Three Essays Analyzing Microfinance Institutions, Housing Policy and Agricultural Banking

By

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A dissertation submitted to the Graduate Faculty of
Auburn University
In partial fulfilment of the
Requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
May 1, 2020

Keywords: cost complementarity, credit constraint, portfolio substitution,
capital-gap, liquidity

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Abstract

Chapter 1 evaluates if MFIs can realize cost savings from lending in both rural and urban markets, which would mean that the MFIs would exhibit economies of scale and cost complementarities. The presence of cost complementarities would suggest that the marginal costs of producing urban loans would decline as the rural loan portfolio expanded, and vice versa. A translog cost function with its respective share equations are estimated as a SUR model via maximum likelihood estimation separately for lending-only MFIs and deposit-lending MFIs. This was done to consider potential technological heterogeneity across the MFIs. In addition, two sets of translog cost functions were estimated for each MFI type. The first imposed both homogeneity and symmetry while the second relaxed the homogeneity restrictions. Based on the likelihood ratio test, the less restrictive model was a superior statistical fit to the MFI data. The results indicate that both MFI types exhibited economies scale averaging about 1.55 for lending-only MFIs and 1.52 for deposit-lending MFIs. Moreover, lending-only MFIs derived greater scale savings from rural loans which yielded a cost elasticity of 0.275 compared to urban loans which yielded a cost elasticity of 0.37. On the other hand, deposit-lending MFIs derived greater scale savings from urban loans which yielded a cost elasticity of 0.211 as compared to rural loans which yielded a cost elasticity of 0.45. Positive sample estimates for cost complementarities, and computed point estimates illustrate the potential for cost savings from the joint production of both rural and urban loans. Lending-only MFIs had 19.81% of the sample benefiting from marginal cost reductions while lending-deposit MFIs had 33.44% of the sample benefiting from marginal cost reductions because of the joint production of rural loans and urban loans.

Chapter 2 assesses the impact of the 2010 increase in the up-front mortgage insurance premium from 1.75% - 2.25% on the LTV ratios pursued by homebuyers. The results indicate that first-time home buyers are affected the worst as their LTV ratios decline by 2.4% - 3.7%. The impact of the policy was also analyzed based on income groups. The first income group had incomes ranging between $37,067 - $73,124 and the second income group had incomes ranging $74,000 - $149,987. As expected, the impact of the policy was on the lower income group led to an LTV ratio decline of between 2.1% - 2.9% while the higher income group had decline in the LTV ratio of 1.5%. The credit constraint hypothesis and the portfolio substitution hypothesis were

as well analyzed. The results indicate that First-time home buyers faced a credit constraint in their LTV ratio decision while higher income group did not face the constraint. In the case of the portfolio substitution hypothesis, first-time home buyers and borrowers in both income groups seem to consider housing assets and non-housing assets as substitutes. Based on the two hypotheses, there are potential indirect effects of the increase in the up-front MIP which warrant further empirical analysis: (1) a possible rebalancing of homebuyers' housing and non-housing consumption, (2) possible shift in homebuyers' in investment towards non-housing assets, (3) possible liquidation of non-housing assets to overcome the liquidity constraint, and (4) possible down-shift for cheaper homes by homebuyers who face a high income constraint and lack assets to liquidate.

Chapter 3 analyzes the lending dynamics of US agricultural banks over the period 2011-2019 primarily focusing on liquidity and the capital-gap, their potential interaction and how this interaction manifests itself in both capital-deficit states and capital-surplus states. The results indicate a symmetric effect of liquidity on lending across both capital-states. Small banks in the sample show no link between liquidity and lending. On the other hand, medium-sized banks, and large banks report -0.013% and -0.049% decline in lending expected from a 1% increase in liquidity. However, this negative effect diminishes as the capital deficit is reduced but increases as the capital surplus is increased. The effect of the capital-gap is asymmetric across capital-states in all bank samples. In the case of small banks, it is only statistically significant in the capital-deficit state and the results indicate that a 1% decline in the capital-gap will lead to a 0.21% increase in lending. In the case of medium-sized banks and large banks the capital-gap is only statistically significant in the capital-surplus state. A 1% increase in the capital gap will lead to a 0.19% and a 0.29% increase in lending in medium-sized banks and large banks, respectively. In addition, both the effect of the capital-deficit gap in small banks and the effect of the capital-surplus gap in the case of medium-sized banks and large banks was lower at higher liquidity positions. The interaction between the capital-gap and liquidity, across all bank sizes, was found to be statistically significant but only in the capital-deficit state. In small banks, the capital-gap and liquidity interacted as substitutes in the lending process while in medium-sized banks and large banks they were found to be complements. In addition, when medium-sized banks and large banks were in a capital-deficit state the marginal effects of their capital-gap on lending were greater at higher liquidity levels. However, in the case of small banks the marginal effects of the capital gap across capital-states decline at higher liquidity levels.

Acknowledgements

I would like to express my sincerest gratitude to the Department of Agricultural Economics and Rural Sociology for facilitating both the infrastructure and environment which enabled me the opportunity to efficiently pursue my coursework and research. Most of all I would like to thank Professor Valentina Hartaska and Professor Denis Nadolnyak, who from the very inchoate stage of the graduate program articulated the educational objectives and with an unrelenting dedication offered encouragement and advice which guided me through the program. Their fervent desire for economic research has been a great motivating factor in the choice of the research topic, empirical methodology applied and final completion of the dissertation. Thank You Very Much!!

I would as well like to thank the members of the committee. The impact of your advice on the structure of this research has been profound. Even though it demanded a lot more work and time. This research and the rigorous curriculum have engrained in me a work ethic, a persistent curiosity and most of all a reverence for the elements which encapsulate successful economic research. Thank You Very Much!

Finally, I would like to thank my parents for their undying support and love through the years. You made me understand the value of an education. Words cannot express the love and admiration that I have for you, Thank You very much!! To my siblings, well, your sarcasm and bizarre ways of encouragement, I will hold dearly. The warmth, laughs and brain picking kept me in good spirit and cheered me on every step of the way, Thank You Very Much!!

Table of Contents

List of Tables

List of Figures

Chapter 1

Cost dynamics of MFIs with Joint Rural-Urban loan Portfolios

1.1 Introduction

Microfinance expansion in both depth and breadth of outreach has undoubtedly made microfinance institutions (MFIs) important for improving financial inclusion. However, a salient feature of this growth is that the buildout of microfinance credit services has predominantly been experienced in urban areas and less so in their rural counterparts. Schreiner (2001) illustrates that in Latin America MFI expansion has been largely in urban areas. Charitonenko (2004) analyzing MFI performance and challenges of MFIs in Africa illustrates that MFI penetration into rural areas has been less successful in rural areas as compared to penetration into urban areas. Beck (2011) analyzing households which utilize financial services in transition economies found strong evidence of financial inclusion gap between urban and rural areas. This enduring trend is a serious concern as it is indicative of persistent limited accessibility to micro-credit services by rural residents. In this chapter, I seek to provide robust empirical analysis of the cost dynamics involved in the joint production of urban and rural loan products across different MFI categories.

It would be benighted to assume that the decision by MFIs to broaden their services in urban areas rather than in rural areas is based entirely on the MFIs internal structure. Their decisions are also determined by both push and pull factors. Therefore, to attenuate the askew distribution of MFIs credit services requires a multifaceted policy framework. Despite this, an analysis of cost dynamics of MFIs which is the objective of this research provides several contributions to the current literature.

The first contribution is derived primarily from the objective. Most of the scope studies in the MFI literature such as, Hartaska et al. (2011), Delgado et al. (2015) and Malikov and Hartaska (2018) have examined the possibility of scope economies derived from joint offering of loans and savings. This is the first empirical analysis, to the best of my knowledge, which performs an in-depth empirical analysis into the cost dynamics of the joint production of rural and urban loan products. In addition, most of the studies have focused on the overall economies of scope in the provision of loans and deposits (savings facilities). This research instead focuses on the existence of cost complementarities in the joint production of rural and urban loans. The cost complementarities will be estimated and compared across the aggregate MFI sample, deposit providing MFIs (Deposit-and-lending MFIs) and non-deposit providing MFIs (Lending-only MFIs).

The second contribution also stems from this objective. For instance, D'espallier et al. (2013), Cull et al. (2009) and Diop et al. (2017) analyzed the criteria used to award subsidies, and their impact on the financial performance and outreach of MFIs but do not distinguish urban and rural areas. In contrast, I analyze the cost structures and estimate scale and scope economies for MFIs offering loans in rural and urban areas. This paper will therefore provide new and essential empirical information to assist researchers and policy makers configure more effective incentives to rectify the disproportionate supply of financial services and at the same time encourage sustainable growth of MFIs in both urban and rural areas.

The data utilized in this study are obtained from the Mix Market and includes over 1000 MFIs and runs between 2008-2015. To briefly preview the results: I find statistically significant evidence of increasing economies of scale in both Deposit-and-lending MFIs and Lending-only MFIs. In the case of Lending-only MFIs the estimated urban loan cost elasticity was greater than rural loan cost elasticity. It is as well found that over the sample period the rural loan cost elasticity and urban loan cost elasticity for Lending-only MFIs has declined. In Deposit-and-lending MFIs, the urban loan cost elasticity has declined while the rural loan cost elasticity had risen over the same sample period. Predicted cost shares were also estimated. The results indicate that the costs of finance share increased over the sample period for both Lending-only MFIs and Deposit-and-lending MFIs. On the other hand, labor cost share in the case of Lending-only MFIs slightly declined but rose over the same sample period in the case of Deposit-and-lending MFIs. Allen elasticities were also computed. Across both Lending-only MFIs and Deposit-and-lending MFIs labor-Financial inputs were the strongest substitutes while financial-capital were the weakest. Finally, cost complementarities across the MFIs categories were computed. The results indicate that a larger percentage of Deposit-and-lending MFIs were experiencing negative cost complementarities from joint provision of rural and urban loans as compared to Lending-only MFIs.

The rest of the paper is structured as follows. Section two provides a brief review of pertinent literature in microfinance. Section three provides a brief description of the conceptual framework of the model and the methodology utilized to estimate scale economies, cost complementarities and elasticities of substitution. Section four describes the properties of the microfinance data used in this study. The empirical findings and discussion of the results are provided in section five and the last section presents concluding remarks and comments.

1.2 Literature Review

There is a large body of work examining diversification in commercial financial institutions. However, the literature on MFI diversification is more limited and focused on the joint supply of loans and savings products. This can be attributed to the recent trend of MFIs to offer savings and deposit services as they traditionally only offered loan products.

For instance, Hartarska et al. (2011) estimate scope economies for MFIs offering savings and loan products. They note that MFIs benefit from spreading fixed costs across the outputs but did not find much evidence of cost complementarities. Equally, Malikov and Hartaska (2018), estimate economies of scope in MFIs integrating similar financial products. In their choice of methodology, they correct for endogeneity (caused by self-selection in the group of Deposit-and-lending MFIs) and just like the present study, consider the effects of possible heterogeneity of technology across MFI types. Their primary results indicate that from the sample of over a thousand MFIs, the estimated median degree of scope economies was statistically indistinguishable from zero, but scope economies and scope diseconomies were present for part of the sample. Their results also illustrate that scope economies may be overestimated if self-selection into a business model (loans only versus loans-deposits) is ignored. They, however, arrive at the conclusion that even though integration may not lower costs, it still plays a vital role in outreach and poverty alleviation.

In this study, I consider overall MFIs diversification into rural loans and urban loans. Malikov et al. (2014) in their diversification of analysis of credit unions consider different degrees of diversification and utilize bounds to control for any potential effects that might have been due to cannibalization from different loan products. Their results illustrate that between 27% and 91% of credit unions across degrees of diversification and cost quantiles benefited from scope economies. Scale economies in MFIs have also been estimated but with older data. Hartarska et al (2012) examine Lending-only MFIs and Lending-Saving MFIs. They consider two forms of output: (1) Output measured in monetary terms and (2) Output measured in client numbers. In both cases they find increasing returns to scale. Moreover, the magnitude of economies of scale slightly differs across output measure. Delgado et al. (2015) examine a set of MFIs between 1999-2006.

They find economies of scale predominantly in smaller MFIs and diseconomies of scale in larger MFIs. They also illustrate that within their sample most of the MFIs which exhibited economies of scope were experiencing diseconomies of scale.

As mentioned earlier the studies of the role of financial product diversification and its effects on MFI costs is recent. Most of the literature has focused mainly on two other MFIs' concerns. The first has been the efficacy of subsidies as a tool for MFIs to cushion themselves from higher costs and lower profits from serving the poor. The second has been on group lending as an instrument to reduce lending costs and risks.

The impact of subsidies on MFIs has as well been analyzed. For instance, D'Espallier et al (2013) in their examination of social performance of both subsidized and non-subsidized MFIs, found definitive evidence that the lack of subsidies decreases social outreach. They also note that there is still a large proportion of MFIs receiving subsidies and as expected, MFIs across different regions adopt different techniques to achieve financial efficiency. On the other hand, Cull et al (2007) analyze the outreach level of commercialized or profit-driven MFIs as compared to not-for-profit MFIs. Their results illustrate that the commercialized MFIs faired poorer compared to their counterparts. Many MFIs across the world receive grants and subsidies from government institutions as an incentive to increase outreach. Diop et al (2017) argue that there should be a robust criterion on the provision of subsidies based on financial performance and outreach. Hudon (2010) performs an empirical analysis of the impact of subsidies in MFIs management. He finds a strong positive correlation between the quality of management and the level of subsidies. In addition, Basharat et al (2015) find that some MFIs invest subsidies toward capacity building and incentives for employees who have in turn enhanced efficiency and lowered operating costs.

However, it must be mentioned that the MFI revolution is characterized by shift from both subsidies and directed lending to more commercial or profit-driven lending. However, according to Charitonenko (2014) are still leveraged to reach a greater depth of rural clients. Other authors such as Von Pischke (1991) highlight the failure of subsidies in reaching the rural farmers while Krahnen and Schmidt (1994) highlight the negative impact of subsidies and directed lending on the rural poor.

Following Charitonenko (2014), group lending has been adopted by numerous MFIs to mitigate risk amongst borrowers as well as lower lending and monitoring costs in rural areas. A great deal of literature both theoretical and empirical have highlighted the positive impact of social capital on financial development (Guiso et al 2014), to curtail moral hazard (Eijkel et al. 2011) and promote economic development. Besley and Coates (1995) analyze the determinants of successful group lending programs. They advance the argument that despite the potential of group lending to enhance loan repayment, it as well has the potential to discourage a borrower from repaying a loan that they would have ordinarily paid had they taken out an individual loan. Like Arnold et al. (2013) and Akram and Jayant (2013) they as well conclude that the success of joint liability is dependent on both contract enforcement and social enforcement. Contract enforcement would generally be executed by the financial institution while social enforcement would be executed by society in the form of social sanctions and/or social reciprocity. Guiso et al (2014) illustrate that group lending can mitigate moral hazard because a group's investment is based on bolstering long-term relationships and ensuring sustainable financial longevity of each group member. In addition, Bhattacharya et al. (2008) find that group lending can be used to overcome asymmetric information between borrowers and MFIs. They note that in the presence of strong social cohesion, groups can have access to information about individual borrowers and other societal dynamics. This, if made accessible to the MFI could in turn lower MFI transaction costs and market costs.

As mentioned earlier there are push and pull factors which determine MFIs location between rural areas and urban areas. Pull factors are environmental conditions in urban areas which lead MFIs to offer their services in urban rather than rural areas. Push factors are environmental conditions in rural areas, which make it difficult for the MFIs to operate and ultimately lead the MFIs to offer services in urban areas. For instance, Caudill (2009) suggest that low population density and under-developed infrastructure in rural areas could raise MFIs' operating expenses. In addition, the primary activity in rural areas is agriculture which is susceptible to weather fluctuations and according to Meyer (2011) this raises systemic credit risk concerns which in-turn makes rural lending less attractive. On the other hand, there is one pull factor in rural areas which stands out. Deyoung (2012) argues that social capital in rural areas is far more widespread as compared to urban areas and this is a very attractive feature. The strong social interactions in rural areas can indirectly reduce MFIs monitoring costs and curb moral hazard.

The previous studies are pertinent to the microfinance literature and related to this study as they offer insights on how MFIs can benefit from serving the joint production of loans and savings, group lending and subsidies to enhancing social outreach. However, none of these studies analyze the impact of jointly producing rural and urban loans on the cost dynamics of MFIs. This paper is therefore vital since integrating rural and urban loans could have the potential to costs and significantly raise the level of financial inclusion. In addition, analyzing the production costs of urban and rural loans will provide new information to relevant stakeholders interested in crafting policies geared towards reducing the financial exclusion of the poor in both urban and rural areas.

1.3 Methodology

The cost function has its arguments based on output levels and input prices. To best represent the MFIs cost structure this study will adopt the second order Taylor approximation translog function commonly used in the literature. The general form of the translog cost function is given below. Where ($\mathrm{lnc_{it}}$) denotes the logarithm of the cost of production, where ($\mathrm{lny_{it}}$) denotes the logarithm of the output, ($\mathrm{lnw_i}$) and ($\mathrm{lnw_j}$) represents the logarithm of the input factors.

$$\mathrm{lnc_{it}} = \alpha_o + \sum_i \beta_i \,\mathrm{lny_i} + \frac{1}{2}\sum_i \sum_j \beta_{ij} \,\mathrm{lnw_i lnw_j} + \varepsilon_{it} \tag{1}$$

There is well developed literature in the finance discipline which provides excellent insight on the appropriate techniques to estimate the cost functions of financial institutions. To mention a few studies; Goisis et al. (2010), Altunbas and Molyneux (1996) and Huang and Wang (2001) utilize a trans-logarithmic function to estimate economies of scope and scale in the European banking sector, while Kim (1986) utilizes a similar function to analyze credit unions in British Colombia. The specific form of the translog cost function adopted for this study is provided below.

$$\begin{aligned}\mathrm{lnc} &= \alpha_o + \sum_i \beta_{it} \,\mathrm{lny_{it}} + \frac{1}{2}\sum_i \sum_j \beta_{it} \,\mathrm{lny_{it} lny_{jt}} + \sum_i \gamma_{it} \,\mathrm{lnw_{it}} + \frac{1}{2}\sum_i \sum_j \gamma_{it} \,\mathrm{lnw_{it} lnw_{jt}} + \\ &\sum_i \sum_j \delta_{it} \,\mathrm{lnw_{it}} \,\mathrm{lny_{it}} + \varphi_{it}\mathrm{ln}r_{it} + \frac{1}{2}\varphi_{it}\mathrm{ln}r_{it}^2 + \sum_i \varphi_{it}\mathrm{ln}r_{it}\mathrm{lny_{it}} + \sum_i \varphi_{it}\mathrm{lnw_{it}ln}r_{it} + \varphi_{it}\mathrm{ln}r_{it}t_i + \\ &\omega_{it}t_i + \frac{1}{2}\omega_{it}t_i^2 + \sum_i \omega_{it}t_i\mathrm{lny_{it}} + \sum_i \omega_{it}\mathrm{lnw_{it}}t_i + \varepsilon_{it}\end{aligned} \tag{2}$$

Where ($\mathrm{y_{it}}$) are rural loans, ($\mathrm{y_{jt}}$) are urban loans, ($\mathrm{w_{it}}$) are input prices, (r_{it}) is loan portfolio risk and (t_i) is the time trend. The input prices ($\mathrm{w_{it}}$) encompasses three MFI input prices, namely administrative expenses (k), labor expense (l) and financial expenses(fk).

Before the estimation of the model I impose symmetry restrictions; $\beta_{ij} = \beta_{ji}, \gamma_{ij} = \gamma_{ji}, \delta_{ij} = \delta_{ji}$, $\varphi_{ij} = \varphi_{ji}$ *and* $\omega_{ij} = \omega_{ji}$ and homogeneity restrictions; $\sum_{i} \gamma_{i} = 1, \sum_{i} \sum_{j} \gamma_{ij} = 0, \sum_{i} \sum_{j} \delta_{ij} = 0$ and $\sum_{i} \omega_{i} = 0$. To enhance efficiency of the estimation, I estimate the translog cost function jointly with its cost share equations. The cost share equations were derived using Shepard's Lemma and are provided below. They provide information on the share of each input's cost in total cost.

$$\frac{\partial \ln c}{\partial \ln w_{i}} = s_{it} = \gamma_{it} + \sum_{j} \gamma_{ijt} \ln w_{jt} + \sum_{i} \delta_{it} \ln y_{it} + \varphi_{it} \ln r_{it} + \omega_{it} t + \varepsilon_{sit} \tag{3}$$

Where (s_{it}) is the share each of the input factor cost in total cost and encompasses the share costs of MFI inputs, namely, share of administrative expenses (sk_{it}), share of labor expense (sl_{it}) and share of financial expense (sfk_{it}).

The entire system of equations is estimated using the maximum likelihood seemingly unrelated regression (SUR) method. Shepard's Lemma as well implies that cross-equation restrictions are imposed. This makes the coefficients in equation (3) should be equal to those in equation (2). The system of equations is then estimated using ordinary least squares. To ensure efficient and accurate inference standard errors are bootstrapped.

