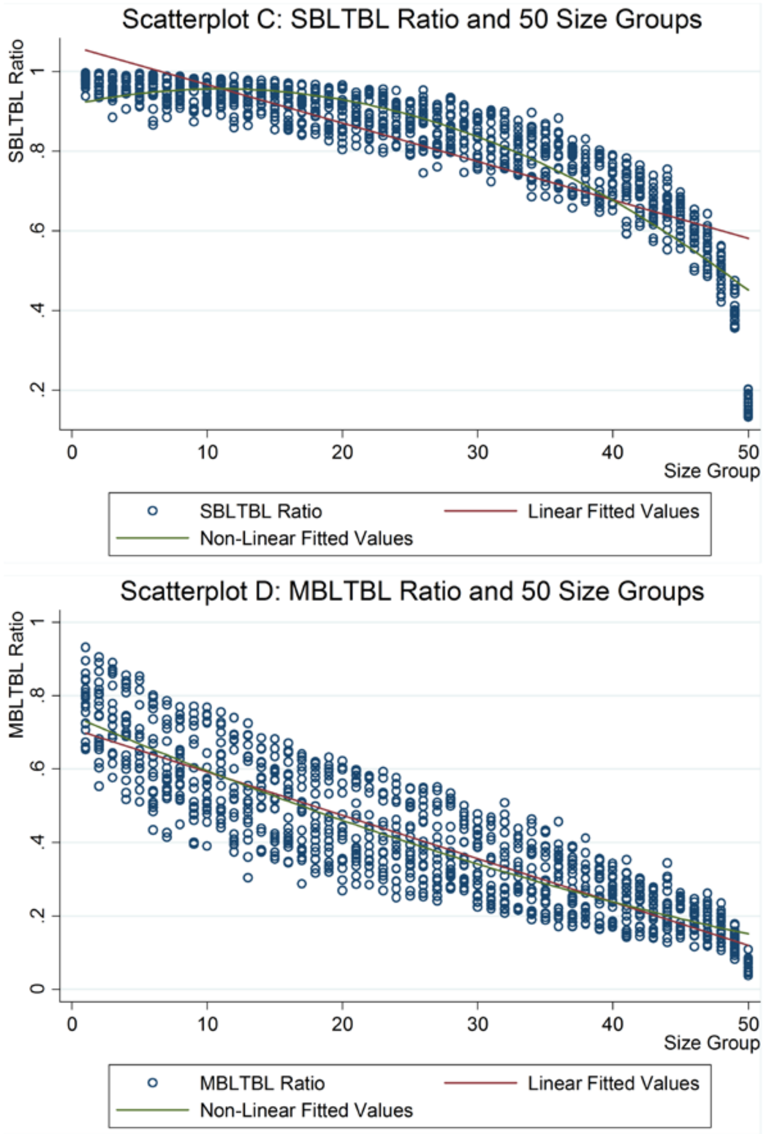




Note: This figure includes two scatterplots of the relationship between lending propensity and bank size for 9 size groups of U.S banks. The scatterplot A illustrates the relationship between the SBLTBL ratio and bank size. The scatterplot B illustrates the relationship between the MBLTBL ratio and bank size. Each observation (circle) represents the lending propensity of a size group in a specific year. The number of years plotted are 20 years from 1994 to 2013.

For robustness, I split banks into 50 peer groups in order to approximate a continuous line by having many more categories. The scatter plots (C) and (D) in Figure 4.2, below, confirm the strong negative correlations between bank size and each of the SBLTBL and MBLTBL ratios. It is worth mentioning that the negative correlation seems to be slightly stronger between bank size and the very small businesses (i.e. micro businesses). It can be concluded that bank size is highly correlated with small and micro business lending.

Figure 4.2 Correlation between SBLTBL and MBLTBL Ratios and Bank Size for 50 Groups



Note: This figure includes two scatterplots of the relationship between lending propensity and bank size for 50 size groups of U.S banks. The scatterplot C illustrates the relationship between the SBLTBL ratio and bank size. The scatterplot D illustrates the relationship between the MBLTBL ratio and bank size. Each observation (circle) represents the lending propensity of a size group in a specific year. The number of years plotted are 20 years from 1994 to 2013.

4.4 Model Specification

The model specification in this chapter seeks to examine the proposition (i.e. H1) that bank size has a negative impact on lending propensity to small and micro businesses in the U.S over the period from 1994 to 2013. To do that, I employ the fixed-effects panel data approach presented in section (3.2) of Chapter 3. Recall Equation (3.2), as follows:

$$\begin{aligned} PROPNS_{it} &= \beta_1 SIZE_{it} + \beta_2 NPL_{it} + \beta_3 ROA_{it} + \beta_4 LEV_{it} + \beta_5 MBHC_{it} + \\ &\beta_6 MDS_{it} + \beta_7 GDP_{it} + \beta_8 IIEA_{it} + \beta_9 MSA_{it} + \beta_{10} BLTL_{it} + \beta_{11} AGE_{it} + \\ &\beta_{12} YD_t + \beta_{13} RD_i + \varepsilon_{it} \end{aligned} \tag{3.2}$$

where, *i* represents the bank and *t* the year. The dependent variable is $PROPNS_{it}$ which represents each of the lending propensity ratios (i.e. SBLTBL and MBLTBL ratios). $SIZE_{it}$ is the size of the bank as the main explanatory variable of interest. The rest of the variables are control variables to account for regional bank-market characteristics (i.e. Market Deposit Share (MDS) and Metropolitan Statistical Area (MSA)), regional economic characteristics (i.e. Gross Domestic Product per capita (GDP)), and bank specific characteristics (i.e. Non-Performing Loans (NPL), Return on Assets (ROA), Multi-Bank Holding Company (MBHC), Interest Income to Earning Assets (IIEA), Business Loans to Total Loans (BLTL), and bank Age (AGE)). YD_t is the set of yearly dummy variables. RD_i is the set of bank dummy variables, and ε_{it} is the error term. The Equation (3.2) is estimated twice, that is, firstly by using the SBLTBL ratio as a measure of lending propensity to small businesses, and secondly by using the MBLTBL ratio as a measure of lending propensity to microbusinesses. Subsequently, both estimations are also repeated for different sub-periods and subsamples as robustness regressions.

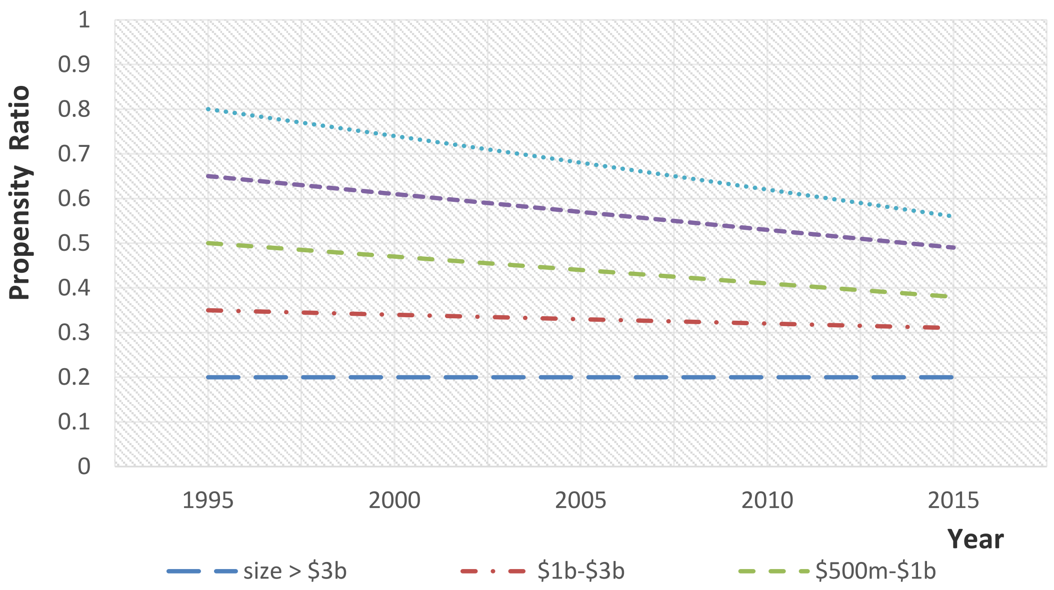
As mentioned in section 3.2, the standard errors are robust and I account for serial correlation by allowing for clustering of the error term at the bank level. Moreover, the F-statistic and Hausman tests are reported in the following sections to lend support to my decision on adopting fixed-effects panel approach over pooled and random-effects approaches.

4.5 Empirical Analysis

4.5.1 Graphical Analysis

Before commencing the regression analysis, I consider the *a priori* theoretical propositions using a graph in order to hypothesise the bank lending behaviour over time. Figure 4.3, below, shows a theoretical graph with five lines, each representing the ratio of the SBLTBL or the MBLTBL of each bank size group over the period 1994-2013. The graph envisages a scenario that is consistent with my hypothesis: it shows that as banks become smaller there would be more of a downward trend, while as I move to the lower lines (i.e. groups of larger banks), there should be more a horizontal line. This is the sort of picture I could expect: as banks grow and merge, they get larger and if the hypothesised negative correlation between bank size and small business lending holds, they would tend to lend less to small businesses over time as they grow larger. This would be most pronounced with the very small banks. On the other hand, the largest banks may no longer show a noticeable change, as they no longer increase the share of small business lending. Hence, the line representing their propensity to lend to small and micro businesses should stay constant overtime. Consistent with my proposition, Peterson and Rodengren (1998) assert that larger banks do not only tend to have, on average, a smaller portfolio share of SME loans, but their share tends to shrink faster over time or grows more slowly.

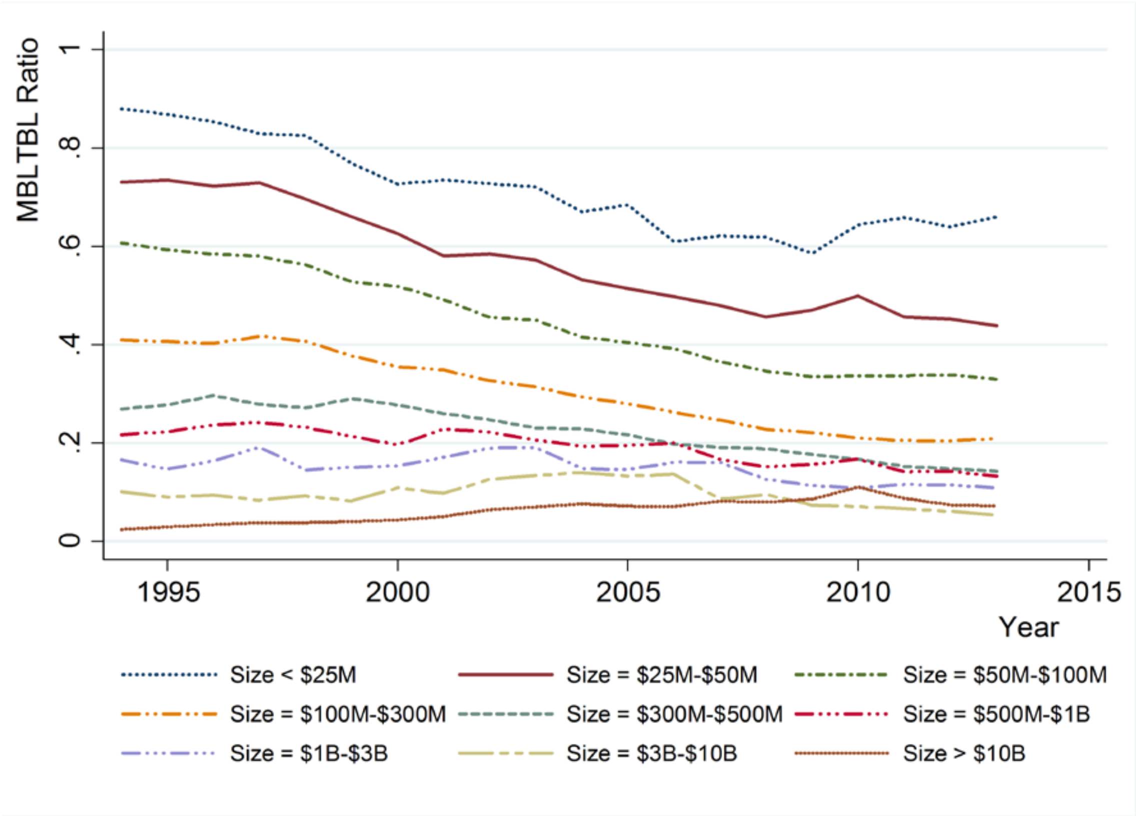
Figure 4.3 Theoretical Graph of the MBLTBL and SBLTBL Ratios for Peer Groups



Note: This graph illustrates the theoretical behaviour of bank lending to SMEs over time for U.S banks. Each line represents the lending propensity of each of five bank size groups over the period from 1994 to 2013.

As for the actual lending behaviour, I use the same categorisation of the nine peer groups used in the scatter plots in the data chapter. The actual data yield the correlations shown in Figure 4.4, below. As can be seen, when bank size group increases, the MBLTBL ratio decreases. There is a sharp decline (i.e. over 60%) as bank size exceeds 500 million of assets. In other words, small banks appear to be more interested in dealing with small businesses, as they allocate a significantly higher proportion of their loans to small businesses. Over time, a slight decrease in the MBLTBL ratio for smaller banks may indicate decreased interest in small business lending, as these banks themselves grow over time. However, for larger banks, this ratio remains the lowest and stays fairly steady over time, suggesting an unchanged lending policy toward small businesses.

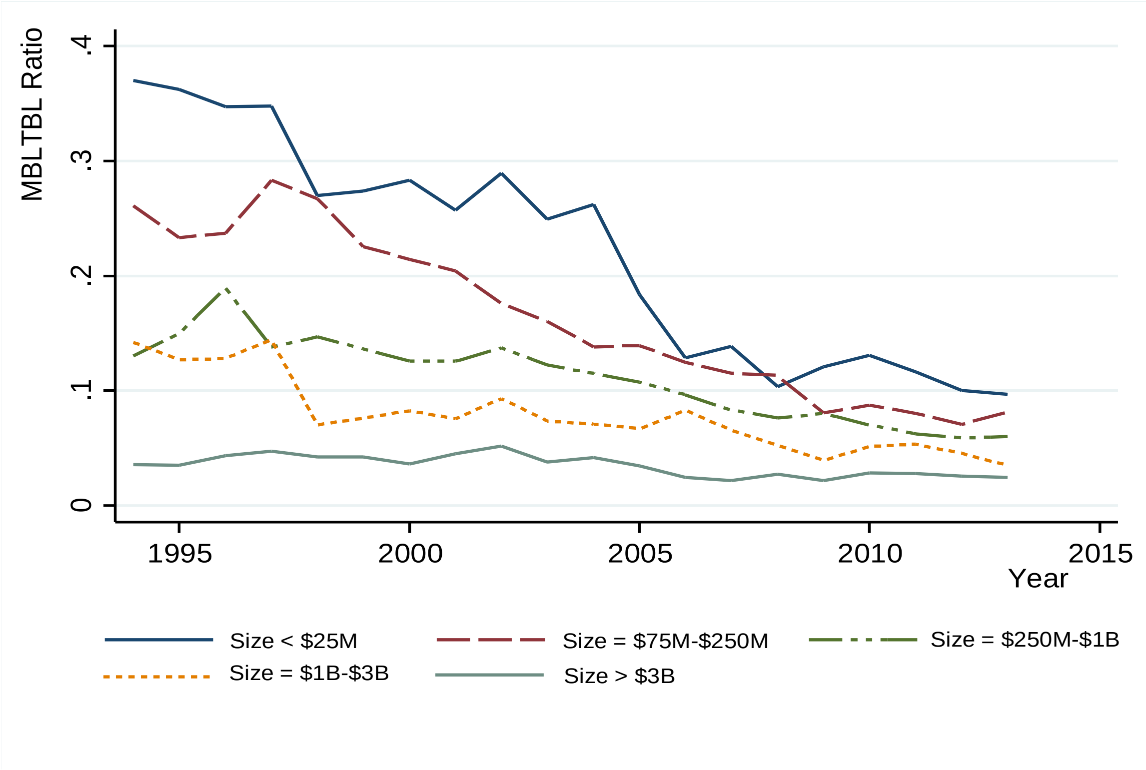
Figure 4.4 Actual MBLTBL Ratio for 9 Peer Groups



Note: This graph illustrates the actual behaviour of bank lending to micro businesses over time for U.S banks. Each line represents the lending propensity of each of nine bank size groups over the period from 1994 to 2013. The lending propensity to micro businesses is computed as the ratio of Micro Business Loans to Total Business Loans (MBLTBL) for each size group.

It should be noted that it is a strong result to find that the order of the loan propensity schedules shown in Figure 4.4 remains the same. In Figure 4.5, below, the micro-business lending behaviour is shown for five size groups of banks solely specialised in commercial lending and headquartered in the largest 34 cities. As can be seen, the five size groups follow the same pattern as was shown in Figures 4.3 and 4.4. A lower MBLTBL ratio and a steeper decrease by the smaller groups over time can be observed.

Figure 4.5 Actual MBLTBL Ratio for 5 Peer Groups of Banks in the Largest 34 Cities



Note: This graph illustrates the actual behaviour of bank lending to micro businesses over time for U.S banks in the largest 34 U.S cities. Each line represents the lending propensity of each of five bank size groups over the period from 1994 to 2013. The lending propensity to micro businesses is computed as the ratio of Micro Business Loans to Total Business Loans (MBLTBL) for each size group.

The pattern shown in Figures 4.3-4.5, above, are consistent with the findings of DeYoung (1998) and DeYoung *et al.*, (1999) that the old banks become large and begin to behave more like large banks, and also with the findings of Berger *et al.*, (1998), Peek and Rosengren (1998), and Karceski *et al.*, (2005) that the propensity to lend to small businesses for the consolidated institution converges toward the pre-merger ratio of the acquirer. Consequently, lending propensity of small banks declines over time.

4.5.2 Main Regression Analysis

The following section reports the regression results of the main model presented in Equation (3.2). Prior to regression estimations, I perform a Hausman test to verify the use of fixed-effects approach. The test results reject the null hypothesis of no difference between the two estimations for all regressions, including robustness regressions (Hausman test statistics and their rejection probabilities are reported in the tables). Accordingly, I can confirm that fixed-effects estimation is consistent, while the random-effects estimation is not.

The first regression (Model 1) in Table 4.2, below, models the effect of bank size on the SBLTBL ratio for loans with original amounts of less than $1 million, while the second regression (Model 2) models the effect of bank size on the MBLTBL ratio for loans with original amount less than \$100,000. The key result in both regressions is that bank size has a statistically significant negative effect on the SBLTBL and MBLTBL ratios. That is, the bank propensity to lend to small and micro businesses is negatively affected by the bank size. In other words, as bank size increases, the relative share of small and micro business loans held by the bank diminishes. These results are consistent with the findings of Keeton, (1995), Strahan and Weston, (1998), Haynes *et al.*, (1999), Berger and Udell, (2002), Berger *et al.*, (2005), and Mudd (2012), that is, small banks lend more to small businesses and large banks are more advantaged in lending to large businesses. In this line, the findings of this chapter also lend support to the claim that bank M&As are detrimental to small businesses by reducing the latter's chances to secure funds (e.g. Peek and Rosengren, 1996; Berger *et al.*, 1998; Bonaccorsi di Patti and Gobbi, 2007; Francis *et al.*, 2008; Degryse *et al.*, 2009). Moreover, my findings refute the opposite claims that there is no effect of bank size on small business lending (e.g. Berger and Udell, 2006; Berger *et al.*, 2007; De La Torre *et al*., 2010; Berger and Black, 2011), large banks lend more to small businesses than small banks do (e.g. Ongena *et al.*, 2011), and bank consolidations help small businesses through increased lending (e.g. Strahan and Wetson, 1998; Jayaratne and Wolken, 1999; Black and Strahan, 2002; Erel, 2009).

What is more, Table 4.2, below, shows that most of the control variables have predictable signs. For instance, in both models, the multi-bank holding company coefficients show a negative sign, indicating that banks are less interested in lending to small businesses when these banks are partially, or fully, owned by multi-bank holding companies. This may result from the imposed lending policy by the holding company (e.g. Keeton, 1995) or the acquiring bank (e.g. Peek and Rosengren, 1998; Karceski *et al.*, 2005).

Consistent with Peterson and Rodengren, (1998), I find that a larger proportion of non-performing loans may negatively influence bank lending in general, and small business lending in particular, as NPLs can be expected to increase banks' aversion to risk. Since many banks regard small business lending as risky, they may be more reluctant to lend to small businesses, which can be a source of non-performing loans. Similarly, banks with a higher leverage ratio tend to reduce risky loans by lending less to potentially opaque small businesses. On the other hand, other variables illustrate significant positive coefficients in Models 1 and 2. For instance, a higher return on assets, increased total interest income to average earning assets, and a larger deposit share in the bank local market are all expected to increase the size of small business lending portfolios. That is, improved lending performance increases the share of small business loans as Carter and McNulty (2005) find. The positive deposit share variable indicates, as Peterson and Rajan (1995), and Akhigbe and McNulty (2003) assert, that a bank with greater market power is more likely to extend its lending to more small and micro businesses in the local markets. Contrary to Peterson and Rodengren (1998), higher profitability, measured by return on asset ratio, increases the local supply of credit to small businesses. Improved bank profitability may give a space to and encourage banks to be involved in riskier loans as the case of small and micro businesses. Moreover, the level of a region's urbanisation (MSA) and level of development (GDP) seem to have a significantly negative impact on bank lending propensity to small and micro businesses. Banks, especially small ones, tend to increase their lending to SMEs in more rural areas, while they struggle more to obtain bank finance in more urbanised regions. The negative effect of bank age on lending propensity to small businesses, in Model 1, is consistent with the findings of DeYoung (1998) and DeYoung *et al.*, (1999). This negative impact can be attributed to changes in bank lending behaviour over time. That is, the old banks become large and begin to behave more like large banks. However, the positive effect of bank age on the lending propensity to micro businesses can be the products of U.S development programmes such as the Community Reinvestment Act (CRA), which requires large banks to allocate a share of their loans to micro businesses. Therefore, large banks have had to increase their lending to micro businesses during the sample period, i.e. 1994 – 2013.

Table 4.2 Fixed-Effects Regressions for Model 1 and 2 All-Sample

Variables	Model 1 SBLTBL	Model 2 MBLTBL
Log. Assets	-9.541565***	-7.334459***
	(-90.50)	(-45.76)
Non-performing Loans	-0.1753629***	0.0268057
	(-9.97)	(1.00)
ROA	0.1927039***	0.2050129***
	(6.23)	(4.36)
Leverage	-0.1520507***	-0.0035444
	(-21.28)	(-0.33)
Multi-Bank Holding Company	-1.59743***	-3.54008***
	(-10.16)	(-14.80)
Market Deposit Share	0.0123119	0.5323706***
	(0.27)	(7.75)
Log. GDP per capita	-2.107229***	-2.654262**
	(-3.02)	(-2.50)
Interest Income/Earning Assets	0.497508***	0.0048192
	(11.07)	(0.07)
MSA	-0.7294275*	-6.449522***
	(-1.70)	(-9.86)
Business Loans/Total Assets	-0.4639655***	-0.7759058***
	(-58.12)	(-63.94)
Log. age	-0.916927***	6.416471***
	(-4.95)	(22.81)
Year Dummies	Included	Included
Bank Dummies	Included	Included
No. Observations	173,692	173,692
No. Banks	14,453	14,453
Prob > F	0.0000	0.0000
Hausman test statistic	973.79	1370.40
Hausman test (Prob>chi2)	0.0000	0.0000
R-sq: within	0.2259	0.3267
R-sq: between	0.5360	0.4612
R-sq: overall	0.4280	0.4250

Note: This table reports results from Fixed-Effects estimations of the effects of bank assets on bank propensities to lend to micro and small business loans. The dependent variables are the measures of lending propensities to micro and small businesses, i.e. (1) Micro Business Loans to Total Business Loans and (2) Small Business Loans to Total Business Loans. The key independent variable is the logarithm of total bank assets. The period covers the years 1994 to 2013. T-statistics between parentheses. The symbols ***, ** and * indicate the levels of significance, 1%, 5% and 10%, respectively.

Furthermore, I break the sample period into two sub-periods and then run the same models for each period. For instance, to rule out the possibility that the recent financial crisis may influence such results, I run two regressions for the periods 1994-2007 and 2008-2013. The regressions' results in Table 4.3, below, show that bank size coefficients change marginally during the period before the credit crisis compared to the all-sample coefficients (i.e. -8.62 and -7.85, respectively). As for the years during the crisis, there are also slight economic changes, where the SBLTBL ratio coefficient decreases by 1.17%, while it is slightly more considerable for the MBLTBL ratio by 1.69%. However, the impact of bank size on the two ratios remains statistically significant for both pre- and post-crisis, as well as all-sample periods. Therefore, it can be concluded that the results from the all-sample regressions are robust and, hence, the inverse relationship between bank size and bank propensities toward small and micro business lending appears not to have been substantially influenced by the 2008 credit crisis.

Table 4.3 Fixed-Effects Regressions for Pre and Post the 2008 Credit Crisis

Variables	Model 1 SBLTBL	Model 2 MBLTBL	Model 3 SBLTBL	Model 4 MBLTBL
	1994 – 2007		2008 – 2013	
Log. Assets	-8.62239***	-7.854647***	-7.457246***	-6.169715***
	(-68.31)	(-37.91)	(-19.79)	(-14.11)
Non-performing Loans	-.0335493	-.0577149	.0316545	.0738509**
	(-1.28)	(-1.34)	(1.08)	(2.17)
ROA	.1568539***	.2488841***	.0229563	.0265731
	(3.96)	(3.83)	(0.43)	(0.43)
Leverage	-.1270777***	-.0202912	-.0732918***	-.0060452
	(-16.07)	(-1.56)	(-3.27)	(-0.23)
Multi-Bank Holding Company	-1.728474***	-3.386097***	-1.39424***	-2.349929***
	(-10.13)	(-12.09)	(-2.62)	(-3.80)
Market Deposit Share	-.0225343	.6479314***	-.0048923	.1447121
	(-0.44)	(7.65)	(-0.04)	(1.07)
Log. GDP per capita	-3.22378***	-2.961471*	-.7968813	-2.726113*
	(-3.45)	(-1.93)	(-0.57)	(-1.69)
Interest Income/Earning Assets	.2999385***	-.0329389	.4693207***	.6368938***
	(6.39)	(-0.43)	(3.23)	(3.78)
MSA	1.358602***	-6.832038***	-2.668207*	-4.438309**
	(2.64)	(-8.10)	(-1.76)	(-2.53)
Business Loans/Total Assets	-.3569564***	-.764582***	-.9698446***	-.8219291***
	(-39.96)	(-52.15)	(-42.42)	(-31.00)
Log. age	-.0637153	5.895814***	.4642277	7.323071***
	(-0.26)	(14.93)	(0.70)	(9.56)
Year Dummies	Included	Included	Included	Included
Bank Dummies	Included	Included	Included	Included
No. Observations	129,729	129,729	43,963	43,963
No. Banks	14,133	14,133	8,183	8,183
Prob > F	0.0000	0.0000	0.0000	0.0000
Hausman test statistic	518.63	601.94	313.72	451.05
Hausman test (Prob>chi2)	0.0000	0.0000	0.0000	0.0000
R-sq: within	0.1610	0.2578	0.0849	0.0663
R-sq: between	0.5027	0.4672	0.4948	0.3437
R-sq: overall	0.4076	0.4104	0.4190	0.3001

Note: This table reports results from Fixed-Effects estimations of the effects of bank assets on bank propensities to lend to micro and small business loans. The dependent variables are the measures of lending propensities to micro and small businesses, i.e. (1) Micro Business Loans to Total Business Loans and (2) Small Business Loans to Total Business Loans. The key independent variable is the logarithm of total bank assets. The regression models (1) to (2) contain results for the period prior to the 2008 financial crisis, i.e. 1994-2007. Regression models (3) to (4) contain results for the period followed the 2008 financial crisis, i.e. 2008-2013. T-statistics between parentheses. The symbols ***, ** and * indicate the levels of significance, 1%, 5% and 10%, respectively.

In order to ensure equal exposure of all bank types and sizes to similar market characteristics, I repeatedly re-estimate the same MBL and SBL models, after having the dataset restricted to only banks with more homogenous market and economic characteristics (i.e. only urban areas) and merely specialised in commercial banking. This sequence of regressions ensures robust conclusions for the impact of bank size on micro and small business lending propensities.

4.5.3 Robustness Tests

As with the first robustness regression, I exclude all banks that are headquartered in non-MSAs (i.e. rural counties), limiting my dataset to banks headquartered in counties that are part of MSAs, that is to say, banks headquartered in urban areas. As a result, the number of observations declined by approximately 45%, with 8,938 banks remaining from the main sample. Secondly, I further limit my sample to banks solely specialising in commercial lending, and rerun the same regressions. Finally, I re-estimate the same MBL and SBL models using the subsample of banks in the largest 34 U.S cities. The final subsample consists of 912 banks with 7,188 observations. Since all banks in the robustness regressions are headquartered in MSAs, I drop the MSA variable from the three additional regressions.

Tables 4.4 and 4.5, below, summarise and compare the outcomes of the baseline regression and the additional three robustness regressions for the effect of bank size on the SBLTBL and MBLTBL ratios, respectively. The former shows that the negative effect of bank size on the SBLTBL ratio remains statistically and economically significant, with a coefficient slightly increasing across the four regressions, from 9.54 to 11.69 %.

Table 4.4 Comparison between Bassline and Robustness Regressions for SBL Model

Variables	Model 1	Model 2	Model 3	Model 4
Log. Assets	-9.541565***	-9.661569***	-9.848837***	-11.68784***
	(-90.50)	(-65.74)	(-47.62)	(-20.47)
Non-performing Loans	-.1753629***	-.1584559***	-.0694681**	-.0926968
	(-9.97)	(-6.80)	(-2.35)	(-1.20)
ROA	.1927039***	.1722361***	.2166824***	.2269533*
	(6.23)	(4.46)	(4.03)	(1.68)
Leverage	-.1520507***	-.1364262***	-.1415178***	-.2791901***
	(-21.28)	(-15.80)	(-9.66)	(-6.32)
Multi-Bank Holding	-1.59743***	-2.312771***	-2.444052***	-4.813207***
Company	(-10.16)	(-9.89)	(-8.28)	(-5.19)
Market Deposit Share	.0123119	.0932253*	.2947704***	.7280725***
	(0.27)	(1.83)	(2.59)	(3.17)
Log. GDP per capita	-2.107229***	-2.194682**	-1.359292	-1.31404
	(-3.02)	(-2.26)	(-1.09)	(-0.43)
Interest Income/Earning	.497508	.5650747***	.324623***	.6744221**
Assets	(11.07) ***	(9.01)	(3.38)	(2.37)
MSA	-.7294275*	----	----	----
	(-1.70)			
Business Loans/Total Assets	-.4639655***	-.4768992***	-.4719874***	-.5414475***
	(-58.12)	(-44.01)	(-35.74)	(-15.71)
Log. age	-.916927***	-.2736665	2.121389***	1.348041
	(-4.95)	(-1.13)	(6.80)	(1.38)
Year Dummies	Included	Included	Included	Included
Bank Dummies	Included	Included	Included	Included
No. Observations	173,692	95,393	57,128	7,188
No. Banks	14,453	8,938	6,577	912
Prob > F	0.0000	0.0000	0.0000	0.0000
Hausman test statistic	973.79	581.86	258.28	64.86
Hausman test (Prob>chi2)	0.0000	0.0000	0.0000	0.0000
R-sq: within	0.2259	0.2415	0.2706	0.2789
R-sq: between	0.5360	0.5567	0.5340	0.6261
R-sq: overall	0.4280	0.4568	0.4465	0.5499

Note: This table reports results from Fixed-Effects estimations of the effects of bank assets on bank propensities to lend to small business loans.. The dependent variable is the measure of lending propensity to small businesses, i.e. the Small Business Loans to Total Business Loans. The key independent variable is the logarithm of total bank assets. The regression model (1) contains results including banks in all counties. The regression model (2) contains results including banks in MSA Counties only. The regression model (3) contains results including only commercial banks in MSA counties only. The regression model (4) contains results including only commercial banks in the largest cities only. The period covers the years 1994 to 2013. T-statistics between parentheses. The symbols ***, ** and * indicate the levels of significance, 1%, 5% and 10%, respectively.

Moreover, Table 4.5, below, indicates that although the size effect on the MBLTBL ratio decreases from -7.33% to -2.1%, the effect remains negative as well as statistically and economically significant. It is worth noting that, as I restrict my sample to banks located in urbanised and denser regions, the effect of bank size on the SBLTBL ratio increases, while it decreases for the MBLTBL ratio. Such patterns can be attributable to two correlating reasons: firstly, a smaller presence of smaller banks in the largest, densest cities in the United States and, secondly, smaller banks seem to become more prone, in the denser areas, to increase the size of their small business loans by targeting larger and more secure businesses than micro, opaque businesses. That is to say, those banks tend less to disperse their small business loans in order to reduce the due-diligence, transactions, and monitoring costs.

Table 4.5 Comparison between Bassline and Robustness Regressions for MBL Model

Variables	Model 1	Model 2	Model 3	Model 4
Log. Assets	-7.334459***	-5.172862***	-4.310591***	-2.103479***
	(-45.76)	(-27.56)	(-20.75)	(-4.75)
Non-performing Loans	0.0268057	-0.0122925	0.0140835	0.0318352
	(1.00)	(-0.41)	(0.47)	(0.53)
ROA	.2050129***	0.0521211	0.165622***	0.076485
	(4.36)	(1.06)	(3.07)	(0.73)
Leverage	-0.0035444	0.0264224**	-0.031319**	0.0007443
	(-0.33)	(2.40)	(-2.13)	(0.02)
Multi-Bank Holding Company	-3.54008***	-2.762401***	-1.539053***	-2.274027***
	(-14.80)	(-9.25)	(-5.19)	(-3.17)
Market Deposit Share	0.532371***	0.3838***	0.844012***	0.528763***
	(7.75)	(5.91)	(7.37)	(2.97)
Log. GDP per capita	-2.654262**	-1.30609	-0.4454841	-3.163668
	(-2.50)	(-1.05)	(-0.36)	(-1.33)
Interest Income/Earning Assets	0.0048192	0.1004549	0.380559***	.4371092**
	(0.07)	(1.25)	(3.95)	(1.98)
MSA	-6.449522***	----	----	----
	(-9.86)			
Business Loans/Total Assets	-0.775906***	-0.669536***	-0.439123***	-0.338486***
	(-63.94)	(-48.37)	(-33.10)	(-12.67)
Log. age	6.416471***	5.173096***	2.446076***	-0.4213027
	(22.81)	(16.73)	(7.80)	(-0.56)
Year Dummies	Included	Included	Included	Included
Bank Dummies	Included	Included	Included	Included
No. Observations	173,692	95,393	57,128	7,188
No. Banks	14,453	8,938	6,577	912
Prob > F	0.0000	0.0000	0.0000	0.0000
Hausman test statistic	1370.40	1288.07	851.34	95.90
Hausman test (Prob>chi2)	0.0000	0.0000	0.0000	0.0000
R-sq: within	0.3267	0.3115	0.2834	0.2174
R-sq: between	0.4612	0.3621	0.2686	0.3142
R-sq: overall	0.4250	0.3740	0.2811	0.2853

Note: This table reports results from Fixed-Effects estimations of the effects of bank assets on bank propensities to lend to Micro business loans. The dependent variable is the measure of lending propensity to micro businesses, i.e. the Micro Business Loans to Total Business Loans. The key independent variable is the logarithm of total bank assets. The regression model (1) contains results including banks in all counties. The regression model (2) contains results including banks in MSA counties only. The regression model (3) contains results including only commercial banks in MSA counties only. The regression model (4) contains results including only commercial banks in the largest cities only. The period covers the years 1994 to 2013. T-statistics between parentheses. The symbols ***, ** and * indicate the levels of significance, 1%, 5% and 10%, respectively.