Both cost elasticities and economies of scale (SE) will be analyzed. Equation (4) and equation (5) below provide the formula to the cost elasticity with respect to output and economies of scale respectively. Following Baumol (1986) and Panzar and Willig (1977) the measure of overall scale economies for a firm is given by the inverse of its cost-output elasticity. This is the inverse of the derivative of the translog model with respect to output and is in fact the ratio of the marginal cost to average cost of the firm.

$$\frac{\partial \ln c_{it}}{\partial \ln y_{it}} = \beta_{it} + \beta_{it} \ln y_{it} + \sum_{j} \delta_{ij} \ln w_{it} + \varphi_{i} \ln r_{it} + \omega_{it} t_{i} \tag{4}$$

$$SE = \frac{1}{\sum_{i} \left(\frac{\partial \ln c_{it}}{\partial \ln y_{it}} \right)} \tag{5}$$

MFIs expend resources to efficiently utilize a given set of inputs with the goal to produce a maximum level of output.

I include a time index (t_i) to act as an index for technological change, following Hunter and Timme (1991) who investigated the impact of technological change in large commercial banks in the United States of America, Hunter and Timme (1986) in their study of a panel of commercial banks in the American banking system, Apergis and Rezitis (2004) in their analysis of Greek banking sector and Simper (1999) in his empirical study of Italian savings banks. This index captures not only possible internal sources of technological advancement but also external environmental factors such as laws, policies and market innovations which may influence the production process of the MFIs. In this model, the change in MFIs' cost of production is measured by the equation below. It gives us the percentage change in total costs resulting from a unit change in the technology index. If the value of the derivative is less(greater) than zero then a change in technology, holding all other factors ceteris paribus, the MFI can produce the same or a higher level of output at a lower (greater) cost.

$$\frac{\partial \mathrm{lnc}}{\partial \mathrm{t}} = \omega_{\mathrm{it}} + \omega_{\mathrm{it}} t_i + \sum_{\mathrm{i}} \omega_{\mathrm{it}} \mathrm{lny}_{\mathrm{it}} + \sum_{\mathrm{i}} \omega_{\mathrm{it}} \mathrm{lnw}_{\mathrm{it}} + \mathrm{ln} r_{it} \tag{6}$$

MFIs are in the business of lending and to ensure sustainability they cannot afford to offer bad loans, so they evaluate the creditworthiness of each of their borrowers. In general, MFIs utilize two broad techniques to evaluate borrowers' creditworthiness- appraisal of the repayment capacity and collateral-based (asset backed) lending. However, the MFIs' like any other lender will face asymmetric information in the loan market and moral hazard by the borrowers. Therefore, despite the tools at their disposal to evaluate the borrowers' risk, the certainty of repayment is still not guaranteed. To account for default risk, like Hartaska et al. (2011) and Malikov and Hartaska (2018), Hartaska et al (2010), to measure default risk, I utilize the portfolio at risk-thirty days (r_{it}) which is the percentage rate of the total loan portfolio currently outstanding for more than thirty days. The impact of a higher default risk on the cost of MFIs is captured by the equation (7). It gives the percentage change in cost from one percentage change in risk level of the portfolio. If the value of the derivative is less (greater) than zero then a change in default risk, holding all other factors ceteris paribus, then the MFI costs would decrease (increase).

$$\frac{\partial \mathrm{lnc}_{\mathrm{it}}}{\partial \mathrm{lnr}_{\mathrm{it}}} = \varphi_{\mathrm{it}} + \varphi_{\mathrm{it}} \mathrm{ln} r_{it} + \sum_{\mathrm{i}} \varphi_{\mathrm{it}} \mathrm{lny}_{\mathrm{it}} + \sum_{\mathrm{i}} \varphi_{\mathrm{it}} \mathrm{lnw}_{\mathrm{it}} + t_i \tag{7}$$

Financial institutions diversify their financial service portfolio for several reasons: to reduce risk, to increase revenue and to lower production cost. This paper analyzes the determinants of MFIs' cost of urban and rural loans and the effect of their integrated production on the cost dynamics of MFIs.

Economies of scope for MFIs exist when the integrated production of both rural and urban loans is less costly than the combined costs of producing them separately. However, in this study, the potential cost complementarity benefits derived by MFIs when they jointly produce rural and urban loans are computed and analyzed. Following Hardwick (1990), the existence of cost complementarities in MFIs jointly producing both rural and urban loan products would occur if the marginal cost of producing one loan product type would decrease with increases in the production of the second loan product type. The interaction between the marginal cost of one loan product type and the output of the second loan product type is a second order partial derivative whose structure is provided below.

$$\frac{\partial^2 TC}{\partial y_1 \partial y_2} = \frac{TC}{y_1 y_2}\left[\frac{\partial lnTC}{\partial lny_1 \partial lny_2} + \left(\frac{\partial lnTC}{\partial lny_1}\right)\left(\frac{\partial lnTC}{\partial lny_2}\right)\right] \tag{8}$$

Having formally defined cost complementarity and provided its structure above, MFIs which jointly produce rural and urban loans would be experiencing cost complementarities if the value of the derivative were less than zero. This means it is preferred to have the first element in the parenthesis to be both negative and greater in absolute terms than the product of the urban loan cost elasticity and the rural loan elasticity.

Allen partial elasticities of substitution are as well constructed to describe the degree of substitution amongst the MFIs factors of production. The translog cost function partial elasticities of substitution are defined below, where (σ_{ij}) is the elasticity of substitution, (s_i) and (s_j) are the cost shares of the different inputs and (φ_{ij}) is the translog cost function estimated coefficient of the interaction term for factor prices.

$$\sigma_{ij} = \frac{\varphi_{ij}}{s_i s_j} + 1 \text{ where } i \neq j \tag{9}$$

As mentioned earlier this study performs an empirical analysis on three MFI samples. The first sample contains both Deposit-and-lending MFIs (MFIs providing both lending and deposit services) and lending-only MFIs, the second sample includes Lending-only MFIs and the third sample contains only Deposit-and-lending MFIs. For each sample, a translog cost function is estimated in both its restricted form and unrestricted form. The unrestricted form relaxes the homogeneity assumption. To compare the restricted model to the unrestricted model the likelihood ratio test is carried out. Following Baltagi (2008), the likelihood ratio (LR) statistic is provided below.

$$LR = -2\log\left[\frac{maxL(\beta_r,\Sigma)}{MaxL(\beta_{ur},\Sigma)}\right] \tag{10}$$

Where L is the likelihood function to maximize, β_r are the estimated parameters in the unrestricted model, β_{ur} are the estimated parameters in the restricted model and Σ is the covariance matrix.

1.4 Data

The dataset used in this study was obtained from the Microfinance Information exchange (MIX)[1]. It consists of over 1000 MFIs across six different regions of the world and covers a period of nine years (2008-2015). I divided the sample MFIs into three categories: (1) Overall sample of MFIs jointly producing urban and rural loans, (2) MFIs jointly producing urban and rural loans but with no deposits and (3) MFIs jointly producing urban and rural loans and also offer deposit services. Moreover, all the data obtained was initially in nominal USA dollar. It was then converted into 2010 real USA dollars utilizing the consumer price index with 2010 as the base year. All regions in the sample have a significant number of MFIs jointly offering rural and urban loans.

Table (1.1) and table (1.2) provide a summary of the regional distribution of MFIs across the sample. MFIs in the South Asia region and the East Asia region report the largest average amount of total costs of about \$13.9 million and \$8.95 million, respectively. They also produce the largest average amount of total loans of \$30.2 million and \$24.0 million, respectively. The MFIs in Africa and in the Middle East supply the least amount of loans at \$15.8 million and \$13.3 million, respectively. South Asian MFIs supplied the largest amount of rural loans of about \$18.6 million, followed closely by those in East Asia with an average loan portfolio of \$16.4 million. The regions with the lowest share of rural loans were Africa and the Middle East. However, the MFIs in Latin America and the South Asia have the largest average urban loans of about \$10.5 million and \$11.6 million respectively while those in East Asia and in the Middle East have the least average of urban loans of \$7.57 million and \$7.19 million respectively.

MFIs in Latin American, the Middle East and South Asia seem to utilize similar labor cost share of about 59% of total cost. On the other hand, in Africa and East Asia, MFIs have over 60% of their total costs going to labor while MFIs in Eastern Europe have the least share of their total

[1] The MIX is a web-based platform that provides data on MFIs. For more information on the specific metric (Diamond scale) used to evaluate transparency and quality of data visit the website, https://www.themix.org/.

cost derived from labor. The share of administrative expenses in total costs seems to be almost equal across the regions, ranging between 0.23-0.31. However, in Africa MFIs have the smallest share of administrative expenses in total cost averaging 22.60% while in the Middle East they have the largest share averaging about 30.90%. The last input share considered in this study is the share of financial expense to total cost. In Africa and in the Middle East, MFIs have respectively 9.1% and 8.7% of their total cost dedicated to financial expense. On the other hand, in Eastern Europe and in South Asia MFIs have the largest average financial expense across the sample averaging 23.40% and 17.20% respectively.

This study also categorizes MFIs based on those that provide deposit facilities and those MFIs that do not. MFIs offering deposits have total costs averaging 9.52$ million which is about three times the total cost of 3.04$ million for their counterparts. MFIs providing deposits also extended more loans than their counterparts. However, in both MFI categories, their respective loan portfolios were almost evenly distributed across rural and urban loans. MFIs offering no deposits supplied 7.65$ million worth of loans of which 3.73$ million worth of loans were rural loans and 3.75$ million worth of loans were urban loans. In the case of MFIs offering deposit facilities, they supplied an average of 26.4$ million worth of loans of which 12.6$ million loans were urban loans while 13.8$ million loans being rural. In both categories the share of urban loans exceeds that of rural loans.

Turning the attention to factor input shares. The share of labor expenses in total costs across the MFI categories averaged about 59%. However, the share of administrative expenses in total costs of 26.2% in Lending-only MFIs was slightly higher compared to their counterparts share of 22.5%. The share of financial expenses in total costs for Lending-only MFIs was about 4% less as compared to MFIs which provided deposit facilities. Lastly, average risk exposure across both MFI categories averaged about 7%.

1.5 Empirical Results

In this section, results across different MFI categories and model types are compared. Upon categorizing the aggregate MFI sample into Lending-only MFIs and Deposit-and-lending MFIs, two translog structures for each category are estimated. The models (1) - (3) are translog cost functions in which restrictions of homogeneity and symmetry are imposed, while in models (4) - (6) these restrictions are relaxed. The results of the estimated translog cost functions are provided in table (1.4) and table (1.5). The statistics for the goodness of fit are presented at the bottom of the tables. The models (1) - (3) estimates are provided in table (1.4) and had R-squared statistics which ranged between 0.59-0.72. On the other hand, after the relaxation of the homogeneity restrictions the R-Squared statistic in the models (4) - (6) are slightly lower and range from 0.55-0.68.

There are two other important observations worth mentioning. One, the estimated coefficients across MFI sample estimated (overall sample aggregate, Lending-only MFIs, and Deposit-and-lending MFIs) differ significantly. Second, the estimated coefficients across model types based on the imposition of restrictions slightly differ. This means that the estimated sample elasticities and cost complementarities may differ across model type and MFI category.

The Likelihood Ratio tests results are also presented in table (1.6). The results indicate that the unrestricted model is preferred on statistically grounds over the restricted model. The results are significant at the 1% level of significance.

Table (1.7) reports the sample estimates to the scale economies, cost elasticities based on loan type, risk elasticity and technological effect for each MFI category and across model types. First, I discuss the results from the translog cost models with restrictions. Both Lending-only MFIs and Deposit-and-lending MFIs have increasing returns to scale, indicating that they stand to reduce their costs from scaling up production of their respective loan portfolios. Moreover, Deposit-and-lending MFIs seem to be enjoying larger increasing returns to scale of 1.647 compared to Lending-only MFIs' of 1.637.

Loan product cost elasticities were also estimated. Lending-only MFIs reported a higher rural loan cost elasticity of 0.343 compared to urban loans which reported a value of 0.268. Because loans are measured in dollar amounts, this can be interpreted to mean that one percentage increase in rural (urban) loan portfolio will increase total costs by 3.43% (2.68%). However, the results reported from the entire MFI aggregate sample and Deposit-and-lending MFIs indicate that urban loan cost elasticities are significantly lower than rural cost elasticities.

I now shift to the second model type in which no restrictions are imposed and make comparisons to the restricted models. First addressed are the economies of scale and elasticities which are reported in table (1.7). The computed economies of scale have declined across all three

MFIs samples. Deposit-and-lending MFIs experienced the largest drop of 7.59% from 1.647 to 1.522. This was contributed by an 11.05% increase in urban loan elasticity from 0.190 to 0.211 and 6.95% increase in rural loan elasticity from 0.417 to 0.446. Lending-only MFIs economies scale fell by 5.19% from 1.637 to 1.522. This was caused primarily by a 7.24% increase in urban elasticity from 0.343 to 0.370 and a 2.61% increase in rural loan elasticity from 0.268 to 0.257. The rural loan elasticity across the three MFI samples slightly changes, with magnitudes of less than 10%.

Graphical representations of the computed urban loan elasticity and rural loan elasticity annual means are presented in figure (1.1) while annual means of the computed economies of scale are presented in figure (1.2). First, considering Lending-only MFIs presented in the middle section of figure (1.2). The graph illustrates that rural loan cost elasticity across the model types is fluctuating in similar pattern over the sample period. Both the unrestricted model and restricted models are downward trending indicating increasing cost savings from expansion of rural loan production over the sample period. The urban loan cost elasticity graphs in both model types exhibit less fluctuations and both trend downward, an indication that cost savings increase with increases in the urban loan output over the sample period. The economies of scale graph in the middle section of figure (1.2) presents a definitive upward trend. The restricted model seems to have more subtle fluctuations as compared to the unrestricted model. The upward trend represents increasing cost savings from jointly increasing rural and urban loan portfolios.

In the case of Deposit-and-lending MFIs, both computed rural loan elasticities and urban loan elasticities in the unrestricted model exceed those computed from the restricted model. A visible upward trend in rural loan elasticity is observed while a downward trend is observed in the case of urban loan elasticity. This means that over the sample period deposit taking MFIs have been deriving more and more cost savings from producing urban loans as compared to rural loans. The Deposit-and-lending MFIs' economies of scale presented in figure (1.2) illustrate a significantly different pattern. As expected, economies of scale in the restricted models are larger compared to the unrestricted model. In addition, an upward trend is observed in the restricted model, but no discernible trend is observed in the unrestricted model. This upward trend in the restricted model is an indication that the cost of scaling up loan portfolio output has been increasing cost savings over the sample period.

The predicted input cost shares are presented in figure (1.2) and figure (1.3). In both Lending-only MFIs and Deposit-and-lending MFIs the labor cost shares predicted from the restricted model fluctuate in similar fashion and very close in magnitude to those labor cost shares predicted from the unrestricted model. However, Lending-only MFIs illustrate a very mild downward trend over the sample period while the Deposit-and-lending MFIs illustrate an upward trend over the sample period. In the case of predicted finance cost shares, both Lending-only MFIs and Deposit-and-lending MFIs have their respective finance cost shares rising over the entire sample period. Moreover, both restricted models and unrestricted models are of proximate magnitude and fluctuate in similar fashion.

The predicted capital cost shares across the sample period are computed and illustrated in Figure (1.3). First, in both Lending-only MFIs and Deposit-and-lending MFIs, presented in the middle section and bottom section respectively, the predicted capital cost shares from the restricted model and from the unrestricted model are trending downward over the sample period. However, Deposit-and-lending MFIs have a steeper decline compared to Lending-only MFIs have. Second, both restricted and unrestricted models fluctuate in uniformity in both MFIs categories. In summary, over the sample period finance cost share in both MFI categories has risen. Second, there is a decrease in capital cost share in both MFI type with the cost share in Deposit-and-lending MFIs declining at a faster rate as compared to Lending-only MFIs. Lastly, Deposit-and-lending MFIs illustrated a strong upward trend in labor cost share but Lending-only MFI on the other hand presented a much milder rise in labor cost share.

The portfolio at risk-30 days was also included in the translog cost model. It is the percentage rate of loans currently outstanding for more than 30 days. In the restricted model both Lending-only and Deposit-and-lending groups yield a statistically significant risk elasticity. The reported risk elasticity for Lending-only MFIs is 0.083 while that of Deposit-and-lending MFIs is 0.092. This means that a 1% increasing in the percentage share of delinquent loans will increase total costs by 0.08% and 0.092% respectively across both MFI types. However, it would be incorrect to argue that this interaction between delinquent loans and MFIs' costs runs strictly and solely from defaulted loans to the MFI and therefore costs incurred are primarily from the process of their resolution. It could as well be that the MFIs are implementing both ex-ante and ex-post credit policies to minimize their non-performing loan levels. The computed risk elasticity estimates across the MFI categories in the unrestricted model presents a similar picture. However, in the case of Deposit-and-lending MFIs the estimates increase by 46% to 0.134. In the case of Lending-only MFIs the risk elasticity is 0.074 and is statistically significant but approximately 10.8% less in magnitude compared to the estimate computed from the restricted model.

The coefficient estimates of the time index representing technological improvements are statistically significant in all samples. In the case of restricted models, in Lending-only MFIs a one percent increase in technological improvement would decrease total costs by 4.8% while in Deposit-and-lending MFIs technology would reduce total costs by 3.6%. In the unrestricted models, the impact of technological change on total costs does not change much in the case of Lending-only MFIs but it almost doubles in the case of Deposit-and-lending MFIs to about 6.87%. As mentioned earlier, the time index included in the model does not provide information on the source of the innovation. For instance, it could be the possibility that public infrastructure, group lending techniques and/or adoption of mobile and other technologies leading to the reduction of both transaction and monitoring costs amongst these MFIs could explain the results obtained. In comparison, the computed technological effects from the unrestricted model across both MFIs types and aggregate sample are all statistically insignificant.

The Allen-Uzawa elasticities of substitution are presented in table (1.8). They measure the percentage change in factor proportions due to one percent change in their relative prices. The results discussed first are obtained from the translog cost model type in which restrictions are imposed. Lending-only MFIs and Deposit-and-lending MFIs report an almost equal labor-financial elasticities of substitution of about 0.91. However, Lending-only MFIs report much larger labor-capital elasticities of substitution of 0.544 compared to 0.49 amongst Deposit-and-lending MFIs. Moreover, across both MFI categories, financial-capital elasticities of substitution are the smallest compared to other input combinations. Lending-only MFIs and Deposit-and-lending MFIs reported 0.439 and 0.521 financial-capital elasticities of substitution, respectively.

For the case of the unrestricted model specification, Lending-only MFIs, elasticities of substitution that are statistically significant and are higher in all input combinations. The elasticity of substitution labor-Financial increases by 4.7% to 0.949, that of labor-capital increases by 8.5% to 0.629 and the elasticity of substitution financial-capital increases by about 20% to 0.534. The changes in the case of Deposit-and-lending MFIs are different. Elasticities of substitution labor-financial increased by about 3.3% to 0.941, that of labor-capital declined by 16.23% to 0.410 and that of financial-capital increased by 9.98% to 0.573.

Like other estimates computed, elasticity of substitution annual means is graphically represented in figure (1.4) and figure (1.5). There are a few noticeable qualities worth mentioning. First, across both MFIs categories and both model types there is neither an upward nor downward trend over the sample period. Two, there are minimal to no fluctuations across the presentations. Third, in majority of the computed elasticities of substitution values from the unrestricted model are greater than those of the restricted model.

Cost complementarities: Table (1.10) reports the result for the cost complementarities. They provide information on how, in this case, marginal costs of agricultural loan (urban loan) production are affected by increasing the production of urban loans (rural loans). In this context, cost complementarity can also mean that as MFIs provide urban loans, they learn from that and make the costs of providing rural loans lower. Primarily it is preferred that the computed estimates be less than zero. Discussed first are the results obtained from the translog cost model type which included restrictions. Across the different MFIs samples, the estimated cost complementarity estimates were positive and statistically significant. In the sample with all MFIs, the reported cost complementarity sample estimate is 0.005. The percentage of point estimates which were statistically significant and negative across the sample was 22.50%. The case was not very different in the sample with Lending-only MFIs. The sample estimate was 0.009 and as well positive. However, the percentage of statistically significant cost complementarity point estimates which were less than zero dropped significantly to 9.99% suggesting that only 10% of the observations had cost complementarity. On the other hand, the sample of Deposit-and-lending MFIs yielded very different results. Overall, the result was a positive and statistically significant 0.002. However, 33.76% of the MFIs in the Deposit-and-loan sample were experiencing cost complementarities (had negative sign and the coefficient was statistically significant). This was the largest percentage across different MFIs samples. In comparison, the computed cost complementarities from the unrestricted model, sample estimates are much larger in the MFIs aggregate sample and Deposit-and-lending MFIs. There is a 0.002 decline in the case of Lending-only MFIs. A more significant change is the near doubling of the nonpositive point estimates obtained across this category. There are now 19.81% MFIs experiencing negative cost complementarities (negative coefficient). In the case of Deposit-and-lending MFIs, the computed estimate was 0.003 and the percentage of MFIs experiencing negative cost complementarities shrank to 33.44%. The graphical representations of the cost complementarity estimates are presented in figure (1.5). The graphs show no visible trend and as well illustrate a tight uniformity around the zero margin over most of the sample period which mimics the sample estimates which were very close to zero.

1.6 Conclusion

This paper analyzed the cost dynamics of MFIs jointly producing rural loans and urban loans. A maximum likelihood seemingly unrelated regression system was utilized to estimate the MFIs' translog cost models in three separate MFI samples, the aggregate sample, Lending-only MFIs, and Deposit-and-lending MFIs. Both restricted and unrestricted multiproduct translog cost models were estimated but the likelihood ratio test indicated that the unrestricted specification, without the homogeneity restriction, produced a better fit for the MFIs cost structure. The computed elasticities, economies of scale and elasticities of substitution differed significantly across the restricted and unrestricted models. The computed economies of scale illustrate that MFIs which produce deposits (Deposit-and-lending MFIs) and those which do not provide deposit services (Lending-only MFIs) experience increasing returns to scale. Focusing on the unrestricted models, which were found to be a better statistically fit, some interesting results are obtained. The first is that the economies of scale in Deposit-and-Lending MFIs is 1.93% lower than the Lending-only MFIs. This means that Deposit-and-lending MFIs potential to generate cost savings from the expansion of their loan portfolios is reduced by inclusion of deposit services. This creates a challenge for this form of MFIs to attain their double bottom-line objectives of sustainability and financial inclusion. Another interesting result across the MFIs types, is the source of cost savings. The lending-only MFIs obtain greatest savings from urban loans while Deposit-and-lending MFIs derive greater savings from rural loans. This is extremely important as it gives us a prediction regarding which region the respective MFIs type is most probable to provide a loan from a cost perspective. In addition, stakeholders can now provide policy guidelines and/or incentives to ensure balanced spatial expansion which maximizes financial inclusion. Another key result in the analysis is that Lending-only MFIs have economies of scale that increased over the sample period. This can be interpreted as an increased efficacy level in the production of loan services over the sample period by Lending-only MFIs. In the case of Deposit-and-lending MFIs, there is no discernible trend in the economies of scale. However, there is a visible decline in their urban loan cost elasticity over the sample period, but this seems to have been eroded by the rising rural loan cost elasticity over the same period. This means that despite the increasing efficacy levels on the provision of urban loans over the sample period, the cost savings from these improvements have been eroded by the decreasing efficacy levels in the provision of rural loans.

A time index to consider any technological improvement was included. Cost savings of 6.87% and 4.7% respectively was realized from skill enhancement or technology adoption. The results also show that credit risk would raise total cost by 0.074% in Lending-only MFIs and 0.134% in Deposit-and-lending MFIs. These are significant increases in total costs especially in the case of Deposit-and-lending MFIs. These results indicate a need for the re-evaluation of the MFIs credit risk assessment strategies and forms of incentives offered to borrowers to ensure successful loan repayment. The elasticities of substitution illustrate that Lending-only MFIs have larger labor-financial and labor-capital elasticities of substitution, but a smaller financial-capital elasticity of substitution compared to Deposit-and-lending MFIs. Cost complementarities results indicate that majority of MFIs were experiencing non-negative cost complementarities. However, Deposit-and-lending MFIs had about 33.44% of MFIs deriving cost complementarities from the joint production of rural and urban loans while Lending-only MFIs had about 19.81% of the MFIs benefiting from the joint production of rural and urban loans.

Two conclusions can be derived from this result. First, there is potential to derive greater savings from recalibrating their management information systems to ensure more efficient allocation of the resources shared between rural loan production and urban loan production. Second, the inclusion of the provision of deposits across MFIs seems to improve the synergies in the joint production of rural loan urban loan production. This improved synergy in the management information system can be attributed to the production of deposits or information drawn from the savings habits of both rural and urban borrowers which in-turn yield a more efficient allocation of resources toward jointly producing rural loans and urban loans.

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Table 1.1 MFIs Offering Rural and Urban Loans

Variable	Africa	East Asia & the Pacific	Eastern Europe & Central Asia	Latin America & the Caribbean	Middle East & North Africa	South Asia
TC	7.99	8.95	5.50	5.95	4.47	13.9
	(11.0)	(11.7)	(8.81)	(8.78)	(5.13)	(13.1)
Y	15.8	24.0	15.9	18.2	13.3	30.2
	(27.8)	(37.5)	(32.0)	(34.0)	(19.0)	(32.7)
Y_1	6.27	16.4	7.19	7.75	6.14	18.6
	(12.0)	(27.7)	(14.4)	(17.1)	(8.74)	(26.1)
Y_2	9.56	7.57	8.73	10.5	7.19	11.6
	(1.92)	(1.43)	(21.4)	(22.1)	(11.0)	(15.7)
SL	0.684	0.614	0.534	0.593	0.604	0.583
	(0.068)	(0.081)	(0.124)	(0.077)	(0.084)	(0.085)
SK	0.225	0.237	0.233	0.244	0.309	0.245
	(0.051)	(0.061)	(0.071)	(0.056)	(0.066)	(0.060)
SFK	0.091	0.148	0.234	0.163	0.087	0.172
	(0.070)	(0.088)	(0.167)	(0.099)	(0.066)	(0.114)
Risk	0.096	0.057	0.069	0.070	0.062	0.055
	(0.129)	(0.097)	(0.107)	(0.090)	(0.102)	(0.090)
MFIs	156	109	186	251	32	26
Obs.	311	264	507	940	82	86

Notes: TC is total cost, Y is total loan portfolio, Y_1 is total rural loans, Y_2 is total urban loans, SL share of labor expense, SK share of capital expense, SFK is the share of financial expense, Risk is the risk portfolio at 30 days. Column values for TC, Y, Y_1 and Y_2 are rounded to the nearest million dollars. The values in the parentheses are the standard deviations.

Table 1.2 Global and Regional Summary of MFIs Offering Rural and Urban Loans

	Sample	Africa	East Asia & the Pacific	Eastern Europe & Central Asia	Latin America & the Caribbean	Middle East & North Africa	South Asia
Overall MFIs in sample							
Observations	2,190	311	264	507	940	82	86
#MFIs	760	156	109	186	251	32	26
Lending-only MFIs							
Observations	934	11	18	276	549	61	19
MFIs	295	8	10	97	150	25	5
Deposit-and-Lending MFIs							
Observations	1,256	300	246	231	391	21	67
MFIs	530	151	100	125	118	14	22

Note: Full Sample includes both Lending-only MFIs and Deposit-and-Lending MFIs. Deposit-and-Lending MFIs are MFIs are those MFIs which provide deposit services and Lending-Only MFIs are those MFIs that do not provide deposit services.

Table 1.3 Means of Variables Used in the Estimation

Variable	Full sample	Lending-only MFIs	Deposit-and-Lending MFIs
TC	6.75	3.04	9.52
	(9.80)	(2.54)	(12.0)
Y	18.3	7.52	26.4
	(32.8)	(8.80)	(40.9)
Y_1	8.83	3.73	12.6
	(18.1)	(5.16)	(22.8)
Y_2	9.52	3.79	13.8
	(20.2)	(5.06)	(25.5)
SL	0.595	0.598	0.592
	(0.100)	(0.085)	(0.110)
SK	0.240	0.262	0.225
	(0.062)	(0.061)	(0.058)
SFK	0.165	0.140	0.184
	(0.123)	(0.104)	(0.132)
Risk	0.071	0.070	0.072
	(0.102)	(0.103)	(0.102)
MFIs	760	295	530
Obs.	2,190	934	1,256

Notes: TC is total cost, Y is total loan portfolio, Y_1 is total rural loans, Y_2 is total urban loans, SL share of labor expense, SK share of capital expense, SFK is the share of financial expense, Risk is the risk portfolio at 30 days. Column values for TC, Y, Y_1 and Y_2 are rounded to the nearest million dollars. The values in the parentheses are the standard deviations.

Table 1.4 Regression Results Models with Restrictions Imposed

Variable	Full Sample	Lending-only MFIs	Deposit-and-Lending MFIs
$\ln(Y_1)$ (rural loans)	0.441***	0.445***	0.481***
	(0.045)	(0.065)	(0.057)
$\ln(Y_1)^2$	0.112***	0.106***	0.122***
	(0.009)	(0.014)	(0.011)
$\ln(Y_2)$ (urban loans)	0.373***	0.539***	0.268***
	(0.048)	(0.082)	(0.052)
$\ln(Y_2)^2$	0.105***	0.107***	0.107***
	(0.008)	(0.014)	(0.010)
$\ln(Y_1)*\mathrm{Ln}(Y_2)$	-0.054***	-0.030**	-0.066***
	(0.008)	(0.014)	(0.009)
Ln(L) (Labor expense)	0.600***	0.623***	0.592***
	(0.004)	(0.010)	(0.010)
Ln(K) (Capital expense)	0.199***	0.219***	0.175***
	(0.004)	(0.006)	(0.005)
Ln(FK) (Financial expense)	0.201***	0.158***	0.233***
	(0.004)	(0.012)	(0.012)
$\mathrm{Ln}(L)^2$	0.059***	0.055***	0.068***
	(0.003)	(0.004)	(0.003)
$\mathrm{Ln}(K)^2$	0.033***	0.036***	0.032***
	(0.002)	(0.004)	(0.003)
$\mathrm{Ln}(FK)^2$	0.071***	0.063***	0.077***
	(0.003)	(0.005)	(0.005)
Ln(L)*Ln(K)	-0.010***	-0.014***	-0.011***
	(0.002)	(0.003)	(0.002)
Ln (L)*Ln (FK)	-0.048***	-0.041***	-0.056***
	(0.003)	(0.004)	(0.004)
Ln(K)*Ln (FK)	-0.023***	-0.022***	-0.020***
	(0.001)	(0.002)	(0.002)
$\mathrm{Ln}(Y_1)$* Ln(L)	-0.006***	-0.008***	-0.003
	(0.002)	(0.002)	(0.002)
$\mathrm{Ln}(Y_1)$* Ln(K)	-0.000	-0.003**	0.001
	(0.001)	(0.001)	(0.001)
$\mathrm{Ln}(Y_1)$* Ln(FK)	0.006***	0.012***	0.002
	(0.002)	(0.002)	(0.002)
$\mathrm{Ln}(Y_2)$* Ln(L)	-0.016***	-0.007***	-0.023***
	(0.002)	(0.002)	(0.002)
$\mathrm{Ln}(Y_2)$* Ln(K)	-0.003***	-0.001	-0.006***
	(0.001)	(0.002)	(0.001)
$\mathrm{Ln}(Y_2)$* Ln(FK)	0.019***	0.007***	0.029***
	(0.002)	(0.003)	(0.003)
Time (Time index)	-0.071**	-0.143***	-0.038
	(0.031)	(0.041)	(0.043)

$Time^2$	0.006**	0.007**	0.007**
	(0.002)	(0.003)	(0.004)
Time*Ln(Y_1)	-0.002	-0.006	-0.001
	(0.005)	(0.006)	(0.006)
Time*Ln(Y_2)	-0.009**	-0.009	-0.011**
	(0.004)	(0.008)	(0.005)
Time*Ln(L)	-0.002***	-0.001	-0.003**
	(0.001)	(0.001)	(0.001)
Time*Ln(K)	0.000	0.001	0.001*
	(0.000)	(0.001)	(0.001)
Time*Ln(FK)	0.001**	0.001	0.002
	(0.000)	(0.001)	(0.002)
Time*Ln(PR)	0.003	-0.015**	0.014**
	(0.005)	(0.007)	(0.006)
Ln(PR) (Portfolio risk)	0.099**	0.246***	0.059
	(0.049)	(0.079)	(0.073)
$Ln(PR)^2$	0.013**	0.015*	0.011*
	(0.005)	(0.008)	(0.006)
Ln(PR)*Ln(Y_1)	0.004	0.024	-0.002
	(0.009)	(0.015)	(0.011)
Ln(PR)*Ln(Y_2)	0.007	0.029	-0.005
	(0.010)	(0.020)	(0.012)
Ln(PR)*Ln(L)	0.004***	0.010***	0.001
	(0.001)	(0.002)	(0.002)
Ln(PR)*Ln(K)	-0.009***	-0.009***	-0.009***
	(0.001)	(0.002)	(0.001)
Ln(PR)*Ln(FK)	0.005***	-0.001	0.008***
	(0.001)	(0.003)	(0.002)
Constant	0.578***	1.133***	0.242
	(0.129)	(0.195)	(0.153)
Observations	2,190	934	1,256
R-squared	0.672	0.589	0.715

Notes: Y_1 is the total rural loans, Y_2 is the total urban loans, L is the labor expense, K is the capital expense, FK is financial expense, PR is the risk portfolio at 30 days. Full Sample includes both Lending-only MFIs and Deposit-and-Lending MFIs. Deposit-and-Lending MFIs are MFIs are those MFIs which provide deposit services and Lending-only MFIs are those MFIs that do not provide deposit services. The standard errors in the parentheses are bootstrapped standard errors with ***p<0.01, **p <0.05 and *p<0.1.

Table 1.5 Regression Results: Models with no Restrictions Imposed

Variable	Full Sample	Lending-only MFIs	Deposit-and-Lending MFIs
ln(Y_1) (rural loans)	0.443***	0.470***	0.494***
	(0.043)	(0.065)	(0.053)
ln(Y_1) ^{2}	0.111***	0.113***	0.118***
	(0.009)	(0.013)	(0.010)
ln(Y_2) (urban loans)	0.409***	0.637***	0.298***
	(0.047)	(0.087)	(0.054)
ln(Y_2)^2	0.121***	0.137***	0.122***
	(0.009)	(0.014)	(0.011)
ln(Y_1) *Ln(Y_2)	-0.065***	-0.050***	-0.076***
	(0.010)	(0.018)	(0.010)
Ln(L) (Labor expense)	0.599***	0.633***	0.596***
	(0.006)	(0.011)	(0.010)
Ln(K) (Capital expense)	0.202***	0.226***	0.178***
	(0.004)	(0.006)	(0.005)
Ln(FK) (Financial expense)	0.367***	0.313***	0.453***
	(0.054)	(0.072)	(0.099)
Ln(L)^2	0.057***	0.067***	0.059***
	(0.005)	(0.006)	(0.005)
Ln(K)^2	0.042***	0.043***	0.045***
	(0.003)	(0.004)	(0.003)
Ln(FK)^2	0.154***	0.142***	0.204***
	(0.031)	(0.035)	(0.051)
Ln(L)*Ln(K)	-0.007***	-0.008**	-0.007***
	(0.002)	(0.003)	(0.003)
Ln (L)*Ln (FK)	-0.049***	-0.033***	-0.065***
	(0.004)	(0.006)	(0.005)
Ln(K)*Ln (FK)	-0.020***	-0.018***	-0.018***
	(0.002)	(0.002)	(0.002)
Ln(Y_1)* Ln(L)	-0.004***	-0.008***	-0.001
	(0.001)	(0.002)	(0.002)
Ln(Y_1)* Ln(K)	0.000	-0.003**	0.002
	(0.001)	(0.001)	(0.001)
Ln(Y_1)* Ln(FK)	0.021	0.052***	-0.012
	(0.023)	(0.019)	(0.030)
Ln(Y_2)* Ln(L)	-0.016***	-0.009***	-0.020***
	(0.002)	(0.002)	(0.002)
Ln(Y_2)* Ln(K)	-0.005***	-0.002	-0.009***
	(0.001)	(0.002)	(0.001)
Ln(Y_2)* Ln(FK)	0.029	0.016	0.058**
	(0.018)	(0.021)	(0.026)
Time (Time index)	-0.081***	-0.137***	-0.059

	(0.030)	(0.039)	(0.054)
$Time^2$	0.006***	0.006**	0.006*
	(0.002)	(0.003)	(0.003)
Time*Ln(Y_1)	0.001	-0.004	-0.000
	(0.005)	(0.006)	(0.006)
Time*Ln(Y_2)	-0.008*	-0.016**	-0.007
	(0.004)	(0.008)	(0.005)
Time*Ln(L)	-0.002***	-0.002*	-0.004***
	(0.001)	(0.001)	(0.001)
Time*Ln(K)	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Time*Ln(FK)	-0.007	0.002	-0.016
	(0.005)	(0.010)	(0.010)
Time*Ln(PR)	0.003	-0.015**	0.015***
	(0.005)	(0.007)	(0.006)
Ln(PR) (Portfolio risk)	0.091*	0.233***	0.100
	(0.049)	(0.075)	(0.088)
$Ln(PR)^2$	0.013**	0.014*	0.010*
	(0.005)	(0.008)	(0.006)
Ln(PR)*Ln(Y_1)	0.006	0.031**	-0.001
	(0.008)	(0.015)	(0.009)
Ln(PR)*Ln(Y_2)	0.011	0.039*	-0.002
	(0.010)	(0.020)	(0.010)
Ln(PR)*Ln(L)	0.003**	0.010***	0.001
	(0.001)	(0.002)	(0.002)
Ln(PR)*Ln(K)	-0.010***	-0.009***	-0.010***
	(0.001)	(0.001)	(0.001)
Ln(PR)*Ln(FK)	-0.004	-0.036*	0.023
	(0.008)	(0.020)	(0.020)
Constant	0.570***	1.144***	0.222
	(0.135)	(0.192)	(0.143)
Observations	2,190	934	1,256
R-squared	0.640	0.545	0.684

Notes: Y_1 is the total rural loans, Y_2 is the total urban loans, L is the labor expense, K is the capital expense, FK is financial expense, PR is the risk portfolio at 30 days. Full Sample includes both Lending-only MFIs and Deposit-and-Lending MFIs. Deposit-and-Lending MFIs are MFIs are those MFIs which provide deposit services and Lending-only MFIs are those MFIs that do not provide deposit services. The standard errors in the parentheses are bootstrapped standard errors with ***p<0.01, **p <0.05 and *p<0.

Table 1.6 Likelihood Ratio Test Statistics for Homogeneity

	Full Sample	Lending-only-MFIs	Deposit-and-Lending MFIs
LR Chi^2 Statistic	209.720	166.160	213.57
P-value	0.000	0.000	0.000

Notes: Full Sample includes both Lending-only MFIs and Deposit-and-Lending MFIs. Deposit-and-Lending MFIs are MFIs are those MFIs which provide deposit services and Lending-only MFIs are those MFIs that do not provide deposit services.

Table 1.7 Scale Economies and Elasticities

Models with Restrictions Imposed			
	Full Sample	Lending-only-MFIs	Deposit-and-Lending MFIs
Rural loan elasticity	0.357***	0.268***	0.417***
	(0.011)	(0.016)	(0.015)
Urban Loan Elasticity	0.257***	0.343***	0.190***
	(0.011)	(0.017)	(0.014)
Economies of Scale	1.629***	1.637***	1.647***
	(0.028)	(0.046)	(0.035)
Risk Elasticity	0.054***	0.083***	0.092**
	(0.020)	(0.029)	(0.036)
Technological Effect	-0.043***	-0.048**	-0.036
	(0.013)	(0.019)	(0.022)
Models with no Restrictions Imposed			
	Full Sample	Lending-only-MFIs	Deposit-and-Lending MFIs
Rural loan elasticity	0.369***	0.275***	0.446***
	(0.011)	(0.016)	(0.016)
Urban Loan Elasticity	0.275***	0.370***	0.211***
	(0.012)	(0.018)	(0.015)
Economies of Scale	1.552***	1.552***	1.522***
	(0.028)	(0.045)	(0.033)
Risk Elasticity	0.042**	0.074***	0.1343***
	(0.198)	(0.027)	(0.043)
Technological Effect	-0.053***	-0.047***	-0.0687***
	(0.013)	(0.017)	(0.025)

Notes: Full Sample includes both Lending-only MFIs and Deposit-and-Lending MFIs. Deposit-and-Lending MFIs are MFIs are those MFIs which provide deposit services and Lending-only MFIs are those MFIs that do not provide deposit services. The standard errors in the parentheses are obtained via the delta method with ***p<0.01, **p <0.05 and *p<0.