Moreover, state development initiatives to support small businesses, such as those run by the U.S Small Business Administration (SBA) and the Federal Financial Institutions Examination Council

(FFIEC), introduced in 1953 and 1977, respectively, may have alleviated the negative effect of bank size on micro business loan share at large banks.

The Community Reinvestment Act (CRA) requires banks with an asset size over $300 million to report their small business loans to the FFIEC, in order to encourage larger banks to allocate a greater share of their loans to small businesses. One-third of the banks in the subsample have assets greater than $300 million. Therefore, the decline in the coefficient of the effect of bank size on the MBLTBL ratio could be mainly attributed to such initiatives.

From the above robustness tests, I know that the regression results from the main sample – that large banks issue large loans and small banks issue small loans – remain robust when controlling for different market and economic conditions by focusing on banks in urban areas.

4.6 Conclusion and Policy Implications

The objective of this chapter was to examine the impact of bank size on the propensity of banks to lend to small and micro businesses, using a representative dataset with a long time span covering the two decades from 1994 to 2013. This research introduced two new measures of bank propensity to small business lending, namely, the ratio of small business loans to total business loans and the ratio of micro business loans to total business loans.

My findings revealed an inverse relationship between bank size and the relative share of small and micro business loans held by the banks. In other words, the propensity of banks to lend to small businesses decreases as the size of the banks become larger, and vice versa. The results hold for the sub-periods before, and during, the 2008 financial crisis, as well as for banks that are only specialised in commercial lending and which operate in a more homogeneous environment with respect to market and economic conditions, proving the robustness of my findings. Since my sample consists of all domestically active and inactive banks which the FDIC has insured over the past two decades, the results support the conventional wisdom, and can be generalised to be representative of the United States of America, which possesses one of the largest economies in the world and is home to the largest number of banks in any one country. Thus, it is likely that the findings are also relevant for other countries.

The findings have policy implications for the industrial organisation of the banking sector. It is well known that the vast majority of businesses in most countries are small and very small firms. These firms also account for the majority of employment in most countries, and any given amount of money invested in such small firms tends to create more jobs than the same amount invested in a large or very large firm. As a result, policy-makers in many countries have recently emphasised the importance of ensuring adequate funding of SMEs. Such firms are not usually able to tap into capital markets and are, therefore, dependent on borrowing from banks. The research presented in this chapter shows that such bank funding is only likely to be forthcoming, if the economy is characterised by a large number of small banks.

In this chapter, the important question of finance constraints was examined anew. The debate about the role of the shape of the banking sector in causing financing constraints had been undecided, and this chapter presents the largest empirical examination hitherto existing on this question. Through careful empirical examination, it is shown that, on balance, large banks lend to large firms, and small banks only lend to small firms. Thus, banking systems which do not include a significant proportion of small banks, such as is the case in the U.K, will hamper the growth of small businesses, whereas systems, such as that in the U.S, with a large number of small and community banks, are more conducive to their growth.

This means that a key barrier to growth by SMEs - including growth in their exports - can be overcome by shaping the structure of the banking system such that it is dominated by a large number of small, local banks, as is the case in the U.S and Germany, but distinctly not so in the United Kingdom. Amidst the rise of crowdfunding and peer to peer lending structures, it can be noted that community banks, in operation for 200 years in Germany, have been the original 'crowd funders'. Belleflamme *et al.*, (2014) concluded that "Building a community that supports the entrepreneur is crucial for crowdfunding to be a viable funding mechanism." This is what community banks have been offering for the past centuries.

In this chapter, I have confirmed the need for banking systems that are not concentrated but, rather, characterised by a large number of small banks. Furthermore, even in an economy that boasts many small banks, I have shown that it will continue to be necessary to launch initiatives to newly establish independent small banks, because the old banks become large and, over time, begin to behave more like large banks. As this research has focused on the relationship between bank size and borrower size, it has not attempted to quantify the impact on economic growth of differing bank sizes. This can be addressed more directly in further research.

Chapter 5

Local Banks and Regional Growth: A Distributional Analysis

Chapter 5: Local Banks and Regional Growth: A Distributional Analysis

5.1 Introduction

Recent theoretical and empirical work has demonstrated that local banks and small business lending are very effective in promoting local economic growth, especially in regions with lower initial endowments and acute credit rationing (Hakens *et al.,* 2015). However, recognising the effectiveness of small/local banks in regional economic development vis-à-vis large-banks, has not been straight-forward. Indeed, the extant literature is replete with evidence that the present clear trend of banking systems towards greater market concentration (see, among others, Carbo-Valverde *et al.,* 2009; Koetter *et al.,* 2012), scale economy (for instance, DeYoung, 2012; Wheelock and Wilson, 2012), and too-big-to-fail firms (for instance, Stolz and Wedow, 2010) is paving the way towards large banks. However, as argued by Hakens *et al.,* (2015), these banks seriously exploit financial safety nets and have succumbed to systemic risk during the recent financial crisis. Kendall (2012) and Hakens *et al.,* (2015), and others, provided both a theoretical underpinning and robust empirical evidence in the case of developing and developed countries' local economic development contexts, and demonstrated that, due to the very nature of relational lending and extensive dealing with individual (not aggregate) uncertainties, the growth of the local banks and their persistent lending strategies are instrumental in promoting local economic growth. Given the sparsity of this line of research, any desirable policy interventions require robust evidence of the definitive roles of local banks in regional growth dynamics, especially the nature of the heterogeneous effects that local banks would exert on the distribution of regional economic growth over time.

This is important for a number of reasons. For instance, there is no guarantee that local banks will exert similar effects on local economic development at various points in the distribution of local economic growth. As one would normally expect, the effects can be large and positive for regions at the lower end of the distribution of economic growth, mainly because the persistent supply constraint may motivate the local economies to exploit resources from the local banks. However, along its growth trajectory, when a local economy faces competition of choice among a larger number of local banks, the selection bias may lead some of the banks to exit. Some medium to large size banks intervene in the market and take advantage of the growth opportunities by offering competitively priced loans and wider access to financial markets. The continuous crowding-out effects may lead local economies to choose between a mix of small and large banks, depending on the amount and type of credit they would like to borrow.

Moreover, this is also a time which sees a rapid growth of human capital (due to the growth-human capital nexus). With greater human capital, the economies might see an increase in new entrepreneurs, leading to a process of higher economic growth in the long-run. The mix of new entrepreneurs, small and large banks in the region and the experience of growth take-off may lead to a relationship where the net contribution of local banks to regional economic growth will be positive, but smaller in magnitude (due to the fact that some of the positive effects are taken away by the intervention of large banks and a shift of entrepreneurial strategy to bigger investments). At a higher quantile of growth, there can be two possibilities: (i) local banks will contribute to the net growth of the economy by focusing on new local entrepreneurs (the only condition is that population growth is above the replacement level and that human capital should be growing monotonically as well) and, hence, the net effect can still be positive, but smaller in magnitude, and, (ii) due to high competition, some local banks will exit the market, giving way to large banks. Because small banks have limited access to government safety nets and are generally weak at loan diversification, there will be little they can do in terms of innovation to ensure sustainability during high-growth periods. The net growth effects in this case, then, can be very insignificant. Due to the perceived heterogeneous effects of local banks on both the short- and long-run growth objectives of regions, policy interventions may be needed to ensure that: (i) localisation effects are sustained, because of the comparatively minimal cost required to minimize individual (in relation to aggregate) uncertainties, and, (ii) local stability can be relied upon to achieve global stability.

As discussed in details in Chapter 2, the importance of a greater presence of local banks in local economies cannot be overemphasized. For instance, Ashcraft (2005) finds that the closure of healthy banks, as a result of the failures of their mother banks, have detrimental effects on local incomes. Further, a greater presence of community banks helps in reducing the rates of home foreclosures (Fogel *et al.*, 2011), and prevents capital drain from poor to rich regions, as small banks spur regional development in all regions and more prominently in less developed ones (Hakenes *et al.*, 2015). Although my hypothesis employs the findings of Ashcraft (2005), Fogel *et al.*, (2011) and Hakenes *et al.*, (2015), their work is not designed to flesh out the distributional aspects of the local bank impact on local growth across regions. Also, my SME lending-based variables of local banking differ from their bank-performance and local deposit measures.

Motivated by the controversies in the extant literature, I collect a representative large county-level dataset from the United States to study the impact of the local banking structure on regional economic development over the period from 1994 to 2013. Specifically, I examine the hypothesis that a greater contribution by locally-operating banks to SME lending spurs local economy. Empirically, I utilise the supply channel of loans to micro and small businesses as a proxy measure for local banking presence. These measures are constructed in order to assess the impact of local banking presence on local economic development. However, the effects of local banks may vary measurably across the distribution of regional economic growth. Therefore, I extend my analysis and test deeper such relationships. That is to say, the positive impact of local banking development may vary in accordance with the level of local economic development. For instance, less developed regions may benefit more from a greater presence of local banks through their exclusivity in lending to small businesses.

While the theoretical basis of my work draws on the overlapping generations model, as in Hakenes *et al.*, (2015), I also recognize the importance of incomplete information and imperfect market structure, which can determine the extent to which growth in small bank business lending would impact local economic growth. I propose an economy with a persistence of uncertainty, leading to information cascades among economic agents. Banks, small or large, like other economic agents, also suffer from this information cascade and may fail to implement strong policies that may promote economic growth, which, at the same time, preserve their objective of profit maximization. Secondly, I consider a scenario where small banks face competition in a region at the lower quantile in its growth distribution, since they are limited in their lending capacity. As the number of banks rises, the greater competition leads to the exiting of some banks or closure of some branches. At the same time, large banks may enter the market as leaders, and will put pressure on small business lending, either to close it down or to innovate in order to succeed, in the face of greater competition. In this case, since small business lending can do little to innovate, their survival, as well as growth, depends on the demographic growth of that region as well as the establishment of new opportunities, which, once again, would rely on small business lending to kick start the growth. With these propositions in mind, as the economy transits from low to high-growth trajectories over time, it is pertinent to ask how the growth of small business lending spurs local economic growth at each point of the distribution of economic growth over time.

To shed deeper light on these questions, I undertake a regression using both a ‘mean’ based panel regression that accounts for endogeneity bias, and a ‘quantile’ based instrumental variable panel regression that exploits the full distributional heterogeneity of the impact of small business lending on local economic growth. I construct a new instrument based on the concept of a yield curve. The findings confirm the hypothesis (i.e. H2) that a greater presence of local banks, through SME lending, has a significant impact on local income and employment. More specifically, the results confirm the hypothesis (i.e. H3) about the distributive consequences of the local banks on local economic development. That is to say, the impact of local banks varies across the distribution of regional economic development.

The remainder of the chapter is outlined as follows – The subsequent section describes the dataset and data sources and then explains the variables used in this study as well as the rationale underpinning their use. The following section presents the model specification, the instrumental variable calculation and the quantile regression approach. Section 5.4 reports the findings and highlights the common results among the models used. The final section concludes the chapter and introduces the implications.

5.2 Data

5.2.1 Local Banks and SME Lending

Since the key hypothesis in this chapter is to examine the impact of local small business lending on local economic growth, I should define what is meant by *local banks and local markets*: Firstly, the local market is defined as the market associated with any county in the United States. I follow previous studies in determining the size of local markets (e.g. Ashcraft, 2005; Huang, 2008; Fogel *et al.*, 2011). According to informal discussions with bank examiners in the Federal Reserve System and with community bankers, 75–90% of the loan customers of typical single-county local banks reside within the county (Yeager, 2004). I, additionally, distinguish between rural and urban markets. The latter is a county, which is part of a Metropolitan Statistical Area (MSA), while the rest are regarded as rural markets (Collender and Shaffer, 2003). Overall, my dataset consists of 2,590 counties, where 1,014 counties are urban and 1,576 counties are rural. The time scale spans over 20 years from 1994 to 2013.

My primary source of banking data is from the Federal Deposit Insurance Corporation (FDIC). “The FDIC collects, corrects, updates and stores Reports of Condition and Income data submitted to the FDIC by all insured national and state non-member commercial banks and state-chartered savings banks on a quarterly basis. Reports of Condition and Income data are a widely used source of timely and accurate financial data regarding a bank’s condition and the results of its operations” (FDIC, 2014). The Statistics on Depository Institutions (SDI) stores data about banks’ balance sheets, while the Summary of Deposits (SOD) contains data about branches and office deposits. Both the SDI and the SOD are managed by the FDIC.

The small business lending and branch office deposits data which is only reported annually as of June 30th. Accordingly, I construct an unbalanced panel dataset of 38,149 observations. Secondly, a local bank is any domestically owned depository institution that has all its branches, including the headquarters, within the geographical borders of a single county (DeYoung *et al.*, 2004; Fogel *et al.*, 2011). For simplicity, I term small and micro business loans made by local banks as local small and micro business lending and all types of depositary institutions as a “bank”.

It is worth noting that the United States consists of 3,143 counties and county equivalents. The reason I only have 2,590 counties in this research is that the excluded counties may not have locally headquartered banks that are insured at the FDIC, relying primarily on branches of banks based in other counties, and/or other types of financial institutions. In addition, it would be ideal if I obtain aggregate the small business lending data of non-local banks (i.e. multi-county banks) at the county-level. Such data would provide further room for comparison between the independent effects of local and non-local banks on local economic growth. Unlike deposit data, the FDIC reports lending data is at bank-level, not branch-level. However, county-level data for non-local banks is only available from the Federal Financial Institutions Examination Council (FFIEC) collected under the Community Reinvestment Act (CRA) for banks with asset size of over $250 million, that is to say, a large number of non-local banks with less than $250 million do not report the amount of small business loans in each county. For instance, 3,646 out of the 6,949 banks operating in 2013 do not meet my definition of locality, as only 850 of them report CRA small business loans to the FFIEC. A very simple calculation reveals that county-level small business loans are not obtainable for 2,796 non-local banks. Therefore, I confine my analysis to the FDIC's available data, based on my definition of bank locality.

5.2.2 Local Economic Development (Dependent Variable)

Since there is no available data for GDP at county-level to represent local economic development, I interchangeably employ two of the most widely used measures of economic activities in the empirical literature as dependent variables. Firstly, I use income measures, i.e. the growth rate of per capita real income and the logarithm of total real income, which are collected from the U.S Bureau of Economic Analysis (BEA). Secondly, employment measures, i.e. the growth rate of total employment and the logarithm of total employment, which are collected from the Bureau of Labour Statistics (BLS) as the number of jobs in a county. The rationale behind using income measures is to capture the extent to which changes in the quantity of SME loans may lead to changes in the locally available purchasing power, a proportion of which can be expected to be local income. In addition, I use employment measures to capture how many jobs in a county are created by an increase in SME loans.

5.2.3 Local Banking Measures (Key Explanatory Variable)

The FDIC defines the small business loans (SBL) as the amount of currently outstanding commercial and industrial loans with original amounts less than $1,000,000 held in domestic offices. In addition, I consider loans with original amounts less than $100,000 to be the micro business loans (MBL) (i.e. loans granted to the smallest of the small businesses). Small business lending data is available at bank-level from the FDIC. I aggregate all small business loans that are reported each year by all local banks in a county. For simplicity, I use the terms Local Small Business Loans (LSBL) and Local Micro Business Loans (LMBL) for Small Business Loans and Micro Business Loans that are provided by local banks, respectively. Both the LSBL and the LMBL variables are transformed into logarithms.

A number of researchers have adopted the FDIC definition of small business loans, such as Keeton (1995), Strahan and Wetson (1998), Peek and Rosengren (1998), Carter and McNulty (2005), Carter *et al.,* (2004), and Berger *et al.,* (2011). Although, in theory, the data is based on the loan size, not the company size, it is reasonable to interpret the data in the way in which the FDIC and authors have done it. That is to say, because of the due-diligence and transactions costs, it is highly likely that large companies will not take out very small loans, while small companies cannot take out large loans. Therefore, this approximation is very reasonable and has become the standard in the literature. According to the Community Reinvestment Act (CRA), on average 93% of small business loans have loan amounts less than $100,000. The CRA requires banks with an asset size greater than $300 million to report their small business loans. In addition, primary surveys have established a close correspondence between loan size and the size of the borrower. For instance, according to the 1989 NSSBF, 80 percent of loans to businesses with less than $1 million in annual sales amounted to less than $100,000 each (Board of Governors). Earlier surveys have shown similar results (Keeton, 1995).

5.2.4 Control Variables

A set of control variables are inserted into the model specifications to isolate the impact of local small business lending on local economic activities. The selected variables may affect local activities and, hence, their omission could generate biased regression estimations.

Return on Asset (ROA): This is defined as the return on average total assets of local banks (Source: FDIC). That is to say, net income after taxes and extraordinary items (annualised) as a percent of average total assets. I use it to control for the performance of the local banks (also used by Hakenes *et al.*, 2015).

Equity Ratio: This is the total equity capital as a percent of total assets (Source: FDIC). Hakenes *et al.*, (2015) argue that banks with a lower equity ratio may have a relatively greater return on equity, resulting in biased estimations. Additionally, this ratio controls for the level of management risk-taking.

Non-interest income/interest income: This represents the percentage of non-interest income relative to interest income (Source: FDIC). According to Hakenes *et al.*, (2015), a number of local banks may tend to maximise their profits through potentially higher marginal commission services, which may positively incorporate bank profitability and efficiency measures. Consequently, I, as Hakenes *et al* do, control for bank non-interest income to isolate such an effect.

Inflation: I use the annual U.S Consumer Price Index (CPI). Fluctuations in the inflation rates may lead to an unstable economy. For instance, higher inflation makes investors more reluctant to invest in local economies, causing slower economic growth. Adding an inflation variable helps to control for such macroeconomic fluctuations.

Labour Force: In this chapter I use the number of total adults who are able to work. This measure is a proxy for human capital. Previous studies have shown a strong positive relationship between human capital and local economic growth (e.g. Glaeser, 2000); Kirchhoff *et al.*, 2007). (Source: U.S Bureau of Labour Statistics, BLS). The labour force is expected to have a positive impact on economic development.

Population Growth: I also use the growth rate of population in a county. This measure is an alternative proxy for human capital. The U.S Bureau of Economic Analysis (BEA). The population growth is expected to have a positive impact on economic development.

Herfindahl-Hirschman Index (HHI): A relevant factor to be considered as affecting the credit market is the banking competition or the level of market power in the local market. The deposit market HHI measure is often used in the literature to represent the local market competition. (Source: Summary of Deposits by FDIC).

Degree of Urbanisation: This is a dummy variable which takes the value of '1' if a county is part of a Metropolitan Statistical Area (MSA), which is regarded as an urban county, or '0' if it is a non-MSA, indicating a rural county. This variable indicates the level of market competition and economic development where banks are active (i.e. urbanised areas, as in MSA, exhibit higher market competition and greater economic development than rural Non-MSA ones). (Source: FDIC).

Banking Density: I add a measure of the density of bank branches in a single county. It is calculated as the number of bank branches per 100,000 local residents in a county. (Source: Summary of Deposits by FDIC and BEA). This variable is expected to have a positive impact on local economies.

5.2.5 Preliminary Observations

In Table 5.1, below, I have provided descriptive statistics of both predictors and predicted variables of interest. As noted previously, local economic activity is measured in my study by income per capita growth, employment growth, total income and total employment. From Table 5.1, I observe that the mean per capita income growth is 4.29 and the standard deviation is 5.404 (there is a big dispersion between the minimum of -44.67% and the maximum of 115.20%). Those big outliers represent the very dense and wealthy counties, such as Los Angeles, Cook and New York. In terms of their overall distribution, the above point on distributional dispersion becomes clear; the percentage growth at the 10th quantile of the 2,590 counties is negative (-0.612) whereas the percentage growth at the higher quantile (90th quantile) is 9.001%. The median growth (4.062%) is also smaller than the mean growth (4.298%). If employment level (or growth) is taken as a measure of local economic development, one comes across a similar pattern of significant heterogeneity across quantiles. In sum, I find that across counties there is a significant degree of heterogeneity in local economic growth. This is also supported by the Kernel density plots of per capita income (see Appendix D), which depict spread at the extreme parts of the distribution and indicates that many low-performing regions may be 'clustered' (this is an indication of multimodal distribution). It remained to be seen if such a growth pattern responds uniformly to the impulse of the rising business lending provision at the local level.

As such, investigating the distributional patterns of bank lending in Table 5.1, I observe that the mean LSBL is 19.336, which is measurably greater than the median (8.469). The difference is acute between the average at the 10th quantile (1.617) and the 90th quantile (38.88). A similar pattern emerges for the LMBL (0.901 for the 10th quantile and 17.36 for the 90th quantile). It is expected that a change in the LMBL or the LSBL at the lower quantile may have a largeer positive effect on local economic growth than it is for the higher quantiles, because low performing regions generally look out for opportunities for expansion and such a loan provision can instantly trigger a growth upsurge in this region faster than it is on the higher quantile. This prediction is conditional on various factors, which are investigated in some details in the following section.

Banking density, measured by the number of banks per 100,000 local residents, can be an indicator of local economic prosperity as higher density implies greater access to financial resources by the local entrepreneurs. From Table 5.1, below, I find that the mean bank density is 49.12 per 100,000 local residents with a dispersion of 28.62. Such a high dispersion from the mean implies that some counties experienced very low bank density in comparison to others. This is indeed the case, if I study the distribution of bank density across quantiles: the density at the 10th quantile is approximately the size of the median and more than three times smaller than the number at the 90th quantile. The HHI index (of market concentration) also evinces an interesting pattern, specifically, the 90th quantile displays a market concentration (0.501) which is four times larger than at the 10th quantile (0.119). All these facts lead to an important point: there is a significant degree of heterogeneity of all variables over the distribution. The dispersion between the lower and higher quantiles are acute and such differences are likely to impact my inference regarding the real effect of local SME lending on local economic growth.

Table 5.1 Summary Statistics

Variable	Description	Mean	Min.	Max.	No. Obs.	Std. Dev.	10th Qntle.	Med.	90th Qntle.
Local Economic Activity									
Income per capita growth (%)	Annual growth rate of real income per capita in a county	4.29814	-44.67	115.20	35,281	5.4044	-0.612	4.062	9.001
Employment growth (%)	Annual growth rate of total employment in a county	0.00775	-1	0.732	35,280	0.0398	-0.033	0.008	0.048
Total income (Million)*	Real total income in a county, in million	4314	6.021	466100	38,149	14667	149.8	728.3	9150
Employment ('000)*	Total employment in a county, in thousands	55.2608	0	4201	38,149	178.56	1.79	9.728	122.6
Bank Lending									
LSBL (Million)* (Loans < $1000,000)	Total small business loans provided by local banks in a county, in million	19.336	0.001	2128.7	38,149	53.70	1.617	8.469	38.88
LMBL (Million)* (Loans < $100,000)	Total micro business loans provided by local banks in a county, in million	8.5228	0	1757.5	38,149	26.64	0.901	4.521	17.36
Control Variables									
Bank Specific Variables									
ROA (%)	Return on average total assets for local banks in a county	1.032	-13.93	13.89	38,130	0.999	0.337	1.128	1.786
Equity Ratio (%)	Total equity capital as a percent of total assets for local banks in a county	11.29	0.598	87.12	38,149	4.058	8.038	10.48	15.11
Non-interest income/interest income (%)	Percentage of non-interest income relative to interest income for local banks in a county	12.43	-205.6	499.7	38,138	11.27	5.784	12.07	16.25
Local Market Variables									
Population growth (%)	Growth rate of population in a county	0.006	-0.534	0.238	35,281	0.015	-.0278	0.004	0.023
MSA dummy	= 1 if a county is MSA, = 0 for Non-MSA	0.399	0	1	38,149	0.49	0	0	1
Inflation %	Annual U.S Consumer Price Index (CPI)	2.448	-0.356	3.84	38,149	0.868	1.558	2.663	3.361
Banking density	Number of bank branches per 100,000 local residents in a county	49.12	4.583	263.5	38,149	28.62	23.83	41.05	84.53
Market concentration (HHI) (%)	Deposit market Herfindahl-Hirschman index in a county	0.272	0.034	1	38,149	0.17	0.119	0.224	0.501
Labour force (Million)	Number of labour force available in a county, in Million.	0.063	0.0002	4.982	38,147	0.188	0.003	0.015	0.144
Instrumental Variable									
Yield Curve (%)	The average interest rates on loans minus the average interest rate on deposits for local banks in a county	0.026	-0.018	0.473	38,149	0.007	0.020	0.026	0.0331
Time Dummies	Twenty dummy variables for the years 1994-2013								

Note: * The LSBL, LMBL total income, and employment variables are displayed in million, while each of them is converted to a natural logarithm when included in the regressions.

5.3 Model Specifications

The following two model specifications seek to test two propositions (i.e. H2 and H3) presented in Chapter 3. The first technique is a dynamic panel data approach which aims to examine the hypothesis that local banks stimulate local growth through SME lending channel. The second approach is a quantile panel IV approach, which investigates the hypothesis that local banks differently stimulate local growth based on the level of development.

5.3.1 Dynamic Panel Estimation

The first model specification in this chapter aims to examine the hypothesis that local banks stimulate local economic growth through SME lending channel. It utilises U.S regional data over the period from 1994 to 2013. To test such proposition, I model and estimate the Equation (3.4) which incorporates the properties of the dynamic panel data model as detailed in section (3.3.1). Therefore, I estimate the following GMM dynamic panel estimation:

$$\begin{aligned} Ygr_{it} &= \alpha Ygr_{it-k} + \beta_1 LOAN_{it} + \beta_2 \{LOAN_i * Y_{1994}\} + \beta_3 Y_{it} + \beta_4 ROA_{it} + \\ &\beta_5 EQV_{it} + \beta_6 INT_{it} + \beta_7 HHI_{it} + \beta_8 LABF_{it} + \beta_9 INF_t + \beta_{10} BDEN_{it} + \\ &\beta_{11} YD_t + \beta_{12} RD_i + \varepsilon_{it} \end{aligned} \tag{3.4}$$

where i represents the county and t the year. Ygr_{it} represents the growth in economic activities, that is to say, I interchangeably use the per capita income growth and the total employment growth. Ygr_{it-k} represents the lags of the dependent variable. $LOAN_{it}$ represents each of the two local banking indicators, firstly, the LSBL and, secondly, the LMBL. $LOAN_i*Y_{1994}$ is the interaction of the lending measure with the initial per capita income or total employment. Y_{it} is the level of income. The rest is a set of control variables, namely, return on asset (ROA), equity ratio (EQV), non-interest income/interest income (INT), Herfindahl-Hirschman index (HHI), labour force (LABF), inflation (INF), Metropolitan Statistical Area (MSA), and banking density (BDEN). YD_t is the set of yearly dummy variables. RD_i is the set of region dummy variables, and ε_{it} is the error term.

To test the overall validity of the instruments used in the regressions, I report the Hansen test of over-identifying restrictions for each regression. Additionally, I employ the autoregressive (AR) test to check for serial correlation between the error term and both the difference regression and the system difference-level regressions. Serial correlation must not exist at the second order of the differenced error term or at a higher order. Accepting the null hypotheses of both tests grants support to the validity of the instruments and the no serial correlation assumption; consequently, the estimated model is consistent. I also report the results of the IPS test for stationarity in Appendix A.

5.3.2 Estimating Distributional Heterogeneity

The second model specification in this chapter is an instrumental quantile panel approach which investigates the hypothesis that local banks differently stimulate local growth based on the level of development of the regions. It also utilises U.S regional data over the period from 1994 to 2013. To do that, I recall the model in Equation (3.13) which invokes the properties of quantile panel data regressions (see section 3.3.2):

$$Y_{it} = \alpha\ (q) + \delta_1(q)LOAN_{it} + \delta_2(q)ROA_{it} + \delta_3(q)EQV_{it} + \delta_4(q)INT_{it} + \\ \delta_5(q)HHI_{it} + \delta_6(q)LABF_{it} + \delta_7(q)INF_t + \delta_8(q)BDEN_{it} + \varpi i(q) \tag{3.13}$$

where i represents the county and t the year. Ygr_{it} represents the economic activities, that is, I interchangeably use the total income and the total employment, both in logarithm. $LOAN_{it}$ represents each of the two local banking variables, firstly, the LSBL and, secondly, the LMBL. The rest is a set of control variables, namely, return on asset (ROA), equity ratio (EQV), non-interest income/interest income (INT), Herfindahl-Hirschman index (HHI), labour force (LABF), inflation (INF), Metropolitan Statistical Area (MSA), and banking density (BDEN). $\varpi i(q)$ represents the error term at each quantile. Also, $\alpha(q)$ and $\beta(q)$ represent the unknown parameters associated with the q^{th} quantile, $q \in (0,1)$. I present the estimations of five quantiles, i.e. (0.1), (0.2), (0.5), (0.7), and (0.9), below.

In order to control for the potential endogeneity of the LSBL or the LMBL I employ Powell (2015)'s unconditional quantile panel IV method (discussed in section 3.3.2). Unlike the GMM analysis, which uses lags of the dependent variable as instruments, I construct an instrumental variable based on regional yield curve (details are in section 5.4.2).

5.4 Empirical Analysis

My empirical analyses are divided into two parts. Firstly, I present results from the conventional panel GMM estimation, where endogeneity in the model is accounted for by using various lags of the dependent variable as regressors. I intend to compare the results from this estimation with related work that employed the mean-based dynamic panel data method (although in different country contexts).

My second set of results follows the lead of my objective: study of the effects of the local SME lending at various parts of the distribution of regional economic growth. To this effect, I have estimated panel quantile regression with endogenous regressors. As mentioned in the preceding section, I have proposed an instrument and have used this for the estimation of the quantile regression for the panel data.

5.4.1 Panel and Cross-Sectional Regression Evidence (without Distributional Heterogeneity)

I test several hypotheses related to the impact of the local SME lending on local economic growth, conditional on various assumptions. My empirical model is based on the convergence-pattern hypothesis. Prior to estimating the GMM regressions, I perform an IPS unit-root test for unbalanced panel data to verify the stationarity of the included variables. The results of all unit-root tests, shown in Appendix A), reject the null hypothesis and confirm that all variables are stationary in the level format and do not need to be differenced. Therefore, all relevant variables enter this empirical analysis in the level format.

In Tables 5.2-5.5, below, I present the two sets of results. Tables 5.2 and 5.4 present results from the cross-sectional regression, i.e., regression results corresponding to each five years gap beginning in 1995. This time period also roughly corresponds to an election cycle or the full terms of governance (although the period varies from county to county). Moreover, the span of five years also reflects the dynamics that, starting from a bank's establishment until realising the full-economic growth effect as well as devising strategies for further growth, takes about a full-planning year with an elected government in office (because the change in governance might also diversify policy emphases). Tables 5.3 and 5.5 present the estimated results from the dynamic panel regression (which covers the whole sample).

Moreover, Tables 5.2-5.5, below, show estimates for two measures of local economic growth, namely, per capita real economic growth for the region (Tables 5.2 and 5.3) as well as the growth of employment as a proxy for local economic development (Tables 5.4 and 5.5). I have estimated four models which correspond to the various columns in each table, representing whether an initial per capita income/employment level has been used and interacted with the explanatory variables. For the cross-sectional regression, I have estimated four five-annual periods, specifically, 1995, 2000, 2005, and 2010.

Table 5.2 Cross Sectional Regressions for Income per Capita with Different Initial Conditions

Dependent Variable: Income Capita Growth	1995		2000		2005		2010	
LMBL	5.445***	---	1.762***	---	.581***	---	.735***	---
	(80.76)	---	(15.71)	---	(5.65)	---	(6.59)	---
LSBL	---	5.185***	---	1.691***	---	.535***	---	.651***
	---	(76.29)	---	(14.91)	---	(4.82)	---	(5.40)
LMBL × Initial Capita Income	-.293***	---	-.090***	---	-.036***	---	-.039***	---
	(-95.23)	---	(-19.45)	---	(-9.08)	---	(-10.73)	---
LSBL × Initial Capita Income	---	-.280***	---	-.087***	---	-.0357***	---	-.036***
	---	(-90.64)	---	-(19.37)	---	(-9.56)	---	(-10.81)
Capita Income	4.494***	4.470***	1.013***	1.028***	.389***	.417***	.344***	.350***
	(97.56)	(92.83)	(21.40)	(21.23)	(11.92)	(12.40)	(12.92)	(13.04)
Inflation	---	---	---	---	---	---	---	---
	---	---	---	---	---	---	---	---

ROA	.2382***	.194**	-.024	-.017	.036	.029	.144	.136
	(2.88)	(2.26)	(-0.25)	(-0.17)	(0.29)	(0.24)	(1.34)	(1.27)
HHI	1.622***	1.967***	-.372	-.141	3.443***	3.341***	4.347***	4.401***
	(6.91)	(7.98)	(-0.68)	(-0.25)	(5.41)	(5.18)	(5.59)	(5.61)
Labour Force	2.761***	3.357***	1.080**	1.185**	1.023*	1.181**	-.289	-.154
	(10.07)	(11.63)	(2.04)	(2.20)	(1.94)	(2.20)	(-0.50)	(-0.26)
Non-interest income/interest income	.0381*	.042*	.086*	.083*	.0158**	.0156*	-.003	-.001
	(1.79)	(1.89)	(1.76)	(1.69)	(1.97)	(1.94)	(-0.32)	(-0.09)
Equity Ratio	-.026*	-.025	-.027	-.025	-.0444	-.044	-.024	-.023
	(-1.71)	(-1.63)	(-1.08)	(-1.01)	(-1.54)	(-1.51)	(-0.67)	(-0.63)
Banking Density	-.0102***	-.0127***	.0127***	.0122***	-.004	-.005	-.010**	-.011***
	(-6.34)	(-7.60)	(4.06)	(3.83)	(-1.17)	(-1.60)	(-2.55)	(-2.73)
Constant	-83.42***	-82.341***	-21.65***	-21.844***	-6.759***	-6.671***	-9.458***	-9.161***
	(-72.37)	(-68.99)	(-11.90)	(-11.43)	(-4.38)	(-3.79)	(-5.59)	(-4.74)
Number of Obs.	2,354	2,354	1,987	1,987	1,723	1,723	1,495	1,495
R-squared	0.8317	0.8180	0.2048	0.2027	0.1147	0.1197	0.1483	0.1499

Note: This table reports results from simple cross-sectional estimations of the effects of local banks on regional economic development at different years. The dependent variable is the growth rate of Income per Capita at county-level. The measures of local bank SME lending include two indirect indicators at county-level — (1) Local Micro Business Loans (LMBL) and (2) Local Small Business Loans (LSBL). Regression models (1995) to (2010) correspond to each five years gap beginning in 1995. Each year, the regression is firstly estimated with the LMBL and secondly with the LSBL. The period covers the years 1994 to 2013. P-values are reported in parentheses. The symbols ***, ** and * indicate the levels of significance, 1%, 5% and 10%, respectively.