Table 1.8 Allen Elasticities of Substitution

Models with Restrictions Imposed			
	Full Sample	Lending-only MFIs	Deposit-Lending-MFIs
Labor-Financial	0.926***	0.906***	0.911***
	(0.010)	0.015	0.014
Labor-Capital	0.522***	0.544***	0.490***
	(0.012)	0.018	0.016
Financial-Capital	0.452***	0.439***	0.521***
	(0.022)	0.032	0.028
Models with no Restrictions Imposed			
	Full Sample	Lending-only MFIs	Deposit-and-Lending MFIs
Labor-Financial	0.953***	0.949***	0.941***
	(0.011)	(0.015)	(0.013)
Labor-Capital	0.514***	0.629***	0.410***
	(0.017)	(0.024)	(0.023)
Financial-Capital	0.525***	0.534***	0.573***
	(0.027)	(0.038)	(0.035)

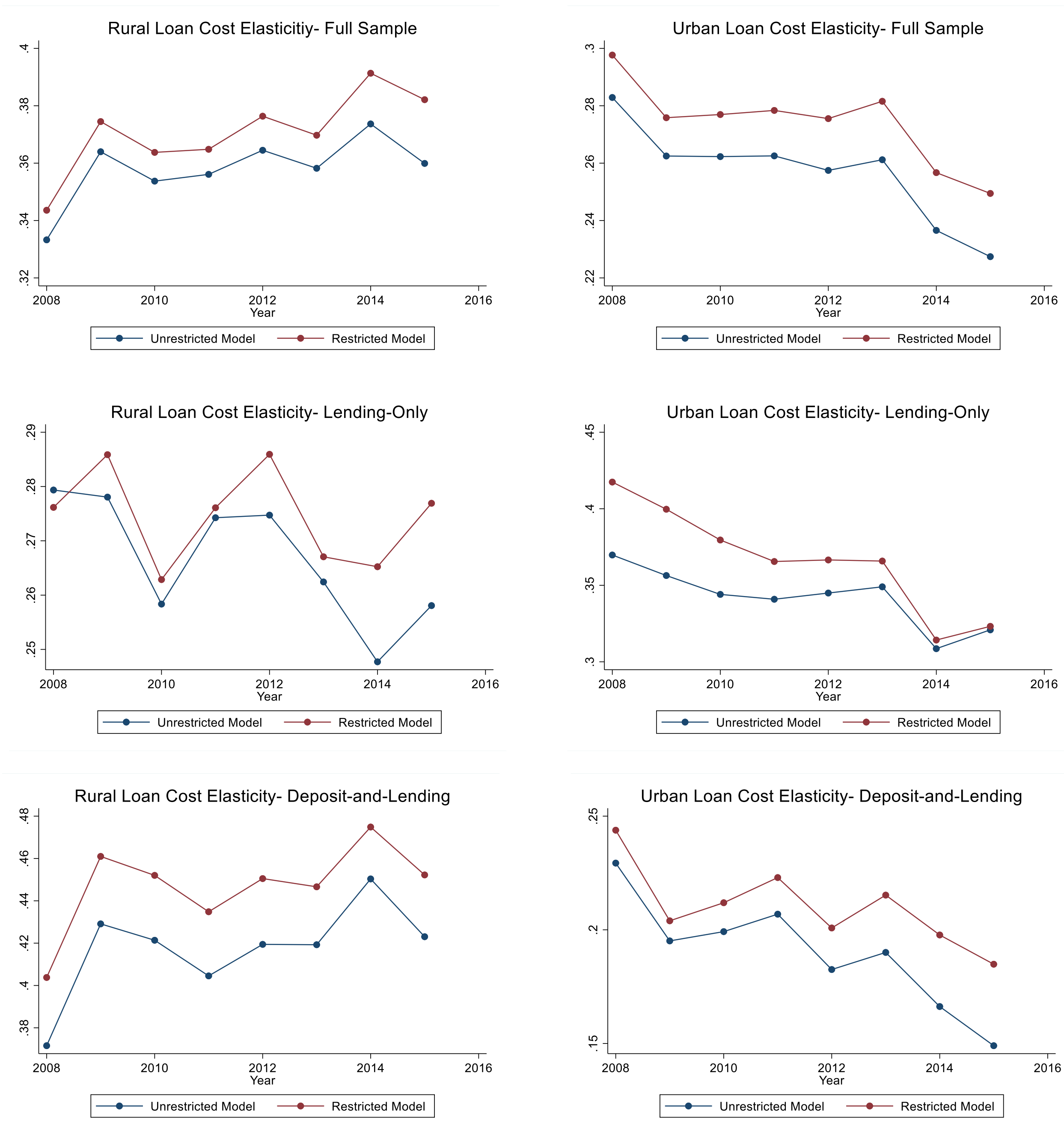
Notes: Full Sample includes both Lending-only MFIs and Deposit-and-Lending MFIs. Deposit-and-Lending MFIs are MFIs are those MFIs which provide deposit services and Lending-only MFIs are those MFIs that do not provide deposit services. The standard errors in the parentheses are obtained via the delta method with ***p<0.01, **p <0.05 and *p<0.

Table 1.9 Cost Complementarities

Models with Restrictions Imposed			
	Full Sample	Lending-only MFIs	Deposit-and-Lending MFIs
Sample Estimate	0.005***	0.009***	0.002**
	(0.000)	(0.001)	(0.001)
Negative	22.50%	9.99%	33.76%
Positive	61.64%	73.48%	35.99%
Models with no Restrictions Imposed			
	Full Sample	Lending-only MFIs	Deposit-and-Lending MFIs
Sample Estimate	0.005***	0.007***	0.003**
	(0.001)	(0.001)	(0.001)
Negative			
	27.45%	19.81%	33.44%
Positive	59.59%	61.88%	40.68%

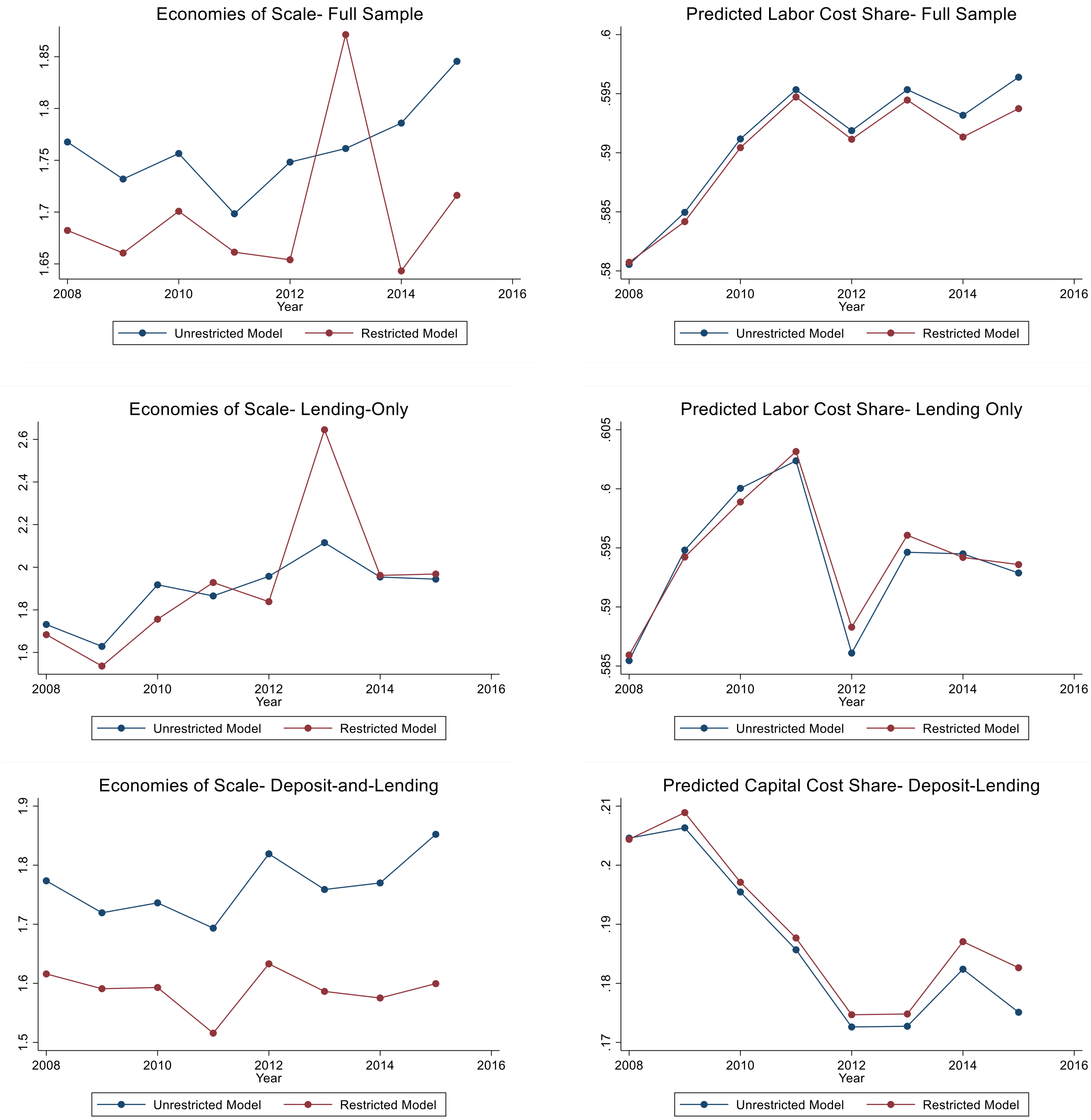
Notes: Full Sample includes both Lending-only MFIs and Deposit-and-Lending MFIs. Deposit-and-Lending MFIs are MFIs are those MFIs which provide deposit services and Lending-only MFIs are those MFIs that do not provide deposit services. The standard errors in the parentheses are obtained via the delta method with ***p<0.01, **p <0.05 and *p<0.

Figure 1.1 Computed Urban Loan and Rural Loan Cost Elasticity across MFIs and Models



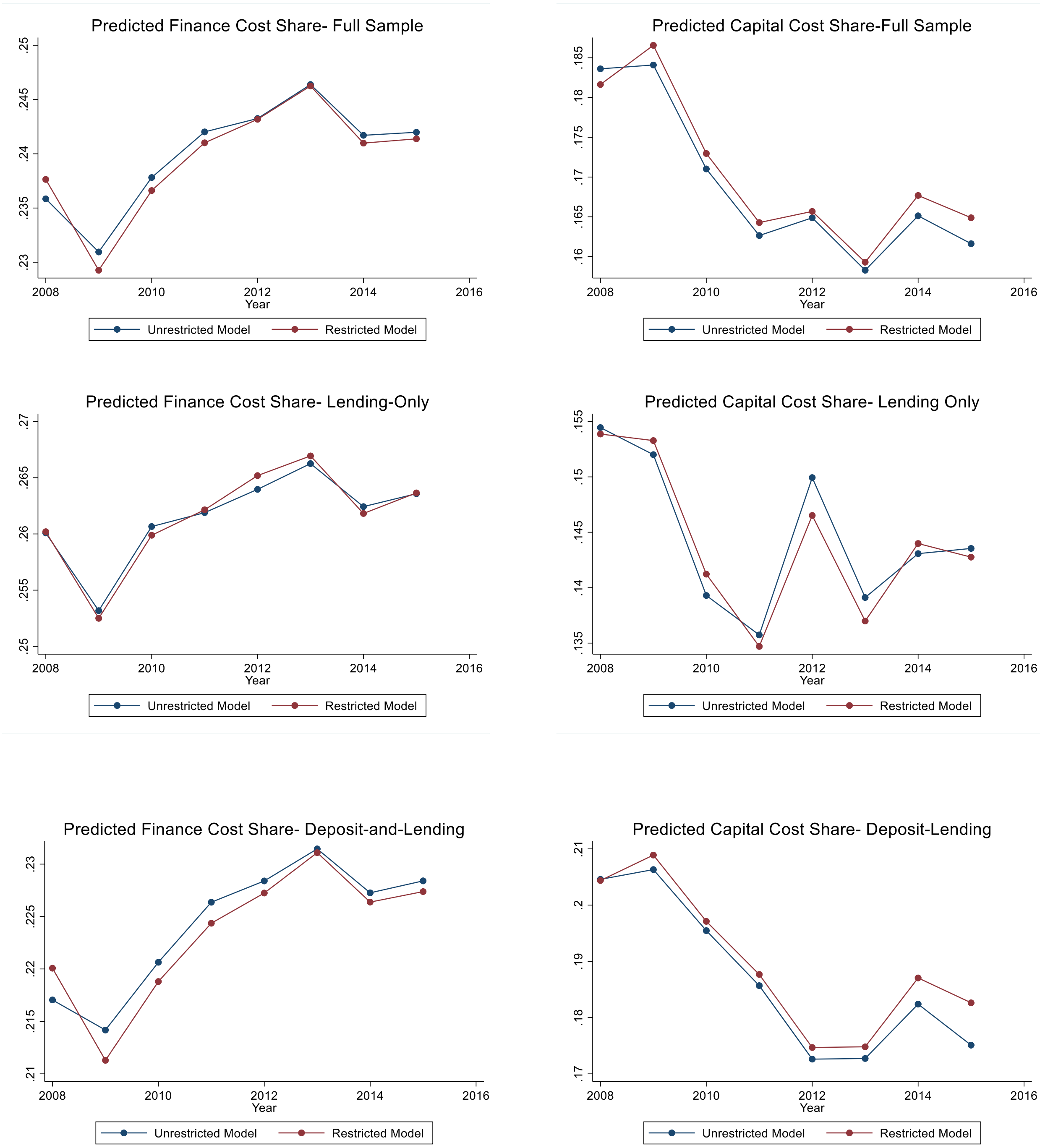
Notes: The top section of the figure represents the entire MFI sample, the middle section of the figure represents Lending-only MFIs (MFIs not offering deposits) and the bottom section represents Deposit-and-lending MFIs (MFIs offering deposits).

Figure 1.2 Computed Economies of Scale and Predicted Labor cost Shares across Models and Samples



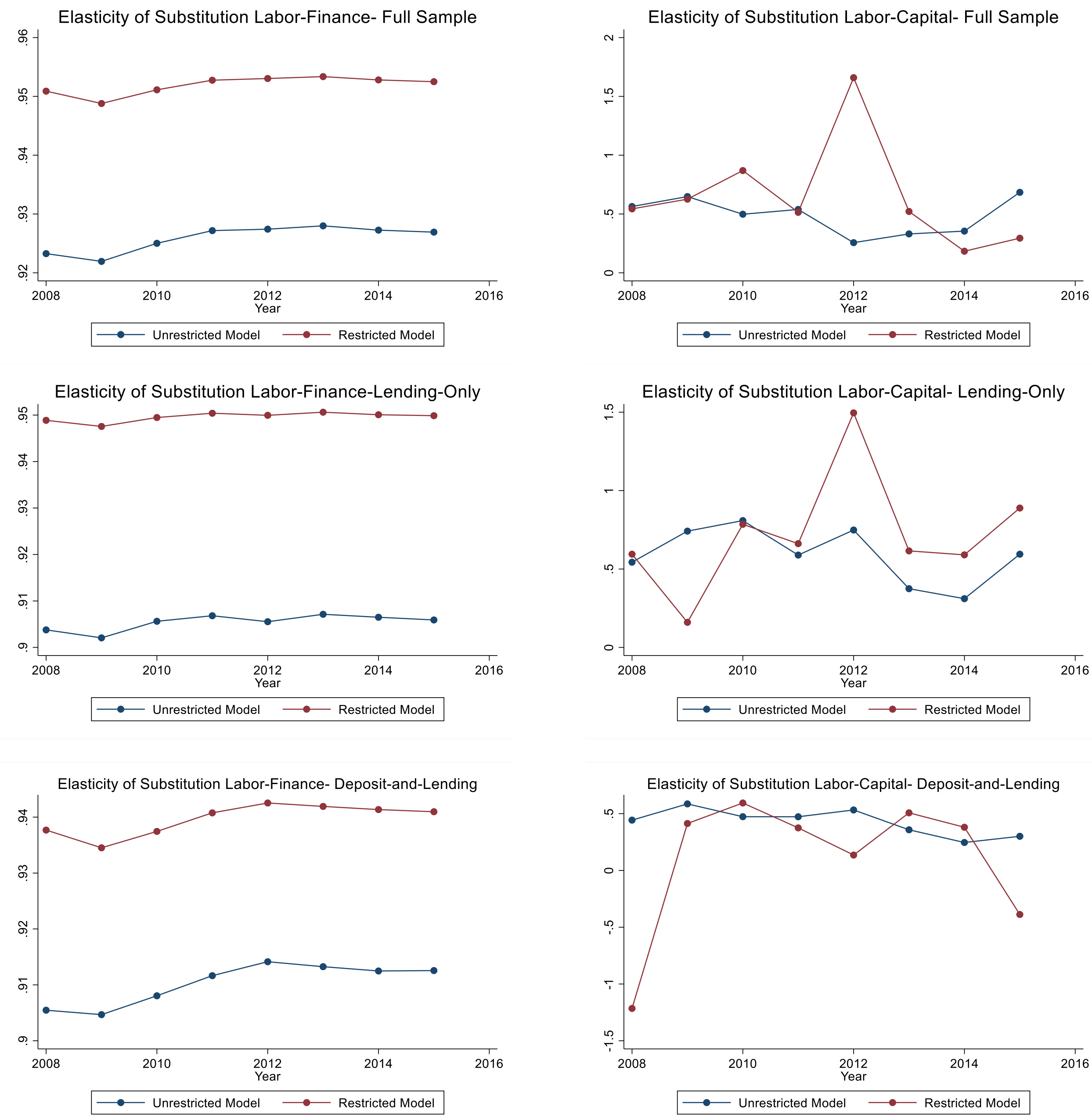
Notes: Notes: The top section of the figure represents the entire MFI sample, the middle section of the figure represents Lending-only MFIs (MFIs not offering deposits) and the bottom section represents Deposit-and-lending MFIs (MFIs offering deposits).

Figure 1.3 Predicted Finance cost Shares and Capital Cost Shares across Models and Samples



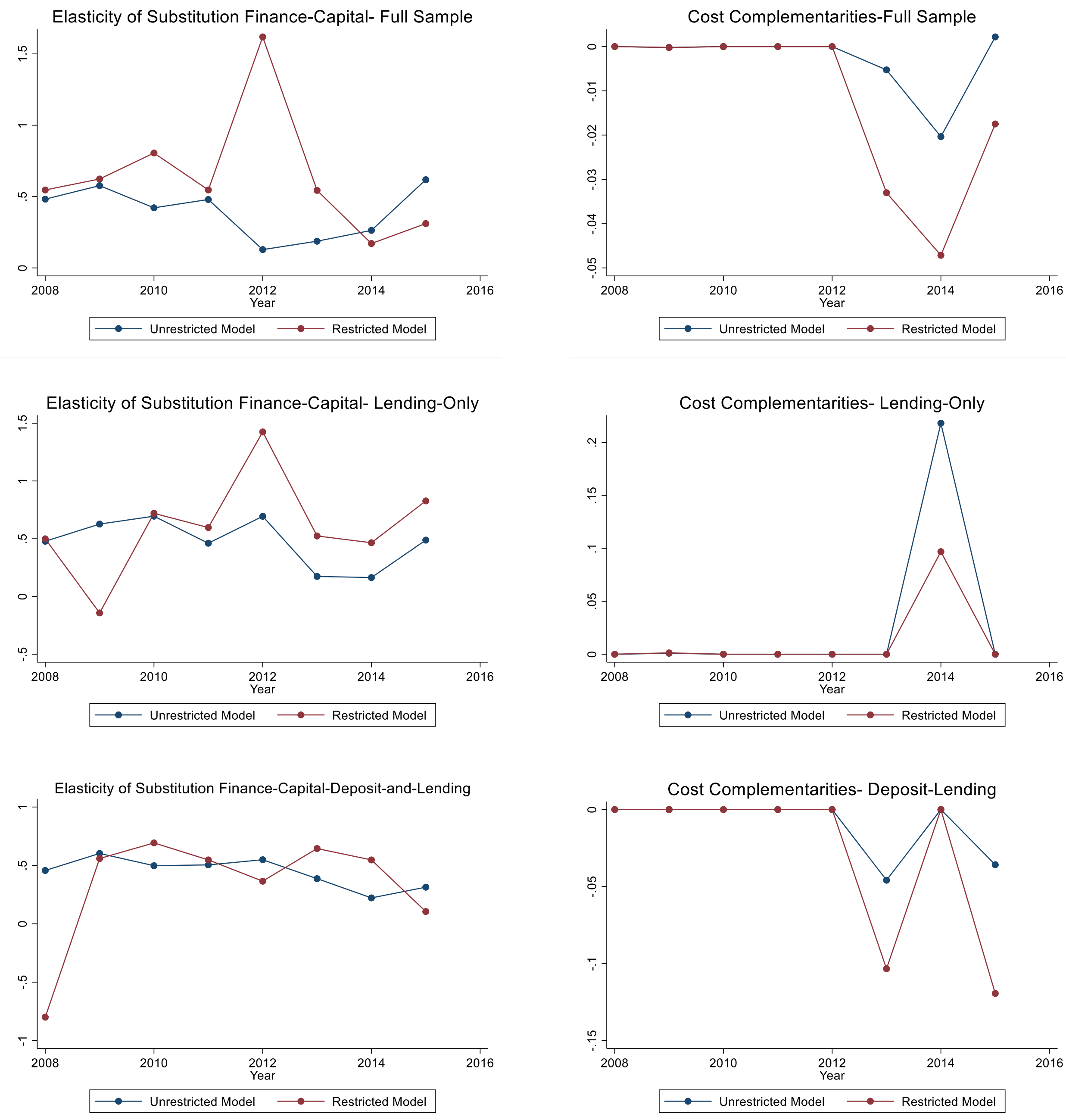
Notes: Notes: The top section of the figure represents the entire MFI sample, the middle section of the figure represents Lending-only MFIs (MFIs not offering deposits) and the bottom section represents Deposit-and-lending MFIs (MFIs offering deposits).

Figure 1.4 Computed Elasticity of Substitution Labor-Finance and Labor-Capital across Models and Samples



Notes: The top section of the figure represents the entire MFI sample, the middle section of the figure represents Lending-only MFIs (MFIs not offering deposits) and the bottom section represents Deposit-and-lending MFIs (MFIs offering deposits).