Table 5.3 Convergence-Type Income per Capita Growth Regression: Dynamic Panel Model

Dependent Variable: Income Capita Growth	**Model 1**	**Model 2**	**Model 3**	**Model 4**
L1.Income Capita Growth	-.922***	-.985***	-1.225***	-1.249***
	(0.000)	(0.000)	(0.000)	(0.000)
LMBL	21.101**	---	86.419**	---
	(0.054)	---	(0.033)	---
LSBL	---	85.231***	---	138.825**
	---	(0.008)	---	(0.045)
LMBL × Initial Capita Income	---	---	-4.161**	---
	---	---	(0.053)	---
LSBL × Initial Capita Income	---	---	---	-6.104**
	---	---	---	(0.050)
Capita Income	---	---	2.213***	1.877***
	---	---	(0.000)	(0.000)
Inflation	.548	-2.253	-.167	-.503
	(0.496)	(0.154)	(0.797)	(0.691)
ROA	12.670**	27.614***	14.149***	18.115***
	(0.050)	(0.008)	(0.008)	(0.026)
HHI	-404.574**	-579.036**	-176.731	-239.8938
	(0.058)	(0.053)	(0.228)	(0.287)
Labour Force	1903.606**	2909.518**	-907.670	-1296.145
	(0.047)	(0.030)	(0.296)	(0.249)
Non-interest income/interest income	-.598	-.839	.585	.592
	(0.312)	(0.233)	(0.223)	(0.344)
Equity Ratio	-11.205***	-2.951	-3.892	-2.993
	(0.002)	(0.586)	(0.159)	(0.457)
Banking Density	0.866	.293	-1.884***	-2.283***
	(0.182)	(0.694)	(0.001)	(0.000)
Constant	-272.372	-1999.936**	-166.350	-334.071
	(0.362)	(0.015)	(0.507)	(0.609)
Year Dummies	Yes	Yes	Yes	Yes
Number of Obs.	24,643	24,643	24,643	24,643
No. Regions	2,095	2,095	2,095	2,095
Sargan test (p-value)	0.1415	0.4497	0.7653	0.7708
AB test AR(1) (p-value)	0.1972	0.4462	0.2793	0.4890
AB test AR(2) (p-value)	0.7092	0.5269	0.2371	0.3731

Note: This table reports results from GMM estimations of the effects of local banks on regional economic development. The dependent variable is the growth rate of Income per Capita at county-level. The measures of local bank SME lending include two indirect indicators at county-level — (1) Local Micro Business Loans (LMBL) and (2) Local Small Business Loans (LSBL). Regression models (1) to (2) contain results without including the different initial conditions. Regression models (3) to (4) contain results including the different initial conditions. The period covers the years 1994 to 2013. P-values are reported in parentheses. The symbols ***, ** and * indicate the levels of significance, 1%, 5% and 10%, respectively.

Table 5.4 Cross Sectional Regressions for Employment Growth with Different Initial Conditions

Dependent Variable: Employment Growth	1995		2000		2005		2010	
LMBL	.0001797	---	.0013388	---	.0002868	---	-.0001564	---
	(0.21)	---	(1.89	---	(0.44	---	(-0.25)	---
LSBL	---	-.0001856	---	.0020883	---	.0013396	---	-.0002158
	---	(-0.23)	---	(2.91)	---	(1.75)	---	(-0.31)
LMBL × Initial Employment Growth	-1.39e-06	---	-2.17e-06	---	-3.98e-06	---	-3.53e-07	---
	(-1.28)	---	(-2.32	---	(-4.20	---	(-0.40)	---
LSBL × Initial Employment Growth	---	-1.30e-06	---	-2.14e-06	---	-3.59e-06	---	-3.22e-07
	---	(-1.25)	---	(-2.41)	---	(-4.25)	---	(-0.41)
Employment	---	---	---	---	---	---	---	---
	---	---	---	---	---	---	---	---
Inflation	---	---	---	---	---	---	---	---
	---	---	---	---	---	---	---	---
ROA	-.0011169	-.0010709	-.0024923	-.0024935	.0035221	.003288	.0032764	.0032652
	(-0.61)	(-0.59)	(-2.85	(-2.87)	(3.17	(2.97)	(4.31)	(4.33)
HHI	-.0064432	-.0073509	-.0147432	-.0119637	-.0194419	-.0167196	.0021271	.0018868
	(-1.28)	(-1.44)	(-3.04	(-2.40)	(-3.54	(-2.94)	(0.40)	(0.35)
Labour Force	.0099875	.0102725	.0406405	.0401645	.056109	.0530495	.0061778	.0065172
	(0.53)	(0.54)	(2.72	(2.65)	(3.94	(3.81)	(0.50)	(0.53)
Non-interest income/ interest income	-.0004113	-.0004231	-.0001725	-.0001418	-.000041	-.0000369	-.0000152	-.0000139
	(-0.88)	(-0.90)	(-0.39	(-0.32)	(-0.56	(-0.51)	(-0.24)	(-0.22)
Equity Ratio	-.0007192	-.0007417	-.0003188	-.00025	-.0001956	-.0001057	-.0002502	-.000256
	(-2.17)	(-2.24)	(-1.41	(-1.10)	(-0.75	(-0.40)	(-0.99)	(-1.00)
Banking Density	-.000257	-.0002591	-.0000701	-.0000596	-.0002565	-.000249	.0000316	.0000309
	(-7.66)	(-7.64)	(-2.45	(-2.06)	(-8.80	(-8.44)	(1.19)	(1.16)
Constant	.0522847	.0586835	.0071429	-.0078518	.0255331	.006722	-.0038332	-.0026059
	(3.25)	(3.66)	(0.53)	(-0.55)	(2.25	(0.48)	(-0.36)	(-0.21)
Number of Obs.	2,354	2,354	1,987	1,987	1,723	1,723	1,495	1,495
R-squared	0.0340	0.0340	0.0322	0.0345	0.0785	0.0798	0.0154	0.0155

Note: This table reports results from simple cross-sectional estimations of the effects of local banks on regional economic development at different years. The dependent variable is the growth rate of Total Employment (number of jobs) at county-level. The measures of local bank SME lending include two indirect indicators at county-level — (1) Local Micro Business Loans (LMBL) and (2) Local Small Business Loans (LSBL). Regression models (1995) to (2010) correspond to each five years gap beginning in 1995. Each year, the regression is firstly estimated with the LMBL and secondly with the LSBL. The period covers the years 1994 to 2013. P-values are reported in parentheses. The symbols ***, ** and * indicate the levels of significance, 1%, 5% and 10%, respectively.

Table 5.5 Convergence-Type Local Employment Growth Regression: Dynamic panel model

Dependent Variable: Employment Growth	Model 1	Model 2	Model 3	Model 4
L1. Employment Growth	-.0083202	.0310239	-.075388	-.0099593
	(0.936)	(0.774)	(0.495)	(0.930)
LMBL	.0214871***	---	.0257795***	---
	(0.001)	---	(0.001)	---
LSBL	---	.01668**	---	.0297441**
	---	(0.022)	---	(0.017)
LMBL × Initial Employment	---	---	-.0000281**	---
	---	---	(0.019)	---
LSBL × Initial Employment	---	---	---	-.0000447**
	---	---	---	(0.031)
Employment Growth	---	---	---	---
	---	---	---	---
Inflation	.0072608***	.0066949***	.0066768***	.0064204***
	(0.000)	(0.000)	(0.000)	(0.000)
ROA	.0084437**	.0119658***	.0097731**	.0103954**
	(0.033)	(0.001)	(0.020)	(0.013)
HHI	.0556865	.055387	.0559604	.0537789
	(0.421)	(0.472)	(0.243)	(0.542)
Labour Force	.6908059***	.6842785***	.7140761***	.8376509***
	(0.002)	(0.002)	(0.000)	(0.001)
Non-interest income/interest income	-.0010687***	-.0012715***	-.0015765***	-.0016135***
	(0.011)	(0.001)	(0.001)	(0.001)
Equity Ratio	.0038129***	.0039575***	.0041673***	.0038713***
	(0.006)	(0.002)	(0.001)	(0.006)

Banking Density	-.0074483***	-.008289***	-.0071724***	-.008486***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-.0675649	.0129854	-.087257	-.167347
	(0.687)	(0.941)	(0.631)	(0.480)
Year Dummies	Yes	Yes	Yes	Yes
Number of Obs.	24,642	24,642	24,642	24,642
No. Regions	2,095	2,095	2,095	2,095
Sargan test (p-value)	0.3074	0.1046	0.3615	0.2088
AB test AR(1) (p-value)	0.0000	0.0000	0.0000	0.0000
AB test AR(2) (p-value)	0.7440	0.1046	0.2371	0.6322

Note: This table reports results from GMM estimations of the effects of local banks on regional economic development. The dependent variable is the growth rate of Total Employment (number of jobs) at county-level. The measures of local bank SME lending include two indirect indicators at county-level — (1) Local Micro Business Loans (LMBL) and (2) Local Small Business Loans (LSBL). Regression models (1) to (2) contain results without including the different initial conditions. Regression models (3) to (4) contain results including the different initial conditions. Regression models (3) to (4) contain results with the inclusion of the interaction variables. The period covers the years 1994 to 2013. P-values are reported in parentheses. The symbols ***, ** and * indicate the levels of significance, 1%, 5% and 10%, respectively.

A look at the results in Tables 5.2-5.5 reveals interesting dynamics in the relationship between local economic growth and local SME lending. On average, I find – across all tables – that both the LSBL and the LMBL exerts significant and positive effects on local economic growth (irrespective of the measure). Competition (measured by the HHI index) demonstrates – as expected – a negative effect on growth, implying that excess competition hurts local economic growth. Thirdly, there is evidence of convergence of local economic growth, that is to say, poorer regions' growth is converging to the richer regions over time. The estimated coefficient for the initial level is negative and its interaction with the LSBL and the LMBL is also largely negative. When I look at the cross-sectional regression, I also find that the partial effects of the LSBL and the LMBL are positive and significant, and that the effects are declining over time. The interaction with the initial level of development (irrespective of the measures) also appears to be negative, implying that for every five-annual period there is evidence of regional convergence of economic growth. However, the declining positive effects of the LSBL and the LMBL means that over time, as the economy is growing, large banks might be replacing the LSBL and the LMBL. This may also be reflected by the large negative estimates for competition (HHI). Furthermore, I also note the varying signs of inflation on local economic development. Macroeconomic theory says that inflation exerts negative effects on local economic development. In my results, the presence of positive effects of inflation might also imply that there is sufficient demand pressure in the economy, which means that the local economy is expanding and that local banks would make a positive contribution to such development. As expected, I also find a positive effect of the labour force in local economic development, across all the models.

Whether my estimates are consistent can be known by accounting for endogeneity bias. The instruments used in my regression are the lagged differences in their original variables, and the lagged levels are used to instrument the difference regression. The validity of the instruments has been tested; the P-values in Hansen test and AR (2) post-estimation test suggest that the instruments are valid. Indeed, the tests accept the null hypotheses of no over-identification and no second-order serially correlated error terms.

5.4.2 Distributional Heterogeneity with Quantile IV Regressions

I now present the results of the panel quantile estimation by taking into account possible endogeneity issues. In contrast to the dynamic panel regression in the mean-based environment, it is difficult to employ such mechanisms in the quantile estimation environment. The various lag lengths of the dependent variable have distinct implications for the quantile function than is the case in the conventional mean-based function. To avoid such problems, I have created an instrument for bank lending. However, the literature on instruments for bank lending is very thin, usually using demand side effects (such as deposit-based instrument, e.g. Driscoll, 2004; Kendall, 2012). As a result of such a limitation, most empirical papers employ the conventional dynamic panel data technique with the system GMM approach to identify instruments. It is well-known that using lags of the dependent variable as a possible instrument can work well in the absence of a valid instrument. As such, this strategy can produce instruments which are weakly exogenous and are heavily data dependent. As a contribution to this literature I propose a Yield Curve approach as a possible instrument for bank lending.

5.4.2.1 Description of the Instrument

How do banks determine their lending? While some economists argue that lending is largely demand-determined, there is significant literature indicating that banks ration lending (e.g. Stiglitz and Weiss, 1981). In that case, bank lending is decided largely by the supply-side. How, then, do banks determine their loan extension? Werner (1995) argues that a major determinant of bank lending is the shape of the yield curve. The slope of the yield curve determines the profitability of bank lending. Since banks borrow at short-term interest rates (largely the rate paid to depositors) and lend at longer term interest rates (the rate at which banks lend), the difference is the profit margin of banks. A steep yield curve encourages banks to increase lending, as this activity becomes highly profitable in this case. A flat yield curve makes bank lending less profitable. Hence, one should expect a close positive correlation between bank lending and the yield curve (for instance measured by the difference between the long-term lending rate and the short-term lending rate). Hence, the yield curve acts as a proxy for the banks' profit margin. One can also use the actual profit margin, calculated as an interest differential, whereby the lending rate is calculated using the data on interest income and the amount of loans, while the borrowing rate is calculated using the data on interest payments and the amount of deposits.

The interest margin or the yield curve can be expected to lead bank lending by a significant amount of time. Consequently, it should be a good proxy or instrument for bank lending. I calculate a county-level yield curve for local banks in three stages as follows:

1. I compute the Average Interest Rates on Loans:

$$Average\ Interest\ Rates\ on\ Loans\ = \frac{Total\ Interest\ Rate\ Income}{Total\ Loans\ and\ Lease} \qquad (5.1)$$

where Total Interest Rate Income is the total interest and fee income on loans held in domestic offices, and Total Loans and Lease is total loans and lease financing receivables minus unearned income and loan loss allowances (Source: FDIC). Each is calculated for all local banks in a county.

2. I compute the Average Interest Rates on Deposits:

$$Average\ Interest\ Rates\ on\ Deposits\ = \frac{Total\ Interest\ Rate\ Expense}{Total\ Domestic\ Deposits} \qquad (5.2)$$

where Total Interest Rate on Deposits is the total interest expense on deposits held in domestic offices, and Total Domestic Deposits is the total domestic deposits (Source: FDIC). Again, each is calculated for all local banks in a county.

3. Finally, I compute the Yield Curve as the spread between (5.1) and (5.2):

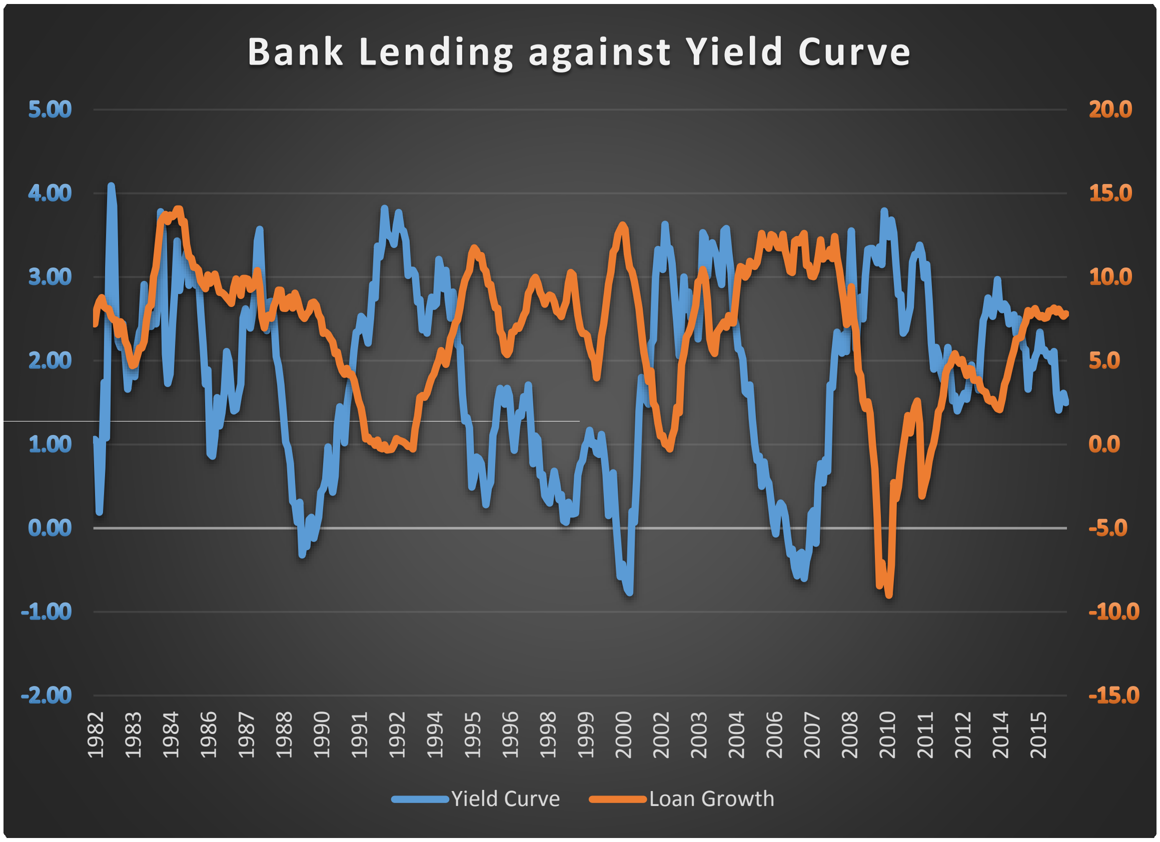
Yield Curve = Average Interest Rates on Loans – Average Interest Rates on Deposits (5.3)

5.4.2.2 Supporting Evidence, Validity and Limitations of the Instrument

To ensure a robust instrument for bank lending, I plot the monthly U.S yield curve against bank loan supply from January 1982 to May 2016. The yield curve is defined as the 10-year treasury constant maturity minus 3-month treasury constant maturity, while the bank lending is the percentage change from the previous year of total loans and leases in bank credit for all commercial banks in the U.S. Both national-level series are not seasonally adjusted and are readily available from the Federal Reserve Bank of St. Louis.

Figure 5.1, below, shows an inverse relationship between loans and the yield curve, as they noticeably fluctuate opposite each other throughout most of these 33 years. This pattern may indicate two scenarios: firstly, one series leads another (i.e. one series follows a similar pattern to that of the second one after a period) or, secondly, bank lending and yield curve are, in fact, negatively correlated.

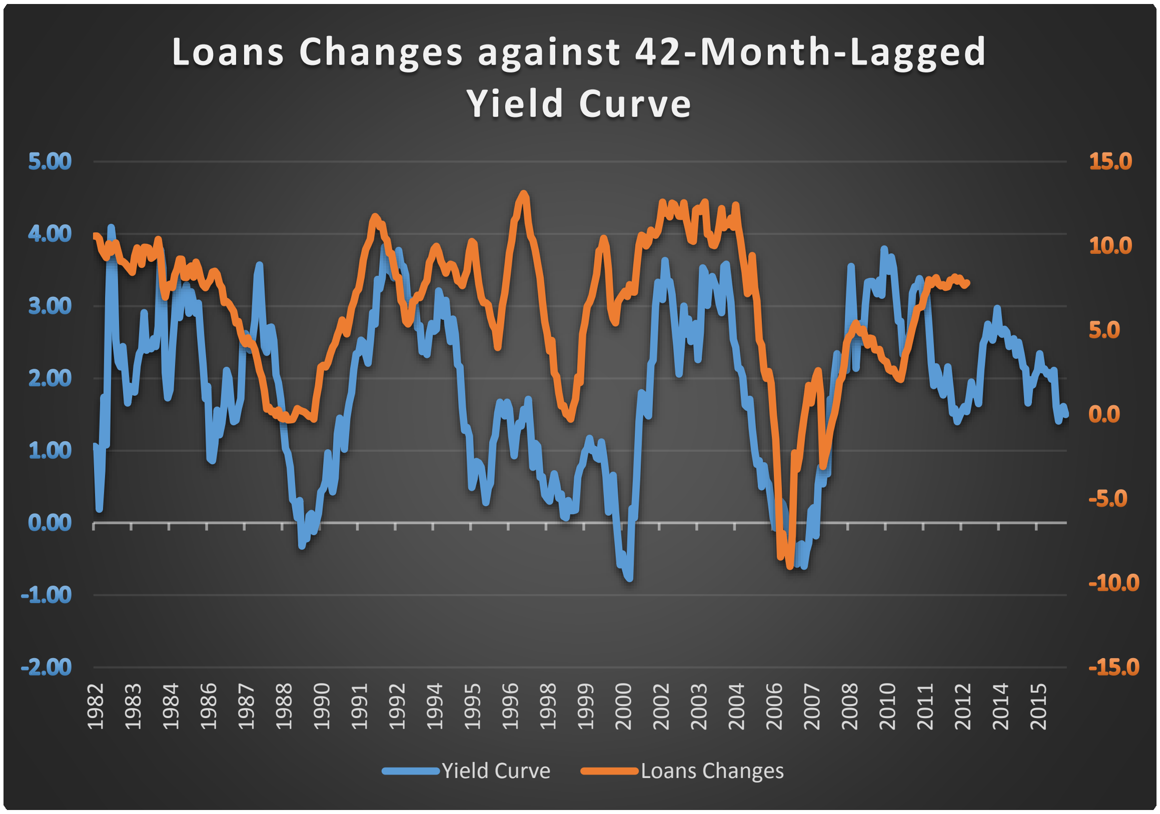
Figure 5.1 U.S Bank Lending and Yield Curve – Jan 1982 to May 2016



Note: This figure illustrates the U.S yield curve against the bank loan supply growth from January 1982 to May 2016 (monthly observations at national level). The yield curve is calculated as the 10-year treasury constant maturity minus 3-month treasury constant maturity. The bank loan supply growth is the percentage change from the previous year of total loans and leases, net of unearned income for commercial banks in United States (Not Seasonally Adjusted). Source (Economic Research at the Federal Reserve Bank of St. Louis, 2016).

I have repeatedly plotted the bank lending against past yield curve observations to investigate the possible existence of a unidirectional relationship, running from the latter to the former, and to assess the amount of time that it may take for it to be translated. I have finally reached the pattern shown in Figure 5.2, below. This pattern lends support to the first scenario. That is to say, the yield curve leads bank lending by 42 months. In other words, the impact of the yield curve on bank lending takes three and a half years to be incorporated.

Figure 5.2 U.S Bank Lending and 42-Month-Lagged Yield Curve – Jan 1982 to May 2016

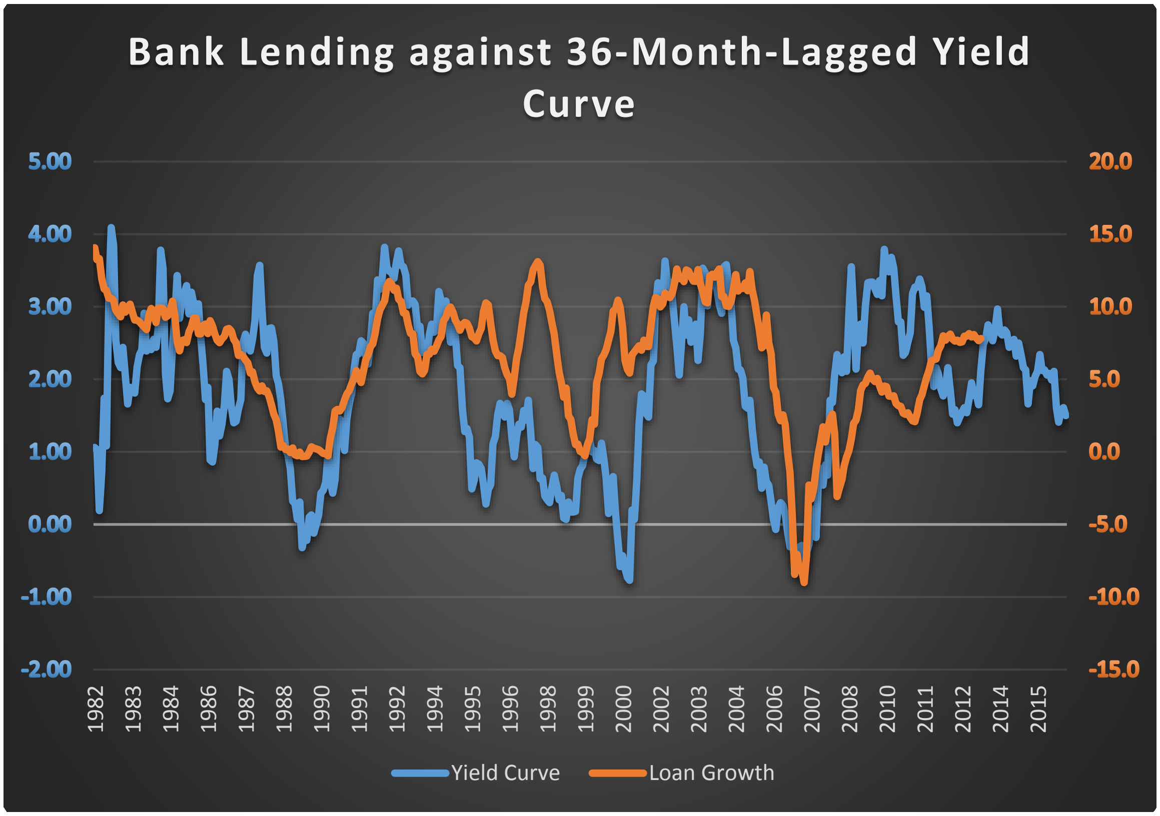


Note: This figure illustrates the 42-month lag of U.S yield curve against the bank loan supply growth from January 1982 to May 2016 (monthly observations at national level). The yield curve is calculated as the 10-year treasury constant maturity minus 3-month treasury constant maturity. The bank loan supply growth is the percentage change from the previous year of total loans and leases, net of unearned income for commercial banks in United States (Not Seasonally Adjusted). Source (Economic Research at the Federal Reserve Bank of St. Louis, 2016).

However, the accessible bank-level data for computing my yield curve instrument is only available yearly, for instance, the survey data from the Summary of Deposits is annually conducted as of June 30th for all FDIC-insured institutions. Therefore, instead of following the pattern of the 42-month-lagged yield curve in determining the number of lags for my proposed instrument in the IV regressions, I am forced to follow the 36-month pattern displayed in Figure 5.3, below. Therefore, I use the three-year lags of my computed yield curve as an instrument for SME loan supply by local banks.

As can be seen from Figure 5.3, the correlation is still satisfactory, especially when one remembers that the yield curve has been calculated on the basis of data for all U.S banks and, thus, a perfect fit cannot be expected.

Figure 5.3 U.S Bank Lending and 36-Month-Lagged Yield Curve – Jan 1982 to May 2016



Note: This figure illustrates the 36-month lag of U.S yield curve against the bank loan supply growth from January 1982 to May 2016 (monthly observations at national level). The yield curve is calculated as the 10-year treasury constant maturity minus 3-month treasury constant maturity. The bank loan supply growth is the percentage change from the previous year of total loans and leases, net of unearned income for commercial banks in United States (Not Seasonally Adjusted). Source (Economic Research at the Federal Reserve Bank of St. Louis, 2016).

5.4.2.3 Quantile Regression Results

Prior to employing quantile regression to my data, I perform tests to confirm whether my data is suitable for quantile regression. As a first step, I plot the kernel density function of the dependent and explanatory variables. It can be observed from the graphs in Appendix D that the distribution of the variables is skewed. This skewness indicates that there might be an existence of multiple modes in the data, suggesting that the distribution of the dependent variable is biased, and hence, the estimation cannot be based on the assumption of normal distribution. In particular, I test whether the bivariate normality could be rejected. As a second step, I perform the Likelihood Ratio test for heteroscedasticity in panel data to demonstrate that there is a significant degree of heterogeneity in the data; hence, the conventional OLS based methods may not be suitable. I find that the chi-square (2) is 124.40, with p value of zero, concluding that the data is heteroscedastic. The skewness (for regional economic growth) is 3.418, whereas the Kurtosis is 18.208. Finally, I also perform the Doornik-Hansen test of Bivariate normality (local income-local banks): chi-square = 9366.95 (p=0.000). All these point to the fact that the dependent variable does not follow a normal distribution and, therefore, an estimation procedure other than the mean-based regression needs to be employed. Therefore, it is necessary to address this issue. To do this, I perform a quantile regression for the panel data with an instrumental variable. Tables 5.6 and 5.7, below, present estimations (both baseline and instrumental variables) with Local Micro Business Loans (LMBL) as a measure of local business lending. Tables 5.8 and 5.9, below, present the same estimations, but for Local Small Business Lending (LSBL). The impact variables remain the same in both sets of regressions (total income and total employment).

(a) Baseline regression

I first discuss my baseline regression results (summarized in Table 5.6, below). The estimated coefficients are not corrected for endogeneity bias. However, this table presents some interesting features, which I will qualify after bias-correction. If total income is taken as a measure of economic development, I find in Table 5.6 that the LMBL exerts a significant positive effect on economic growth at the lower quantiles (i.e. 10th and 20th quantiles) and negative effects at the median as well as at the higher quantiles. This is not a theoretically expected outcome as – irrespective of the distributional differences – higher access to loan (that is, a rise in the LMBL or the LSBL) should in principle raise economic growth. This conclusion changes when employment is taken as a measure of economic development. This measure is suitable for my purpose because theoretically, as access to SME lending improves, it leaves a direct positive effect on employment growth. In that sense, the impact of the LMBL or the LSBL on economic growth is via employment generation and, hence, a net contribution towards the productivity growth. As such, I find that the LMBL exerts a positive and significant impact on economic development (measured by employment) across all quantiles (with a larger effect at the 10th quantile and a smaller, but positive, effect at the 90th quantile, much in line with the theoretical expectation). Irrespective of the results that I have obtained, I need to be careful about their implications, as I had not yet corrected the estimates for endogeneity bias. The instrumental variable regression estimates are next presented, in order to arrive at valid inferences regarding the impact of the LMBL on local economic development. In Table 5.8, I present the re-estimated results for the LSBL. Interestingly, the effects are positive and significant for both measures of local economic development (i.e. total income and total employment). Once again, as expected, I find a greater impact of the LSBL on economic development (for both measures) at the lower quantiles and a smaller, but positive, effect at the higher quantiles.

(b) Endogeneity Bias-Corrected Results

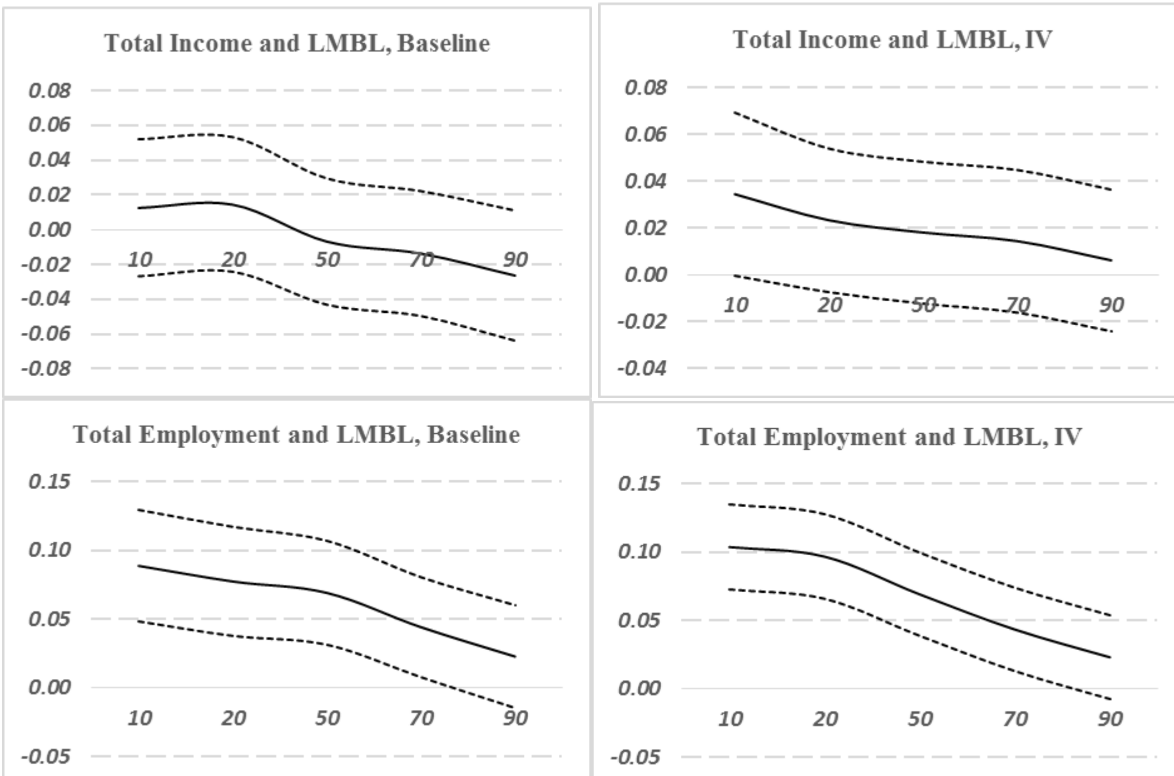
As noted in the previous section, to account for endogeneity bias, I have created an instrument in the form of a yield curve. I have already discussed its importance and validity in the present context. However, a note on the exogeneity of this instrument at various quantiles is in order. Normally, any instrument that is built by a researcher needs to be subject to an exogeneity test. In mean-based regression, Hansen's overidentification[8] test is popular and well-received. However, such a test does not lend a direct translation for quantiles as one has to test for the uniform exogeneity of this instrument at each quantile of the distribution of the dependent variable. Thus far – to my knowledge – such a powerful test procedure has not been developed. Nevertheless, for my purpose, I perform exogeneity test of this instrument to the error term in the regression specific to each quantile. I find that for all quantiles E(error, yield curve) = 0. Using this instrument, I perform panel quantile estimation for both the LMBL and the LSBL as measures of SME lending. Tables 5.7 and 5.9, below, report these results. Several interesting features arise. Firstly, the coefficients of the LMBL and the LSBL in these tables are of theoretically expected signs at each quantile. Secondly, the effects are larger for total employment as a measure of local economic development. Thirdly, the effects for the LSBL is six times larger in the case of the LSBL at the 10th quantile than the LMBL at the same quantile, whereas it is approximately three times as large for the LSBL as the LMBL (Tables 5.7 and 5.9). Fourthly, the effects are larger at the lower quantiles and smaller at the higher quantiles (this is theoretically expected).