Figure 1.5 Computed Elasticity of Substitution Finance-Capital and Cost Complementarities across Models and Samples



Notes: The top section of the figure represents the entire MFI sample, the middle section of the figure represents Lending-only MFIs (MFIs not offering deposits) and the bottom section represents Deposit-and-lending MFIs (MFIs offering deposits).

Chapter 2

An Impact Analysis Study of the 2010 Hike in the Upfront Mortgage Premium on Loan-To-Value Ratios

2.1 Introduction

It has been the primary objective of the Federal Housing Policy to ensure an accessible, stable, and liquid mortgage market. One of the institutions established to ensure that these properties of the mortgage market are maintained is the Federal Housing Administration. The role of the FHA in market stabilization and ensuring market stability is evidenced by its market share dynamism in times of economic booms and economic recessions. For instance, in 2001 the FHA insured 14% of mortgages, but during the housing boom which was up until 2006 this percentage had dropped to about 1%. However, in the wake of the crisis, the share of the FHA mortgages was roughly 30% and by 2011 it was about 40%. This as well illustrates that the FHA acts countercyclically in the mortgage market and as a 'near' automatic economic stabilizer. This is because during times of crises or economic downturns conventional mortgage lenders curtail their risk exposure by reducing their lending levels and tightening their credit standards, however, the FHA still issues insured mortgage loans providing the much-needed stability and liquidity in the mortgage market.

Another crucial role played by the FHA is facilitating access to mortgage loans. Potential homebuyers with weaker credit histories and who are unable to raise a substantial mortgage down-payment are often unable to obtain a mortgage at an affordable interest or are unable to qualify for a conventional mortgage. To ensure that potential homebuyers who would have otherwise not been served in the conventional mortgage market, the FHA provides insurance as an alternative. This is because it is willing to accommodate mortgage borrowers who can meet minimal mortgage down payments from and/or have an impaired credit history. Mortgage borrowers who submit a lower mortgage down-payment and have a poor credit history are considered a high default risk. Therefore, for a creditor to offer such applicants mortgage loans, the applicants need to pay a form of mortgage insurance which will protect the creditor against losses in the event of a default. The FHA mortgage loan insurance provides this protection to creditors.

There are two primary components of the FHA mortgage loan insurance. The first is the up-front mortgage premium (UFM) and the second is the annual mortgage premium. Prior to 2010, the up-front mortgage premium was 1.75%. In April 2010, the FHA announced a 0.5% increase in the up-front mortgage premium, raising it to 2.25%. However, the annual premiums remained unchanged.

This change would have probably influenced potential homebuyers' decision to buy a house, the homebuyers' mortgage choice and/or the homebuyers' mortgage loan-to value ratio. Despite the potential impact of this policy change on the other factors, this research will restrict its objective to analyzing the impact of the 2010 up-front mortgage insurance hike on the FHA mortgage loan loan-to-value (LTV) ratios. This research will therefore attempt to shed light on the sensitivity of a heterogenous set of mortgage borrowers to 2010 policy change across different mortgage products.

To briefly preview the results: The sample utilized in this research is an annual survey carried out by the Federal Housing finance Agency (FHFA). This survey is a 5% representation of the total residential mortgages across the United States of America. The annual surveys are merged to form a single panel data sample which runs from the year 2009 - 2014. Three sub-samples based on income category, purchase only mortgages and first-time homebuyers were as well constructed. A DiD research design which considers the FHA mortgage loan borrowers as the treatment group and the Conventional Loan borrowers as the control groups was implemented. In both the overall sample and the subsamples, an expected statistically significant negative estimate indicative that the increase in the up-front mortgage insurance premium reduced the mortgage loan LTV ratios for FHA mortgage borrowers.

In the case of the initial overall sample, the policy effect led to a 1.5% decline in the LTV ratios of FHA loan borrowers. However, the pre-policy mean income gap between FHA mortgage loan borrowers and the conventional loan borrowers was over $20,000. To correct for this, two sub-samples based on income category were constructed. The first sub-sample included mortgage borrowers with incomes between $37,076 - $73,124 while the second sub-sample included mortgage loan borrowers with incomes between $74,003 - $149,978. The policy effect estimates for the first income group was between 1.3% - 1.4% while that of the higher income group was between 0.08% - 1.5%. To overcome any effects from possible data limitations and ensure validity of the empirical results obtained, a robustness check was implemented. The choice of methodology was a hybrid model of match-DiD research design. The results obtained for the full sample which included all incomes the policy effect estimates ranged between 1.5% - 2.1%. The policy effect estimates for the lower income category ranged between 1.9% - 2.9% while the estimates in the higher income group ranged between 0.9% - 1.5%. The results are in line with the DiD approach.

The results, however, illustrate with more clarity that the increase in the up-front mortgage insurance premium had a more profound impact on lower income borrowers as compared to higher income borrowers.

2.2 Literature review

There is significant empirical literature on the factors affecting the loan-to-value (LTV) ratio decision, mortgage loan term decision, mortgage pricing and mortgage choice between FHA and conventional loans. For instance, Bruechner (1994) provides a theoretical framework to explain the homebuyer's loan-to-value ratio decision. He assumes the LTV ratio to be a function of the mortgage interest rate and interest earned on non-housing assets. Initially he assumes certainty of non-housing returns. This means the relative magnitudes of the two interest rates determine the optimal LTV ratio. He illustrates utilizing a utility function that when the interest earned on non-housing assets is higher than the mortgage rate the homebuyer will pursue the least LTV ratio possible and if the reverse is true then the homebuyer will pursue the highest LTV ratio possible. In either instance, a corner solution is the outcome. However, he relaxes the certainty assumption of the returns from non-housing assets and instead considers them to be random. In this case he illustrates that the homebuyer's optimal LTV ratio can be less than the maximum allowable amount. In other words, an optimal solution for the homebuyer would be for he or she to pursue a strategy which includes balance of both investment in non-housing assets and an LTV ratio below the maximum allowable amount. Follain and Alm (1984) using a theoretical model and simulation place more emphasis on liquidity constraints as the primary determinant of the LTV ratio choice. They as well illustrate that high LTV ratios are preferred for consumption smoothing purposes. Ling and McGill (1998) empirically analyze demand for mortgage debt. They find that larger LTV ratios are associated with higher income values but negatively with house prices. On the other hand, Cho et al (1995) utilizing a simultaneous equation model with sequential choices find a negative relationship between the LTV ration and the homebuyer's income. They as well find a positive relationship between non-mortgage debt and the LTV ratio. This they argued illustrates the substitution effect between non-housing assets and housing assets. In summary the studies above advance two main hypotheses. First is the portfolio substitution hypothesis which assumes that mortgage debt is a substitute for non-housing wealth and second, is the credit rationing hypothesis which assumes that the both the lenders perceived variability of the borrower's income and the borrower's current income impose a constraint on the mortgage loan amount.

Courchane (2007) and Kau and peters (2005) utilizing microlevel data find empirical evidence that mortgage price differentials are determined more by market conditions, underwriting techniques and less by demographic factors. Al-Bahrani and Su (2015) perform a quantile regression analysis to determine how the creditworthiness of the borrower and loan-to-value (LTV) ratio influences mortgage pricing. They find an unbalanced distributions of beneficial price changes accrued by borrowers. As the LTV falls or when the borrower's creditworthiness rises, the magnitude of the fall in mortgage price is uneven across the price spectrum when conditioned on these characteristics. Park (2017) analyzes the impact of the loan limit increases stipulated in the 2009 Economic Stimulus Act. He finds that the introduction of higher loan limits raised the quantity of the mortgage loan originations but the expiry of the loan limit in 2013 had no noticeable effect in the mortgage loan market. Park (2019) studies the impact of the 2015 MIP reduction based on mortgage loan term decision (greater than 15 years and 15 year or less). He finds that the reduction in the MIP led to a 34% reduction in the odds of borrowers taking up an FHA loan with a term of 15 years or less. Bhutta and Rhingo (2017) utilizing regression discontinuity design analyzed the impact of the 2015 MIP reduction in on FHA mortgage originations and found an increase of about 14% in FHA loan originations. LaFayette et al. (1997) estimates the change in demand for FHA loans in 1984 compared to 1983 after the annual MIP was replaced by an up-front MIP. They find that the FHA loan demand declined by about 0.25%. In the early 2000s the US mortgage market experienced significant growth. Analyzing the mortgage market over this period, Couchrane et al. (2012) empirically illustrate that the rapid expansion of credit was the primary driver for the significant increase in mortgage originations. Chomsisengphet et al. (2006) illustrates that over the same period the increases in accessibility to credit caused a decline in the share of FHA loans in the mortgage market. This illustrates the countercyclical property of FHA loans in the mortgaged market. In addition, Courchane et al. (2014) argue that over the same period, because subprime lenders would often offer mortgages with 100% LTV ratios as compared to FHA loans which require at least 3% of the mortgage as a down payment, also lead borrowers to shift away from FHA loans and seek the alternative mortgages which at the time were predominantly subprime. Adelino et al. (2012) empirically investigate the impact of the loan limit increases between 1998 and 2005 on housing prices. They find that house that were just above the loan limit experienced a decline in price of about 1.16$ per square foot. Lo (2016) utilizing a regression discontinuity model finds that from a 0.25% reduction in the interest rate, the amount of mortgage rises 10% (intensive margin) while the probability to take a loan rises about 50% (extensive margin).

2.3 Data

This analysis utilizes mortgage loan level data from the Federal Housing finance Agency (FHFA). The Housing and Economic Recovery act of 2008 amended the Federal Housing Enterprises Financial Safety and Soundness Act of 1997 which now requires the FHFA to periodically collect data through a survey to determine the characteristics of both mortgage loan borrowers and mortgage loans. This is a nationwide survey which is undertaken annually, and it is a 5% representation of the total residential mortgage uptakes in the United States of America. The mortgage loan level data utilized in this research is a merged dataset of yearly surveys which run from 2009 - 2014. However, the primary empirical investigation will only focus on the data in the years 2009 and 2011 to analyze the impact of the Mortgage insurance premium (MIP) hike which occurred in 2010. This will therefore include data 4 - 16 months before the policy was implemented and 8 - 20 months after the policy was implemented. Because of data limitations, this study will only consider fixed rate mortgages (FRMs), first lien loans and mortgages with amortization periods of 15 years. In addition, the type of house occupancy considered will be principal residence, commonly referred to as owner occupied. Also, the property type considered in this study is a single family detached. The sample as well contained conventional mortgages and six types of federal mortgages which include FHA loans, VA loans, FMHA-Guaranteed Rural Housing loans, HECM loans and Title 1-FHA loans. However, only FHA loans and conventional loans are considered in this research.

To construct the treatment and control group several factors were considered to ensure the validity of the estimation procedure. Historically, creditors across the United States have regarded an LTV ratio of at least less than or equal to 0.8 as a sufficient portrayal of mortgage a borrower’s interest in a house and commitment to make payment up until the full settlement of the mortgage. However, numerous borrowers across the country cannot meet this threshold. Increasing the LTV ratio further increases the probability of a borrower to default. To mitigate the credit risk on such loans with LTV ratios greater than 0.8, insurance products have been made available to potential homebuyers. Two main insurance products include the private mortgage insurance (PMI) which serves conventional mortgage loan borrowers’, and the second type of mortgage is the mortgage insurance premium (MIP) offered by the Federal Housing Administration. The MIP was primarily meant to serve mortgage borrowers of lower income groups who are unable to meet the 20% down-payment and/or borrowers who have limited credit history. However, there is neither no rule nor law prohibiting higher income earners with a pristine credit history from utilizing the MIP product.

The FHA insurance product, MIP, is structured to be deliberately cheaper and more accessible to potential homebuyers with impaired credit and unable to raise the 20% mortgage down-payment as compared to the PMI. This means that the MIP is carefully calibrated taking into consideration market and economic conditions to ensure that a potential mortgage borrower who seeks an FHA insured loan will pay a total amount in interest and premiums less than if the same borrower seeks a conventional loan of the same amount. This will be discussed in detail later in the section.

As mentioned earlier, the data utilized in this research was obtained from the FHFA annual nationwide survey which is a 5% representation of the total residential mortgage loan originations in the United States. Initially the survey included both FHA loans and conventional loans with LTV ratios from close to zero to LTV ratios which were equal to one. The first step was to drop the FHA loans and conventional loans which had LTV ratios less or equal to 0.8. This was done to ensure that both FHA loan borrowers and conventional loan borrowers have met the threshold to warrant mortgage insurance.

The next step was to drop both FHA borrowers and conventional borrowers who had LTV ratios equal to one and create two new sub-sample based on LTV ratios. The first sub-sample would include: (1) FHA borrowers whose LTV ratios are greater than 0.8 but less than one and (2) Conventional borrowers whose LTV ratios are greater than 0.8 but less than or equal to 0.95. The second sub-sample would include: (1) FHA loan borrowers whose LTV ratios are greater than 0.8 but less than or equal to 0.95 and (2) Conventional loan borrowers whose LTV ratio are greater than 0.8 but less than or equal to 0.95. The first reason for performing this step is that it is only until 2014 when PMI was offered to mortgage loan borrowers who made a mortgage down-payment of less than 5%. The second reason is to analyze the empirical implication of including FHA borrowers who had an LTV ratio of greater than 0.95 of the policy effect's estimate.

There are several differences between the MIP offered by the FHA and the PMI. The first is that the MIP insurance is structured to include both an up-front premium and an annual premium.

The PMI on the other hand only includes the annual premium. The second difference is that the PMI premium cut-offs are based on a 20-year mortgage term while the MIP insurance premium is based on a 15-year mortgage term. This means that annual insurance premiums are adjusted upwards when the mortgage term exceeds 20 years in the case of the PMI and 15 years in the case of the MIP insurance. To resolve the imbalance caused by the different annual insurance premium cut-offs across the MIP and the PMI products, only mortgages with loan terms of 30 years are considered.

The third difference is the role of the borrower's credit history in determining the mortgage premium. In the case of the MIP, the insurance premium is a function of the mortgage down-payment and the length of the mortgage term. However, the borrowers credit determines the minimum mortgage down payment the mortgage borrower must meet. On the other hand, in the case of the PMI, the insurance premium is a function of the down-payment, the mortgage loan term and the Mortgage borrower's credit history. In the previous section summary statistics and balance tests to both the overall sample and sub-samples were presented which illustrated that FHA borrower had significantly lower credit scores compared to conventional mortgage loan borrowers. This has an implication which is highlighted below.

In summary four factors have been addressed which make the choice of the treatment group and control group justifiable. The first is the FHA pricing structure and strategy of the MIP, the second is the loan-to-value (LTV) ratio, the third is the mortgage loan term and the last is the credit score. The treatment group will include FHA loan borrowers with an LTV greater 0.8 but less or equal to 0.95 while the control group will include conventional loan borrowers with an LTV ratio greater 0.8 but less or equal to 0.95. Both the treatment group and the control group have mortgage loan terms of 30 years. The FHA MIP pricing structure and the credit score pricing structure of the PMI which ensure that the FHA MIP is cheaper than the PMI are seen to act as deterrents which permit two strong assertions. The first, is in the dissimilarity in the pricing structure of the MIP and the PMI. Those who qualify for conventional loans cannot find a cheaper option in the FHA loan. The second is that it would prevent potential FHA borrowers from shifting to convention mortgage loans because of the up-front premium hike. This is because the conventional loan would still not be a cheaper option.

Table (2.1) presents summary statistics of both conventional loans and FHA loans for the years 2009 and 2011. Table (2.2) and table (2.3) further categorize the respective loan types by loan-to-value ratios. Loans with loan-to-value ratios less than or equal to 0.95 are distinguished from loans with loan-to-values greater than 0.95. Table (2.2) provides the summary statistics for FHA loans while Table (2.3) provides summary statistics for conventional loans.

A quick examination of the data summary statistics provided in tables (2.1) through table (2.3) portrays the main arguments of the paper. For, instance, following table (2.1), the mean FHA loan loan-to-value ratio (LTV) decline from 0.957 in 2009 to 0.951 in 2011. This is a 0.63% decline after the 2010 policy change. This is of course requiring further examination but provides a sense of relevance for the study. Further categorization of FHA loans by LTV (Category 1: LTV<=0.95 and Category 2: LTV>0.95) is provided in table (2.2). FHA loans with an LTV of less or equal to 95% of the home value (LTV<=0.95) had a 0.45% decline in the LTV ratio between 2009 and 2011. On the other hand, FHA loans with an LTV of greater than 0.95 had a 1.12% decline in the LTV ratio over the same period.

Summary statistics for the entire sample over the two years 2009 and 2011 are provided in table (1). The mean mortgage real dollar amount for FHA loans is lower than conventional loans both across the sample and respective years. Conventional borrowers had a mean income of $75,982.99 which was about $18,000 more than FHA loan borrowers' mean annual income of $57,098.41. However, conventional loan borrowers' front ratio and back ratio were lower than those of FHA loan borrowers. The front ratio is commonly referred to as the mortgage debt-to-income ratio (i.e.) the total amount of income allocated to servicing mortgage debt. Conventional loan borrowers had a mean front ratio of 0.193 while FHA borrowers had a mean of 0.231. This means that 19.3% of conventional borrowers' income would be directed towards mortgage payments while an average of 23.1% would apply to FHA borrowers. The back ratio is the percentage of an individual's income which goes towards servicing non-mortgage debt. Conventional borrowers had a back ratio of 0.302 while FHA borrowers had a slightly lower average of 0.306.

The loan-to-value (LTV) ratio sample mean for conventional borrowers stood at about 0.831. This means that given the dollar amount of the house value, conventional borrowers would on average take out a mortgage amount worth 83.1% of the house value. FHA borrowers would on average borrow 95.5% of the house value.

The Bocredit variable which reflects the borrowers’ credit score was as well in the sample and utilized in the analysis. This variable is an indicator variable with categorizations based on the borrowers’ credit score. The categories include 620 - 660, 661 - 700, 701 - 760 and >761. Conventional borrowers had mean Bocredit of 4.423 which means that their credit score was greater than 760. On the other hand, FHA borrowers had a mean Bocredit of 3.1 which means that their mean credit score was between 701 and 760.

The rate variable is the annual mortgage interest rate paid by the borrower. Conventional borrowers had a mean interest rate of 4.8% while FHA borrowers had an average interest rate of 5.1%. Given the above characteristic of conventional borrowers, it is no surprise that their mean annual mortgage interest rate is lower than FHA borrowers. The acqtyp variable is an indicator variable which equals one if a mortgage borrower utilized cash to pay for the down payment and zero otherwise. Across both conventional borrowers and FHA borrowers we find that the over 60% of the borrowers utilized cash as the form of down payment as compared to credit enhancement.

The department of Housing and Urban Development (HUD) also considers some areas as underserved. The Geog variable is an indicator variable which is equals to one if the house is in an underserved census tract and zero if it is not located in an underserved census tract. HUD defines a census tract as underserved area if (1) the median income is no greater than 90% of the area’s income of (2) if minorities account for at least 30% of the tract’s population and the tracts median income is no greater than 120% of the area’s median income.

The sample as well categorized loans by their purpose. The loan could either be used to purchase a house, for refinancing an existing mortgage loan, second mortgage, new construction, or rehabilitation. However, this research only considers loans towards home purchases and refinancing. It can be viewed from table (2.1) that for FHA loans 71.74% of the loan originations were for purchasing purposes while in the case of conventional loans the 43.30% of the loan originations were for home purchasing.

The First-Time variable is an indicator variable which equals to one if a mortgage borrower was fist time home buyer and zero otherwise. In the case of conventional loan borrowers, first-time home buyers were about 13%. This is rather different in the case of FHA loan originations. These loans are nearly evenly distributed with first-time home buyers constituting about 45.57% of the sample and non-first-time home buyers constituting about 54.25%.

Across both FHA and conventional loan categories in the sample, the percentage of male borrowers dominated the number of loan originations. In the case of conventional loans, 76% of the loan originations were male and in the case of FHA loan originations, 65% were made by male. The coborrower variable is an indicator variable which equals one if the borrower had a coborrower and zero otherwise. Both conventional loan and FHA loan borrowers had smaller percentage of their applicants having coborrowers. FHA had about 43% of the applicants having coborrowers while conventional loans had about 39% of their borrowers apply with a coborrower.

Prior to estimation, balance tests and parallel trend analysis across FHA loan borrowers (treatment group) and conventional borrowers (control group) are performed. The balance tests results are reported in table (2.4) through to table (2.13). Table (2.4) reports results for the entire sample while table (2.5) report results for the entire sample but restricts LTV ratio to be less than or equal to 0.95. First, it is evident from both tables that despite of the statistically significant difference in means across both loan categories, they are still within range of comparability. Secondly, after the LTV is restricted majority of the covariate mean differences shrink significantly.

Table (2.6) and table (2.7) provide balance test results across all incomes but restricts the sample to mortgages for purchase only loan originations. From table (2.6) it can be viewed that there is a 13% mean LTV ratio gap, $17,000 mean income difference and an eight-year age difference across FHA borrowers and conventional borrowers. When the LTV ratio is restricted as in table (2.7), the LTV ratio gap fell to 5.9%, the age difference fell by about two years, but the income difference increased to $20,000.