The Figures (a) and (b) in Figure 5.4, below, present the plots of the estimates for both baseline and instrumental variable quantile regressions. Reflecting on the above discussion, I find a positive, but declining, effect of SME lending on local economic growth across different quantiles. In the upper panel of each of Figure (a) and Figure (b), I present graphs with respect to the baseline estimation (left) and the panel quantile IV estimation (right). In the lower panels, I present the same, but with respect to the alternative dependent variable, i.e. total employment. Interesting patterns emerge, the baseline results depict a positive but declining trend for total income as the dependent variable, with the impact of the LMBL on total income being negative at the median and the upper quantiles. However, after correcting for endogeneity bias, the IV regression depicts positive effects of both the LMBL and the LSBL on income growth, with larger effects at the smaller quantiles. For total employment as the dependent variable and as a proxy for economic growth, I find that the effects of the LSBL and the LMBL on total employment are largely positive (turning smaller for the upper quantiles). The endogeneity-bias corrected estimates (i.e. IV results) also depict a positive effect of changes in the LSBL and the LMBL on employment growth. The magnitude of the effects evince a discernible pattern; that is to say, it is positive but smaller, on average, at the upper and median quantiles, but very large and positive at the lower quantiles.

[8] This instrumental variable encounters a limitation that there is no straightforward test for the instrumentation validity in quantile regressions. In other words, there is no a Sargan Type test or a Hausman type test where the error term with instrumental variable can be tested. That is because a validity test in a quantile regression has to be uniquely applicable at each quantile. In order to further alleviate such limitation, I also compute the correlations of the error term with the instrument. The results in Appendix B show that the instrumental variable (i.e. three-year lag of the Yield Curve) is not correlated with the dependent variables and any of the control variables. Therefore, this can be an evidence that my instrumental variable satisfies the validity conditions of instrumentation.

Figure 5.4 Generalised Quantile Regressions with Non-Additive Fixed Effects

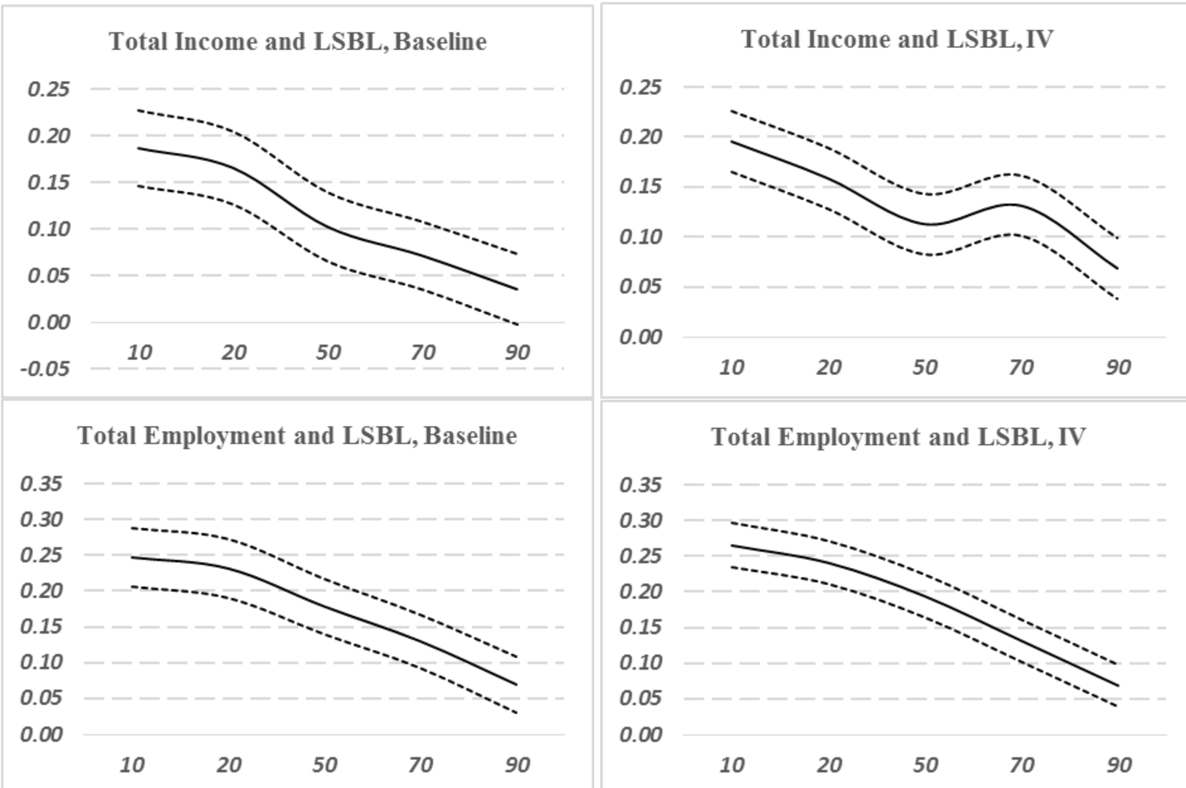
Figure (a) LMBL with Total Income and Total Employment



Note: This figure illustrates the response of local economic growth to micro business lending. The upper two graphs show the benchmark estimation (left) and the panel quantile IV estimation (right) of micro business lending and total income. The lower two graphs show the same estimation but with respect to the alternative dependent variable, i.e. the total employment. The horizontal axis represents the quantiles, while the vertical one represents the estimation coefficients.

To summarise, I find that SME lending helps local economic growth after correcting for the endogeneity issue in the regression, and that the effects are generally smaller at the upper quantiles, but larger at the lower quantiles. This is plausible as I already know that in the upper quantile distribution of local economic growth, SME lending not only spurs local entrepreneurs towards innovation and growth, but also improves the productivity channel of the process of local economic growth.

Figure (b) LMBL with Total Income and Total Employment



Note: This figure illustrates the response of local economic growth to small business lending. The upper two graphs show the benchmark estimation (left) and the panel quantile IV estimation (right) of small business lending and total income. The lower two graphs show the same estimation but with respect to the alternative dependent variable, i.e. the total employment. The horizontal axis represents the quantiles, while the vertical one represents the estimation coefficients.

The magnitude of the results can be studied in the various Tables 5.6-5.9, below. The key results can be summarized as follows. Firstly, from the growth regression, I find that: (i) in the lower quantile, the contributions of the LSBL and the LMBL are larger, becoming smaller in the higher quantiles, (ii) there is evidence of a varied rate of convergence of poor regions to the growth path of rich regions, (iii) the effect of competition is higher around low to median quantiles, and smaller in the higher quantiles (though negative overall), (iv) the effect of human capital and population growth is larger in the lower quantiles than in the higher quantiles, and, (v) with growing diversification of funds, the net growth effect of the LSBL and the LMBL may be smaller. By looking at the results from total income and the LSBL and the LMBL models, I find that the impacts of the LSBL and the LMBL on growth are positive and significant. All other control variables also display the expected signs, such as the impact of inflation on growth, where I find a negative significant coefficient. Moreover, I also find that competition has a consistently negative impact on growth in all quantiles, with a large negative effect in the higher quantiles and a small and negative one in the lower quantiles. As such, population growth, as a fundamental demographic determinant of growth, displays a positive and significant effect, which is expected.

Table 5.6 Baseline Quantile Regressions for LMBL with Total Income and Total Employment

Dependent Variable	Total Income					Total Employment				
	10th	20th	50th	70th	90th	10th	20th	50th	70th	90th
LMBL	0.0125	0.0144	-0.0068	-0.0137	-0.0263	0.0888	0.0774	0.0692	0.0442	0.0229
ROA	-0.1122	-0.1305	-0.1156	-0.1144	-0.1227	-0.0780	-0.0847	-0.0896	-0.0725	-0.0738
HHI	-4.6038	-4.4700	-3.7932	-3.4774	-3.0393	-4.7756	-4.6552	-4.0876	-3.6762	-3.1138
Inflation	-0.0385	-0.0289	-0.0249	-0.0244	-0.0185	-0.0027	0.0077	0.0088	0.0080	0.0141
NII/II	0.0031	0.0042	0.0035	0.0031	0.0033	0.0051	0.0053	0.0035	0.0035	0.0035
Equity Ratio	-0.0053	-0.0050	-0.0071	-0.0045	-0.0047	-0.0079	-0.0136	-0.0074	-0.0079	-0.0076
Pop. Growth	0.0347	0.6684	0.1705	0.3945	0.7941	1.6266	1.0586	-0.6958	-0.6341	0.6916
Labour Force	2.6581	3.7746	6.2152	6.8409	7.7082	2.6821	3.7753	5.7721	6.4584	7.6103
MSA	0.4315	0.4984	0.6535	0.6638	0.5706	0.0907	0.2354	0.4888	0.5708	0.5227
Bank. Density	-0.0180	-0.0173	-0.0148	-0.0138	-0.0125	-0.0187	-0.0190	-0.0171	-0.0165	-0.0153
Constant	21.6492	21.7426	22.1530	22.3450	22.7187	9.2197	9.6362	9.9052	10.3962	10.8599

Note: This table reports results from basic quantile estimations of the effects of local banks on regional economic development without including an instrumental variable. The dependent variables are the logarithm of Total Income and the logarithm of Total Employment (number of jobs) at county-level. The measure of local bank SME lending is the Local Micro Business Loans (LMBL). The columns contain results of the estimations at five different quantiles. The first five quantiles contain the estimations with the logarithm of total income, while the second five quantiles contain the estimations with the logarithm of total employment. The period covers the years 1994 to 2013. Coefficients are significant at the 5% level.

Table 5.7 Quantile IV Regressions for LMBL with Total Income and Total Employment

Dependent Variable	Total Income					Total Employment				
	10th	20th	50th	70th	90th	10th	20th	50th	70th	90th
LMBL	0.0344	0.0233	0.0181	0.0144	0.0062	0.1036	0.0967	0.0692	0.0435	0.0232
ROA	-0.0362	-0.0553	-0.0597	-0.0373	0.0183	-0.0235	-0.0158	-0.0804	-0.0732	-0.0722
HHI	-4.5820	-4.3979	-3.7918	-2.9875	-2.4887	-4.6635	-4.5361	-4.1143	-3.6831	-3.1174
Inflation	-0.0488	-0.0506	-0.0332	-0.0685	-0.0464	-0.0310	-0.0107	0.0074	0.0075	0.0144
NII/II	0.0024	0.0041	0.0047	0.0079	-0.0068	0.0016	0.0025	0.0027	0.0038	0.0038
Equity Ratio	-0.0022	-0.0083	-0.0072	-0.0047	0.0057	-0.0088	-0.0108	-0.0066	-0.0078	-0.0078
Pop. Growth	2.0404	3.7428	3.7774	9.9709	11.1221	2.7295	3.4232	-0.2803	-0.4221	1.0440
Labour Force	2.7572	3.8645	6.1316	6.6988	7.7574	2.8302	3.7728	5.7550	6.4530	7.6057
MSA	0.3867	0.4370	0.6478	0.5503	0.3383	0.0932	0.2029	0.4858	0.5710	0.5179
Bank. Density	-0.0179	-0.0176	-0.0144	-0.0144	-0.0134	-0.0189	-0.0189	-0.0172	-0.0164	-0.0152

Note: This table reports results from quantile IV estimations of the effects of local banks on regional economic development. The instrumental variable used here is the three-year lag of the Yield Curve. The dependent variables are the logarithm of Total Income and the logarithm of Total Employment (number of jobs) at county-level. The measure of local bank SME lending is the Local Micro Business Loans (LMBL) at county-level. The columns contain results of the estimations at five different quantiles. The first five quantiles contain the estimations with the logarithm of total income, while the second five quantiles contain the estimations with the logarithm of total employment. The period covers the years 1994 to 2013. Coefficients are significant at the 5% level.

Table 5.8 Baseline Quantile Regressions for LSBL with Total Income and Total Employment

Dependent Variable	Total Income					Total Employment				
	10th	20th	50th	70th	90th	10th	20th	50th	70th	90th
LMBL	0.187	0.166	0.102	0.072	0.036	0.247	0.232	0.179	0.130	0.070
ROA	-0.127	-0.152	-0.144	-0.141	-0.149	-0.081	-0.105	-0.100	-0.092	-0.090
HHI	-3.971	-3.972	-3.530	-3.301	-2.957	-4.209	-4.171	-3.753	-3.453	-3.031
Inflation	-0.038	-0.027	-0.025	-0.021	-0.023	0.001	0.005	0.011	0.008	0.007
NII/II	0.004	0.005	0.004	0.004	0.003	0.006	0.006	0.004	0.003	0.003
Equity Ratio	0.001	0.003	0.002	0.003	0.000	-0.003	-0.005	0.000	-0.003	-0.002
Pop. Growth	-0.216	0.227	0.320	0.351	0.468	1.509	0.952	-0.242	-0.556	0.254
Labour Force	2.352	3.461	5.788	6.499	7.434	2.338	3.378	5.281	5.975	7.368
MSA	0.432	0.497	0.644	0.656	0.583	0.096	0.203	0.484	0.558	0.518
Bank. Density	-0.017	-0.016	-0.014	-0.013	-0.012	-0.018	-0.018	-0.016	-0.016	-0.015
Constant	18.623	19.100	20.270	20.879	21.721	6.429	6.916	7.930	8.888	10.046

Note: This table reports results from basic quantile estimations of the effects of local banks on regional economic development without including an instrumental variable. The dependent variables are the logarithm of Total Income and the logarithm of Total Employment (number of jobs) at county-level. The measure of local bank SME lending is the Local Small Business Loans (LSBL) at county-level. The columns contain results of the estimations at five different quantiles. The first five quantiles contain the estimations with the logarithm of total income, while the second five quantiles contain the estimations with the logarithm of total employment. The period covers the years 1994 to 2013. Coefficients are significant at the 5% level.

Table 5.9 Quantile IV Regressions for LSBL with Total Income and Total Employment

Dependent Variable	Total Income					Total Employment				
	10th	20th	50th	70th	90th	10th	20th	50th	70th	90th
LMBL	0.1955	0.1587	0.1129	0.1314	0.0686	0.2650	0.2406	0.1938	0.1314	0.0686
ROA	-0.0436	-0.0523	-0.0688	-0.0913	-0.0898	-0.0189	-0.0513	-0.0458	-0.0913	-0.0898
HHI	-3.9337	-3.9702	-3.6611	-3.4442	-3.0337	-4.0293	-4.0466	-3.6620	-3.4442	-3.0337
Inflation	-0.0629	-0.0360	-0.0124	0.0074	0.0076	-0.0289	-0.0228	0.0205	0.0074	0.0076
NII/II	0.0036	0.0026	0.0029	0.0035	0.0029	0.0026	0.0025	0.0061	0.0035	0.0029
Equity Ratio	-0.0024	0.0084	0.0160	-0.0028	-0.0019	0.0033	-0.0001	0.0049	-0.0028	-0.0019
Pop. Growth	2.0271	2.5184	6.0245	-0.4992	0.3017	1.7445	3.0929	3.4419	-0.4992	0.3017
Labour Force	2.4144	3.4657	5.8121	5.9728	7.3679	2.4774	3.3959	5.3665	5.9728	7.3679
MSA	0.3870	0.4442	0.6340	0.5553	0.5180	0.1228	0.1790	0.4554	0.5553	0.5180
Bank. Density	-0.0174	-0.0178	-0.0148	-0.0160	-0.0151	-0.0181	-0.0183	-0.0172	-0.0160	-0.0151

Note: This table reports results from quantile IV estimations of the effects of local banks on regional economic development. The instrumental variable used here is the three-year lag of the Yield Curve. The dependent variables are the logarithm of Total Income and the logarithm of Total Employment (number of jobs) at county-level. The measure of local bank SME lending is the Local Small Business Loans (LSBL) at county-level. The columns contain results of the estimations at five different quantiles. The first five quantiles contain the estimations with the logarithm of total income, while the second five quantiles contain the estimations with the logarithm of total employment. The period covers the years 1994 to 2013. Coefficients are significant at the 5% level.

The above results can be put into perspective. Firstly, as expected, in the lower quantiles of local economic development, the net effects of the LSBL and the LMBL are smaller than in the higher quantiles, because in the lower quantiles of growth distribution, one can find clusters of poor regions (although varied in their trajectories to growth acceleration). In the higher quantiles, there are clusters of high performing regions. Hence, one might expect the dual presence of large banks and a smaller number of small local banks. It is also possible that, due to high growth momentum, the region might benefit from increasing innovation and the creation of new opportunities for small business growth. That is to say, there can be complementarity between large and small banks in the higher quantiles, whereas in the lower quantiles of the growth distribution, there will be stiff competition. Indeed, from my results listed in Tables 5.6-5.9, I find evidence of this. Secondly, I find varied rates of convergence across the quantiles. This makes sense, because within similarly growing regions, there might be some evidence of convergence; that is to say, evidence of slight divergence or weak convergence in one quantile can be evidence of global convergence when the whole sample is considered. The partial effects of the LSBL and the LMBL are also growing over time and across quantiles. These results are consistent with the conclusions of Guiso *et al.*, (2004), and Hakenes *et al.*, (2015), that SMEs, with more difficulties in obtaining credits, in less developed regions grow faster if those regions have more local banks. Also, the findings of this quantile analysis confirm that SME lending, through local banks, is a key factor to boost convergence of regions' growth rates.

5.5 Concluding Remarks and Policy Implications

This chapter has built upon the important findings of Chapter 4 which emphasise the key role played by small banks in SME lending. This chapter has attempted to quantify the direct impact of such lending on local growth. In other words, the empirical approaches, presented in Chapter 3, have examined the effect of local banking development on local economic growth for a large representative dataset, with more than 2,500 U.S counties, over two decades from 1994 – 2013. The chapter, additionally, has investigated whether the magnitude of such effect is heterogonous across the distribution of regional growth within a single-country framework. Empirically, this research presents the SME lending channel as an indicator of local banking development. To do so, I have undertaken regressions using both a 'mean' based dynamic panel regression that accounts for endogeneity bias, and a 'quantile' based panel IV regression that exploits full distributional heterogeneity in the impact of SME lending on local economic growth.

The findings of the dynamic panel regression confirm Hypothesis 2 of the thesis' conceptual framework, suggesting that a greater contribution of locally-operating banks to small and micro lending spurs local economies. What is more, the quantile panel IV regression proves Hypothesis 2, confirming the presence of distributional heterogeneity in the impact of SME lending on regional economic growth. Specifically, I find large and positive effects of local banks' SME lending for regions at the lower end of the distribution of economic growth, mainly because the persistent supply constraint may motivate local economies to exploit resources from the local banks. However, along its growth trajectory, when a local economy faces competition of choice amongst a larger number of local banks, medium to large sized banks intervene in the market and take advantage of the growth opportunities by offering competitively priced loans and wider access to financial markets. This creates a mix of small and large banks. Moreover, rapid growth of human capital, in line with economic growth, increases the number of entrepreneurs, leading to higher economic growth in the long-run. The mix of new entrepreneurs, small and large banks in the region and the experience of growth take-off explains my finding that the net contribution of local banks to regional economic growth is positive, but smaller in magnitude. In a higher quantile of growth, I find that there can be two possibilities: (i) local banks contribute to the net growth of the economy by focusing on new local entrepreneurs (the only condition being that population growth is above the replacement level and that the human capital should be growing monotonically as well) and, hence, the net effect is positive but smaller in magnitude, and, (ii) due to high competition, some local banks exit the market, giving way to large banks. The net growth effects, in this case, are insignificant.

The empirical evidence is in line with my theoretical argument of an economy with persistence of uncertainty leading to information cascades among economic agents. Banks, small or large, like other economic agents, also suffer from this information cascade and may fail to undertake strong policies that may promote economic growth while, at the same time, they can preserve their profit maximization objective. Secondly, I consider a scenario whereby small banks face competition in a region in the lower quantile in its growth distribution, since they are limited in their lending capacity. As the number of banks rises, the greater competition leads to the exit of some banks or closure of some branches. At the same time, large banks may enter the market as leaders, and will put pressure on small business lending, either to close down or to innovate to succeed in the face of greater competition. In this case, since SME lending can do little to innovate, SME survival (as well as growth) depends on the demographic growth of that region, as well as the establishment of new opportunities, which once again would rely on small business lending to kick start growth.

I have demonstrated the heterogeneous effects of local banks on both the short- and long-run growth of regions. The policy implication is that policy-makers need to ensure that localisation effects are sustained, because of the comparatively minimal cost required to minimize individual (in relation to aggregate) uncertainties, and that local stability can be relied upon to achieve global stability. Both can be done by supporting the creation, and continued viability, of local banks. For this, a positive yield curve is required – which currently central banks in many countries are not delivering.

Chapter 6

A Spatial Econometric Analysis of Local Banking-Growth Nexus

Chapter 6: A Spatial Econometric Analysis of Local Banking-Growth Nexus

6.1 Introduction

The local banking development factor is one of the key regional factors offering support to local economic performance (as shown in Chapter 2 and Chapter 5). Over the past decade, the space factors have also been growingly considered as important indirect factors in quantifying the real effect of regional banking development on regional growth (see section 2.5). However, neglecting the spatial factors may have been one of the main causes of producing mixed findings in the regional banking-growth literature. For instance, the effect of banking development on regional growth is found to be negative (e.g. Becker, 2007), neutral in other studies (e.g. Guevara and Maudoa, 2009), or positive in most of them (e.g. Ashcraft, 2005; Fogel *et al.*, 2011; Kendall, 2012; Hakenes *et al.*, 2015). Yet, where the effect is found to be positive, the magnitude of the effect may vary based on the regions' level of development (e.g. Hakenes *et al.*, 2015; and Chapter 5), level of urbanisation (e.g. Collender and Shaffer, 2003), exposure to shocks (e.g. Ashcraft, 2005), or the timing of introducing new regulations (e.g. Freeman, 2002; Wall, 2004; Huang, 2008). Such mixed findings combined with the presence of spatial factors provide a strong evidence that interregional disparities or spatial heterogeneities are persistent in the long-term, hindering diffusion processes and hence economic convergence. Accordingly, despite the re-equilibrating processes, the developments of banking sectors of different regions cannot be considered as equally important to their regions' growth rates.

Drawing on the conflicting findings of regional banking-growth literature, the heterogeneities and the interdependencies in both local banking development and the growth paths, across regions, may raise concerns of unobserved spatial effects (spatial externalities), creating spurious correlation between local banking development and local growth. Therefore, regional banking-growth studies should neither treat regions as entirely interdependent on nor independent from each other, as well as, they should not assume homogeneity of the effects of local banking development on local growth across regions. Alternatively, these studies should allow for the possibility that economic growth in a region may depend systematically on banking development in neighbouring regions (Anselin, 1988).

Moreover, spatial externalities may arise when many entrepreneurs in a region, for instance, consider moving to adjacent regions because of better local amenities and local externalities in the latter regions – especially between neighbouring regions with no borders' restrictions. That is, healthier economic conditions and superiorly more facilitated business operations, in a region than other regions, can be a crucial source of spatial externalities. In the context of SME lending as an externality, those entrepreneurs may be encouraged to take loans and consume in neighbouring regions with high density of local banks, which may process their savings more efficiently. This may lead to a pull effect, causing a negative spatial effect on regional growth. (Hasan *et al.*, 2009). On the other hand, entrepreneurs may consume those loans in their own region (rather than in the neighbouring ones where the loans are taken from), causing a positive spatial effect on regional growth of their region, where credits are invested. Consequently, policy instruments such as SME lending and other macroeconomic indicators may create local externalities and spillover effects. That is to say, local SME lending in a region may indirectly affect the economic growth of other regions (adjacent regions in particular). To this end, the spatial spillover effects of banking development indicators, therefore, remain an empirical question and has not yet been sufficiently investigated in the empirical literature (especially in the U.S context).

Over the past decade, the role of space as a determinant of growth in regional finance-growth literature has received growing attention. However, the number of attempts that account for space in regional banking-growth link is scarce. Although most of those studies are based on EU regional data and adopted a similar spatial-lag model approach, they exhibit contradicting findings of the role of space in determining the effect of regional banking development on regional growth. For instance, two studies detect significant spatial spillover effects of bank lending volume (see Hasan *et al.,* 2009), and bank profit efficiency (see Belke *et al.,* 2016) on local economies. On the other hand, there is neither spatial nor non-spatial effect of banking development on regional growth in Austria (Burgstaller *et al.,* 2013). As for the U.S context, a small number of studies question previous work for not taking the spatial factors into consideration. For instance, Garrett *et al*., (2005) observe that banking deregulations in some states are announced after witnessing a positive effect of similar deregulations on other states' growth rates, expecting similar future local growth. This pattern implies the existence of spatial dependence across states. In contrast, Huang (2008) assert that banking deregulation does not have a significant impact on local growth or spillover effect on growth rates of neighbouring counties. Thus, Huang rejects previous claims that cross-county spillovers of banking deregulation effects invalidate the empirical design due to.

It can be noticed that the aforementioned U.S studies have merely focused on the effects of banking regulatory changes on regional growth, taking into account the spatial spillovers. On the other hand, this chapter contributes to and expand the extant literature on spatial banking-growth models by introducing macroeconomic lending variable and develop an analytical framework that captures spatial spillover effects among U.S counties. I examine the properties of this model, and determine the extent of bias in the estimates of local SME lending variations. This bias is then empirically quantified by estimating a dynamic spatial panel model for U.S counties over two decades since 1994.

Motivated by lack of empirical research that takes into account the spatial frictions in the analysis of the regional banking-growth relationship, I extend the analyses of the precedent chapters on the importance of banking structure to the local economies through SME lending channel. That is, since the empirical examination of Chapter 5 has confirmed the presence of distributional heterogeneity in local banking-growth relationship among regions, this chapter takes a different approach by accounting for spatial externalities in the impact of local banking development on regional economic performance. I assume that spatial local SME lending externalities play a key role in explaining differences in growth paths between regions. I use a dataset that consists of 2,590 U.S counties over the period 1994-2013 to test for spatial dependence on local banking development by incorporating spatial externalities directly into an empirical model. In particular, I compare between the estimation of a baseline panel regression model without accounting for spatial spillover effects and the estimation of a Spatial Durbin Model (SDM) which accounts for spatial spillover effects of local banking development on local economic growth. To the best of my knowledge, this chapter is the first study to consider dynamic spatial interdependencies across local banking and SME lending markets.

The U.S county-level dataset, used in this chapter, also motivates the adoption of spatial banking-growth model to gauge the relationship between local banks and regional growth. The dataset contains explicit spatial relationships, because counties are likely to be subject to both observable and unobservable common disturbances. Such disturbances may lead to spatial correlation which can be explained by various channels of interdependence. That is, spatial correlation may occur due to regional business cycles, access to bank branches, economic shocks, policy harmonisation, and regional disparities (e.g. Garrett *et al.*, 2005), and more importantly the theory of human interactions (Comin *et al.*, 2012). Additionally, spatial correlation may also occur as a result of the boundary mismatch problems; that is, when the economic notion of a market does not correspond well with the county's boundaries (Rey and Montouri, 1999).

I find strong evidence that 'space' is an important factor in determining the regional banking-growth relationship. Specifically, spatial spillover effect of local banks contributes positively to local economic growth. That is, economic growth of a region is influenced by the small business loans supplied by local banks in other regions. These finding are robust when the micro business lending used as an alternative measure of local banking development. In other words, the results from the SDM estimations confirm the presence of the positive spatial spillover effects of local SME lending on local economic growth.

The rest of this chapter is organised as follows – The subsequent section describes the dataset and data sources and then explains the variables used in this study as well as the rationale underpinning their use. It also presents a graphical analysis of the data. The following section shows the model selection and the spatial weight matrix. Section 6.4 reports the findings and highlights the common results among the models. The final section concludes the chapter and introduces the implications.

6.2 Data

6.2.1 Local Banks and SME Lending

Since the key hypothesis in this chapter is to examine the impact of local small business lending on local economic growth, I should define what is meant by *local banks and local markets*: Firstly, the local market is defined as the market associated with any county in the United States. I follow previous studies in determining the size of local markets (e.g. Ashcraft, 2005; Fogel *et al.,* 2011). According to informal discussions with bank examiners in the Federal Reserve System and with community bankers, 75–90% of the loan customers of typical single-county local banks reside within the county (Yeager, 2004). I, additionally, distinguish between rural and urban markets. The latter is a county, which is part of a Metropolitan Statistical Area (MSA), while the rest are regarded as rural markets (Collender and Shaffer, 2003). Overall, my dataset consists of 2,590 counties, where 1,014 counties are urban and 1,576 counties are rural. The time scale spans over 20 years, from 1994 to 2013.

My primary source of banking data is from the Federal Deposit Insurance Corporation (FDIC). "The FDIC collects, corrects, updates and stores Reports of Condition and Income data submitted to the FDIC by all insured national and state non-member commercial banks and state-chartered savings banks on a quarterly basis. Reports of Condition and Income data are a widely used source of timely and accurate financial data regarding a bank's condition and the results of its operations" (FDIC, 2014). The Statistics on Depository Institutions (SDI) stores data about banks' balance sheets, while the Summary of Deposits (SOD) contains data about branches and office deposits. Both the SDI and the SOD are managed by the FDIC.

The small business lending and branch office deposits data which is only reported annually as of June 30th. Accordingly, I construct an unbalanced panel dataset of 38,149 observations used in the preliminary analysis and a balanced dataset of 25,700 observations for the regression analysis. Secondly, a local bank is any domestically owned depository institution that has all its branches, including the headquarters, within the geographical borders of a single county (DeYoung *et al.,* 2004) and (Fogel *et al.,* 2011). For simplicity, I term small and micro business loans made by local banks as local small and micro business lending and all types of depositary institutions as a "bank".

It is worth noting that the United States consists of 3,143 counties and county equivalents. The reason I only have 2,590 counties in this research is that the excluded counties may not have locally headquartered banks that are insured at the FDIC, relying primarily on branches of banks based in other counties, and/or other types of financial institutions. In addition, it would be ideal if I obtain aggregate the small business lending data of non-local banks (i.e. multi-county banks) at the county-level. Such data would provide further room for comparison between the independent effects of local and non-local banks on local economic growth. Unlike deposit data, the FDIC reports lending data is at bank-level, not branch-level. However, county-level data for non-local banks is only available from the Federal Financial Institutions Examination Council (FFIEC) collected under the Community Reinvestment Act (CRA) for banks with asset size of over \$250 million, that is to say, a large number of non-local banks with less than \$250 million do not report the amount of small business loans in each county. For instance, 3,646 out of the 6,949 banks operating in 2013 do not meet my definition of locality, as only 850 of them report CRA small business loans to the FFIEC. A very simple calculation reveals that county-level small business loans are not obtainable for 2,796 non-local banks. Therefore, I confine my analysis to the FDIC's available data, based on my definition of bank locality.

6.2.2 Local Economic Development (Dependent Variable)

Since there is no available data for GDP at county-level to represent local economic development, I employ one of the most widely used measures of economic activities in the empirical literature as a dependent variable, that is, the total real income, which is collected from the U.S Bureau of Economic Analysis (BEA). The rationale behind using an income measure is to capture the extent to which changes in the quantity of SME loans may lead to changes in the locally available purchasing power, a proportion of which can be expected to be local income. The total income enters the regressions in the logarithm form.

6.2.3 Local Banking Measures (Key Explanatory Variable)

The FDIC defines the small business loans (SBL) as the amount of currently outstanding commercial and industrial loans with original amounts less than \$1,000,000 held in domestic offices. In addition, I consider loans with original amounts less than \$100,000 to be the micro business loans (MBL) (i.e. loans granted to the smallest of the small businesses). Small business lending data is available at bank-level from the FDIC. I aggregate all small business loans that are reported each year by all local banks in a county. For simplicity, I use the terms Local Small Business Loans (LSBL) and Local Micro Business Loans (LMBL) for Small Business Loans and Micro Business Loans that are provided by local banks, respectively. Both the LSBL and the LMBL variables are transformed into logarithms.

Several researchers have adopted the FDIC definition of small business loans, such as Keeton (1995), Strahan and Wetson (1998), Peek and Rosengren (1998), Carter and McNulty (2005), Carter *et al.*, (2004), and Berger *et al.*, (2011). Although, in theory, the data is based on the loan size, not the company size, it is reasonable to interpret the data in the way in which the FDIC and authors have done it. That is to say, because of the due-diligence and transactions costs, it is highly likely that large companies will not take out very small loans, while small companies cannot take out large loans. Therefore, this approximation is very reasonable and has become the standard in the literature. According to the Community Reinvestment Act (CRA), on average 93% of small business loans have loan amounts less than $100,000. The CRA requires banks with an asset size greater than $300 million to report their small business loans. In addition, primary surveys have established a close correspondence between loan size and the size of the borrower. For instance, according to the 1989 National Survey of Small Business Finance, 80 percent of loans to businesses with less than $1 million in annual sales amounted to less than $100,000 each (Board of Governors). Earlier surveys have shown similar results (Keeton, 1995).

6.2.4 Control Variables

A set of control variables are inserted into the model specifications to isolate the impact of local small business lending on local economic activities. The selected variables may affect local activities and, hence, their omission could generate biased regression estimations.

Return on Asset (ROA): This is defined as the return on average total assets of local banks (Source: FDIC). That is to say, net income after taxes and extraordinary items (annualised) as a percent of average total assets. I use it to control for the performance of the local banks (also used by Hakenes *et al.*, 2015).

Equity Ratio: This is the total equity capital as a percent of total assets (Source: FDIC). Hakenes *et al.*, (2015) argue that banks with a lower equity ratio may have a relatively greater return on equity, resulting in biased estimations. Additionally, this ratio controls for the level of management risk-taking.

Herfindahl-Hirschman Index (HHI): A relevant factor to be considered as affecting the credit market is the banking competition or the level of market power in the local market (Source: Summary of Deposits by FDIC). The deposit market HHI measure is often used in the literature to represent the local market competition.

Non-interest income/interest income: This represents the percentage of non-interest income relative to interest income. According to Hakenes *et al.*, (2015), a number of local banks may tend to maximise their profits through potentially higher marginal commission services, which may positively incorporate bank profitability and efficiency measures. Consequently, I, as Hakenes *et al* do, control for bank non-interest income to isolate such an effect.

Inflation: I use the annual U.S Consumer Price Index (CPI). Fluctuations in the inflation rates may lead to an unstable economy. For instance, higher inflation makes investors more reluctant to invest in local economies, causing slower economic growth. Adding an inflation variable helps to control for such macroeconomic fluctuations.

Population Growth: In this chapter, I use the growth rate of the number of individuals who reside in a county. This measure is a proxy for human capital. Previous studies have shown a strong positive relationship between human capital and local economic growth (e.g. Glaeser (2000); Kirchhoff *et* *al.*, (2007)). The U.S Bureau of Economic Analysis (BEA). The population is expected to have a positive impact on economic development.

6.2.5 Preliminary Analysis and Summary Statistics

Descriptive statistics and variable descriptions are shown in Table 6.1, below. Most notably, the LSBL, the LMBL, the total income, and population variables exhibit extreme outliers. Those outliers represent the very dense and wealthy counties, such as Los Angeles, Cook and New York. Additionally, the outliers may partly explain the variations in standard deviations; however, none of the variables shows extreme standard deviations. The median and the mean of the LSBL and the LMBL indicate that almost half of the SME loans in the dataset are micro business loans.

Table 6.1 Summary Statistics

Variable	Description	Mean	Min.	Max.	No. Obs.	Std. Dev.	Median
Local Economic Activity							
Total income (Million) *	Real total income in a county, in million	4314	6.021	466100	38,149	14667	728.3
Bank Lending							
LSBL (Million)* (Loans < $1000,000)	Total small business loans provided by local banks in a county, in million	19.336	0.001	2128.7	38,149	53.70	8.469
LMBL (Million)* (Loans < $100,000)	Total micro business loans provided by local banks in a county, in million	8.5228	0	1757.5	38,149	26.64	4.521
Control Variables							
Bank Specific Variables							
ROA (%)	Return on average total assets for local banks in a county	1.032	-13.93	13.89	38,130	0.999	1.128
Equity Ratio (%)	Total equity capital as a percent of total assets for local banks in a county	11.29	0.598	87.12	38,149	4.058	10.48
Non-interest income/interest income (%)	Percentage of non-interest income relative to interest income for local banks in a county	12.43	-205.6	499.7	38,138	11.27	12.07
Local Market Variables							
Market concentration (HHI) (%)	Deposit market Herfindahl-Hirschman index in a county	0.272	0.034	1	38,149	0.17	0.224
Population growth (%)	Growth rate of population in a county	0.006	-0.534	0.238	35,281	0.015	0.004
Inflation %	Annual U.S Consumer Price Index (CPI)	2.448	-0.356	3.84	38,149	0.868	2.663

Note: * The local SBL, local MBL and total income variables are displayed in million, while each of them is converted to a natural logarithm when included in the regressions.

Hot and cold spot analysis

Table 6.2 shows the distance matrix of the U.S counties. The mean distance between two counties is approximately 1,241.566 km. The minimum and maximum distances are 0.219 km and 4,455.518 km, respectively.

Table 6.2 Distance Matrix of the U.S Counties

	Obs.	Mean	S.D.	Min.	Max
Distance	1037520	1241.566	724.307	0.219	4455.518

Note: This table shows the distance matrix of the U.S counties. That is, the longest distance between two counties and the shortest one. It also shows the standard deviation of distance and the average distance between all counties.

Tables 6.3 and 6.4, below, display the summary of the hypothesis testing results of the complete spatial randomness at the 1% and 5% levels. In 1994, for instance, the numbers of hot spot counties of micro business loans at the 1% and 5% levels are 26 and 49, respectively. On the other hand, there is no cold spot counties of the LMBL. The numbers of hot spots have declined over 20 years to arrive at 14 and 16 at the 1% and 5%, respectively, in 2013. All banking variables shown in the tables follow similar pattern over time.

Table 6.3 Hot and Cold Counties

Variable	**LMBL**		**LSBL**		**Bank Density**		**Share of local branches**		**Per capita Income**		**Total income**		**Employ -ment**	
Year	1994	2013	1994	2013	1994	2013	1994	2013	1994	2013	1994	2013	1994	2013
2.58<=z	49	14	37	38	156	81	109	42	141	55	81	47	81	45
1.96<=z<2.58	26	6	19	7	83	46	122	55	59	43	24	23	31	23
-1.96<z<1.96	2361	1421	2380	1396	2144	1311	2012	1319	2116	1291	2331	1371	2324	1373
-2.58<z<=-1.96	0	0	0	0	43	3	124	25	67	41	0	0	0	0
z<=-2.58	0	0	0	0	10	0	69	0	53	11	0	0	0	0

Note: This table shows the summary of the hypothesis testing results of the complete spatial randomness for the first year of the sample period (1994) and the last year (2013) at the 1% and 5% levels. Only local banking, banking density, and economic variables are displayed.

Table 6.4 Hot and Cold Counties with Conditions

Variable	**Share of Local branches < 50%**		**Share of Local branches > 50%**		**Bank density < 40 per 100, 000**		**Bank density > 40 per 100, 000**		**Share of local branches in urban counties**		**Share of local branches in rural counties**	
Year	1994	2013	1994	2013	1994	2013	1994	2013	1994	2013	1994	2013
2.58<=z	91	49	30	3	78	27	33	22	49	27	19	16
1.96<=z<2.58	37	36	44	7	38	14	16	22	73	21	44	19
-1.96<z<1.96	1247	1205	1086	201	1054	624	1140	695	1339	791	810	564
-2.58<z<=-1.96	15	24	34	5	21	13	22	17	43	1	32	2
z<=-2.58	5	0	38	0	25	1	9	6	8	0	19	0

Note: This table shows the summary of the hypothesis testing results of the complete spatial randomness for the first year of the sample period (1994) and the last year (2013) at the 1% and 5% levels. The local banking and banking density variables are displayed and conditional to population and level of urbanisation.

It can be observed from the small business loans' figure in 1994, i.e. Figure 6.1, that the biggest hot spots are concentrated in the central and the upper side of the central such as Wisconsin, Illinois, and Minnesota. The far western States, California in specific also have many hot spot counties, while on the other side of the U.S, the LSBL are mostly concentrated in and around Massachusetts. Florida contains many hot spot counties too.

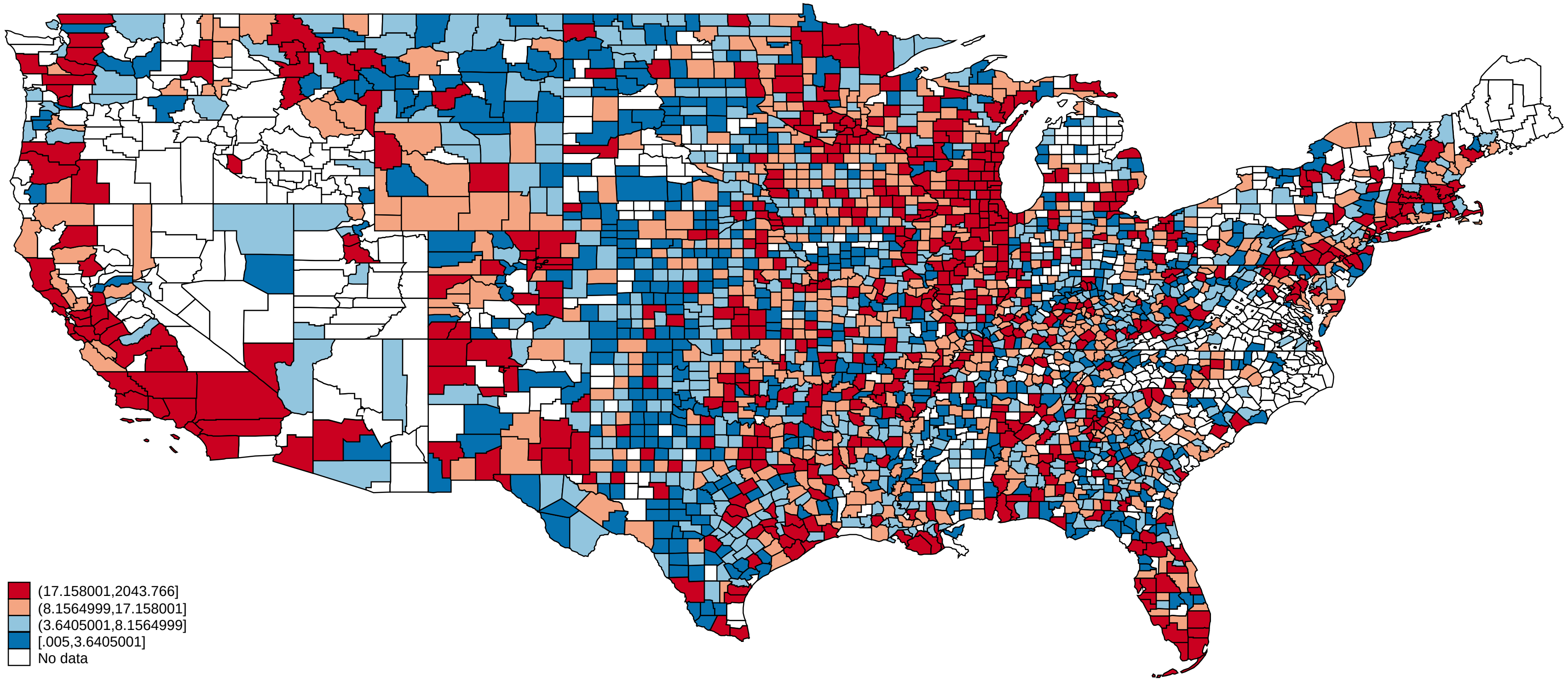
However, the spatial pattern dynamically changes over 20 years. For example, areas with the most concentrated LSBL had decreased over 20 years. The changes can be observed in Figure 6.2, which shows the heat maps of county LSBL in 2013. Although the states with the highest level of LSBL had continuously remained on top from 1994 to 2013, the number of their hot spots had shrunken. What is more, the rest of maps in 2013 follow the same pattern as that for the LSBL in 2013 (see the figures in Appendix E).

Most of the white counties represent those do not have local banks; yet, they may rely on other types of intermediaries, branches of cross-county banks or nationwide banks. Those counties do not have LSBL and LMBL by local banks, not only due to unavailable data. The increase in the number of white areas between 1994 and 2013 can be mainly attributed to the shrinkage in the number of banks, especially those small locally-operating ones.

The highest income counties that have, at most, half of their bank branches are local, are concentrated in the sides of the U.S, especially, North Eastern (e.g. Massachusetts), far Western (e.g. California), the upper central (e.g. Illinois and Michigan), and Florida counties (see Figure 6.3). On the other hand, Figure 6.4 shows that the highest income counties with, at least, half of their bank branches are local, are concentred in the central and the upper side of the central counties.

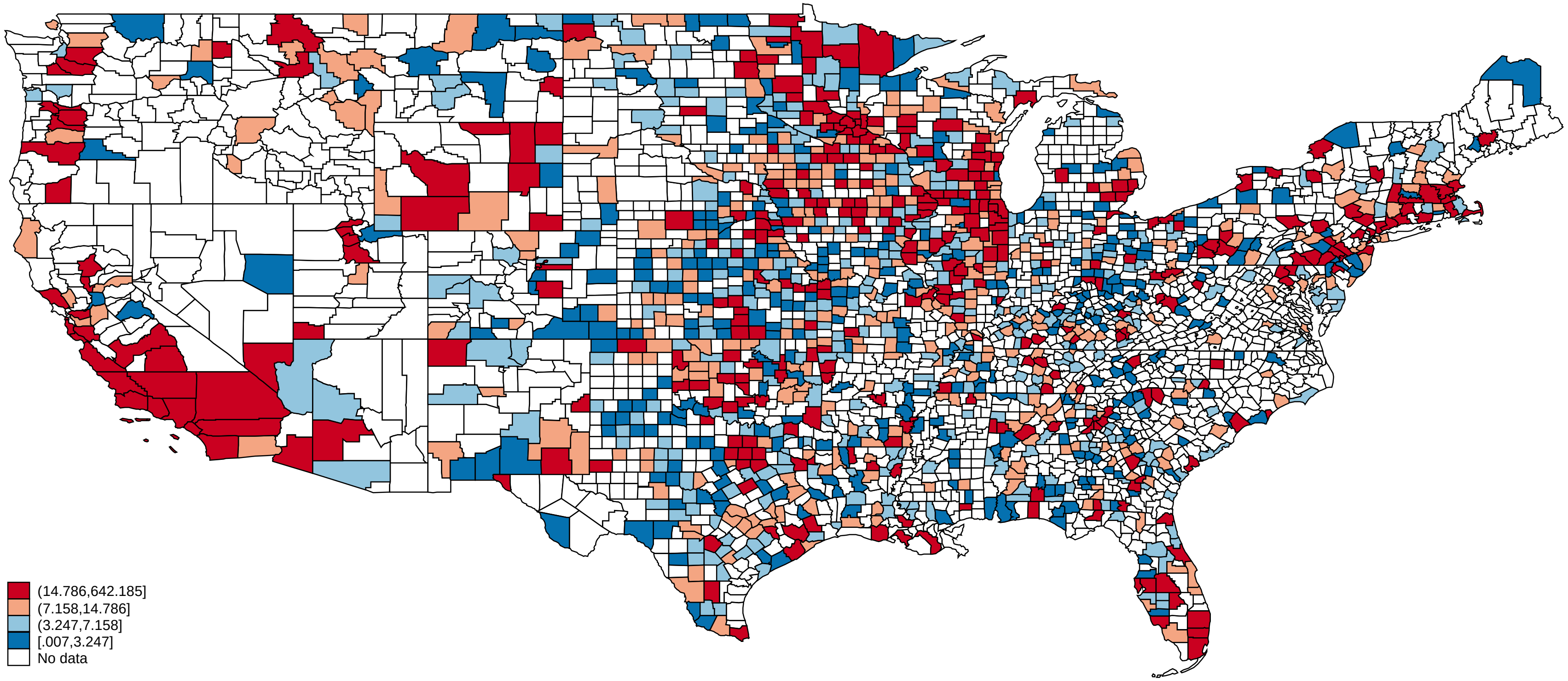
The shrinkage in the number of local banks and increased centralisation can be observed from Figures 6.15 – 6.16 (see Appendix E). The number of counties with large share of local bank branches to total bank branches had declined over 20 years from 1994 to 2013. Interestingly, these counties are concentrated in the middle of the U.S. What is more, Figures 6.17 – 6.20 (see Appendix E) shows that the highest share of local bank branches to total bank branches are found in rural areas. The bank density in Figures 6.21 and 6.22 (see Appendix E) follows the same pattern of the share of local bank branches to total bank branches.

Figure 6.1 Heat Map of County Small Business Loans in 1994



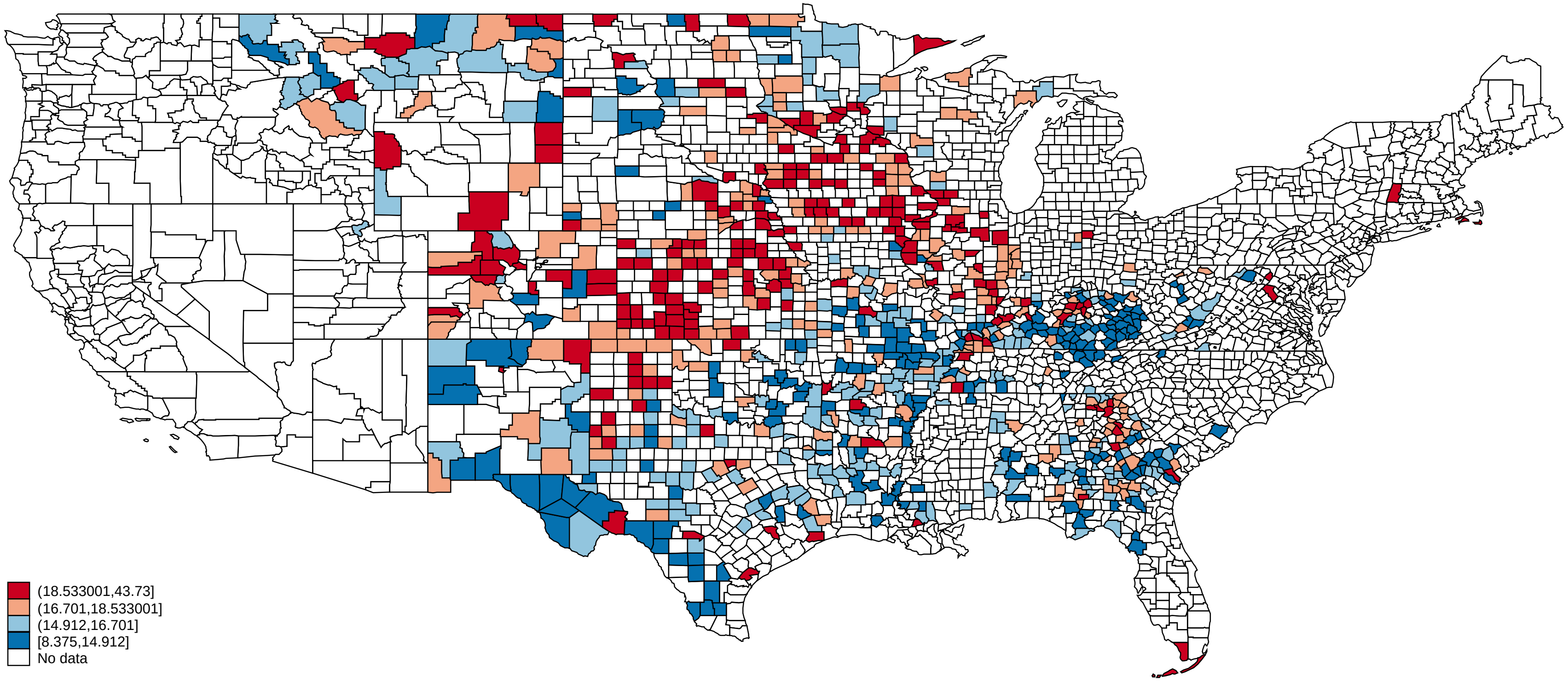
Note: This figure shows a heat map of county LSBL volume in 1994. The dark red colour represents counties with more than $17.16 million of small business loans; the pink and light blue areas represent counties with at least $8.16 million and $3.6 million LSBL, respectively. Dark blue colour represents counties with less than $3.6 million LSBL. White colour areas indicate no data.

Figure 6.2 Heat Map of County Small Business Loans in 2013



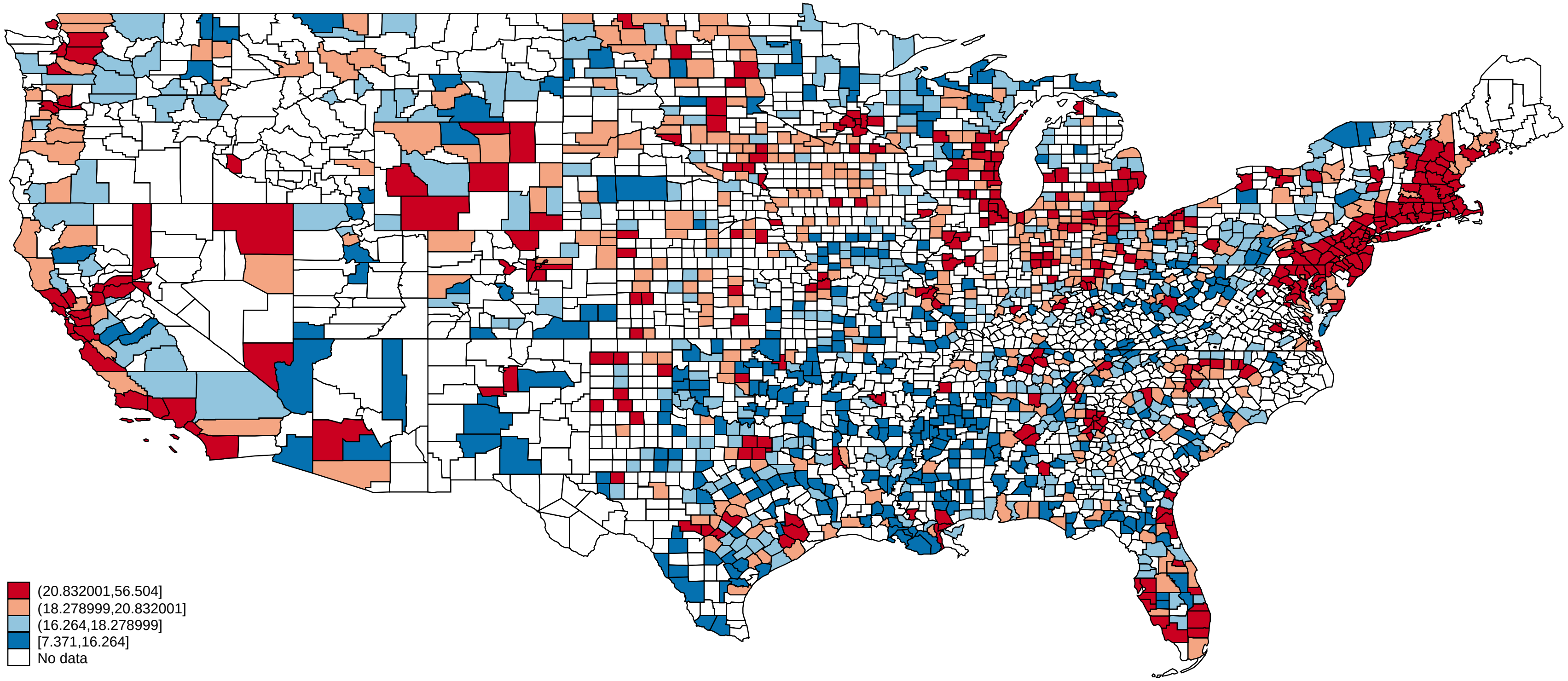
Note: This figure shows a heat map of county small business loans volume in 2013. The dark red colour represents counties with more than $14.79 million of small business loans; the pink and light blue areas represent counties with at least $7.16 million and $3.25 million LSBL, respectively. Dark blue colour represents counties with less than $3.25 million LSBL. White colour areas indicate no data.

Figure 6.3 Heat Map of County per Capita Income for Counties with more than 50% of Local Bank Branches in 1994



Note: This figure shows a heat map of county per capita income for counties with more than 50% of local bank branches to total bank branches in 1994. The dark red colour represents counties with more than \$18, 533 per capita income; the pink and light blue areas represent counties with at least \$16, 701 and \$14, 912, respectively. Dark blue colour represents counties with less than \$8, 375 per capita income. White colour areas indicate no data.

Figure 6.4 Heat Map of County per Capita Income for Counties with less than 50% of Local Bank Branches in 1994



Note: This figure shows a heat map of county per capita income for counties with less than 50% of local bank branches to total bank branches in 1994. The dark red colour represents counties with more than $20, 832 per capita income; the pink and light blue areas represent counties with at least $18, 279 and $16, 264, respectively. Dark blue colour represents counties with less than $7, 371 per capita income. White colour areas indicate no data.

6.3 Model Specification

The model specification in Chapter 6 aims to analyse the proposition that spatial spillover effects of local small and micro business lending are important determinants of regional economic development (i.e. H4, presented in Chapter 3). To test such proposition, I adopt a dynamic spatial Durbin Model (SDM) for U.S county-level data over the period from 1994 to 2013. Accordingly, I recall and estimate the Equation (3.30) to be the dynamic spatial panel specification of this empirical chapter as detailed in section 3.4:

$$Income_{it} = \alpha + \beta Income_{i\,t-1} + \gamma \sum_{j=1}^{N} W_{ij} Income_{it} + \psi \sum_{j=1}^{N} W_{ij} Income_{it-1} + \sum_{k=1}^{K} X_{it} \zeta_k + \sum_{k=1}^{K}\sum_{j=1}^{N} W_{ij} X_{jkt} \eta_k + \theta_i + v_t + \varepsilon_{it} \tag{3.30}$$

where i is an index for the cross-sectional dimension (regions/counties), with $i = 1, \ldots, N$; and t is an index for the time dimension (years), with $t = 1, \ldots, T$. and k is the number of exaplanotry varibales, with k = 1, . . . , K. Furthermore, $Income_{it}$ represents an observation on the total income (i.e. dependent variable) at i and t. also, X_{it} denotes a 1 × K vector of observations on the explanotry variables at i and t. The explanotry variables include the local banking variable (i.e. either the LSBL or the LMBL) and a set of control variables, namely, return on asset (ROA), equity ratio (EQV), non-interest income/interest income (INT), Herfindahl-Hirschman index (HHI), population growth (LABF), inflation (INF), and banking density (BDEN). Whereas W_{ij} is an element of a spatial weight matrix W that describes the spatial arrangement of the regions in the sample. The weights are assigned using geographical coordinates (i.e. latitude and longitude) of each county. Moreover, ($\sum_{j=1}^{N} W_{ij} Income_{it}$) are endogenous interactions of the dependent variable ($Income_{it}$) with the dependent variables ($Income_{jt}$) in neighbouring regions, and ($\sum_{k=1}^{K}\sum_{j=1}^{N} W_{ij} X_{jkt}$) are exogenous interactions of the independent variables X_{it} with the independent variables X_{jt} in neighbouring regions. In addition, α is the constant parameter vector. γ, ψ, ζ and η are coefficients for these above spatial dependencies separately. θ_i and v_t refer to region fixed and time fixed effects with respect to the panel dataset. The above model can be called as a dynamic spatial panel model by controlling the coefficients of time lags ($Income_{it-1}$) and spatial time lags ($W_{ij} Income_{it-1}$) of endogenous variable to be non-zero (Debarsy *et al.*, 2012). ε_{it} indicates the independently and identically normally distributed error terms for all i and t with zero mean and constant variance σ^2.

Prior to estimating the dynamic SDM (i.e. Equation 3.30), it is essential to ensure that all the included variables in the regression are stationary. This helps me to avoid the risk of running spurious spatial regression in the data (e.g. Mur and Trivez, 2003; Baltagi *et al.*, 2007). To do so, I perform three types of panel unit root tests, namely, the LLC test (Levin *et al.*, 2002), IPS test (Im *et al.*, 2003), and Fisher-type test (Choi, 2001) based on augmented Dickey-Fuller test (Dickey and Fuller, 1979).

6.4 Empirical Analysis

In this section, I present the main empirical results. I begin with my findings with regard to model selection. This is followed by the presentation and analyses of the main empirical results and the robustness exercise, where I distinguish between spatial and non-spatial results.

6.4.1 Model Selection

The above model specification has been adopted based on the following selection process. Firstly, I only add the spatial fixed effects and remove the time fixed effects to achieve the convergence requirement of the ML estimation. Based on the results of the Hausman test statistic is 1863.93, which is significantly greater than the critical value of 25.00 at the 5% level of significance, indicates that the SDM with the fixed effects are preferred to the random effects in the case of the SDM (Hausman test statistics for the rest of the regressions are reported in Tables 6.5 and 6.6).

Secondly, I compute the following two LR tests to prove whether the SDM is the most appropriate specification to explain my empirical data (Elhorst, 2010). Specifically, on the basis of both (3.24) and (3.26), firstly, the null hypothesis $H_0: \eta = 0$ tests of whether the SDM can be simplified to the SAR. The LR statistic is 975.89, which exceeds the critical value of 14.07 at the 5% significance level. The second null hypothesis $H_0: \eta + \rho\zeta = 0$ examines whether the SDM can be simplified to the SEM. The LR statistic is 912.26, which is larger than 14.07 at the 5% significance level. Due to the rejections of both null hypotheses above, the SDM is demonstrated to best fit my data. (LR tests for the rest of SDM regressions are reported in Tables 6.5 and 6.6). Finally, I compute an additional LR test to examine whether the static SDM can be extended to be dynamic by the hypothesis $H_0: \beta = \gamma = 0$, and LR = 2 × (−1142.2321 + 1284.1955) = 283.93. The LR statistic is greater than the critical value of 5.99 at 5% significance level, which strongly rejects the null hypothesis, denoting the preferable of dynamic SDM.

Additionally, the results of all unit-root tests, shown in Appendix A, indicate that all my variables are stationary in the level format and do not need to be differenced. Therefore, all variables enters the empirical analysis in the level format.

6.4.2 Discussion of Results

The main regression results of the empirical analysis in this chapter are shown in Table 6.5. Specifically, Columns 1 and 3 describe the results estimated by the OLS approach without considering spatial spillover effects, while Columns 2 and 4 exhibit the coefficients estimated through the dynamic spatial Durbin model (SDM), estimated by the maximum likelihood (*ML*) method, which includes both temporally spatial lag and temporal lag, estimated by the maximum likelihood (ML) method. Besides, Columns 1 and 2 include both the local small business lending and other non-lending regional factors, while Columns 3 and 4 ignore the effect of the non-lending factors on local income. The "Main" section mainly denotes the effects of local income of each specific region provided by the variables within its spatial boundaries, while the "Wx" section describes the spatial spillover effects of local income supplied by spatially distributed regions.

The "Main" section of Table 6 shows several interesting patterns. To begin with, the OLS estimates (without any spatial spillover effects) in Column 1 and Column 3 depict negative effects and greater absolute values of local small business lending than the positive ones estimated by the SDM (in Column 2 and Column 4). This might be due to the consideration of spatial frictions in translating the full effects of bank lending on economic growth. It has been noted in a number of researches that spatial frictions 'absorb' the over-estimated positive/negative effects of the main determinant of growth.

Secondly, the dynamic parameters in the dynamic SDM evince significant effects on local income. For instance, temporal lag of local income (L.Income) exerts a significantly positive effect in both Column 2 (0.79) and Column 4 (0.809). Interestingly, the coefficients of the temporally spatial lag of local income (L.WIncome) in the "Wx" section is negative, which tends to offset the positive effect provided by contemporaneous spatial lag of local income (WIncome). As expected, the summation of the effects of the temporally spatial lag (L.WIncome) and the contemporaneous spatial lag WIncome of local income triggers a significantly positive effect (i.e. 0.249 and 0.203 in columns 2 and 4, respectively), indicating the positive spatial autocorrelation of local income. The presence of such spatial transmission mechanism offers direct evidence in regard to the synchronization of economic cycles across borders of U.S counties.

Thirdly, in the absence of the spatial spill-over effects or other non-lending factors, absolute values of expected effects on local income would be markedly biased. Specifically, the absolute values of the estimated coefficients are over-estimated as a result of ignoring 'space'. For example, the estimated coefficients of all variables in Column 2, considering their absolute values, will be over-estimated if one does not consider spatial spillover effects (see in Column 1). Moreover, neglecting the specific (direct) non-lending factors (e.g. inflation and return on assets) and/or other region-specific factors (e.g. population, and market competition) bias the estimation results of the local banking indicator (i.e. local small business lending variable), while the absolute values of such bias could be either overestimated or under-estimated. For example, in terms of over-estimation, local small business lending exerts greater effects on local income variations in Column 4 (0.0022) than in Column 2 (0.0018). In terms of under-estimation, the spillover effect of small business lending (WLMBL) (see in "Wx" section) on local income variations is smaller in Column 4 (0.0184) than in

Column 2 (0.0256). To sum up, I can mainly conclude that the absolute values of the estimated coefficients without considering spatial spillover effects tend to be significantly over-estimated. In addition, the omission of the direct non-lending factors could also bias the dynamics of local income (either over- or under-estimated). The importance of the other direct control factors on local income determinations is consistent with the evidence suggested by Camagni and Capello (2010), although only the non-interest income to interest income, equity ratio and banking density variables show insignificant effects.

Furthermore, the “Wx” section enables me to clearly quantify the spatial spill-over (indirect) effects of incorporated independent variables on local income. All variables, except market competition, non-interest income to interest income and banking density variables, demonstrate statistically significant positive and negative spatial spill-over effects on local income variations. Moreover, these variables show significant indirect effects in the same direction as their corresponding direct effects in the “Main” section. Interestingly, the direct effect of the inflation variable demonstrates a positive direct effect in the “Main” section, while the sign becomes negative for the indirect effect on local income variations as expected (see in the “Wx” section). A key finding shows that the local small business lending variable exerts a more powerful positive spatial spill-over effect in both Column 2 and Column 4, which is 0.0256 and 0.0184, respectively. Besides, equity ratio exerts an insignificant negative direct effect in the “Main” section, whereas it shows significant and larger indirect effect in the in the “Wx” section as shown in Column 2. Overall, based on my spatial framework, the significant spillover effect of local small business lending and other regional variables enables me to provide the fundamental reason of why regional local income rates are converging, as proved in Chapter 5.

Due to the co-movement of regional banking and other regional fundamentals, the local income rates appear to ’catch-up’ with other local economies and evince a spatial clustering. This is consistent with the Neoclasical theory of economic convergence and the previous result of Garrett *et al.*, (2005 and 2007), and Fidrmuc and Hainz (2013).

Table 6.5 Main Results (Non-spatial Model and Dynamic SDM)

Variables	**Col.(1)**	**Col.(2)**	**Col.(3)**	**Col.(4)**
Main	**OLS**	**SDM**	**OLS**	**SDM**
LSBL	-0.05258***	0.00176***	-0.07590***	0.00221***
	(0.000)	(0.000)	(0.000)	(0.000)
Inflation	-0.02455***	0.00718***		
	(0.000)	(0.000)		
ROA	-0.07905**	0.00109**		
	(0.000)	(0.017)		
HHI	0.10294**	-0.01164*		
	(0.011)	(0.095)		
Population Growth	-2.96723***	0.42215***		
	(0.000)	(0.000)		
Non-interest income/interest income	0.00097***	-0.00001		
	(0.000)	(0.675)		
Equity Ratio	0.00606***	-0.00020		
	(0.006)	(0.136)		
Banking Density	0.01109***	-0.00002		
	(0.000)	(0.673)		
L.Income		0.79034***		0.80922***
		(0.000)		(0.000)
Constant	21.10632***		21.99977***	
	(0.000)		(0.000)	
Wx				
WLSBL		0.02561***		0.01841***
		(0.000)		(0.000)
WInflation		-0.00546***		
		(0.000)		
WROA		0.01342***		
		(0.000)		
WHHI		0.05070		
		(0.441)		
WPopulation Growth		0.38083**		
		(0.034)		
WNon-interest income/interest income		0.00027		
		(0.275)		
WEquity Ratio		-0.00746***		
		(0.000)		
WBanking Density		-0.00015		
		(0.708)		
WIncome		0.87180***		0.98888***
		(0.000)		(0.000)
L.WIncome		-0.62290***		-0.78611***
		(0.000)		(0.000)
Constant				
Residual variance (σ2)		0.00163***		0.00162***
		(0.000)		(0.000)
Region FE	Included	Included	Included	Included
Number of Obs.	24,415	24,415	24,643	24,415
No. Regions	1,285	1,285	2,095	1,285
Hausman Statistic	8518.59	1863.93	272.42	16.23
Prob>chi2	(0.000)	(0.000)	(0.000)	(0.001)

Note: This table reports results from OLS and SDM estimations of the effects of local banks on regional economic development. The dependent variable is the logarithm of Total Income at county-level. The measure of local bank SME lending is the Local Small Business Loans (LSBL) at county-level. Col. (1) and Col. (3) denote the non-spatial panel model estimated by OLS. Col. (2) and Col. (4) denotes the dynamic SDM estimated by the ML. The "Main" denotes the results without spatial spillover effects and "Wx" denotes the results with spatial spillover effects. The test statistics for model selection are reported in the bottom of the table. The period covers the years 1994 to 2013. P-values are reported in parentheses. The symbols ***, ** and * indicate the levels of significance, 1%, 5% and 10%, respectively. P-values are between parentheses.