The sample was then restricted to only include first-time home buyers. Balance tests results are provided in table (2.8) and table (2.9). From table (2.8) it is seen that the mean LTV ratio difference is about 12.7% in favor of FHA borrowers, the income difference is now $8,000 in favor of conventional borrowers and the age difference across the two borrower categories a has declined to about four years with conventional borrowers been a little older. Table (2.9) restricts the LTV ratio to less than or equal to 0.95. The mean LTV ratio difference declines to 4.9% in favor of FHA borrowers, the income mean difference is $10,000 in favor of conventional borrowers and lastly, the conventional borrower is on average three years older than FHA borrowers.

Earlier, the balance tests results reported in table (2.4) and table (2.5) which included borrowers of all incomes was discussed. The mean income difference across FHA borrowers and conventional borrowers ranged between $17,000 and $20,000. This even though comparable is still rather a large difference. To correct for this, the data was segmented into two income categories. The first income category included borrowers whose incomes were between $37,067 - $73,124 and this category's balance tests are reported in table (2.10) and table (2.11). The second income category included borrowers whose incomes were between $74,003 - $149,987 and the balance tests are reported in table (2.12) and table (2.13). From table (2.10) it is evident that the mean income difference has declined to $2,000. There is a seven-year age gap in favor of conventional borrowers and a 12.7% LTV ratio gap in favor of FHA borrowers. This income category is then restricted to include loan originations with LTV ratios less or equal to 0.95, the results are reported in table (2.11). The mean LTV ratio declines to 5.9%, the mean income difference does not change but the mean age difference declines by about four year.

Table (2.12) and table (2.13) reports balance test results to the second income category. At a quick glance it is seen that both average incomes and ages across both loan groups are higher than those in table (2.10) and table (2.11), however, the mean of the back-ratio and front-ratio are significantly lower. From table (2.12) we see the mean LTV difference is 12.8% in favor of FHA loans, the mean difference income is now $7,000 in favor of conventional loan borrowers, higher credit score in favor of conventional borrowers and mean age difference is six year, once again in favor of conventional loan borrowers. When the LTV ratio is restricted to be less or equal to 0.95, the mean LTV ratio gap declines to 6.9%, the mean income difference declines to $4,000 and average mean age difference declines to about 3 years.

2.4 Methodology

On 2010 the Federal Housing Administration (FHA) increased the upfront mortgage premium for all FHA loans from 1.75% to 2.25%. This policy change occurred in April of 2010, but because this research is only limited to yearly data, the years 2009 and 2011 will be considered. This will therefore include data 4 - 16 months before the policy was implemented and 8 - 20 months after the policy was implemented. All the loan origination data prior to 2010 will be in the pre-policy period (pre-treatment period) while all the data after 2010 will be in the post-policy period (post-treatment period).

To achieve the objective of this paper which is to empirically investigate the impact of the 2010 up-front mortgage premium on FHA borrowers' LTV ratio, the Difference-in-Differences (DiD) research design is utilized. The DiD estimates can be obtained using a regression model whose structure is provided below.

$$Ln(LoanToValue_{it}) = \alpha_0 + \beta_0 2010Policy_t + \beta_1 Loantype_{it} + \beta_2 LoanType_{it} * 2010Policy_t + \beta_3 Borrower_{it} + \beta_4 Environment_{it} + \varepsilon_{it} \tag{1}$$

The primary outcome variable ($LoanTovalue_{it}$) is the loan-to-value ratio, ($2010Policy_t$) is an indicator variable for when the policy change in the up-front mortgage (UFM) premium occurred, ($LoanType_{it}$) is an indicator variable for the treatment group, ($Borrower_{it}$) is a set of borrower characteristics which include real income, credit score, front-ratio, back-ratio, age and gender, ($Environment_{it}$) includes other variables such as the rate, geog, and acquisition type, lastly, (ε_{it}) is the error term. A regression model of similar structure is also utilized to analyze different sub-samples to account for a possible heterogenous response to the policy change. These sub-samples include first-time home buyers, only purchase only loans and a sub-sample based on income category. Equation (2) - equation (4) are the alternative specifications to the respective sub-samples. Once again, the coefficient of interest across all models is (β_2) and is the policy effect estimate which captures the percentage change in the LTV ratio of FHA loans relative to conventional loans.

$$Ln(LoanToValue_{it}) = \alpha_0 + \beta_0 2010Policy_t + \beta_1 LoanTypeFirst_{it} + \beta_2 2010Policy_t * LoantypeFirst_{it} + \beta_3 Borrower_{it} + \beta_4 Environment_{it} + \varepsilon_{it} \tag{2}$$

$$Ln(LoanToValue_{it}) = \alpha_0 + \beta_0 2010Policy_t + \beta_1 LoanTypePurchase_{it} + \beta_2 2010Policy_t * LoantypePurchase_{it} + \beta_3 Borrower_{it} + \beta_4 Enviornment_{it} + \varepsilon_{it} \tag{3}$$

$$Ln(LoanToValue_{it}) = \alpha_0 + \beta_0 2010Policy_t + \beta_1 LoanTypeIncomeCat_{it} + \beta_2 2010Policy_t * LoanTypeIncomeCat_{it} + \beta_3 Borrower_{it} + \beta_4 Environment_{it} + \varepsilon_{it} \quad (4)$$

One key assumption of the DiD estimation design is the assumption of parallel trends in both the treatment group and control group. In this study's context, the parallel trend assumption would hold if the pre-policy period FHA borrowers' (treatment group) and conventional borrowers' (control group) LTV ratios illustrated similar dynamics over time. Customarily, to assess the validity of this assumption the number of pre-treatment periods (pre-policy) should be equal or be greater than two. A common test for parallel trends is a graphical analysis of the control and treatment groups over the pre-treatment period and post-treatment period. In this case, it would be the graphical analysis of the annual averages of the LTV ratios for both the FHA loan borrowers and conventional loan borrowers before and after the 2010 UFM increase.

The data used in this analysis is limited to a single period before the policy change. However, a graphical analysis of annual mean LTV ratios over the years 2009 - 2014 is included in the research. The graphs for the parallel trends are presented in figure (2.1) and figure (2.2). Figure (2.1) presents parallel trends for all incomes in 3 main categories: (1) The entire sample, (2) First-time home buyers and (3) Purchase only mortgage loans. In spite of the data limitation in the pre-treatment period, three elements required for the parallel trends assumptions to hold are demonstrated in the graphical analysis: (1) Similar pre-policy period trend of LTV ratios across both FHA borrower and conventional borrower groups, (2) A dip in FHA loan borrowers' LTV ratio post-policy period and (3) An unaltered similar trend for the conventional borrowers' LTV ratio over the pre-policy and post-policy period. Figure (2.2) presents a graphical analysis of the parallel trends by income category. Like figure (2.1) the three elements which support the validity of DiD estimation technique are observable. Moreover, when the LTV ratio is restricted to be less or equal to 0.95, the dip in FHA borrowers LTV ratio post policy is significantly larger as compared to when the restriction is not imposed.

In the previous section, the summary statistics were presented by first analyzing the overall sample. Other sub-samples based on borrowers' income, purchase only mortgage and lastly, first-time home buyers. The purpose of this sub-sampling is to serve two main roles. The first, is to obtain policy effects estimates based on different categories. The second, is to ensure that mortgage borrowers of similar characteristics as possible across the treatment group and the control group are in the estimated sample to ensure more robust estimates. However, it would be false to assume that is categorizing of the data would yield optimal results.

As a robustness check, a hybrid Matching-DiD model is utilized. The DiD design is an econometric methodology utilized to estimate the average treatment effect in the presence of the hidden bias. Moreover, control covariates are included in the DiD design because of the confounding potential of observable heterogeneity. On the other hand, the Matching methodology is an econometric technique utilized to estimate the average treatment effect in the presence of the overt bias. Following Cerulli (2015), the matching technique attempts to resolve weak balancing by utilizing a weighting function (kernel) based on unit characteristics which puts more weight on units in the untreated group that are most similar to the treated group and lesser weight to those that are least similar to the treatment group.

Therefore, reconciling the DiD and the Matching techniques into a hybrid model is more robust to the regular DiD because it now estimates the average treatment effect by jointly resolving the hidden bias and utilizing a weighting function constructed from the control covariates to restrict the conventional mortgage loan borrowers (untreated group) to a sub-sample which will have characteristics that are almost homogenous to the FHA mortgage borrowers (treated group). This ensures a more reliable estimate of the average treatment effect because the units across treatment group and untreated group are better balanced based on their respective characteristics.

2.5 Empirical Results

In this section the empirical results of the 2010 UFM increase on FHA borrowers are discussed. To consider heterogeneity in response to the policy change the sample was categorized based on income, loan purpose and whether the borrower was a first-time home buyer or not.

Table (2.14) reports the DiD estimation results on a sample of all incomes. In this case, we assume a homogeneous response to the policy change across borrowers of different income, different loan purposes and ignoring whether the mortgage borrower was a first-time buyer or not. The reported results are from four regression models. The first two models include the policy effect variables and covariates which represent the borrower characteristics such as the borrowers age, front-ratio, back-ratio, credit score, gender, and income. The last two models add on non-borrower characteristics such as geog, acqtyp and coborrower. The policy effect estimate ($FHA_{it} * UFM_t$) in the table are statistically significant and illustrate that the 2010 increase in UFM lead to an average decline in LTV ratios of about 1.4%. Table (2.15) limits the LTV ratio to less than or equal to 0.95. The reason for this is presented in the summary statistics table (2.3). There were no conventional borrowers with LTVs greater than 0.95. However, despite restricting the LTV ratio, the policy effect estimate does not change significantly. The reported policy effect estimate is 1.6%. Overlap plots to the regression models in table (2.14) and table (2.15) are reported in figure (2.4). The blue plus signs represent FHA loans while the red plus signs represent conventional loans. It is evident from the plots that restricting LTV ratios to less or equal than 0.95 provides a more evenly balanced representation of the data across the treatment and control groups. Table (2.16) reports results to the DiD estimates to a sub-sample which includes first-time home buyers. In this sample the pre-policy average LTV ratio for FHA borrowers and conventional borrowers was 0.97 and 0.85 respectively while their respective average incomes were \$50,000 and \$58,000, respectively. The estimated policy effects estimate is a decline of 2.6% in LTV ratios between 2009 - 2011 and is statistically significant at the 95% confidence interval. When the LTV ratio is restricted to be less than or equal to 0.95 it is seen in table (2.17) that the effect of the policy change lowered the LTV ratio of first-time home buyers by on average 1.7%. The overlap plots to the regression models in both table (2.16) and table (2.17) are presented in figure (2.4). There is a clear reduction in the number of observations in the estimated sample, however, limiting the LTV ratio provides more balance representation across the FHA loan borrower group and the conventional loan borrower group.

A DiD analysis was also performed on a sub-sample which included purchase only mortgage loans. The results are reported in table (2.18) and table (2.19). Table (2.18) illustrates a 2.3% decline in FHA borrowers' LTV ratios between 2009 - 2011. However, table (2.19) reports the results to the same sub-sample when the LTV ratio is restricted to be less or equal to 0.95. In this sub-sample the pre-policy mean LTV ratios for FHA borrowers and conventional borrowers was 0.90 and 0.85 respectively while there mean average incomes were $48,000 and $58,000, respectively. The estimated policy effect declined to 1.5%. The results reported in this sub-sample are slightly less than those reported for first-time home buyers. It must be mentioned however that due to data limitations refinance only mortgages were not analyzed in this study.

Table (2.14) to table (2.19) only considered the impact of the 2010 policy change across different mortgage loan purposes and first-time home buyers but assumes homogenous response across all incomes. Two sub-samples are based on two different real income categories. The first sub-sample included borrowers with incomes ranging between $37,067 - $73,124 and the second subsample included borrowers with incomes ranging between $74,003 - $149,978 categories were created as well analyze. The Table (2.20) and table (2.21) report the estimates for the first sub-sample (lower income category). The DiD estimate reported in table (2.20) indicates that the policy reduced the FHA borrowers LTV ratio by about 1.4%. Table (2.21) reports the policy effects estimates when the same sub-sample is restricted to include borrowers who had taken out a mortgage loan with an LTV ratio of less or equal than 0.95. In this sub-sample the average LTV ratio for FHA borrowers and Conventional borrowers was 0.89 and 0.83 respectively while the mean real income was $53,000 and $55,000, respectively. The estimated policy effect is as well 1.4%. There was no change caused by restricting the data sample by LTV ratio.

Table (2.22) reports the DiD estimate results for the second sub-sample which included the higher income category. In this case the pre-policy mean real income for conventional loans and FHA loans was $1,000,000 and $93,000.00 respectively while the mean LTV ratio was 0.83 and 0.95, respectively. The estimated policy effect on FHA LTV ratio reported was an average decline of 0.8%. However, when the LTV ratios are restricted to less than equal to 0.95 the effect of the policy caused a larger decline on FHA LTV ratios which range between 1.4% - 1.5%. This is an unexpected result. It is assumed that lower income earners would be more sensitive to the increase in the up-front mortgage premium, however, this is not the case. In this case it is found that policy effect across income categories was almost homogenous especially when the LTV ratio is restricted to be less or equal to 0.95.

I now discuss the estimated coefficients to the covariates in the DiD models to the respective sub-samples. I will attempt to use the results obtained to explain if there exists any evidence of the credit constraint hypothesis or the portfolio substitution hypothesis. It must be stated that the DiD design utilized was not structured nor specified to be a demand model. However, it can still shed light on the potential heterogeneity of the elements which influence the two hypotheses and ultimately govern the borrowers LTV ratio decision.

According to the portfolio substitution hypothesis, non-housing wealth should produce a negative effect on the LTV ratio. The data utilized in this study did not contain any variables which directly represent the borrowers' wealth. I instead utilize the back-end ratio as a proxy for wealth. The back-end ratio is the borrowers' non-mortgage debt to income ratio. Across all sub-samples, the coefficient to the back-end ratio is positive but magnitudes differ significantly across the sub-samples. For instance, in the case of first-time homebuyers, results reported in table (2.16) and table (2.17), the back-end ratio coefficient ranges between 0.019% - 0.03%, while for the lower income group, results reported in table (2.20) and table (2.21), it ranges between 0.004% - 0.005% and for the higher income group, results reported in table (2.21) and table (2.22), it ranges between 0.011% - 0.012%. Following Cho et al (1995), it is fair to assume that non-mortgage debt is inversely related to non-housing net wealth. This is in turn permits us to argue that in the case of first-time home buyers, lower income group and higher income group, the portfolio substitution hypothesis holds.

The credit constraint hypothesis states that a positive relationship between LTV ratios and the borrower's income should exist. In the case of first-time homebuyers, results reported in table (2.16) and table (2.17), the income coefficient is positive and ranges between 0.008% - 0.012%. This indicates the existence of the mortgage borrower's constraint. In the case of the lower income group, results reported in table (2.20) and table (2.21), the income coefficient is positive but statistically insignificant. However, in the case of the higher income group, results reported in table (2.22) and table (2.23), a negative income coefficient which ranges -0.009% - -0.011% is reported. This is contrary to the hypothesis and is an indication that higher income earners choice of higher LTV ratios is not influenced by any element within the credit constraint hypothesis.

2.6 Robustness Check

As mentioned in the previous sections some of the limitations in the structure of the data were highlighted. For instance, it was illustrated that the data did not have extended time points in the pre-policy period to strongly reassure the validity of the DiD analysis. In addition, it would be imprudent to assume that categorizing the data for instance by income group would yield optimal empirical estimates to best explain the policy effect on FHA loan-to-value ratios. This section will attempt to provide a robustness analysis of the results reported in the previous section which were obtained using the DiD research design by utilizing a hybrid design which combines the matching and difference and difference design.

The results are provided in table (2.24) through to table (2.33). However, the discussion will be limited to the models in which the LTV was restricted to be less than or equal to 0.95. To recap the structure of the reported results in the tables. The reported results are obtained from estimating four regression models. The first two models include the policy effect variables and covariates which represent the borrower characteristics such as the borrowers age, front-ratio, back-ratio, credit score, gender, and income. The last two models add on non-borrower characteristics such as geog, acqtyp and coborrower.

Table (2.25) reports the results to the whole sample restricted to include only borrowers with an LTV of less or equal to 0.95. Compared to the initial policy effect estimate of 1.6% the estimated policy effect ranges from 1.9% - 2.5%. This is an increase of between 18.75% and 56.25%. In the case of first-time home buyers, model (3) estimates increased by over 100% from 1.7% to 3.7% while model (4) estimate increased by 7% from 1.7% to 2.4%. There is a similar pattern observed in the case of purchase only mortgage loans. Both model (3) and model (4) policy effects increased by about 87% from 1.5% to 2.7% and 1.5% to 2.8% respectively.

The results in the case of the sub-samples based on income categories are slightly different. In the case of the first income category ($37,066 - $73,124), model (3) policy effect estimates increase from 1.3% to 2.9% while model (4) policy effect estimate increased from 1.4% to 2.1%. In the case of the second income category ($74,003 - $149,978), model (3) policy effect estimate increased from 1.4% to 1.5%, the smallest change exhibited. Model (4) policy effect in this income category is statistically insignificant. However, the results obtained utilizing this hybrid model mortgage borrowers of a lower income seem to have a higher sensitivity to the increase in the

UFM which means that the increase in the up-front mortgage premium lowered the LTV ratios by a larger margin compared to higher income borrowers.

2.7 Conclusion

In this study the impacts of the 2010 FHA increase of the up-front mortgage premium from 1.75% to 2.25% was examined. Overall, the policy caused a decline in the LTV ratio across FHA borrowers. The first stage of analyzing the effect of the policy included the estimation of the DiD model on the entire sample not taking into consideration heterogeneity of either mortgage type or borrower characteristics. The estimated results indicate the policy led to a 1.5% decline in the LTV ratio. To account for heterogeneity, three sub-samples were constructed. The first sub-sample included purchase only mortgages, the second sub-sample included first-time homebuyers and the last sub-sample included mortgage borrowers categorized by income level. First considering first-time homebuyers. This group of mortgage borrowers experienced the largest reduction in the LTV ratio which ranged between 1.7% and 2.6%. The second sub-sample includes only mortgages which were used for purchase only. The FHA increase of the up-front mortgage premium led to a drop in the LTV ratio which ranged between 1.5% and 2.3%. The third sub-sample constructed based on the borrowers' income level. Two income categories were considered: The lower income category had income ranging between $37,066 - $73,124 while the higher income category had income ranging between $74,003 - $149,978. The lower income category reported a 1.4% decline in their LTV ratios due to the change in policy while the higher income category experienced a decline in their LTV ratio which ranged between 0.8% and 1.5%. A robustness check was as well conducted utilizing a hybrid matching-DiD model to overcome some of the data limitations experienced. The results reported indicate stronger policy effect in the overall sample and across every sub-sample. First-time homebuyers still experienced the largest decline in LTV ratios. The drop in their LTV ratios ranged between 2.4% and 3.7%. Borrowers who took out mortgages for purchase only purposes reported a decline in their LTV ratios of between 2.7% and 2.8%. Lastly, in the case of the third sub-sample which was based on income, the borrowers in the lower income category reported a decline in their LTV ratios of between 2.1% - 2.9% while borrowers in the higher income category, as expected, reported a smaller decline in LTV ratios of 1.5%.

In addition, the other estimated coefficients in the model are as well utilized to explain the existence or lack thereof the credit constraint hypothesis and the portfolio substitution hypothesis.

In the case of first-time homebuyers, the positive income coefficient which ranged between 0.008% - 0.012% means that their debt levels are constrained by income which is an indication that they face a credit constraint in the choice of their LTV ratio. In the case of the higher income category, the income coefficient reported ranged of between -0.009% - -0.011% is an indication that this group of mortgage borrowers do not face any credit constraint in their choice of LTV ratio. Turning the attention to the portfolio substitution hypothesis and focusing on the first-time homebuyers and the sub-sample constructed based on income, all the back-end ratio coefficients were positive and statistically significant. In the case of the lower income group, the back-end ratio estimate reported ranged between 0.004% - 0.005% the higher income group reported 0.011% - 0.012% and the first-time homebuyers' estimate ranged between 0.019% - 0.030%. This is an indication that across the different sub-samples, the interaction between housing assets and non-housing assets seems to be that of substitutes, with first-time homebuyers portraying the strongest substitutability.

As mentioned earlier, the objective of this study was to first analyze the impact of the 2010 MIP increase on mortgage borrowers' LTV ratios taking into consideration heterogeneity of both mortgage borrowers and mortgage loan products. The second objective was to elaborate on the credit constraint hypothesis and the portfolio substitution hypothesis across the different mortgage borrower sub-samples. Having accomplished the two primary objectives of this research it would be imprudent not to discuss potential unintended consequences and/or possible indirect effects of the policy. First, because of the policy, the homebuyer's liquidity may decline because they would use a larger share of their current income to pay the down-payment, which may in-turn affect the housing and non-housing consumption balance. This means that the borrower may be forced to direct liquid assets towards servicing the new upfront mortgage premium. Second, the policy may lead to rebalancing of the homebuyers' portfolio. Assuming the return on non-housing assets ceteris peribus, this policy may lead homebuyers to shift their income to investment in non-housing assets and earn higher net return relative to the housing asset. Third, related to the first unintended consequence, the increase in the MIP may have homebuyers liquidate non-housing assets to overcome the liquidity constraint, and lastly, if homebuyers face a high-income constraint and lack assets to liquidate, they may opt for a cheaper home. This is an indication that the policy may not only affect household consumption but influence investment profiles and this shock could easily transmit into the macroeconomy.