Robustness Test

To further check the robustness of my main regression in Table 6.5. The local micro business loans (LMBL) measure has been introduced as an alternative proxy for local banking development. The LMBL exerts a positive impact on local growth (proved in Chapter 5). Besides, as mentioned before, the LSBL in this study represents the aggregate small business loans provided by local banks at county-level, where the LSBL includes the aggregate micro business loans. Hence, I conduct this robustness check by replacing the LSBL by the LMBL, and the results are presented in Table 6.6. In terms of the "Main" section, the results broadly mimic my main estimations in Table 6.5. In particular, my replacement variable for the LSBL (i.e. LMBL) is found to exert a significant and positive effect on local income variations. The LMBL exerts a similar direct effect in either the non-spatial panel model (Columns 5 and 7) or the dynamic SDM (Columns 6 and 8).

Table 6.6 Robustness Test (Non-spatial Model and Dynamic SDM)

Variables	**Col.(5)**	**Col.(6)**	**Col.(7)**	**Col.(8)**
Main	**OLS**	**SDM**	**OLS**	**SDM**
LMBL	-0.11830*** (0.000)	0.00111*** (0.005)	-0.14268*** (0.000)	0.00157*** (0.000)
Inflation	-0.01972*** (0.000)	0.00950*** (0.000)		
ROA	-0.06011*** (0.000)	0.00113** (0.015)		
HHI	0.01749 (0.646)	-0.01362* (0.055)		
Population Growth	-2.43380*** (0.000)	0.41017*** (0.000)		
Non-interest income/interest income	-0.00001 (0.949)	-0.00002 (0.550)		
Equity Ratio	0.00062 (0.404)	-0.00024* (0.073)		
Banking Density	0.00969*** (0.000)	-0.000004 (0.926)		
L.Income		0.77985*** (0.000)		0.80941*** (0.000)
Constant	22.21351*** (0.000)		22.97468*** (0.000)	
Wx				
WLMBL		0.06140*** (0.000)		0.01763*** (0.000)
WInflation		-0.00372*** (0.000)		
WROA		0.00338 (0.237)		
WHHI		0.18133*** (0.007)		
WPopulation Growth		0.90483*** (0.000)		
WNon-interest income/interest income		0.00149*** (0.000)		
WEquity Ratio		-0.00351** (0.033)		
WBanking Density		-0.00132** (0.001)		
WIncome		0.72370*** (0.000)		0.98909*** (0.000)
L.WIncome		-0.38554*** (0.000)		-0.77010*** (0.000)
Constant				
Residual variance (σ2)		0.00168*** (0.000)		0.00162*** (0.000)

Region FE	Included	Included	Included	Included
Number of Obs.	24,415	24,415	24,415	24,415
No. Regions	1,285	1,285	1,285	1,285
Hausman Statistic	5114.18	6634.59	66.28	1863.93
Prob>chi2	(0.000)	(0.000)	(0.000)	(0.000)

Note: This table reports results from OLS and SDM estimations of the effects of local banks on regional economic development. The dependent variable is the logarithm of Total Income at county-level. The measure of local bank SME lending is the Local Micro Business Loans (LMBL) at county-level. Col. (5) and Col. (7) denote the non-spatial panel model estimated by OLS. Col. (6) and Col. (8) denotes the dynamic SDM estimated by the ML. The “Main” denotes the results without spatial spillover effects and “Wx” denotes the results with spatial spillover effects. The test statistics for model selection are reported in the bottom of the table. The period covers the years 1994 to 2013. P-values are reported in parentheses. The symbols ***, ** and * indicate the levels of significance, 1%, 5% and 10%, respectively. P-values are between parentheses.

Moreover, consistent with the inference from my main estimations, ignoring spatial spillover effects would result in the over-estimation of the explanatory variables. Besides, the great importance of non-lending variables (e.g. population and inflation) has also been examined. In addition, the significant positive autocorrelation of local income in both spatial and temporal dimensions intuitively demonstrates the existence of diffusion processes and hence regional income convergence (e.g. Chapter 5; Camagni and Capello, 2010). Besides, apart from the positive impact of the LMBL, in the “Main” section, it also triggers a significantly positive spatial spill-over effect on local income (0.0614), which is consistent with the positive spatial spill-over effect of the LMBL, as shown in the main estimations.

6.5 Concluding Remarks and Implications

In this chapter, I extend the analyses of precedent chapters on the importance of banking structure to the local economies through SME lending channel. In particular, this chapter takes a different approach to Chapter 5 regarding the investigation of the impact of local banking development on local economic performance.

Since my dataset consists of small economies (i.e. counties) that are geographically adjacent to each other within a single-country framework, there may exist bilateral spatial spillover effects between those economies. That is, if some positive or negative growth occur in one economy, it is bound to have spillover effects on the other adjacent economies. To this end, I have investigated the effect of spatial frictions and its interactions with small business lending, and other variables, on local economic growth.

Using a dataset that consists of 2, 590 U.S counties over the period 1994-2013, this chapter is divided into two lines of analyses, firstly, I implement an OLS and an SDM regressions in order to examine the relationship between local small business lending and local economic development, without taking into account the spatial frictions among regions. The second line of analysis introduces those spillover effects in my SDM panel regression, accounting for spatial frictions. For the SDM analysis, I built a very large spatial contiguity weight matrix. This method allows the examination of direct and indirect effects of space on other variables.

The results from the OLS regression, in the absence of spatial spillover effects, appeared to be overestimated due to space and time issues. On the other hand, the inclusion of the spatial interactions in the SDM panel regression improved the findings, suggesting a smoothed positive impact of local banks on local economic growth. Besides, the results from the SDM estimations confirm the presence of spatial spillover effects of local business lending on local economic growth.

Spatial externalities may arise when many entrepreneurs in a region, for instance, consider moving to adjacent regions because of local amenities and local externalities in the latter regions. That is, healthier economic conditions and superiorly more facilitated business operations, in a region than other regions, can be a crucial source of spatial externalities. In the context of small business lending as an externality and because those regions are contiguous with no borders' restrictions as such, those entrepreneurs may be encouraged to take loans from other regions with high density of local banks. Consequently, policy instruments such as small business lending and other macroeconomic indicators may create local externalities and spillover effects. That is to say, local small business lending in a region may indirectly affect the economic growth of other regions (adjacent regions in particular).

To smooth out the effects of spatial externalities within a single-country framework, all regions are supposed to be similarly developed. It is not like the case of the U.S-Mexico borders where the spillover effects are well captured. Thus, as long as I can capture this spatial spillover effect, the sum amount of negative externalities of negative effect of other macroeconomic variables, which seemed to be overestimated in the absence of space, will be correctly estimated. To this end, overemphasis on macroeconomic policies should be minimised, and spatial externalities among regions should be taken into account; that is, how much space may act as smoothing factors and absorbing factors of shocks before the economy reacts to the real shocks (e.g. shocks during the migration from one county to another). Therefore, introducing space can give rise to the estimation of real effect of these variables.

I suggest for any estimation of a local banking-growth model within a single-country framework, such as that in the U.S, should take into account the varying spatial effects across regions. That is, in order to estimate a realistic model of the relationship between local banking development and local economic development, the space has to be one of the most important explanatory variables. In this research, the graphical analysis reveals an obvious spillover effect of small business lending from one region to another. Therefore, my analysis contains such effect.

One of the challenges facing policy makers is to prevent capital drain from poor regions to rich ones. That is because spatial externalities may appear in the form of capital inflow and outflow between regions.

Chapter 7

Conclusions, Policy Implications and Future Research

Chapter 7: Conclusions, Policy Implications and Future Research

7.1 Summary of Chapters

The final chapter concludes this thesis and summarises each of the preceding chapters. In addition to highlighting the contributions to the theoretical and empirical literature, it acknowledges a number of limitations that encountered the author. The final section presents the policy implications of this research and recommends several avenues for future research. This thesis offers original contributions to the literature on banking structure, SME lending and economic development. In this thesis, several panel-data econometric approaches such as Fixed-Effects estimations, dynamic approaches, a quantile regression analysis, and spatial econometric techniques are employed at bank-level and county-level to analyse banking and economic data from the United States over two decades from 1994 to 2013.

Chapter 2 presents a review of the literature on regional banking-growth to show whether local banking factors have or have not been major determinants in the success or otherwise of the local economies. It draws on a large number of prior studies from a number of countries, the U.S in particular. This chapter summarises prior theoretical work on whether heterogeneity in banking across regions within a single-country framework. Most of this chapter critically reviews the empirical contributions concerning the impact of regional banking-growth nexus, banking regulatory changes, regional banking distress on regional economic development. When these studies viewed in their entirety, show that regional banking structure has generated much valuable research and, consequently, indicates that this chapter is an important contribution to the regional banking-growth literature. Chapter 2, additionally, reveals further gaps in the extant literature of banking structure and regional growth. It shows that regional banking development is very important in both the developed and emerging economies and hence Chapter 5 and Chapter 6 develop the contribution of this thesis to this important area. Thus, this literature motivates empirical research and justify the methodological approaches used in Chapter 5 and Chapter 6 to examine the extent to which local banking factors have an impact on local economic development. This chapter proposes the local SME lending channel as an alternative measure of local banking development. It shapes the hypotheses 2, 3, and 4 of the thesis and highlights the need for a distributional examination of the regional banking-growth nexus as well as it justifies the need for a local banking-growth investigation that takes into consideration the geographical dispersion of local banks and spatial spillover effects across regions.

The review of regional banking-growth literature in Chapter 2 provides a strong base to construct a conceptual framework which is presented in Chapter 3. This conceptual framework consists of four hypotheses that have been examined in the empirical chapters. Chapter 3 also demonstrates the adopted methodologies to test such hypotheses. Firstly, the fixed-effects approach confirms Hypothesis 1 that bank size has a negative impact on lending propensities to SMEs. Secondly, the dynamic and quantile panel data approaches prove Hypothesis 2 and Hypothesis 3, suggesting a strong positive impact of local banks on local growth, yet the impact varies in relation to the level of regional economic development. The fourth hypothesis (H4) of this thesis is also proved through a theoretical model and a dynamic spatial panel data approach, confirming the presence of a spatial spillover effect of local SME lending on local economic development among U.S counties.

Chapter 4 delivers the starting point for the analysis of the importance of small banks to the local economies. This research attempts to highlight the optimal financial machinery to facilitate credit to and support the SMEs. That is, it empirically examines the impact of bank size on the propensity of banks to lend to small and micro businesses. Unlike most of the previous studies that have relied on survey data, the bank-level dataset analysed in this chapter consists of over 14,000 domestic U.S depositary institutions, that is, approximately all U.S depositary institutions covering two decades from 1994 to 2013. Accordingly, this work is hitherto the largest such empirical examination and hence the findings can be generalised across the U.S. Additionally, this chapter introduces two new measures of bank propensity to small business lending. These ratios are the small business loans to total business loans and the ratio of micro business loans to total business loans. It is worth noting that the introduction of these propensity measures addresses the weakness in prior research of potential biases due to an imprecision in the calculations of propensity ratios. Using a panel data econometric approach, this chapter presents a strong evidence that bank size and the relative share of small and micro business loans held by the banks are inversely associated. In other words, the propensity of banks to lend to small businesses decreases as the size of the banks become larger, and vice versa. What is more, the set of banking and market control variables that are used along with the bank size measure enhance the estimation results of the actual effect of bank size on the propensity to small business lending. The findings remain statistically and economically significant for several robustness tests such as using different sub-periods to control for the 2008 financial crisis, and alternative sub-samples to control for market characteristics, market development, and bank specialisation. To this extent, the findings question previous studies that suggest an insignificant impact of the organisational structure of banks on SME lending, not only in the U.S but also in other countries.

Chapter 5 builds upon the literature reviewed in Chapter 2 and extends the analysis of the regional banking-growth relationship. This chapter, tests the hypothesis that small locally-operating banks contribute significantly to local economic development by showing strong commitment to small businesses through relationship lending. However, the magnitude of the effects of these banks may vary measurably across the distribution of regional/local economic growth. As for the more general hypothesis of a positive impact of small banks on local economies, this chapter utilises a ‘mean’ based dynamic panel regression that accounts for endogeneity bias. To test for heterogeneity in such impact, this chapter employs a 'quantile' based instrumental variable panel regression that exploits full distributional heterogeneity in the impact of local small business lending on local economic activities. To address potential endogeneity issues in the quantile regression, I construct a new instrument based on the concept of the yield curve. Using a large representative dataset consisting of more than 2,500 U.S counties over the period from 1994 to 2013, the findings from a 'mean' based dynamic panel regressions suggest a positive effect of local banking development on local economic growth through small and micro business lending. What is more, the results are consistent with the hypotheses about the distributive consequences of local banks on local growth. That is, at a lower quantile of the regions' economic growth the growth of small banks may evince larger positive effects, whereas, at higher quantiles, the positive effects may monotonically decline (but could still be positive). As the growth of regions becomes stable over time, the net effects of this growth may asymptotically vanish, giving way to direct interplay by large banks in the process. At the median, the net growth effects of local banks can be positive, on average, but the effects could be smaller than at a lower-quantile. Simultaneous growth of human capital and small banks eventually leads to monotonic high economic growth. A battery of robustness checks confirms such predictions. In line with the findings presented in Chapter 4, the results of Chapter 5 emphasise on the importance of small banks as an important supplier of credits to SMEs.

Chapter 6 extends the analyses of precedent chapters on the importance of local banking development to local economic growth through small business lending channel. In particular, this chapter takes a different approach to Chapter 5 regarding the investigation of the impact of the local banks on the local economies. It re-examines the second hypothesis of this thesis (examined in Chapter 5), however, Chapter 6 takes into account the spatial frictions among counties. To this end, this chapter extends the convergence-theoretic model and builds an econometric model with a spatial weight matrix in order to isolate the spatial spillover effects that may bias the estimation of the effects of local banking development on local economic growth. Using a dataset that consists of 2, 590 U.S counties over the period 1994-2013, this chapter is divided into two lines of analyses, firstly, I implement an OLS and an SDM regressions in order to examine the relationship between local small business lending and local economic development, without taking into account the spatial frictions among regions. The second line of analysis introduces those spillover effects in my SDM panel regression, accounting for spatial frictions. For the SDM analysis, I built a very large spatial contiguity weight matrix. This method allows the examination of direct and indirect effects of space on other variables. The findings of Chapter 6 emphasise the importance of local banks to local economies through SME lending channel. More importantly, the findings confirm the Hypothesis 4 of this thesis, that is, spatial spillover effect of local banks is an important determinant of regional growth. Specifically, the results from the OLS regression, which neglects spatial frictions among regions, can be overestimated due to spatial spillover effect.

7.2 Summary and Policy Implications

The small and medium-sized enterprises are the main employers in most economies, accounting for between 65% (UK) and 80% (Japan) of total employment. It is also recognised in the literature that SMEs are likely to be credit rationed and unable to access capital markets. This research shows that large banks mainly lend large amounts of funds, likely benefitting mostly large firms, while small firms are likely to be mainly catered for by small banks. Cheng and Degryse (2010) have demonstrated that local banks and small business lending are very effective in promoting local economic growth, compared to non-bank channels of funding. Kendall (2012) and Hakens *et al.*, (2015), among others, provided both a theoretical underpinning and robust empirical evidence in the cases of developing and developed countries local economic development contexts, and demonstrated that, due to the very nature of relational lending and extensive dealing with individual (not aggregate) uncertainties, the growth of local banks and their persistent lending strategies are instrumental in promoting local economic growth.

The importance of small firms in supporting employment and growth in general, and regional or local development in particular, is recognised by policy-makers in many countries (see, e.g. in the UK: Start Up Loans and Research and development grants). This thesis shows that the ability of small firms to deliver such positive effects depends to a significant extent on the existence of small banks within their region. These results have important policy implications, which are significantly different from earlier studies. Despite the recognition of the importance of small firms and, consequently, the need for small, local banks, there is a major, secular trend of global banking systems towards greater market concentration (see, among others, Carbo-Valverde *et al.*, 2009; Koetter *et al.*, 2012), scale economy (for instance, DeYoung, 2012; Wheelock and Wilson, 2012), and too-big-to-fail firms (for instance, Stolz and Wedow, 2010). In the EU, since 2008, more than 1,100 banks have disappeared, as consolidation in banking is accelerating. In the U.S, almost 1,700 banks have disappeared during this time period.

Given this situation, it is important to quantify the role and impact of local banks on regional growth dynamics, especially reflecting the nature of heterogeneous effects and spatial effects that local banks may exert on the distribution of regional economic growth over time. Accordingly, this research proposes alternative econometric techniques to examine the regional banking-growth nexus, taking into account important factors (e.g. distributional heterogeneity and spillover effects among regions) which are neglected in previous research and may have caused biased and imprecise assessments of such nexus.

This thesis stresses the exclusivity of small banks in lending to SMEs and demonstrates heterogeneous and spatial spillover effects of local banks on both short- and long-run growth of regions. The policy implication is that policy-makers need to ensure that localisation effects are sustained, because of the comparatively minimal cost required to minimize individual (in relation to aggregate) uncertainties and local stability can be relied upon to achieve global stability. Both can be done by supporting the creation and continued viability of local banks. For this, a positive yield curve is required – which currently central banks in many countries are not delivering.

The findings also bear policy implications for the industrial organisation of the banking sector. It is well known that the vast majority of firms in most countries are small and very small firms. These firms also account for the majority of employment in most countries, and any given amount of money invested in such small firms tends to create more jobs than the same amount invested in a large or very large firm. As a result, policy-makers in many countries have recently emphasised the importance of ensuring adequate funding of SMEs. Such firms are not usually able to tap capital markets and are therefore dependent on borrowing from banks. The research presented in this thesis shows that such bank funding is only likely to be forthcoming, if the economy is characterised by a large number of small banks.

In this research, the important question of finance constraints is examined anew. The debate about the role of the shape of the banking sector in causing financing constraints had been undecided and, in this thesis, the largest empirical examination hitherto existing on this question is presented in Chapter 4. In careful empirical examination, it is shown that, on balance, large banks lend to large firms, and small banks lend to small firms. Thus, banking systems not including a significant proportion of small banks, such as that in the U.K, will hamper the growth of small businesses, whereas systems, such as that in the U.S, with a large number of small and community banks, are more conducive to their growth. Overall, the findings have interesting policy implications on the importance of local banks in speeding convergence of regions within a single-country framework or the European Union.

This means that a key barrier to growth by SMEs - including growth in their exports - can be overcome by shaping the structure of the banking system such that it is dominated by a large number of small, local banks, as is the case in the U.S and Germany, but distinctly not so in the United Kingdom. Amidst the rise of crowdfunding and peer to peer lending structures it can be noted that community banks, in operation for 200 years in Germany, have been the original 'crowd funders'. Belleflamme *et al*., (2014) had concluded that "Building a community that supports the entrepreneur is crucial for crowdfunding to be a viable funding mechanism." This is what community banks have been offering for the past centuries.

In this thesis, I have confirmed the need for banking systems that are not concentrated and instead characterised by a large number of small banks. Furthermore, even in an economy that boasts many small banks, I have shown that it will remain necessary to launch initiatives to newly establish independent small banks, because the old banks become large and over time begin to behave more like large banks. As this research has focused on the relationship between bank size and borrower size, it has not attempted to quantify the impact on economic growth of differing bank sizes. This can be addressed more directly in further research.

7.3 Limitations

The empirical analyses of the three empirical chapters rely on a definition of small and micro businesses that is based on the original amount of the loans granted to those businesses. Obtaining a more precise definition of small and micro businesses would enhance the findings, such as a firm-size measure based on the number of employees, asset size or sale volume. Such data are currently only available in the form of surveys (e.g. NSSBF survey for the U.S). However, those surveys are not large and cannot be representative and generalised to the U.S, as the large dataset used in this thesis.

Geographically, a local bank is defined as any depositary financial institution that has all its branches within the geographical boundaries of a county and assumes all the granted loans remain in the boundaries of such county. This definition does not account for loans granted by those banks when invested out of the same county's boundaries. Therefore, a more precise definition of local banks that captures such spillover would also enhance the estimations results. However, the consequences of this limitation is minimised in Chapter 6 by employing a spatial effect approach to account for the effects of the SME loans in a county and invested in other regions.

Other angles not addressed in this dissertation, which can be tackled in future work and extensions include a comparison between large and small banks in terms of their relative performance, for which specific data needs to be obtained (only much smaller data sets seem currently available from the FFIEC); and a study and comparison of the effect of large non-local banks on a local economy.

Income and employment are currently used to proxy real GDP at county-level in Chapters 5 and 6, since real GDP is not available to measure local economic performance. This limitation is common to other work on local development, and it is likely that this limitation is not significant, since there are a number of well-known methodological problems with the definition and calculation of real GDP in any case.

Another potential limitation is the emphasis in this thesis on the supply of credit to SMEs. I have not explicitly modelled the demand for credit. This is also likely to be a manageable limitation without serious problems, if one does not assume a theoretical economic model consisting of perfect information, complete markets, etc., and general equilibrium. There is a significant literature on the existence and importance of banks rationing credit at all times (see, for instance, Keeton, 1979; Stiglitz and Weiss, 1981); moreover, macroeconomic work using the inductive methodology and work in disequilibrium economics emphasises that markets are rationed, following the short-side principle. There is much evidence that in the credit market this is the supply of credit (Werner, 1997, 2005, 2012).

7.4 Future Research

In addition to the possibility of tackling areas of limitations in the current thesis as topics in future research, there are a number of areas in which future research can complement the research of this thesis and give rise to additional questions. Several such avenues for valuable future research can be drawn from this thesis's conclusions:

Firstly, since the aim of this research is to emphasise the important role of small banks as the optimal financial machinery to support SMEs, and hence economic growth, future work should be conducted to suggest efficient policies to boost the performance of those small banks. To this end, shedding deeper light on the relationship between monetary policy and bank performance is required. In particular, future work may examine the process by which banks of different size classes are affected by fluctuations in the Yield Curve at regional-level and bank-level. As argued by Werner (1995) and explained in section (5.4.2), a major determinant of bank lending (and hence economic activity) is the shape of the yield curve, which works via the banks' ability to newly create money (Werner, 2014, 2015).

Secondly, a comparison of the impact of SME lending on local economies between small local banks and large cross-county banks can be an avenue of future research. However, undertaking such analysis is subject to data availability on SME lending by large banks at county-level (i.e. local/regional level).

Thirdly, a geographical banking study could be conducted on how the distance between banks and their customers may affect loan supply.

Appendices

Appendix A

Panel Unit Root Tests

Test	Capita Income growth	Employment Growth	Total Income	Total Employment	LSBL	LMBL	CPI
LLC Test:							
Panel Means	-75.3827	-52.5028	-43.7692	-23.4344	-17.7222	-9.1324	-89.5448
Trend & Panel Means	-70.2271	-44.3490	-26.1541	-35.4133	-25.2369	-26.238	-74.1859
IPS Test:							
Trend &Panel Means	-78.6547	-59.8151	-19.6022	-15.4907	-25.0427	-32.3176	-74.5259
ADF Test:							
Panel means	24,000	13,100	2851.01	4393.27	3520.43	3127.46	16,600

Note: This table includes the results of three types of unit-roots tests. The first test is the Levin–Lin–Chu (LLC) test. The second test is the Im–Pesaran–Shin test (IPS). The third test is augmented Dickey-Fuller (ADF) test. All results of the unit-root tests are significance at 1% level. All variables are in levels.

Panel Unit Root Tests (Continued)

Test	Labour Force	Population Growth	HHI	ROA	NII/II	Equity Ratio	Bank Density	Yield Curve
LLC Test:								
Panel Means	-19.5854	-29.4849	-18.5813	-23.0412	-4.4643	-15.5897	-26.8287	-42.5704
Trend & Panel Means	-16.9379	-32.3138	-27.2709	-31.2429	-1.8413	-21.4983	-55.2814	-37.9208
IPS Test:								
Trend &Panel Means	-6.6456	-55.4426	-37.4799	-47.0932	-24.6385	-29.6601	-31.2520	-37.0258
ADF Test:								
Panel means	2731.56	10,600	5545.78	6420.70	4403.80	4400.56	4730.18	5651.84

Note: This table includes the results of three types of unit-roots tests. The first test is the Levin–Lin–Chu (LLC) test. The second test is the Im–Pesaran–Shin test (IPS). The third test is augmented Dickey-Fuller (ADF) test. All results of the unit-root tests are significance at 1% level. All variables are in levels.

Appendix B

Correlations of the Instrumental Variable with the all variables

Variables	Instrumental Variable
Total Income (dependent variable)	-0.1685
Total Employment (dependent variable)	-0.1478
LMBL	-0.1165
LSBL	0.003
ROA	0.1982
HHI	0.206
Inflation	0.0077
Non-interest income/interest income	0.0607
Equity Ratio	0.0866
Population Growth	0.0749
Labour Force	-0.0432
MSA	-0.0767
Banking Density	-0.1169

Note: This table shows the correlations of the instrumental variable (i.e. 36-month-lag of Yield Curve) with all variables.

Appendix C

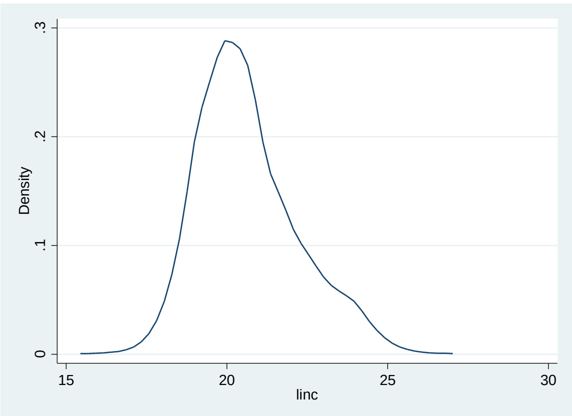
Note on the MCMC Optimization of Panel Quantile Estimation

There are several parameters to tune for adaptive MCMC optimization. Basically, one needs to allow the algorithm to run long enough because it can get stuck at a local extremum of the objective function. 10,000 draws might not be enough. Similarly, the burn period must be long enough, i.e. the number of first draws that are discarded before the algorithm starts adapting ("learning" from past draws to converge towards the correct potential distribution for the parameters; at least that is how I understand it). Also, the algorithm has a mean acceptance rate (between 0 and 1), referring to the fact that only some "correct "draws are accepted.