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Table 2.1 FHA Loans and Conventional Loans

	CVL Loans			FHA loans		
Variable	Sample	2009	2011	Sample	2009	2011
Mortgage	155,000.00	160,000.00	149,000.00	135,000.00	138,000.00	131,000.00
	(71,006.40)	(71,181.09)	(70,368.62)	(62,781.93)	(61,407.71)	(64,650.03)
Income	75,928.99	77,441.86	74254.65	57,098.41	57,030.56	57,201.96
	(30,445.96)	(30,075.58)	(30,766.22)	(25,892.55)	(25,755.921)	(26,108.09)
Front-Ratio	0.193	0.198	0.187	0.231	0.234	0.226
	(0.068)	(0.069)	(0.067)	(0.089)	(0.090)	(0.086)
Back-Ratio	0.302	0.306	0.296	0.376	0.376	0.377
	(0.085)	(0.089)	(0.081)	(0.110)	(0.116)	(0.101)
LTV ratio	0.831	0.827	0.835	0.955	0.957	0.951
	(0.052)	(0.048)	(0.056)	(0.044)	(0.046)	(0.042)
Credit Score	4.423	4.379	4.472	3.100	3.038	3.193
	(0.747)	(0.771)	(0.717)	(1.235)	(1.281)	(1.155)
Rate	0.048	0.051	0.045	0.051	0.054	0.045
	(0.004)	(0.003)	(0.003)	(0.006)	(0.004)	(0.003)
Acqtype						
Cash	66.49	58.04	75.84	60.66	39.35	93.18
Enhancement	33.51	41.96	24.16	39.34	60.65	6.82
Geog						
Yes	10.44	8.09	13.04	22.01	30.59	8.91
No	89.56	91.91	86.96	77.99	69.41	91.09
Purpose						
Purchase	43.30	32.44	55.32	71.74	66.71	79.42
Refinance	56.47	67.45	44.31	28.26	33.29	20.58
First-Time						
Yes	13.07	10.80	15.58	45.75	47.08	43.72
No	86.93	89.20	84.42	54.25	52.92	56.28
Bogender						
Male	75.67	76.65	74.58	65.28	64.10	67.07
Female	22.36	21.60	23.20	32.67	33.02	32.12
Coborrower						
Yes	38.78	37.66	40.01	42.71	42.04	43.72
No	61.22	62.34	59.99	57.29	57.96	56.28
Observations	14,844	7,798	7,046	3,744	2,262	1,482

Notes: LTV is the ratio of the loan amount to value of house, Real Income is the borrowers annual income in real 2010 dollars, Rate is the fixed interest mortgage rate to a 30 year loan term, Back-end is the borrowers non-mortgage debt to income ratio, front-end is the borrowers total debt to income ratio, BoCredit is an indicator for the borrowers credit rating, BoGender is an indicator for the borrower's gender, BoAge is the borrowers age, Geog is indicator for whether the house is in a census tract classified as underserved, Acqtyp is an indicator for the type of acquisition (cash or credit enhancement) and Coborrower is an indicator for whether the borrower had a coborrower.

Table 2.2 FHA Loans Characteristics 2009 and 2011 Categorized by LTV Ratio

	2009		2011	
Variable	LTV<=0.95	LTV>0.95	LTV<=0.95	LTV>0.95
Mortgage	146,000.00	134,000.00	135,000.00	130,000.00
	(65,795.33)	(59,453.64)	(70,895.89)	(62693.27)
Income	60,905.93	55,644.16	56,758.90	57,330.87
	(28,159.12)	(24,701.50)	(26,729.30)	(25,934.98)
Front-Ratio	0.235	0.234	0.231	0.225
	(0.093)	(0.089)	(0.091)	(0.084)
Back-Ratio	0.372	0.377	0.376	0.377
	(0.118)	(0.115)	(0.117)	(0.095)
LTV ratio	0.891	0.981	0.887	0.970
	(0.042)	(0.011)	(0.045)	(0.008)
Credit Score	2.906	3.086	3.147	3.206
	(1.234)	(1.295)	(1.131)	(1.163)
Rate	0.054	0.054	0.045	0.045
	(0.004)	(0.004)	(0.003)	0.003
Acqtype				
Cash	35.57	40.70	95.51	92.51
Enhancement	64.43	59.30	4.49	7.49
Geog				
Yes	28.19	31.45	6.89	9.49
No	71.81	68.55	93.11	90.51
Purpose				
Purchase	23.99	81.99	44.01	89.72
Refinance	76.01	18.01	55.99	10.28
First-Time				
Yes	17.45	57.68	25.15	49.13
No	82.55	42.32	74.85	50.87
Bogender				
Male	64.93	63.81	66.77	67.16
Female	32.05	33.37	32.04	32.14
Coborrower				
Yes	44.63	41.12	50.00	41.90
No	55.37	58.88	50.00	58.10
Observations	596	1,666	334	1,148

Notes: LTV is the ratio of the loan amount to value of house, Real Income is the borrowers annual income in real 2010 dollars, Rate is the fixed interest mortgage rate to a 30 year loan term, Back-end is the borrowers non-mortgage debt to income ratio, front-end is the borrowers total debt to income ratio, BoCredit is an indicator for the borrowers credit rating, BoGender is an indicator for the borrower's gender, BoAge is the borrowers age, Geog is indicator for whether the house is in a census tract classified as underserved, Acqtyp is an indicator for the type of acquisition (cash or credit enhancement) and Coborrower is an indicator for whether the borrower had a coborrower.

Table 2.3 Conventional Loans Characteristics 2009 and 2011 Categorized by LTV Ratio

	2009		2011	
Variable	LTV<=0.95	LTV>0.95	LTV<=0.95	LTV>0.95
Mortgage	160,000.00	-	149,000.00	-
	(71,181.09)	-	(70,371.05)	-
Income	77,441.86	-	74,260.92	-
	(30,075.58)	-	(30,763.90)	-
Front-Ratio	0.198	-	0.187	-
	(0.069)	-	(0.067)	-
Back-Ratio	0.306	-	0.296	-
	(0.089)	-	(0.081)	-
LTV ratio	0.827	-	0.835	-
	(0.048)	-	(0.055)	-
Credit Score	4.379	-	4.472	-
	(0.771)	-	(0.717)	-
Rate	0.051	-	0.045	-
	(0.003)	-	(0.003)	-
Acqtype	58.04			
Cash	41.96	-	75.84	-
Enhancement		-	24,16	-
Geog	8.09			
Yes	8.09	-	13.04	-
No	91.91	-	24.16	-
Purpose				
Purchase	32.44	-	55.32	-
Refinance	67.45	-	44.32	-
First-Time				
Yes	10.80	-	15.57	-
No	89.20	-	84.43	-
Bogender				
Male	76.65	-	74.58	-
Female	21.60	-	23.21	-
Coborrower				
Yes	62.34	-	60.00	-
No	37.66	-	40.00	-
Observations	7,798	-	7,045	-

Notes: LTV is the ratio of the loan amount to value of house, Real Income is the borrower's annual income in real 2010 dollars, Rate is the fixed interest mortgage rate to a 30 year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrowers total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoGender is an indicator for the borrower's gender, BoAge is the borrowers age, Geog is indicator for whether the house is in a census tract classified as underserved, Acqtyp is an indicator for the type of acquisition (cash or credit enhancement) and Coborrower is an indicator for whether the borrower had a coborrower.

Table 2.4 Balance Test All Incomes Across All Loan Types

Variable(s)	Mean Control	Mean Treated	Difference	P-Value
Loan-to-Value	0.827	0.957	0.130	0.000***
Real Income	77,000.00	57,000.00	20,000.00	0.000***
Rate	0.051	0.054	0.003	0.000***
Back	0.306	0.376	0.069	0.000***
Front	0.198	0.234	0.036	0.000***
BoCredit	4.379	3.038	-1.341	0.000***
BoAge	45.372	37.841	-7.531	0.000***

Notes: LTV is the ratio of the loan amount to value of house, Real Income is the borrower's annual income in real 2010 dollars, Rate is the fixed interest mortgage rate to a 30-year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoAge is the borrower's age.

Table 2.5 Balance Test All Incomes Across All Loan Types (LTV<=0.95)

Variable(s)	Mean Control	Mean Treated	Difference	P-Value
LTV	0.827	0.891	0.063	0.000***
Real Income	77,000.00	61,000.00	17,000.00	0.000***
Rate	0.051	0.054	0.003	0.000***
Back-End	0.306	0.372	0.066	0.000***
Front-End	0.198	0.235	0.036	0.000***
BoCredit	4.379	2.906	1.473	0.000***
BoAge	45.372	42.762	2.611	0.000***

Notes: LTV is the ratio of the loan amount to value of house, Real Income is the borrower's annual income in real 2010 dollars, Rate is the fixed interest mortgage rate to a 30-year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoAge is the borrower's age.

Table 2.6 Balance Test All Incomes Only Purchase Only Mortgage

Variable(s)	Mean Control	Mean Treated	Difference	P-Value
LTV	0.839	0.974	0.135	0.000***
Real Income	70,000.00	53,000.00	-17,000.00	0.000***
Rate	0.052	0.055	0.003	0.000***
Back-End	0.306	0.375	0.069	0.000***
Front-End	0.201	0.233	0.032	0.000***
BoCredit	4.374	3.050	-1.324	0.000***
BoAge	43.909	35.110	-8.799	0.000***

Notes: LTV is the ratio of the loan amount to value of house, Real Income is the borrower's annual income in real 2010 dollars, Rate is the fixed interest mortgage rate to a 30-year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoAge is the borrower's age.

Table 2.7 Balance Test All Incomes Only Purchase Only Mortgage (LTV<=0.95)

Variable(s)	Mean Control	Mean Treated	Difference	P-Value
LTV	0.839	0.898	0.059	0.000***
Real Income	70,000.000	50,000.000	20,000.000	0.000***
Rate	0.052	0.055	| 0.003	0.000***
Back-End	0.306	0.364	0.057	0.000***
Front-End	0.201	0.236	0.034	0.000***
BoCredit	4.374	2.895	-1.479	0.000***
BoAge	43.909	37.021	-6.888	0.000***

Notes: LTV is the ratio of the loan amount to value of house, Real Income is the borrower's annual income in real 2010 dollars, Rate is the fixed interest mortgage rate to a 30-year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoAge is the borrower's age.

Table 2.8 Balance Test All Incomes First Time Home Buyers

Variable(s)	Mean Control	Mean Treated	Difference	P-Value
LTV	0.847	0.973	0.127	0.000***
Real Income	58,000.00	50,000.00	8,000.00	0.000***
Rate	0.052	0.055	0.002	0.000***
Back-End	0.297	0.377	0.080	0.000***
Front-End	0.210	0.246	0.036	0.000***
BoCredit	4.311	3.000	-1.311	0.000***
BoAge	37.222	33.271	-3.951	0.000***

Notes: LTV is the ratio of the loan amount to value of house, Real Income is the borrower's annual income in real 2010 dollars, Rate is the fixed interest mortgage rate to a 30-year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoAge is the borrower's age.

Table 2.9 Balance Test All Incomes First Time Home Buyers (LTV<=0.95)

Variable(s)	Mean Control	Mean Treated	Difference	P-Value
LTV	0.847	0.896	0.049	0.000***
Real Income	58,000.000	48,000.000	10,000.000	0.000***
Rate	0.052	0.054	0.002	0.000***
Back-End	0.297	0.365	0.069	0.000***
Front-End	0.210	0.249	0.039	0.000***
BoCredit	4.311	2.923	-1.388	0.000***
BoAge	37.222	33.990	-3.232	0.144

Notes: LTV is the ratio of the loan amount to value of house, Real Income is the borrower's annual income in real 2010 dollars, Rate is the fixed interest mortgage rate to a 30-year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoAge is the borrower's age.

Table 2.10 Balance Test Income Category One Across All Loan Types

Variable(s)	Mean Control	Mean Treated	Difference	P-Value
Loan-to-Value	0.830	0.957	0.127	0.000***
Real Income	55,000.000	53,000.000	2,000.000	0.000***
Rate	0.051	0.054	0.003	0.000***
Back	0.319	0.377	0.058	0.000***
Front	0.214	0.231	0.018	0.000***
BoGender	1.306	1.368	0.063	0.000***
BoAge	44.908	37.872	-7.036	0.000***

Notes: LTV is the ratio of the loan amount to value of house, Real Income is the borrower's annual income in real 2010 dollars, Rate is the fixed interest mortgage rate to a 30-year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoAge is the borrower's age.

Table 2.11 Balance Test Income Category One Across All Loan Types (LTV<=0.95)

Variable(s)	Mean Control	Mean Treated	Difference	P-Value
Loan-to-Value	0.830	0.889	0.059	0.000***
Real Income	55,000.000	53,000.000	2,000.000	0.000***
Rate	0.051	0.054	0.002	0.000***
Back	0.319	0.376	0.057	0.000***
Front	0.214	0.236	0.022	0.000***
BoCredit	4.342	2.812	-1.531	0.000***
BoAge	44.908	42.507	-2.401	0.066*

Notes: LTV is the ratio of the loan amount to value of house, Real Income is the borrower's annual income in real 2010 dollars, Rate is the fixed interest mortgage rate to a 30-year loan term, Back-end is the borrowers non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoAge is the borrower's age.

Table 2.12 Balance Test Income Category Two Across All Loan Types

Variable(s)	Mean Control	Mean Treated	Difference	P-Value
Loan-to-Value	0.825	0.953	0.128	0.000***
Real Income	1,000,000.000	93,000.000	7,000.000	0.000***
Rate	0.051	0.053	0.003	0.000***
Back	0.290	0.350	0.060	0.000***
Front	0.177	0.187	0.010	0.000***
BoCredit	4.427	3.310	-1.118	0.000***
BoGender	1.177	1.319	0.141	0.000***
BoAge	45.970	39.306	-6.663	0.000***

Notes: LTV is the ratio of the loan amount to value of house, Real Income is the borrower's annual income in real 2010 dollars, Rate is the fixed interest mortgage rate to a 30-year loan term, Back-end is the borrowers non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoAge is the borrower's age.

Table 2.13 Balance Test Income Category Two Across All Loan Types (LTV<=0.95)

Variable(s)	Mean Control	Mean Treated	Difference	P-Value
Loan-to-Value	0.825	0.895	0.069	0.000***
Real Income	1,000,000.000	96,000.000	4,000.000	0.013**
Rate	0.051	0.053	0.003	0.000***
Back	0.290	0.344	0.054	0.000***
Front	0.177	0.191	0.014	0.002***
BoCredit	4.427	3.197	-1.231	0.000***
BoAge	45.970	43.140	-2.829	0.059*

Notes: LTV is the ratio of the loan amount to value of house, Real Income is the borrower's annual income in real 2010 dollars, Rate is the fixed interest mortgage rate to a 30-year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoAge is the borrowers age.

Figure 2.1 Parallel Trends All Incomes Across Loan Type and Home Buyer Type

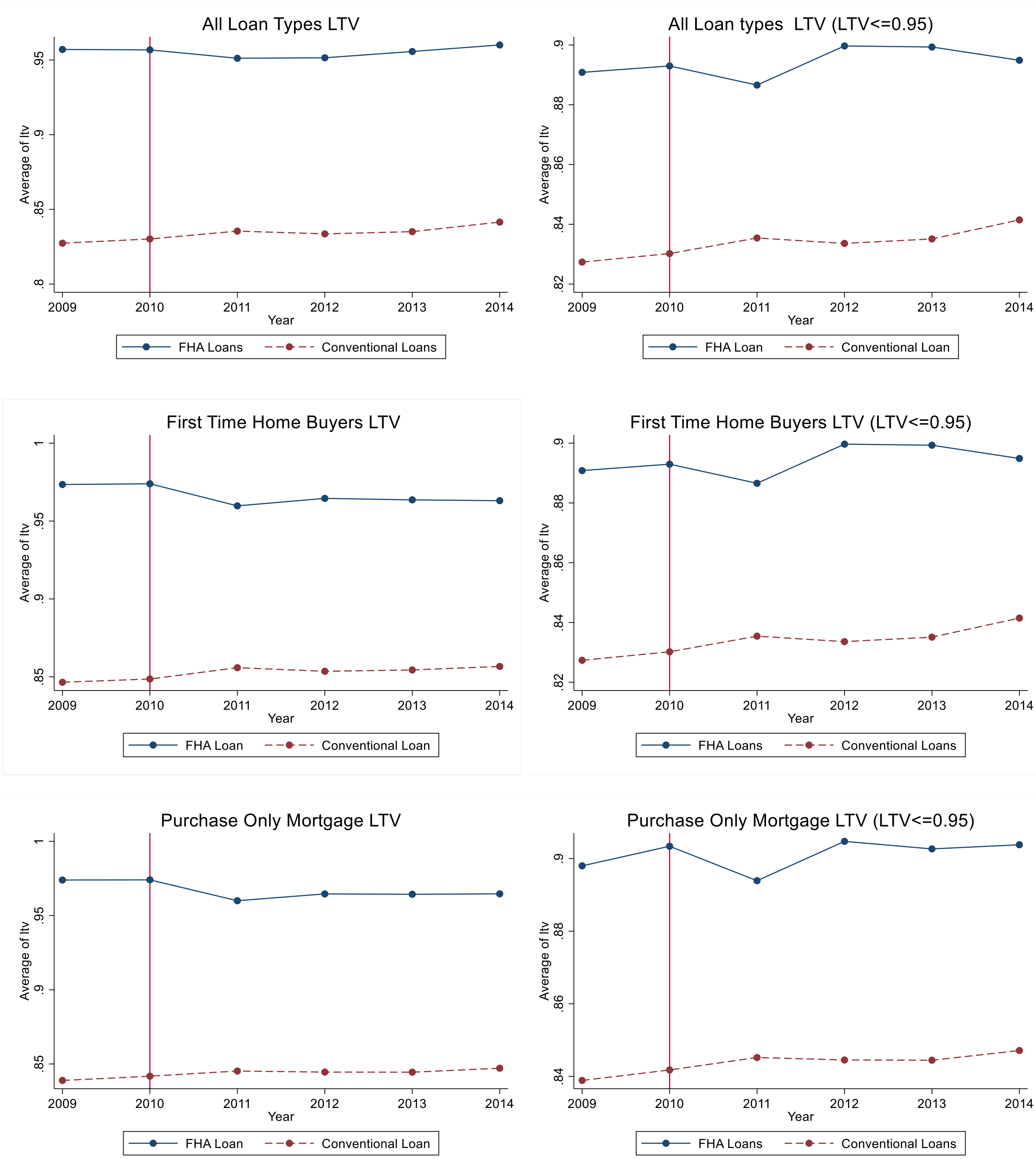

Figure 2.2 Parallel Trends by Income Category for all Loan types

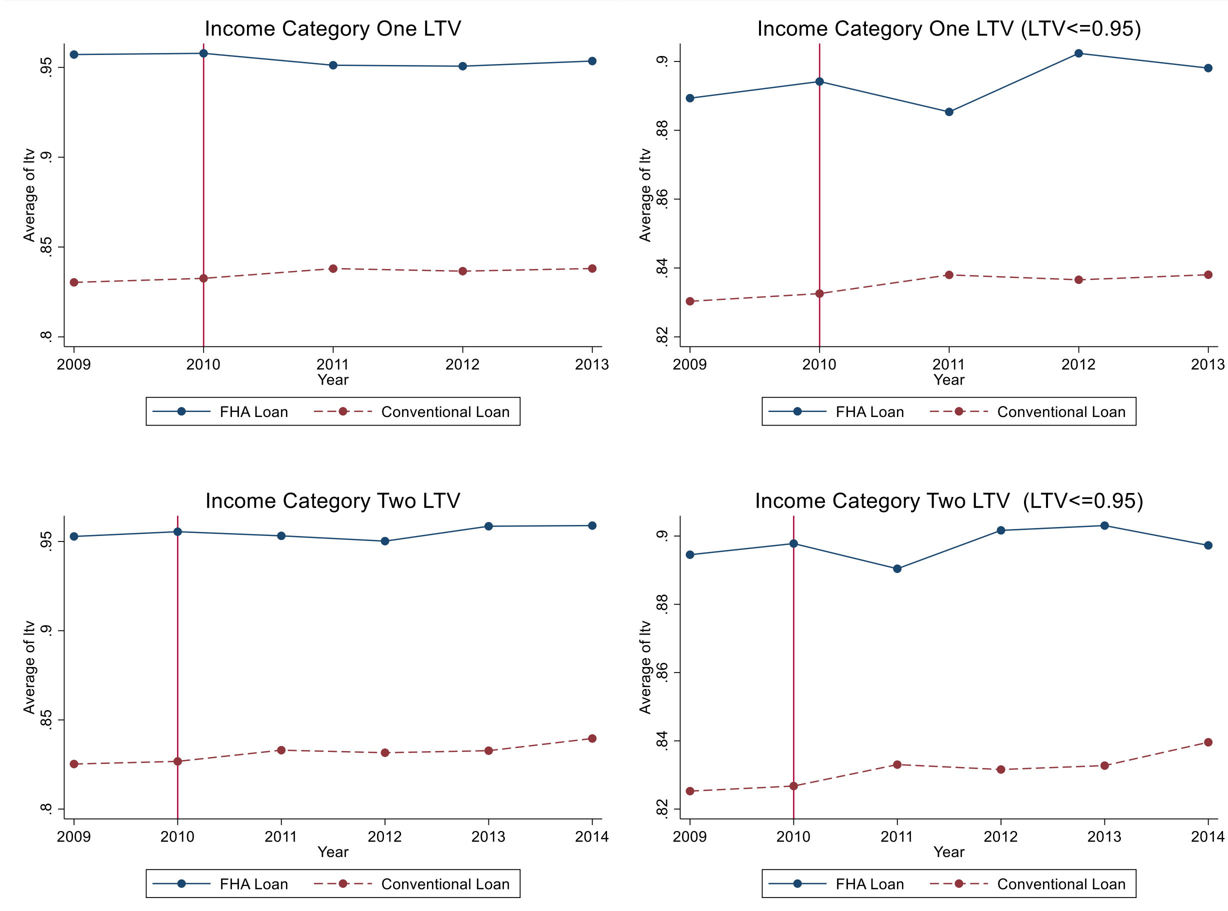

Table 2.14 Difference-in-Differences Regression Results Across All Incomes

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.146***	0.146***	0.147***	0.146***
	(0.002)	(0.002)	(0.002)	(0.002)
FHA	0.014***	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
FHA*UFM	-0.014***	-0.015***	-0.015***	-0.015***
	(0.003)	(0.003)	(0.003)	(0.003)
Log (Real Income)	-0.003***	-0.003***	-0.003**	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Log (Rate)	0.034***	0.033***	0.034***	0.033***
	(0.008)	(0.008)	(0.008)	(0.008)
Log (Front-End)	0.002		0.001	
	(0.001)		(0.001)	
BoCredit (620-660)	0.004	0.003	0.005	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
BoCredit (661-700)	0.009***	0.008**	0.010***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
BoCredit (701-760)	0.019***	0.018***	0.020***	0.018***
	(0.003)	(0.003)	(0.003)	(0.003)
BoCredit (>761)	0.015***	0.014***	0.016***	0.015***
	(0.003)	(0.003)	(0.003)	(0.003)
BoGender	0.001	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Boage	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Geog			0.004*	0.004*
			(0.002)	(0.002)
Acqtyp			0.000	0.000
			(0.001)	(0.001)
Coborrower			0.003***	0.004***
			(0.001)	(0.001)
Log (Back-End)		0.007***		0.007***
		(0.001)		(0.001)
Constant	-0.055**	-0.054**	-0.071***	-0.071***
	(0.024)	(0.024)	(0.025)	(0.025)
Observations	18,588	18,588	18,588	18,588
R-squared	0.490	0.491	0.491	0.492