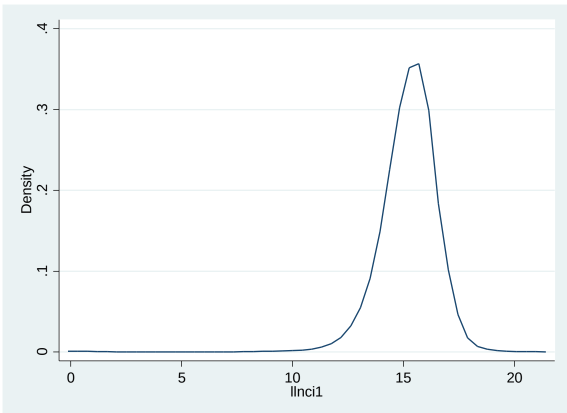
Appendix D

Kernel Density Function of the Dependent and Explanatory Variables

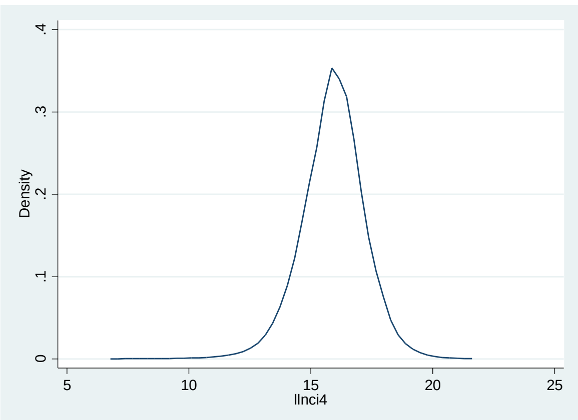
Total Income



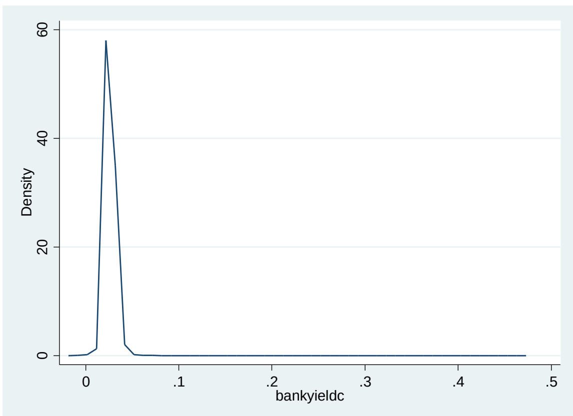
Micro Business Loans



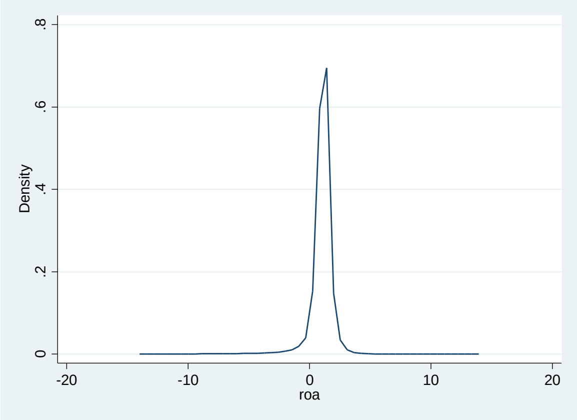
Micro Business Loans



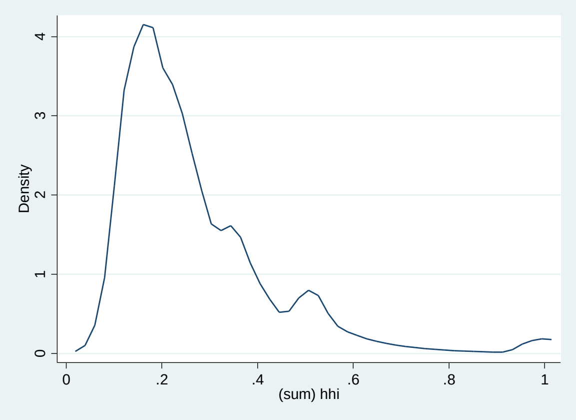
Yield Curve



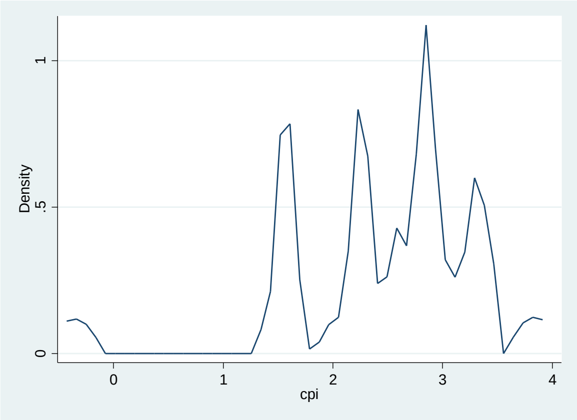
ROA



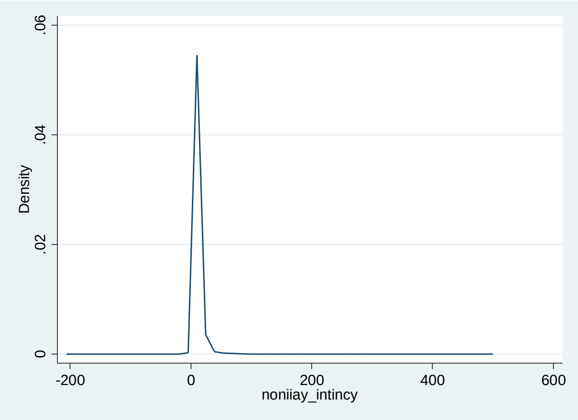
HHI



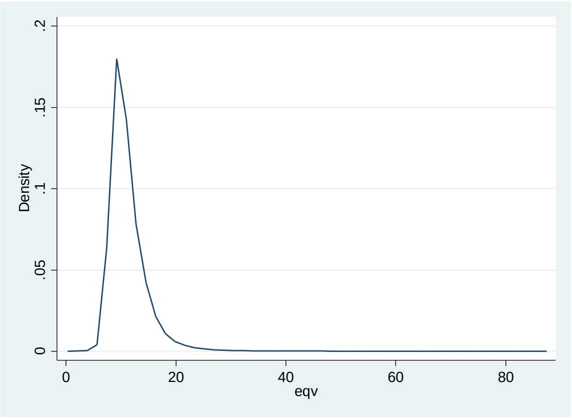
Inflation



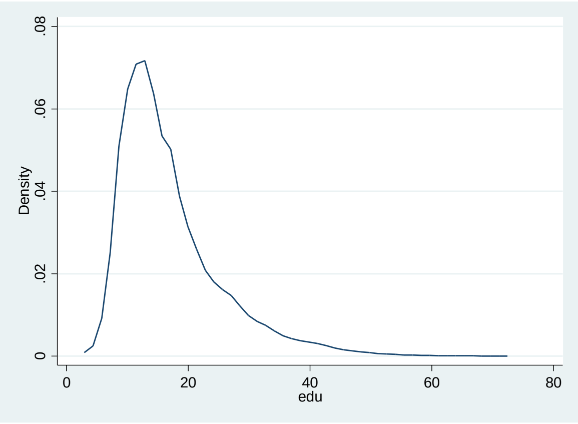
Non-interest income/interest income



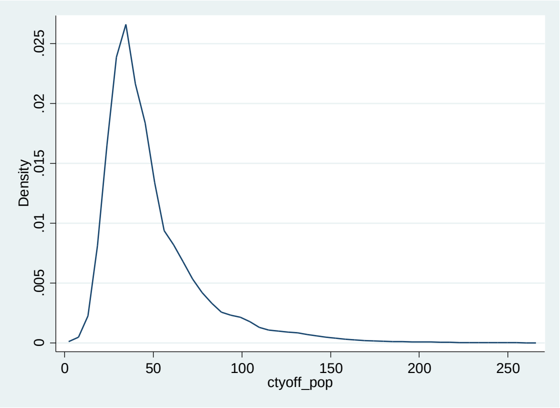
Equity Ratio



Education

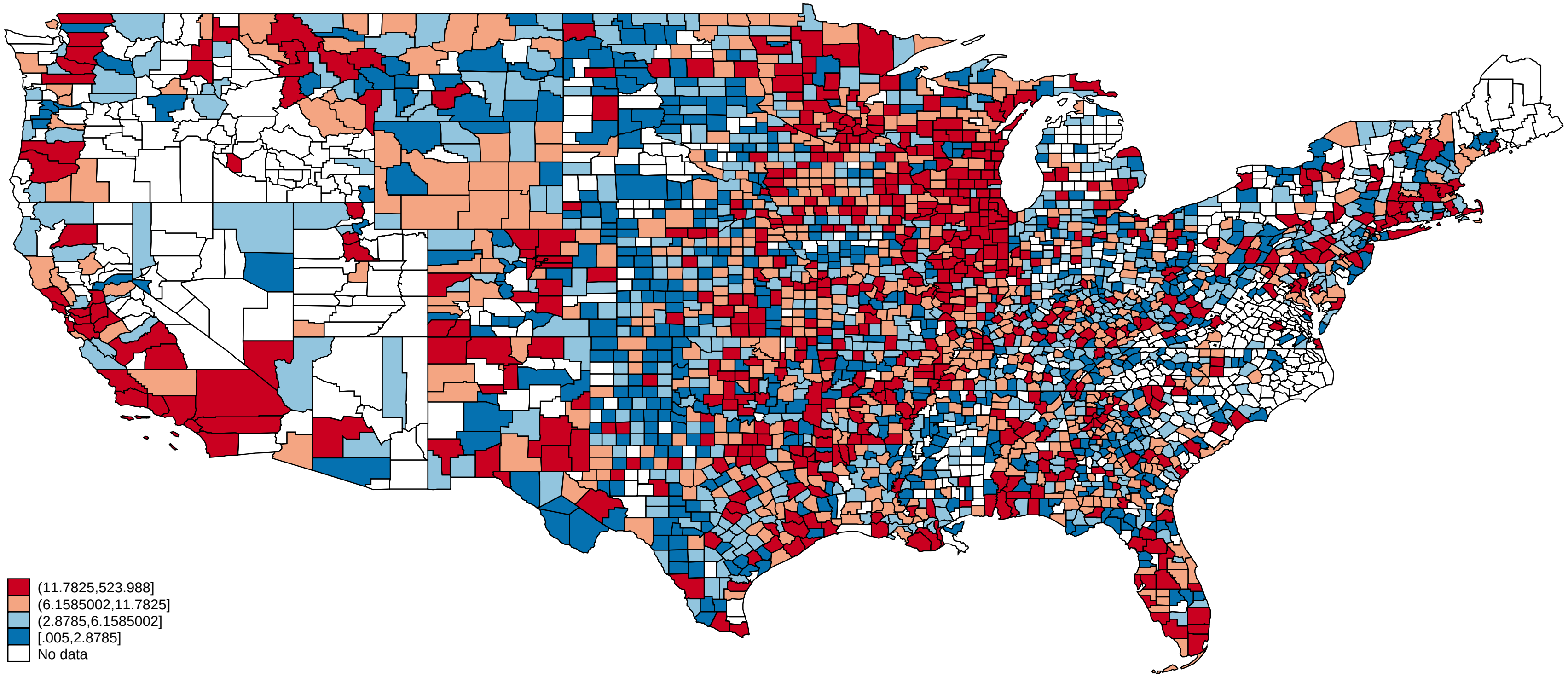


Banking density



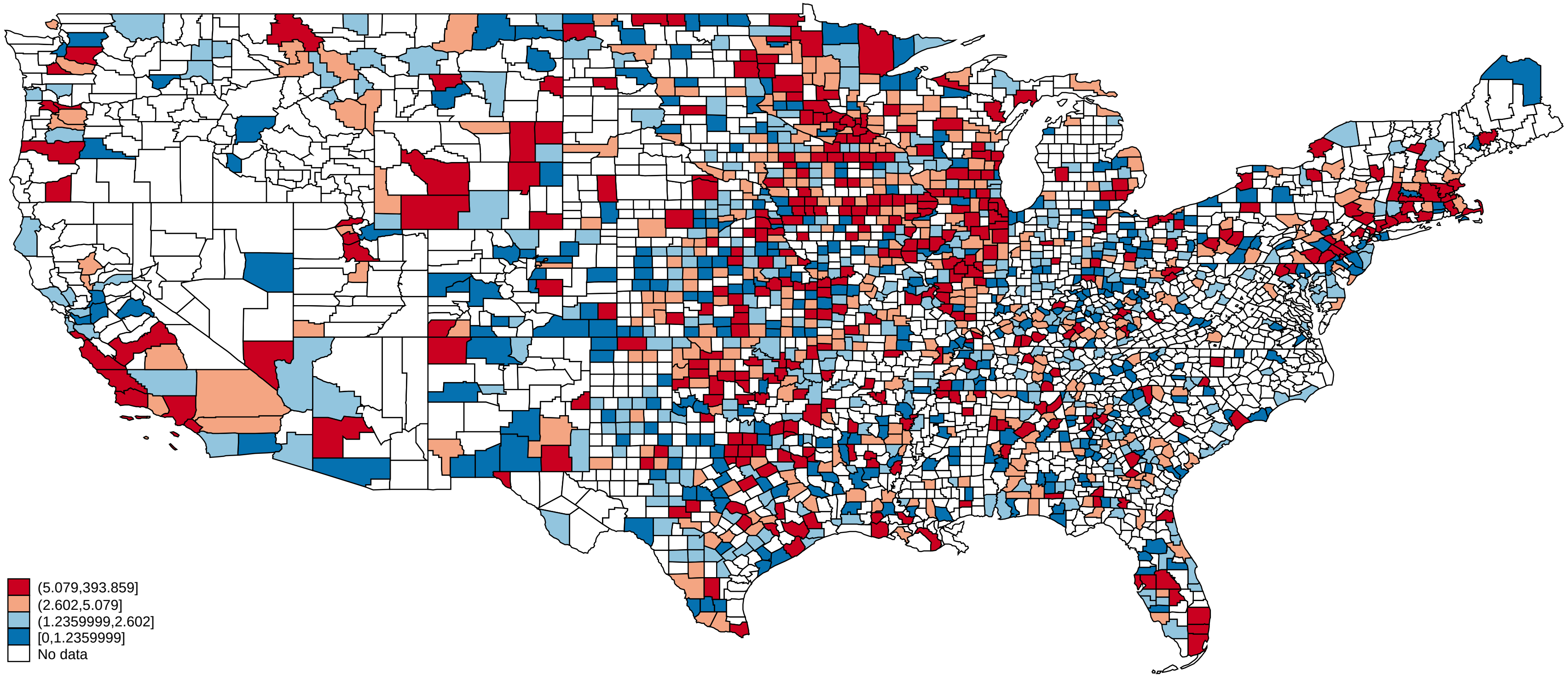
Appendix E

Figure 6.5 Heat Map of County Micro Business Loans in 1994



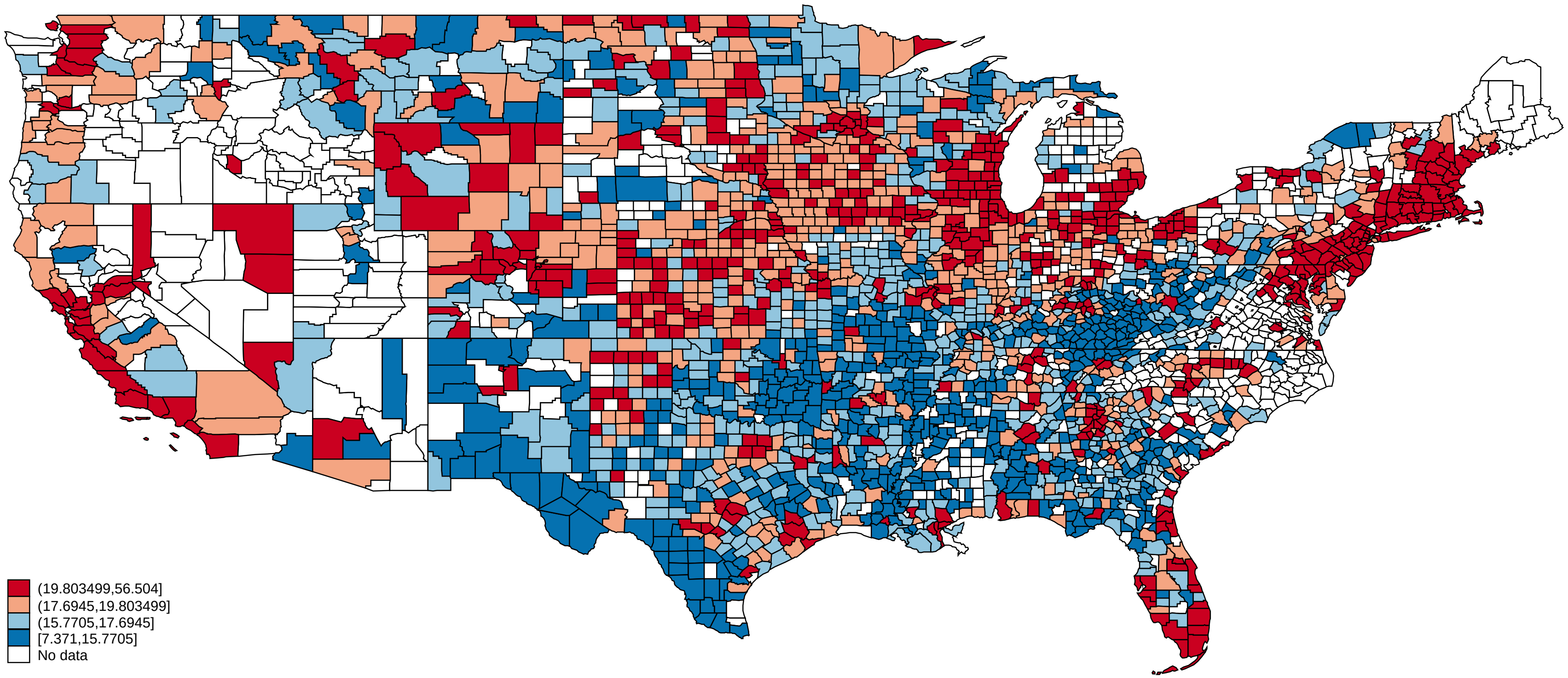
Note: This figure shows a heat map of county micro business loans volume in 1994. The dark red colour represents counties with more than $11.78 million of micro business loans; the pink and light blue areas represent counties with at least $6.16 million and $2.88 million MBL, respectively. Dark blue colour represents counties with less than $2.88 million MBL. White colour areas indicate no data.

Figure 6.6 Heat Map of County Micro Business Loans in 2013



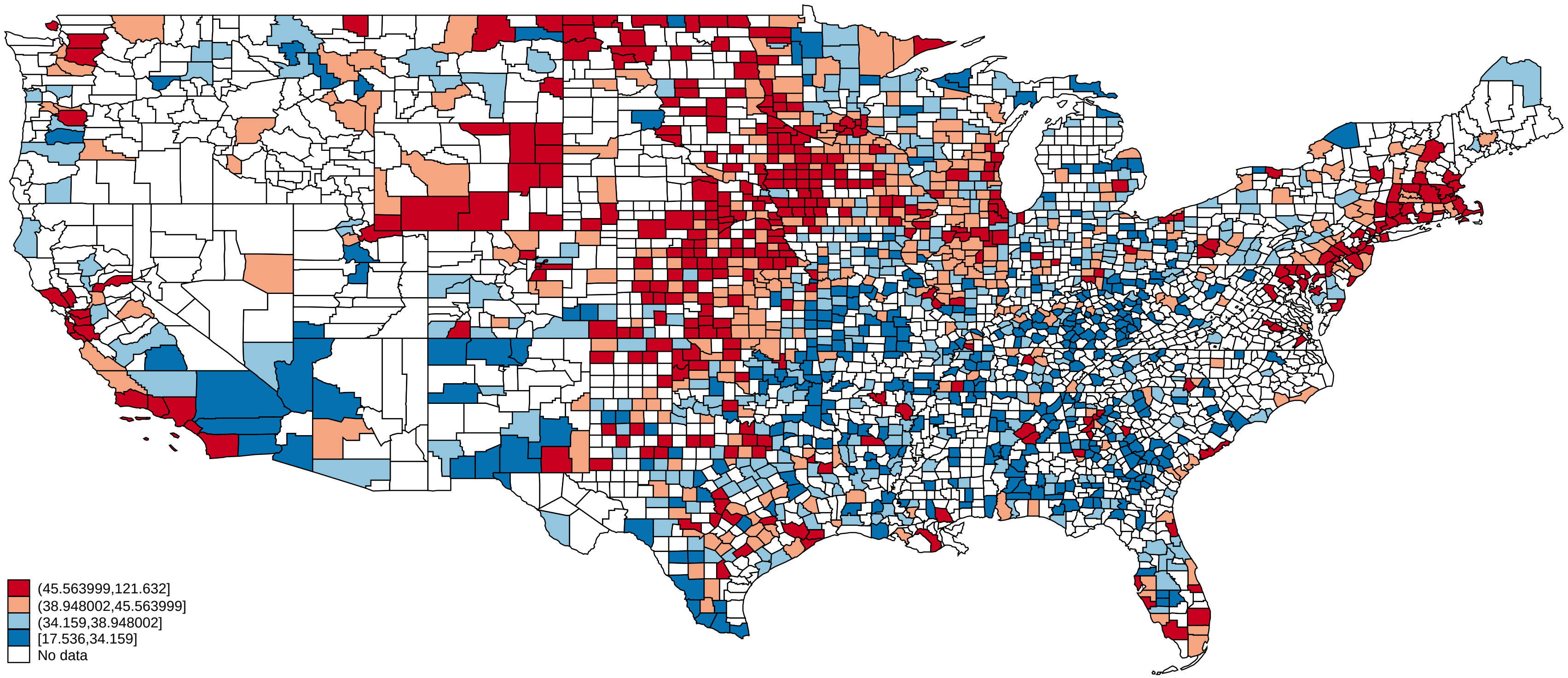
Note: This figure shows a heat map of county micro business loans volume in 2013. The dark red colour represents counties with more than $5.08 million of micro business loans; the pink and light blue areas represent counties with at least $2.60 million and $1.24 million LMBL, respectively. Dark blue colour represents counties with less than $2.88 million LMBL. White colour areas indicate no data.

Figure 6.7 Heat Map of County per Capita Income in 1994



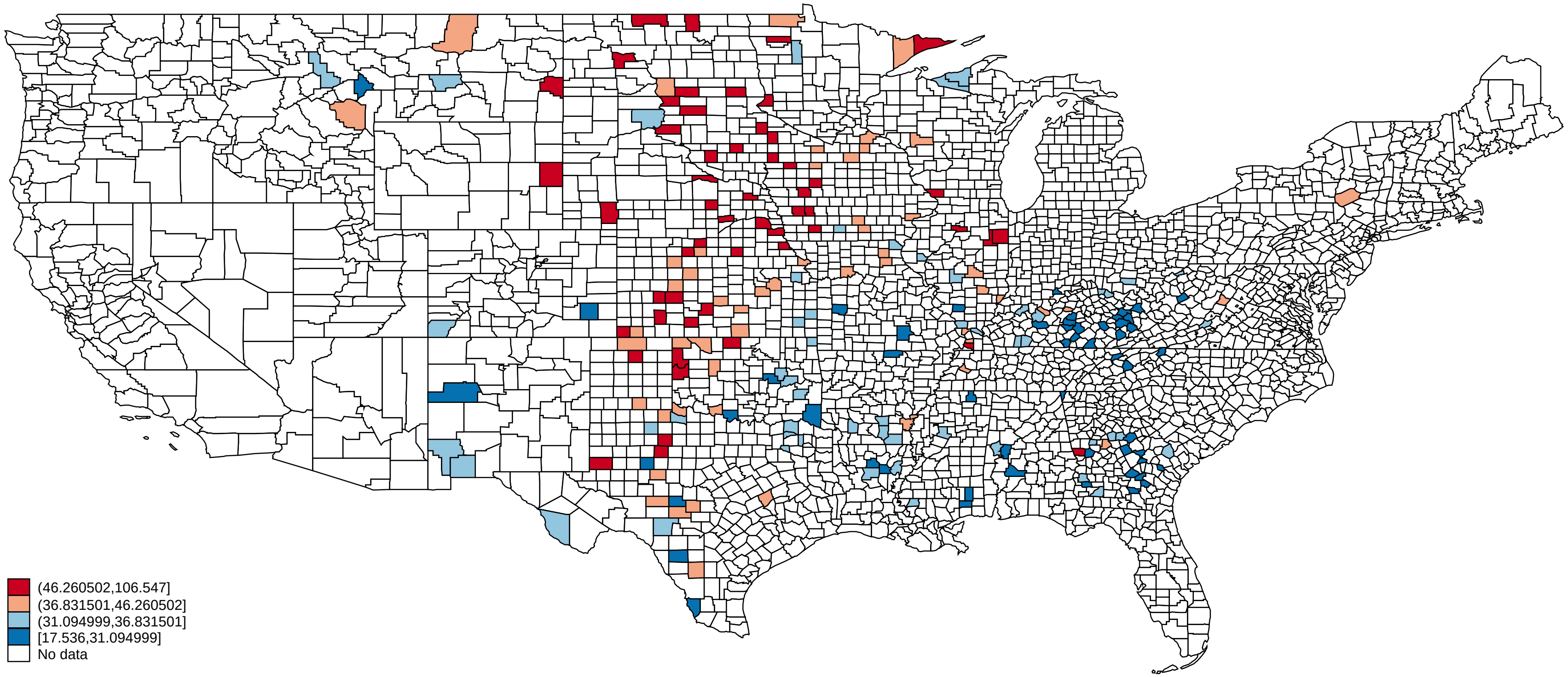
This figure shows a heat map of county per capita income in 1994. The dark red colour represents counties with more than $19, 804 per capita income; the pink and light blue areas represent counties with at least $17, 695 and $15, 771, respectively. Dark blue colour represents counties with less than $15, 771 per capita income. White colour areas indicate no data.

Figure 6.8 Heat Map of County per Capita Income in 2013



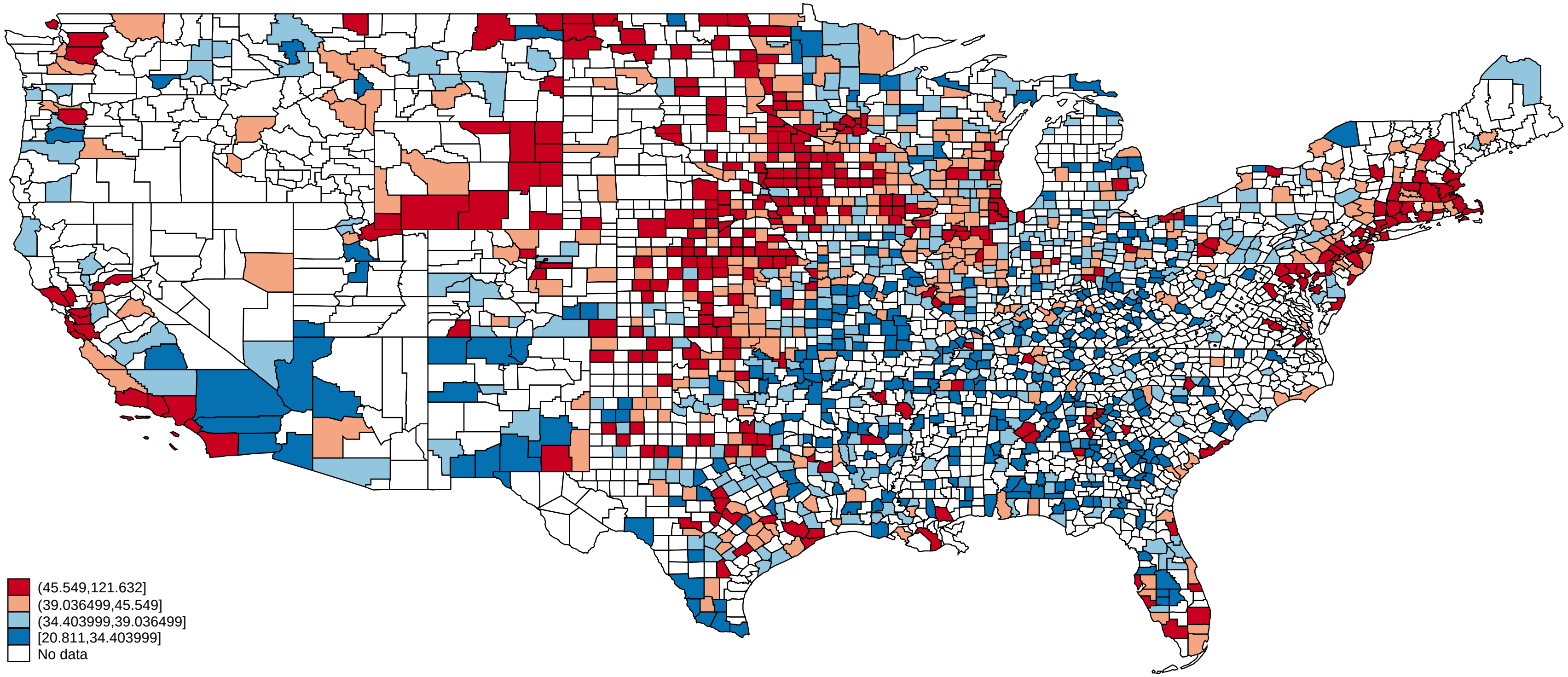
Note: This figure shows a heat map of county per capita income in 2013. The dark red colour represents counties with more than $45, 564 per capita income; the pink and light blue areas represent counties with at least $38, 948 and $34, 159, respectively. Dark blue colour represents counties with less than $17, 536 per capita income. White colour areas indicate no data.

Figure 6.9 Heat Map of County per Capita Income for Counties with more than 50% of Local Bank Branches in 2013



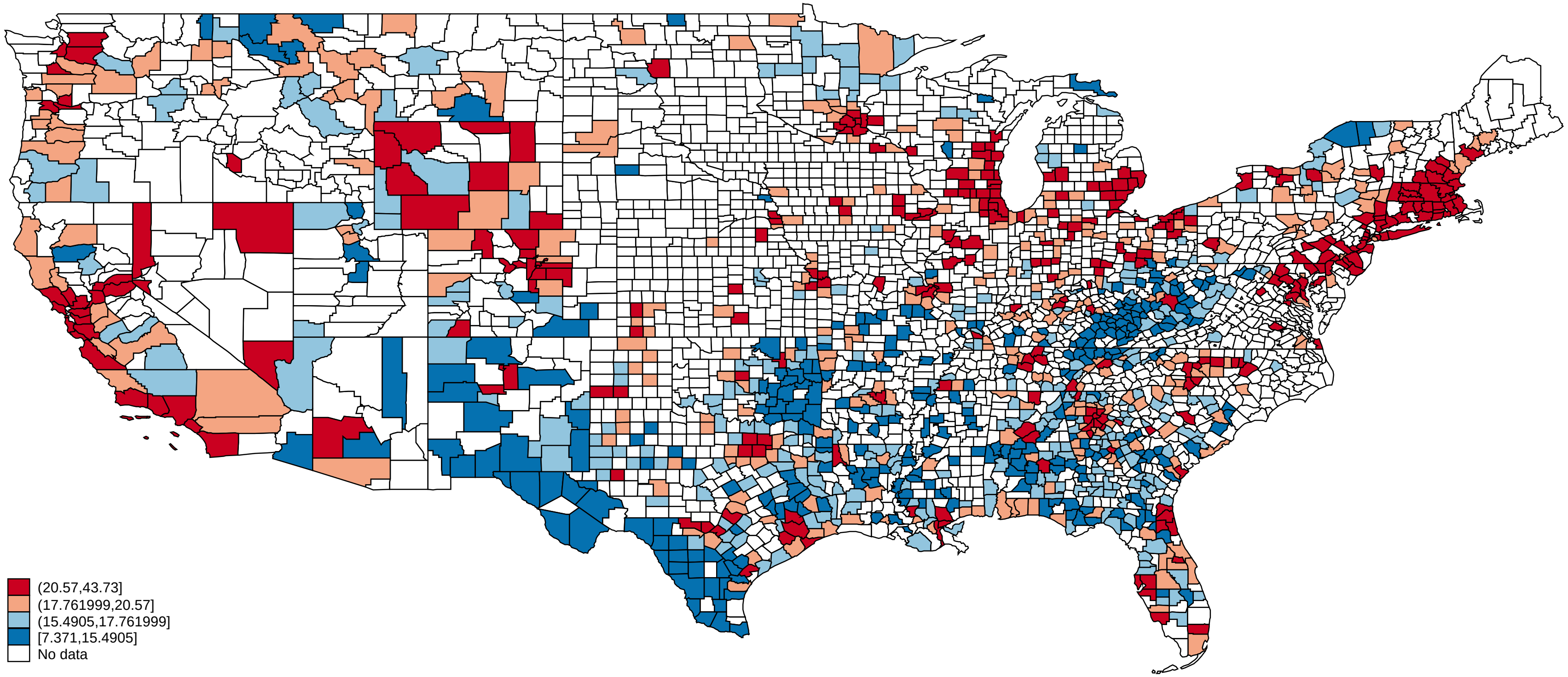
Note: This figure shows a heat map of county per capita income for counties with more than 50% of local bank branches to total bank branches in 2013. The dark red colour represents counties with more than $46, 261 per capita income; the pink and light blue areas represent counties with at least $36, 832 and $31, 095, respectively. Dark blue colour represents counties with less than $17, 536 per capita income. White colour areas indicate no data.

Figure 6.10 Heat Map of County per Capita Income for Counties with less than 50% of Local Bank Branches in 2013



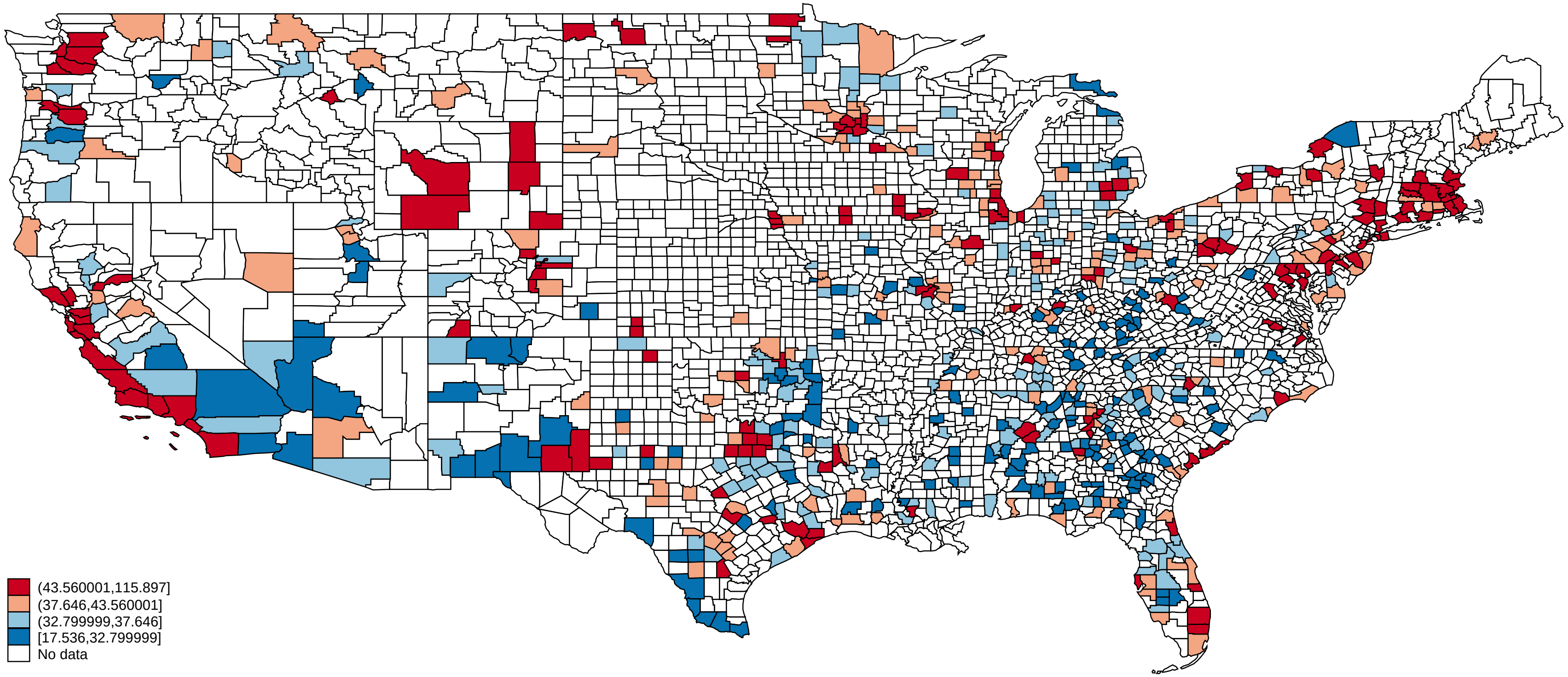
Note: This figure shows a heat map of county per capita income for counties with less than 50% of local bank branches to total bank branches in 2013. The dark red colour represents counties with more than $45, 549 per capita income; the pink and light blue areas represent counties with at least $39, 037 and $34, 404, respectively. Dark blue colour represents counties with less than $20, 811 per capita income. White colour areas indicate no data.

Figure 6.11 Heat Map of County per Capita Income for Counties with less than 40 bank branches per 100, 000 in 1994



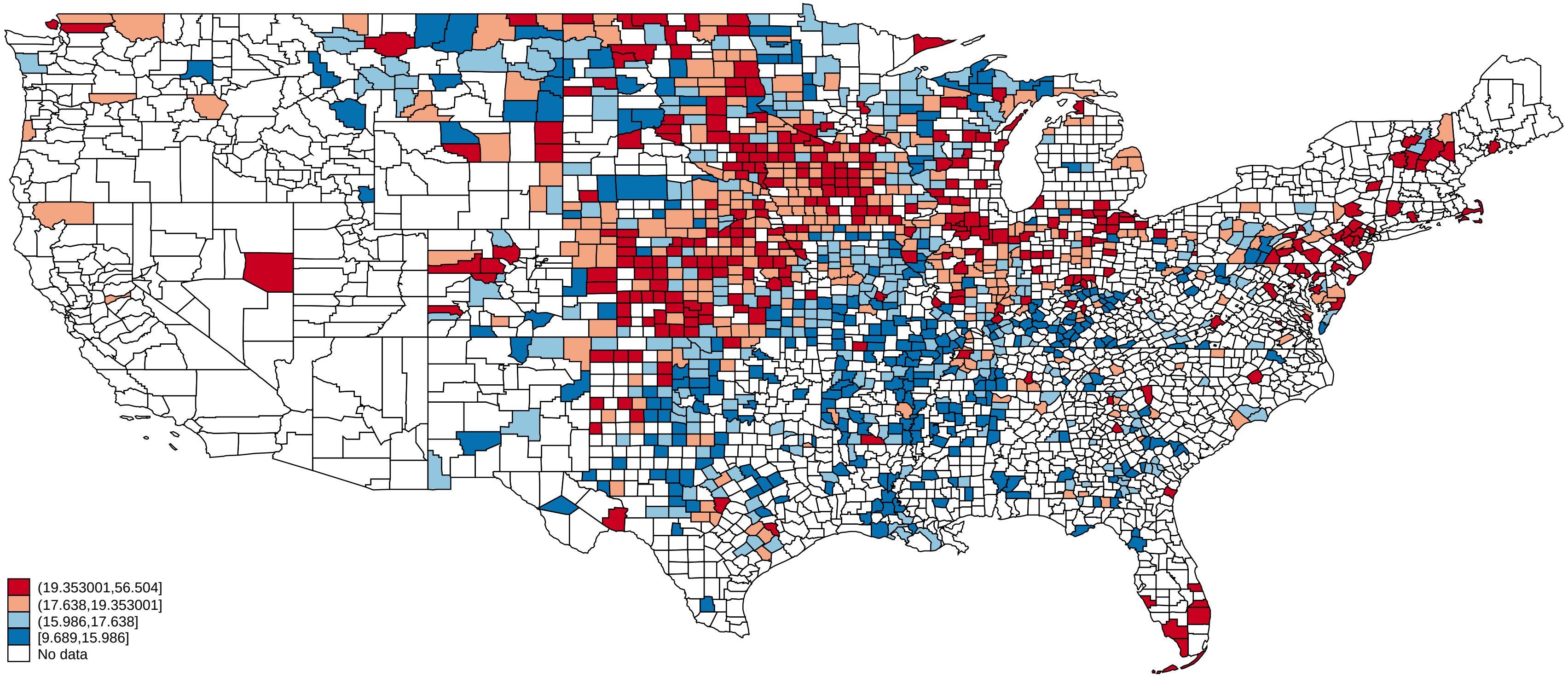
Note: This figure shows a heat map of county per capita income for counties with bank density less than 40 bank branches per 100, 000 residents in 1994. The dark red colour represents counties with more than $20, 574 per capita income; the pink and light blue areas represent counties with at least $17, 762 and $15, 491, respectively. Dark blue colour represents counties with less than $7, 371 per capita income. White colour areas indicate no data.

Figure 6.12 Heat Map of County per Capita Income for Counties with less than 40 bank branches per 100, 000 in 2013



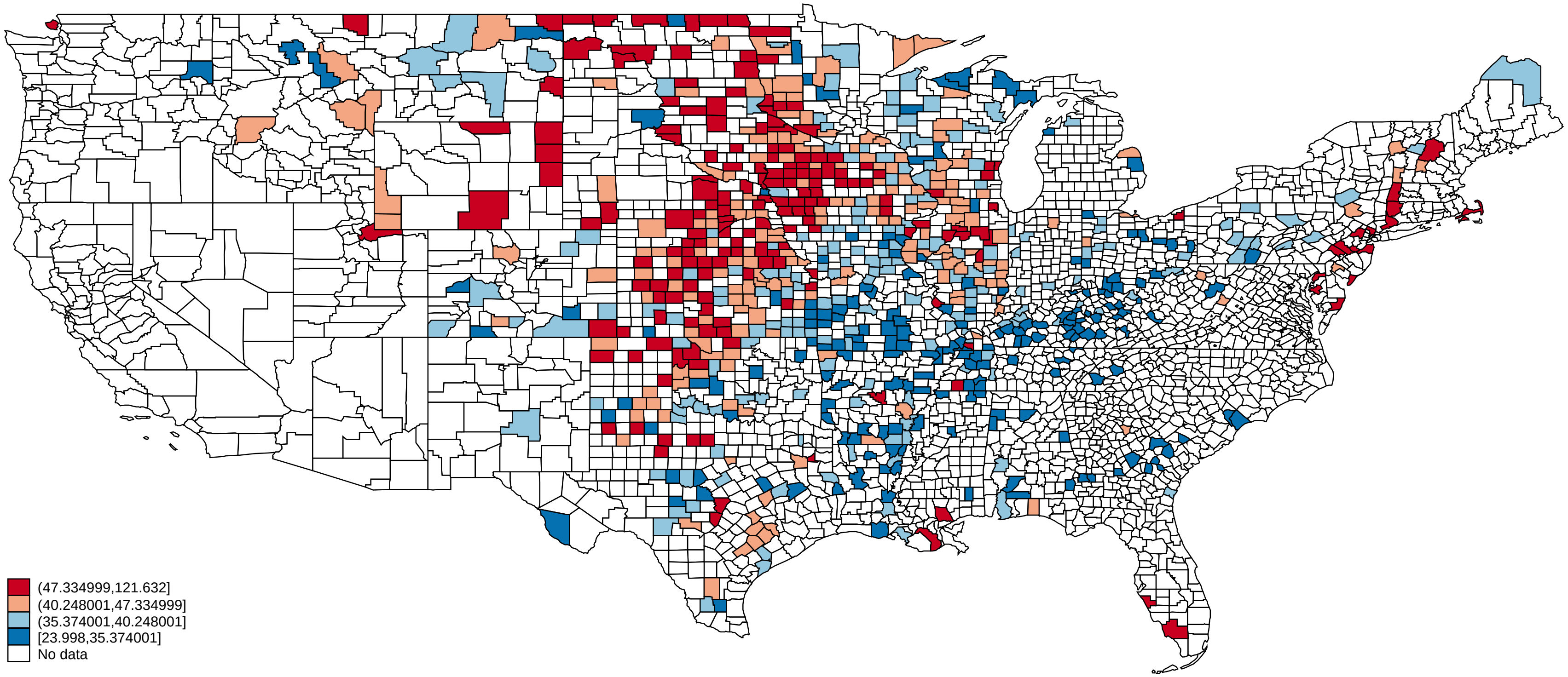
Note: This figure shows a heat map of county per capita income for counties with bank density less than 40 bank branches per 100, 000 residents in 2013. The dark red colour represents counties with more than $43, 560 per capita income; the pink and light blue areas represent counties with at least $37, 646 and $32, 800, respectively. Dark blue colour represents counties with less than $17, 536 per capita income. White colour areas indicate no data.

Figure 6.13 Heat Map of County per Capita Income for Counties with more than 40 bank branches per 100, 000 in 1994



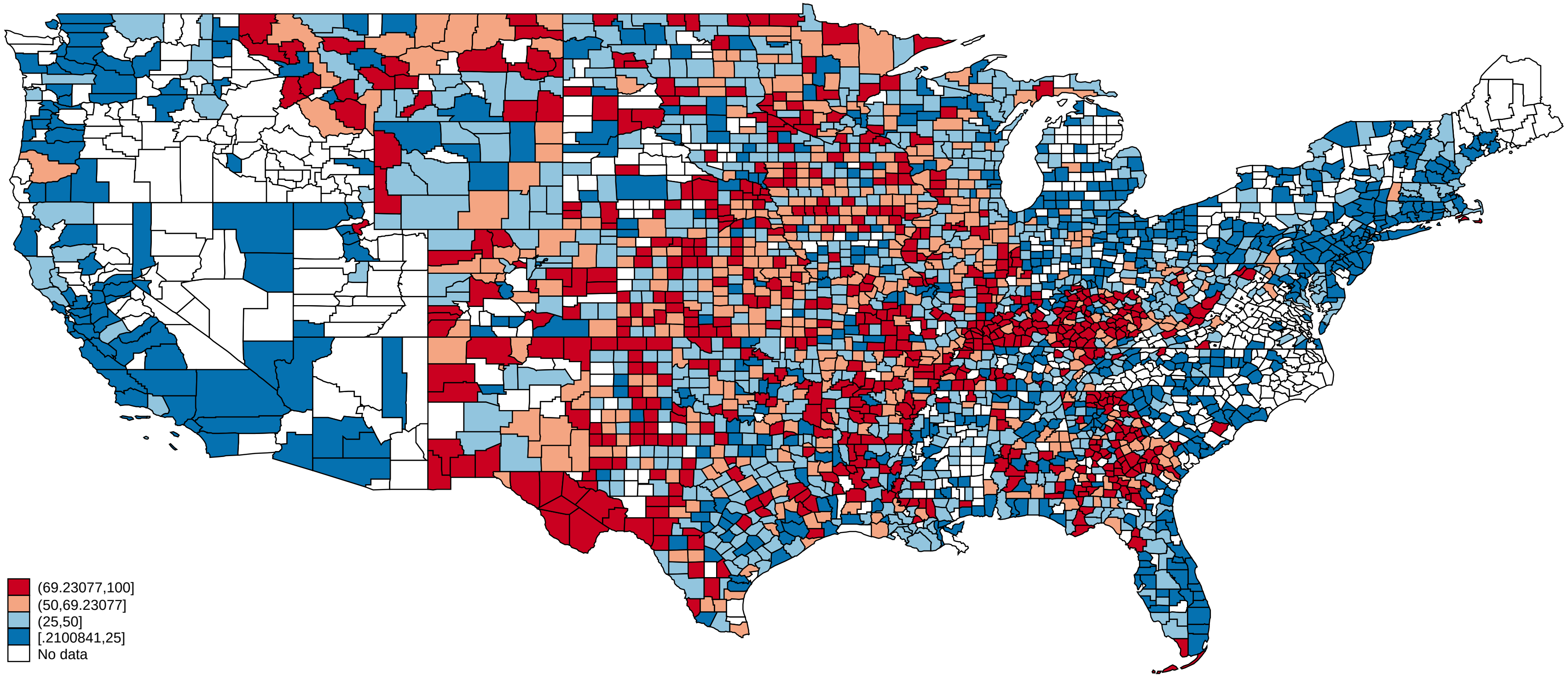
Note: This figure shows a heat map of county per capita income for counties with bank density less than 40 bank branches per 100, 000 residents in 1994. The dark red colour represents counties with more than $19, 353 per capita income; the pink and light blue areas represent counties with at least $17, 638 and $15, 986, respectively. Dark blue colour represents counties with less than $9, 689 per capita income. White colour areas indicate no data.

Figure 6.14 Heat Map of County per Capita Income for Counties with more than 40 bank branches per 100, 000 in 2013



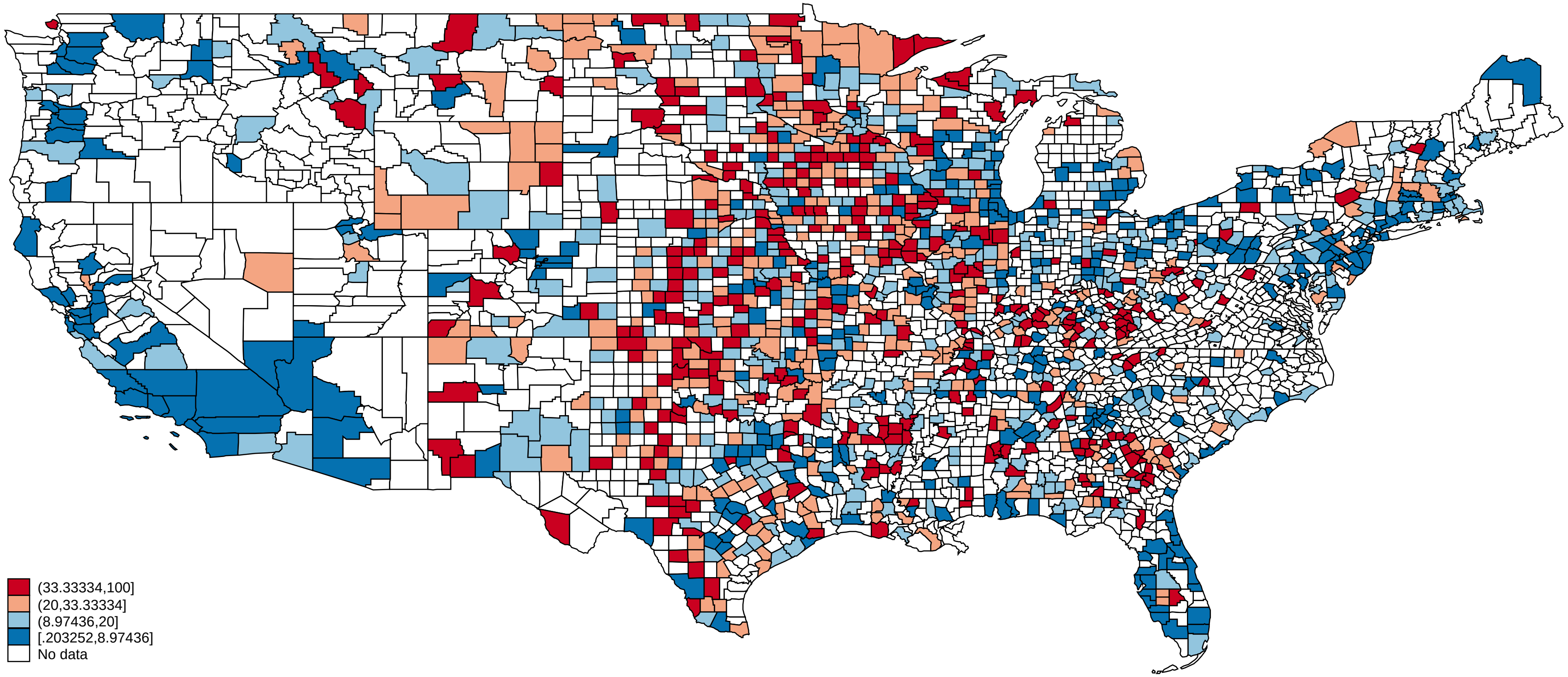
Note: This figure shows a heat map of county per capita income for counties with bank density more than 40 bank branches per 100, 000 residents in 2013. The dark red colour represents counties with more than $40, 335 per capita income; the pink and light blue areas represent counties with at least $35, 374 and $35, 374, respectively. Dark blue colour represents counties with less than $23, 998 per capita income. White colour areas indicate no data.

Figure 6.15 Heat Map of County Share of Local Bank Branches to Total Bank Branches in 1994



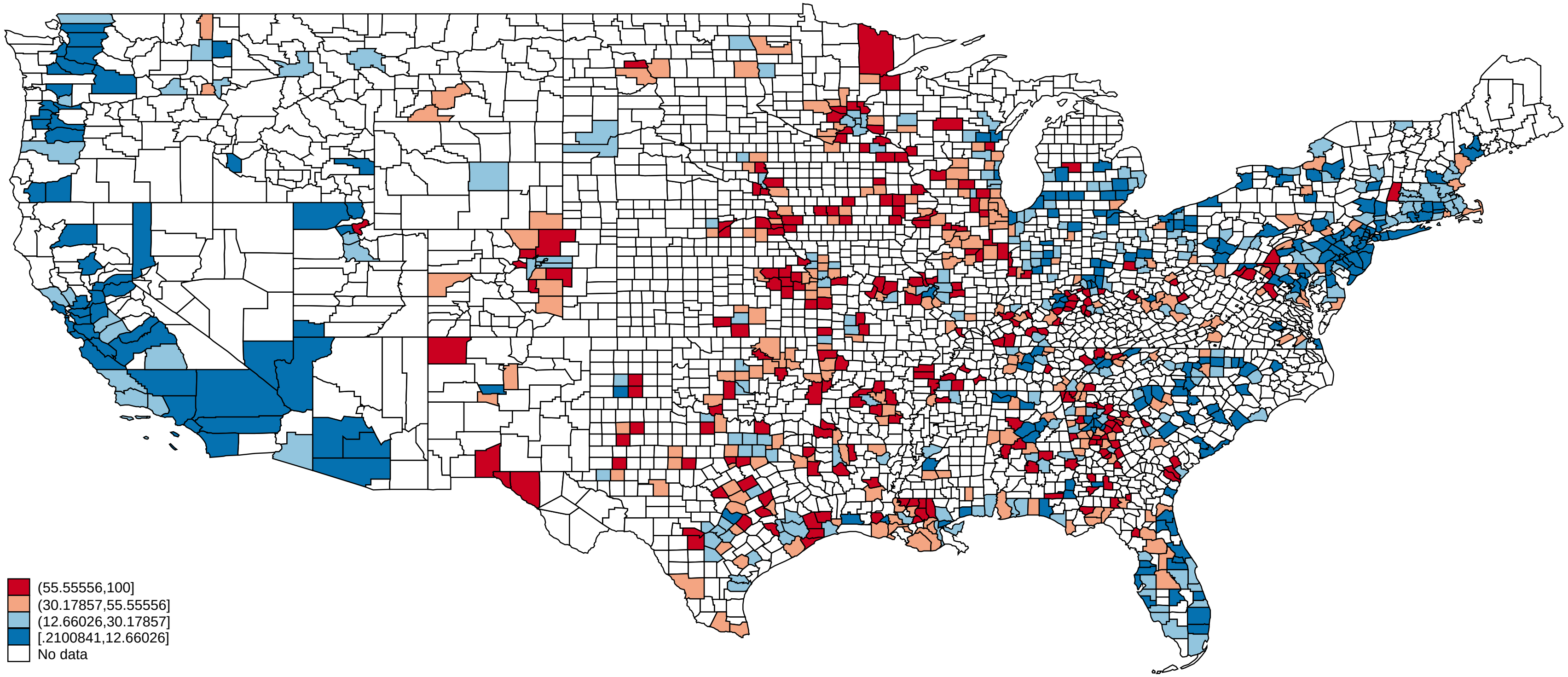
Note: This figure shows a heat map of county share of local bank branches to total bank branches in 1994. The dark red colour represents counties that have more than 69.23% of their bank branches are local; the pink and light blue areas represent counties with at least 60, 70% and 25.5%, respectively. Dark blue colour represents counties that have less than 0.2% of their bank branches are local. White colour areas indicate no data.

Figure 6.16 Heat Map of County Share of Local Bank Branches to Total Bank Branches in 2013



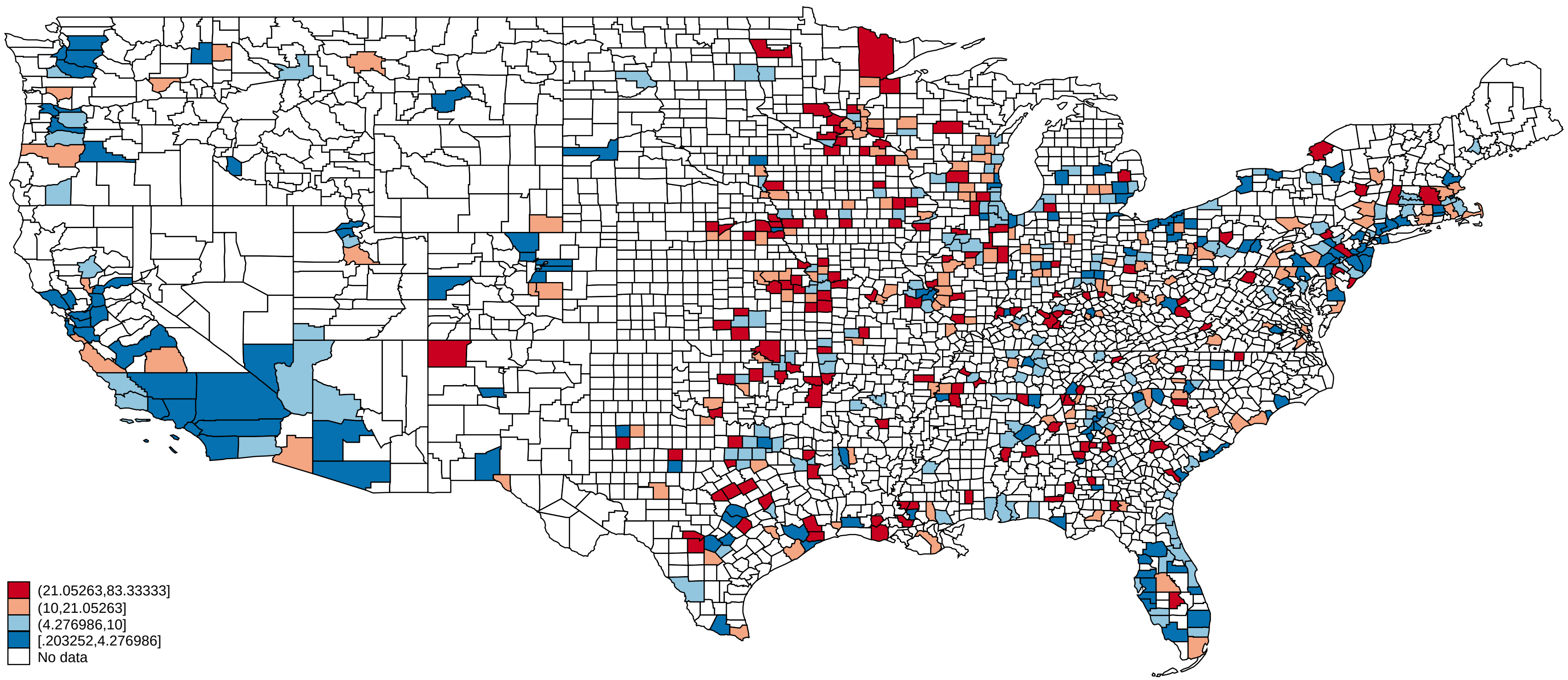
Note: This figure shows a heat map of county share of local bank branches to total bank branches in 2013. The dark red colour represents counties that have more than 33.33% of their bank branches are local; the pink and light blue areas represent counties with at least 20, 33% and 8.97%, respectively. Dark blue colour represents counties that have less than 0.2% of their bank branches are local. White colour areas indicate no data.

Figure 6.17 Heat Map of County Share of Local Bank Branches to Total Bank Branches for Urban Counties in 1994



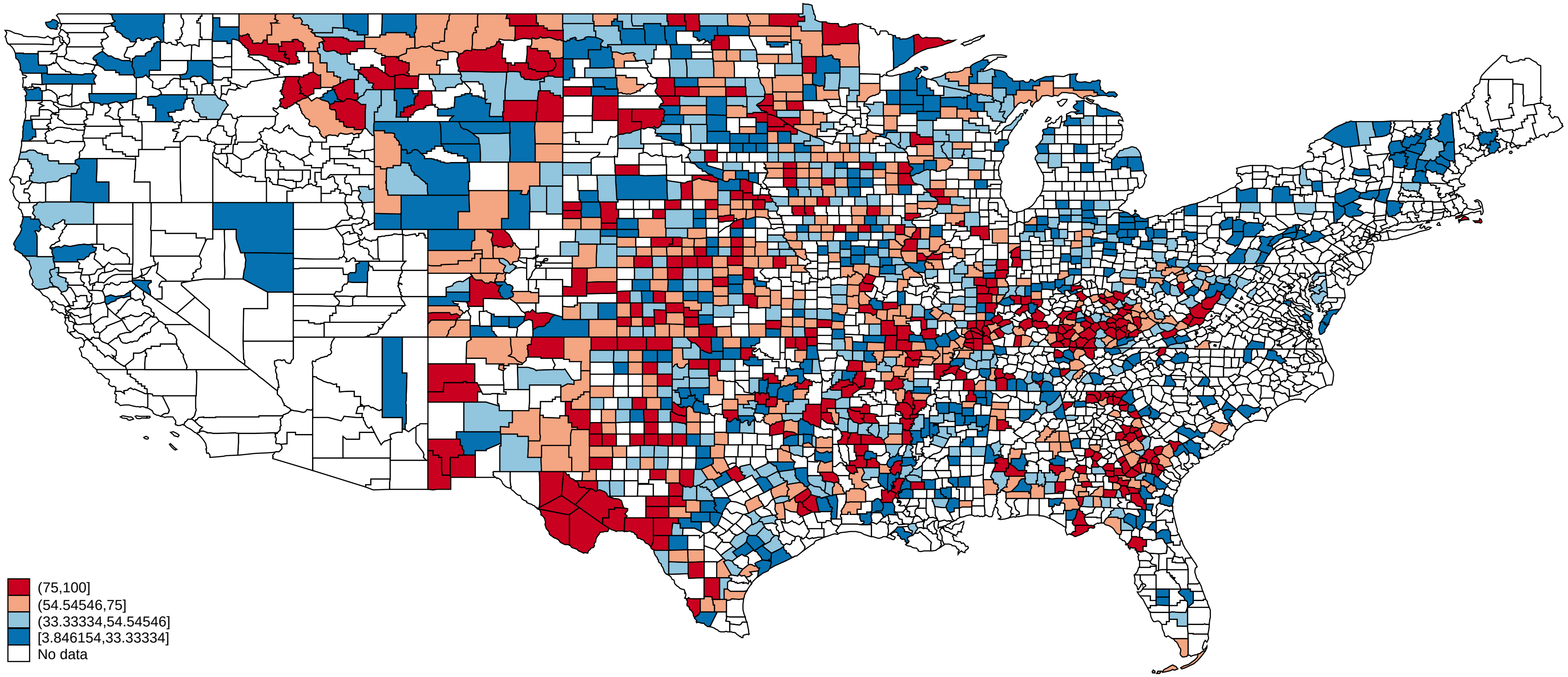
Note: This figure shows a heat map of county share of local bank branches to total bank branches only for urban counties in 1994. The dark red colour represents counties that have more than 55.55% of their bank branches are local; the pink and light blue areas represent counties with at least 30, 18% and 12.66%, respectively. Dark blue colour represents counties that have less than 0.2% of their bank branches are local. White colour areas indicate no data.

Figure 6.18 Heat Map of County Share of Local Bank Branches to Total Bank Branches for Urban Counties in 2013



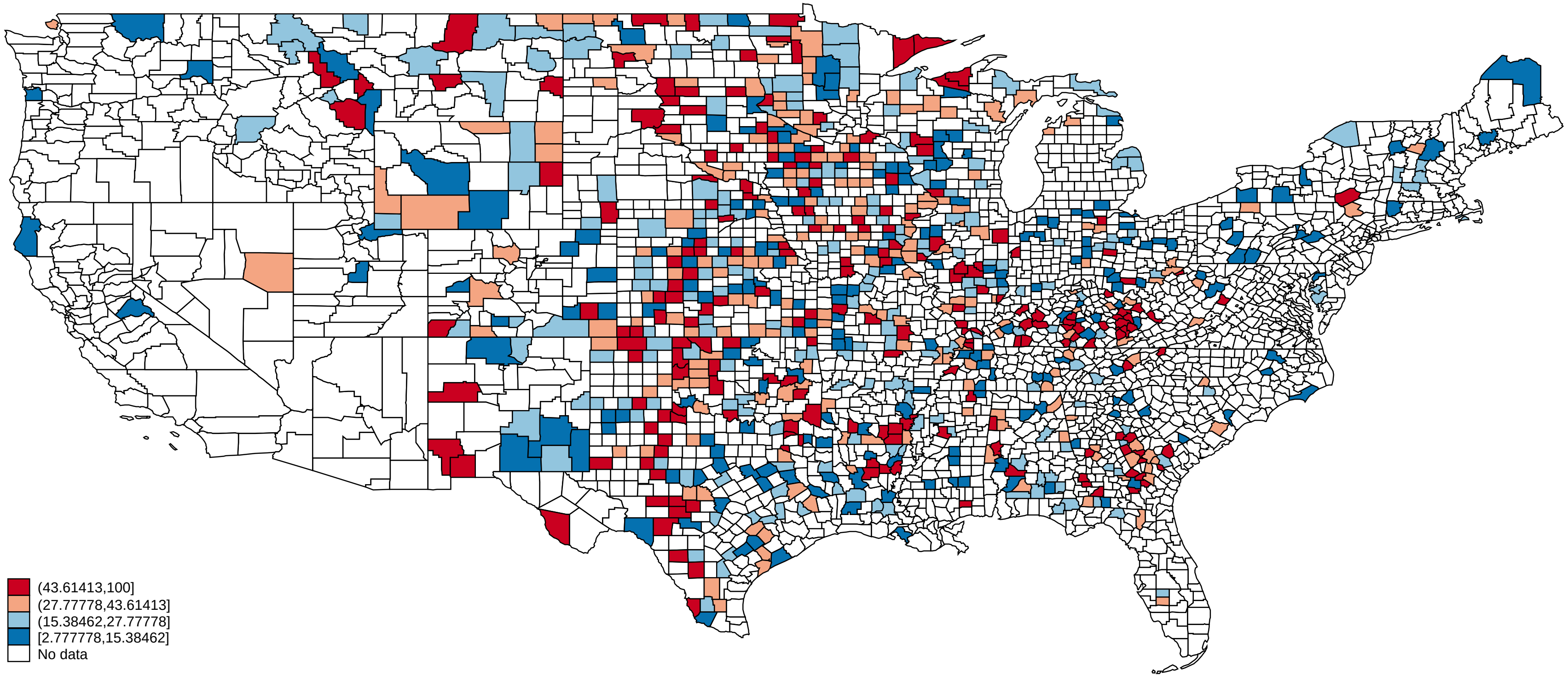
Note: This figure shows a heat map of county share of local bank branches to total bank branches only for urban counties in 2013. The dark red colour represents counties that have more than 21.05% of their bank branches are local; the pink and light blue areas represent counties with at least 10, 21% and 4.28%, respectively. Dark blue colour represents counties that have less than 0.2% of their bank branches are local. White colour areas indicate no data.

Figure 6.19 Heat Map of County Share of Local Bank Branches to Total Bank Branches for Rural Counties in 1994



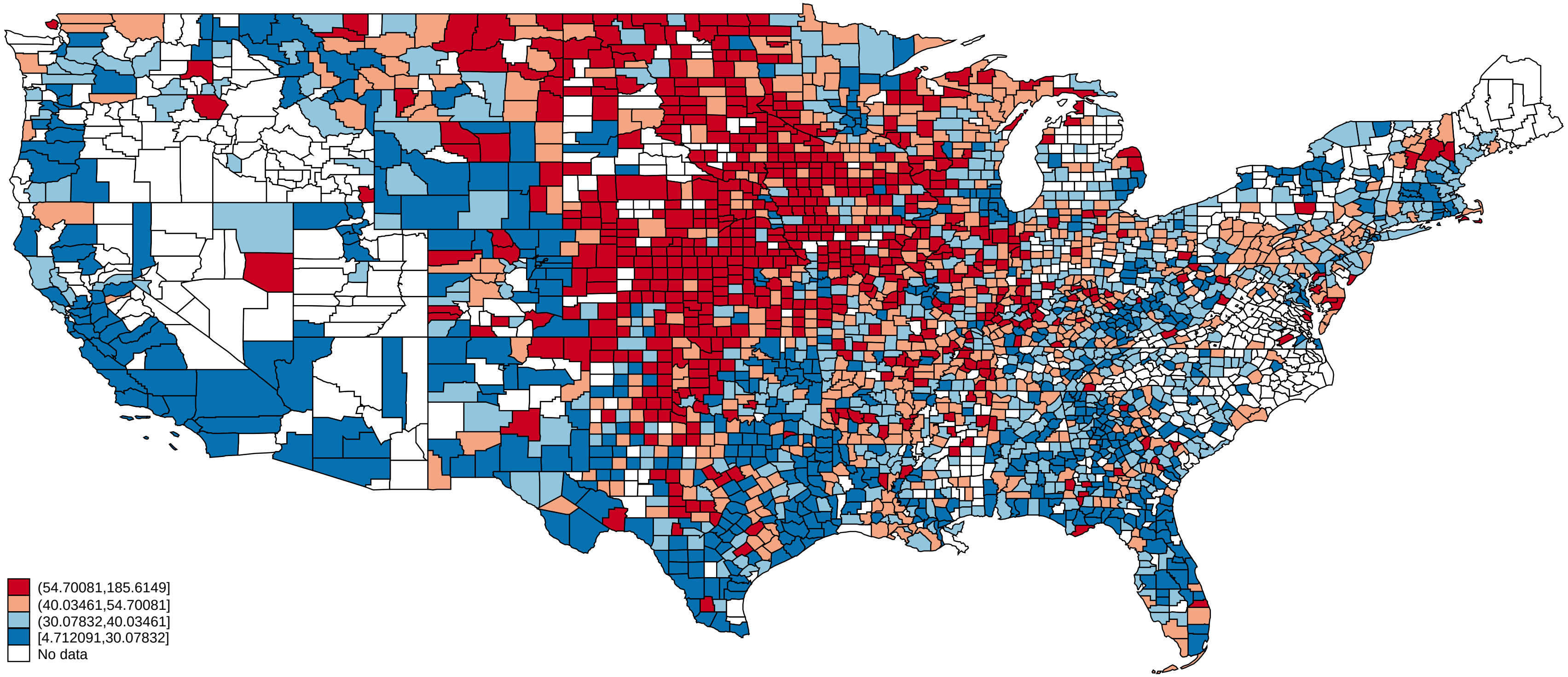
Note: This figure shows a heat map of county share of local bank branches to total bank branches only for rural counties in 1994. The dark red colour represents counties that have more than 75.55% of their bank branches are local; the pink and light blue areas represent counties with at least 54, 54% and 33.33%, respectively. Dark blue colour represents counties that have less than 0.38% of their bank branches are local. White colour areas indicate no data.

Figure 6.20 Heat Map of County Share of Local Bank Branches to Total Bank Branches for Rural Counties in 2013



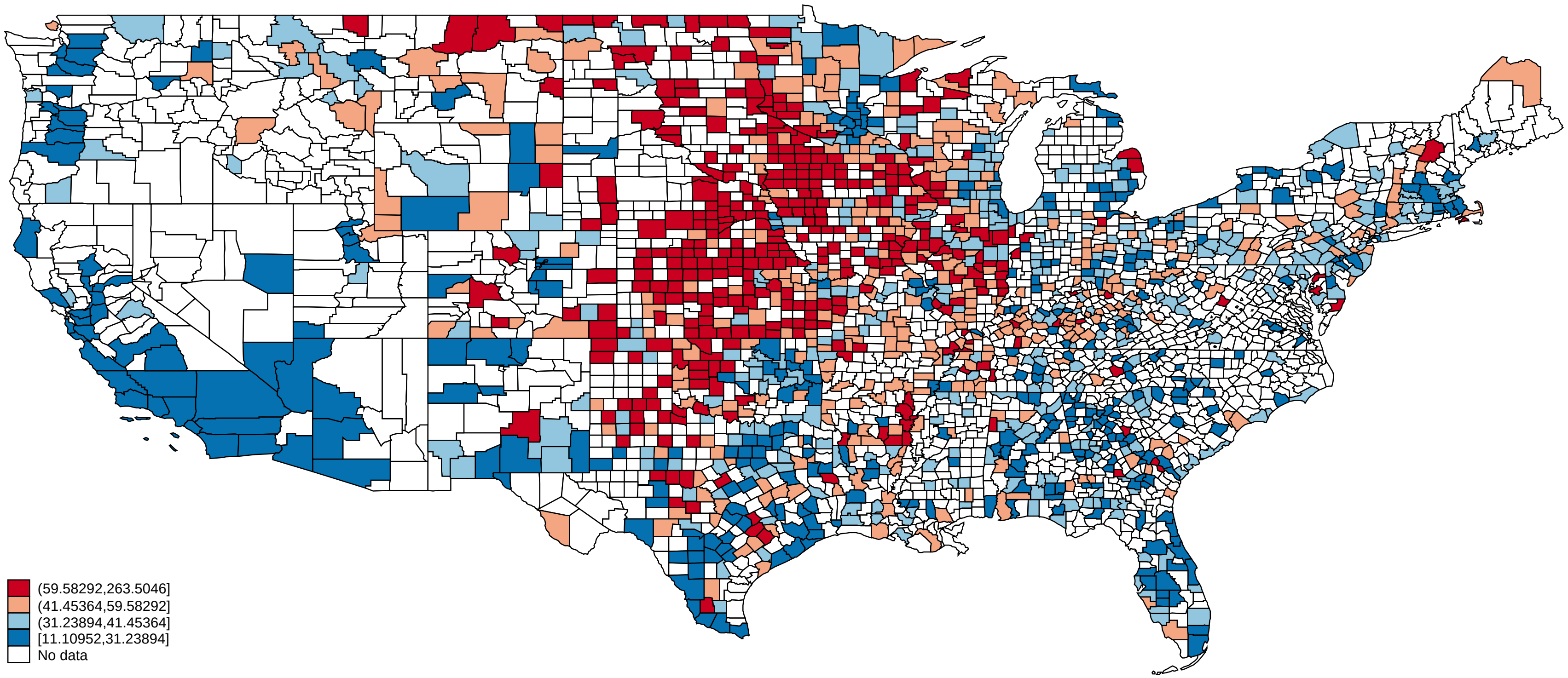
Note: This figure shows a heat map of county share of local bank branches to total bank branches only for urban counties in 2013. The dark red colour represents counties that have more than 43.61% of their bank branches are local; the pink and light blue areas represent counties with at least 27, 77% and 15.39%, respectively. Dark blue colour represents counties that have less than 0.28% of their bank branches are local. White colour areas indicate no data.

Figure 6.21 Heat Map of Bank Branches per 100, 000 (Bank Density) in 1994



Note: This figure shows a heat map of county bank density in 1994 i.e. the number of bank branches per 100,000 residents. The dark red colour represents counties that have more than 55 bank branches per 100,000 residents; the pink and light blue areas represent counties with at least 40 and 30 bank branches per 100,000 residents, respectively. Dark blue colour represents counties that have less than 5 bank branches per 100,000 residents. White colour areas indicate no data.

Figure 6.22 Heat Map of Bank Branches per 100, 000 (Bank Density) in 2013



Note: This figure shows a heat map of county bank density in 2013 i.e. the number of bank branches per 100,000 residents. The dark red colour represents counties that have more than 55 bank branches per 100,000 residents; the pink and light blue areas represent counties with at least 40 and 30 bank branches per 100,000 residents, respectively. Dark blue colour represents counties that have less than 5 bank branches per 100,000 residents. White colour areas indicate no data.

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