Notes: FHA*UFM is average treatment effect of the policy, Real Income is the borrower's annual income in 2010 dollars, Rate is the fixed interest mortgage rate to a 30 year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoGender is an indicator for the borrower's gender, BoAge is the borrower's age, Geog is indicator for whether the house is in a census tract classified as underserved, Acqtyp is an indicator for the type of acquisition (cash or credit enhancement) and Coborrower is an indicator for whether the borrower had a coborrower. The standard errors are clustered at the county level.

Table 2.15 Difference-in-Differences Regression Results Across All Incomes (LTV<=0.95)

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.079***	0.078***	0.080***	0.079***
	(0.003)	(0.003)	(0.003)	(0.003)
FHA	0.014***	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
FHA*UFM	-0.015***	-0.015***	-0.016***	-0.016***
	(0.004)	(0.004)	(0.005)	(0.005)
Log (Real Income)	-0.003**	-0.003**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.002)	(0.001)
Log (Rate)	0.032***	0.031***	0.032***	0.031***
	(0.010)	(0.010)	(0.010)	(0.010)
Log (Front-End)	0.003**		0.003*	
	(0.002)		(0.002)	
BoCredit	-0.004	-0.006	-0.003	-0.005
(620-660)	(0.005)	(0.005)	(0.005)	(0.006)
BoCredit	0.011**	0.009*	0.012**	0.010*
(661-700)	(0.005)	(0.005)	(0.005)	(0.005)
BoCredit	0.020***	0.018***	0.021***	0.019***
(701-760)	(0.005)	(0.005)	(0.005)	(0.005)
BoCredit	0.015***	0.014***	0.016***	0.015***
(>761)	(0.005)	(0.005)	(0.005)	(0.006)
BoGender	0.001	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Boage	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Geog			0.007***	0.007***
			(0.002)	(0.002)
Acqtyp			-0.000	0.000
			(0.001)	(0.001)
Coborrower			0.003**	0.003**
			(0.001)	(0.001)
Log (Back-End)		0.008***		0.008***
		(0.002)		(0.002)
Constant	-0.069**	-0.066**	-0.081**	-0.079**
	(0.030)	(0.030)	(0.032)	(0.031)
Observations	15,773	15,773	15,773	15,773
R-squared	0.085	0.086	0.087	0.088

Notes: FHA*UFM is average treatment effect of the policy, Real Income is the borrower's annual income in 2010 dollars, Rate is the fixed interest mortgage rate to a 30 year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoGender is an indicator for the borrower's gender, BoAge is the borrower's age, Geog is indicator for whether the house is in a census tract classified as underserved, Acqtyp is an indicator for the type of acquisition (cash or credit enhancement) and Coborrower is an indicator for whether the borrower had a coborrower. The standard errors are clustered at the county level.

Table 2.16 Difference-in-Differences Regression Results First Time Home Buyers

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.147***	0.144***	0.148***	0.144***
	(0.004)	(0.004)	(0.004)	(0.004)
FHA_FIRST	0.012***	0.012***	0.012***	0.012***
	(0.004)	(0.004)	(0.004)	(0.004)
FHA_FIRST*UFM	-0.025***	-0.026***	-0.026***	-0.026***
	(0.005)	(0.005)	(0.005)	(0.005)
Log (Real Income)	0.009***	0.011***	0.008***	0.011***
	(0.002)	(0.002)	(0.003)	(0.003)
Log (Rate)	0.007	0.005	0.007	0.005
	(0.016)	(0.016)	(0.017)	(0.017)
Log (Front-End)	0.003		0.002	
	(0.003)		(0.003)	
BoCredit	0.009***	0.007***	0.009***	0.008***
(620-660)	(0.003)	(0.003)	(0.003)	(0.003)
BoCredit	0.006*	0.005	0.007**	0.005
(661-700)	(0.003)	(0.003)	(0.003)	(0.003)
BoCredit	0.020***	0.018***	0.020***	0.019***
(701-760)	(0.002)	(0.002)	(0.003)	(0.003)
BoCredit	0.014***	0.015***	0.015***	0.015***
(>761)	(0.003)	(0.003)	(0.003)	(0.003)
BoGender	-0.001	-0.001	-0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Boage	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Geog			0.004	0.004
			(0.004)	(0.004)
Acqtyp			0.000	0.001
			(0.001)	(0.001)
Coborrower			0.002	0.002
			(0.002)	(0.002)
Log (Back-End)		0.019***		0.019***
		(0.003)		(0.003)
Constant	-0.252***	-0.260***	-0.260***	-0.271***
	(0.053)	(0.054)	(0.053)	(0.053)
Observations	3,653	3,653	3,653	3,653
R-squared	0.559	0.564	0.560	0.564

Notes: FHA_FIRST*UFM is average treatment effect of the policy, Real Income is the borrower's annual income in 2010 dollars, Rate is the fixed interest mortgage rate to a 30 year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoGender is an indicator for the borrower's gender, BoAge is the borrower's age, Geog is indicator for whether the house is in a census tract classified as underserved, Acqtyp is an indicator for the type of acquisition (cash or credit enhancement) and Coborrower is an indicator for whether the borrower had a coborrower. The standard errors are clustered at the county level.

Table 2.17 Difference-in-Differences Regression Results First Time Home Buyers (LTV<=0.95)

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.072***	0.069***	0.075***	0.071***
	(0.008)	(0.008)	(0.008)	(0.008)
FHA_FIRST	0.011**	0.011**	0.011**	0.011**
	(0.005)	(0.005)	(0.005)	(0.005)
FHA_FIRST*UFM	-0.012	-0.013	-0.017*	-0.017*
	(0.010)	(0.010)	(0.010)	(0.010)
Log (Real Income)	0.012***	0.015***	0.008*	0.012***
	(0.004)	(0.003)	(0.004)	(0.004)
Log (Rate)	0.007	0.004	0.006	0.003
	(0.027)	(0.027)	(0.027)	(0.027)
Log (Front-End)	0.004		0.004	
	(0.005)		(0.005)	
BoCredit	0.003	0.000	0.004	0.001
(620-660)	(0.012)	(0.012)	(0.012)	(0.012)
BoCredit	0.020**	0.017*	0.021**	0.018*
(661-700)	(0.009)	(0.009)	(0.010)	(0.010)
BoCredit	0.038***	0.035***	0.040***	0.037***
(701-760)	(0.009)	(0.010)	(0.010)	(0.010)
BoCredit	0.031***	0.030***	0.033***	0.032***
(>761)	(0.009)	(0.010)	(0.010)	(0.010)
BoGender	-0.002	-0.003	-0.002	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Boage	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Geog			0.012**	0.011**
			(0.005)	(0.005)
Acqtyp			-0.002	-0.002
			(0.002)	(0.002)
Coborrower			-0.002	-0.001
			(0.003)	(0.003)
Log (Back-End)		0.030***		0.028***
		(0.005)		(0.005)
Constant	-0.301***	-0.312***	-0.283***	-0.301***
	(0.087)	(0.088)	(0.086)	(0.086)
Observations	2,127	2,127	2,127	2,127
R-squared	0.058	0.073	0.066	0.078

Notes: FHA_FIRST*UFM is average treatment effect of the policy, Real Income is the borrower's annual income in 2010 dollars, Rate is the fixed interest mortgage rate to a 30 year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoGender is an indicator for the borrower's gender, BoAge is the borrower's age, Geog is indicator for whether the house is in a census tract classified as underserved, Acqtyp is an indicator for the type of acquisition (cash or credit enhancement) and Coborrower is an indicator for whether the borrower had a coborrower. The standard errors are clustered at the county level.

Table 2.18 Difference-in-Differences Regression Results Purchase Only Mortgages

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.153***	0.152***	0.153***	0.152***
	(0.003)	(0.003)	(0.003)	(0.003)
FHA_PURCHASE	0.010***	0.010***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
FHA_PURCHASE*UFM	-0.023***	-0.023***	-0.023***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.003)
Log (Real Income)	0.002	0.001	0.002	0.002
	(0.002)	(0.001)	(0.002)	(0.002)
Log (Rate)	0.012	0.011	0.012	0.011
	(0.011)	(0.011)	(0.011)	(0.011)
Log (Front-End)	0.005**		0.005**	
	(0.002)		(0.002)	
BoCredit	0.009***	0.009***	0.009***	0.008***
(620-660)	(0.002)	(0.002)	(0.002)	(0.002)
BoCredit	0.011***	0.010***	0.011***	0.010***
(661-700)	(0.002)	(0.002)	(0.002)	(0.002)
BoCredit	0.023***	0.023***	0.023***	0.023***
(701-760)	(0.002)	(0.002)	(0.002)	(0.002)
BoCredit	0.013***	0.013***	0.013***	0.013***
(>761)	(0.002)	(0.002)	(0.003)	(0.003)
BoGender	-0.002**	-0.002**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Boage	-0.000	-0.000*	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Geog			0.002	0.003
			(0.002)	(0.002)
Acqtyp			0.001	0.001
			(0.001)	(0.001)
Coborrower			0.002	0.003
			(0.002)	(0.002)
Log (Back-End)		0.012***		0.012***
		(0.002)		(0.002)
Constant	-0.162***	-0.151***	-0.173***	-0.166***
	(0.034)	(0.034)	(0.035)	(0.035)
Observations	9,114	9,114	9,114	9,114
R-squared	0.526	0.528	0.526	0.528

Notes: FHA_PURCHASE*UFM is average treatment effect of the policy, Real Income is the borrower's annual income in 2010 dollars, Rate is the fixed interest mortgage rate to a 30 year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoGender is an indicator for the borrower's gender, BoAge is the borrowers age, Geog is indicator for whether the house is in a census tract classified as underserved, Acqtyp is an indicator for the type of acquisition (cash or credit enhancement) and Coborrower is an indicator for whether the borrower had a coborrower. The standard errors are clustered at the county level.

Table 2.19 Difference-in-Differences Regression Results Purchase Only Mortgages (LTV<=0.95)

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.078***	0.077***	0.079***	0.078***
	(0.005)	(0.005)	(0.005)	(0.005)
FHA_PURCHASE	0.010***	0.010***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
FHA_PURCHASE*UFM	-0.013*	-0.013*	-0.015**	-0.015**
	(0.007)	(0.007)	(0.008)	(0.008)
Log (Real Income)	0.002	0.001	0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Log (Rate)	0.015	0.014	0.015	0.013
	(0.015)	(0.015)	(0.015)	(0.015)
Log (Front-End)	0.007***		0.007**	
	(0.003)		(0.003)	
BoCredit	0.001	-0.000	0.002	0.000
(620-660)	(0.009)	(0.009)	(0.009)	(0.009)
BoCredit	0.021**	0.019**	0.022***	0.020**
(661-700)	(0.008)	(0.008)	(0.008)	(0.008)
BoCredit	0.037***	0.036***	0.038***	0.037***
(701-760)	(0.008)	(0.008)	(0.008)	(0.008)
BoCredit	0.024***	0.024***	0.025***	0.025***
(>761)	(0.008)	(0.008)	(0.008)	(0.008)
BoGender	-0.003**	-0.003**	-0.003*	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Boage	-0.000	-0.000	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Geog			0.007**	0.007**
			(0.003)	(0.003)
Acqtyp			-0.001	-0.001
			(0.001)	(0.001)
Coborrower			0.001	0.002
			(0.002)	(0.002)
Log (Back-End)		0.015***		0.015***
		(0.003)		(0.003)
Constant	-0.157***	-0.144***	-0.160***	-0.151***
	(0.048)	(0.047)	(0.049)	(0.048)
Observations	6,717	6,717	6,717	6,717
R-squared	0.050	0.053	0.052	0.054

Notes: FHA_PURCHASE*UFM is average treatment effect of the policy, Real Income is the borrowers annual income in 2010 dollars, Rate is the fixed interest mortgage rate to a 30 year loan term, Back-end is the borrowers non-mortgage debt to income ratio, front-end is the borrowers total debt to income ratio, BoCredit is an indicator for the borrowers credit rating, BoGender is an indicator for the borrower's gender, BoAge is the borrowers age, Geog is indicator for whether the house is in a census tract classified as underserved, Acqtyp is an indicator for the type of acquisition (cash or credit enhancement) and Coborrower is an indicator for whether the borrower had a coborrower. The standard errors are clustered at the county level.

Table 2.20 Difference-in-Differences Regression Results Income Category One

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.144***	0.144***	0.145***	0.145***
	(0.003)	(0.003)	(0.003)	(0.003)
FHA_INCOMECAT	0.016***	0.017***	0.017***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)
FHA_INCOMECAT*UFM	-0.013***	-0.013***	-0.014***	-0.014***
	(0.004)	(0.004)	(0.004)	(0.004)
Log (Real Income)	-0.000	0.000	0.001	0.002
	(0.003)	(0.003)	(0.004)	(0.004)
Log (Rate)	0.054***	0.054***	0.054***	0.054***
	(0.011)	(0.011)	(0.011)	(0.011)
Log (Front-End)	0.001		-0.000	
	(0.002)		(0.002)	
BoCredit	0.002	0.001	0.003	0.001
(620-660)	(0.004)	(0.004)	(0.004)	(0.004)
BoCredit	0.005	0.004	0.006	0.005
(661-700)	(0.004)	(0.004)	(0.004)	(0.004)
BoCredit	0.020***	0.018***	0.021***	0.019***
(701-760)	(0.004)	(0.004)	(0.004)	(0.004)
BoCredit	0.014***	0.013***	0.015***	0.014***
(>761)	(0.004)	(0.004)	(0.004)	(0.004)
BoGender	0.002	0.002	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Boage	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Geog			0.005**	0.004**
			(0.002)	(0.002)
Acqtyp			0.000	0.000
			(0.001)	(0.001)
Coborrower			0.006***	0.006***
			(0.001)	(0.001)
Log (Back-End)		0.004*		0.004*
		(0.002)		(0.002)
Constant	-0.031	-0.034	-0.054	-0.060
	(0.046)	(0.046)	(0.049)	(0.049)
Observations	7,832	7,832	7,832	7,832
R-squared	0.502	0.502	0.504	0.504

Notes: FHA_INCOMECAT*UFM is average treatment effect of the policy, Real Income is the borrower's annual income in 2010 dollars, Rate is the fixed interest mortgage rate to a 30 year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoGender is an indicator for the borrower's gender, BoAge is the borrowers age, Geog is indicator for whether the house is in a census tract classified as underserved, Acqtyp is an indicator for the type of acquisition (cash or credit enhancement) and Coborrower is an indicator for whether the borrower had a coborrower. The standard errors are clustered at the county level.

Table 2.21 Difference-in-Differences Regression Results Income Category One (LTV<=0.95)

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.076***	0.076***	0.077***	0.076***
	(0.003)	(0.003)	(0.004)	(0.004)
FHA_INCOMECAT	0.016***	0.016***	0.016***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
FHA_INCOMECAT*UFM	-0.013**	-0.013**	-0.013**	-0.014**
	(0.005)	(0.005)	(0.005)	(0.005)
Log (Real Income)	0.001	0.002	0.001	0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Log (Rate)	0.049***	0.049***	0.048***	0.048***
	(0.014)	(0.014)	(0.013)	(0.013)
Log (Front-End)	0.001		0.000	
	(0.003)		(0.003)	
BoCredit	-0.015**	-0.017**	-0.014**	-0.016**
(620-660)	(0.007)	(0.007)	(0.007)	(0.007)
BoCredit	0.003	0.001	0.004	0.001
(661-700)	(0.007)	(0.007)	(0.007)	(0.007)
BoCredit	0.016**	0.014**	0.017***	0.015**
(701-760)	(0.006)	(0.006)	(0.006)	(0.006)
BoCredit	0.010	0.008	0.011	0.009
(>761)	(0.006)	(0.007)	(0.006)	(0.007)
BoGender	0.002	0.002	0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.002)
Boage	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Geog			0.006**	0.006**
			(0.002)	(0.002)
Acqtyp			0.000	0.000
			(0.001)	(0.001)
Coborrower			0.006***	0.006***
			(0.002)	(0.002)
Log (Back-End)		0.005*		0.005*
		(0.003)		(0.003)
Constant	-0.061	-0.060	-0.078	-0.079
	(0.056)	(0.056)	(0.059)	(0.059)
Observations	6,412	6,412	6,412	6,412
R-squared	0.087	0.087	0.089	0.090

Notes: FHA_INCOMECAT*UFM is average treatment effect of the policy, Real Income is the borrower's annual income in 2010 dollars, Rate is the fixed interest mortgage rate to a 30 year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoGender is an indicator for the borrower's gender, BoAge is the borrowers age, Geog is indicator for whether the house is in a census tract classified as underserved, Acqtyp is an indicator for the type of acquisition (cash or credit enhancement) and Coborrower is an indicator for whether the borrower had a coborrower.

Table 2.22 Difference-in-Differences Regression Results Income Category Two

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.143***	0.142***	0.143***	0.142***
	(0.003)	(0.003)	(0.003)	(0.003)
FHA_INCOMECAT	0.013***	0.013***	0.014***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)
FHA_INCOMECAT*UFM	-0.008**	-0.008**	-0.008*	-0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
Log (Real Income)	-0.011***	-0.010***	-0.011***	-0.011***
	(0.004)	(0.003)	(0.004)	(0.003)
Log (Rate)	0.027**	0.025**	0.027**	0.025**
	(0.011)	(0.011)	(0.011)	(0.011)
Log (Front-End)	0.005***		0.005***	
	(0.002)		(0.002)	
BoCredit	0.003	0.002	0.003	0.002
(620-660)	(0.010)	(0.010)	(0.010)	(0.010)
BoCredit	0.013	0.011	0.012	0.011
(661-700)	(0.010)	(0.010)	(0.010)	(0.010)
BoCredit	0.017*	0.016	0.017*	0.015
(701-760)	(0.010)	(0.010)	(0.010)	(0.010)
BoCredit	0.014	0.014	0.013	0.014
(>761)	(0.010)	(0.010)	(0.010)	(0.010)
BoGender	0.002	0.002	0.003*	0.003*
	(0.001)	(0.001)	(0.002)	(0.002)
Boage	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Geog			0.005	0.006
			(0.005)	(0.005)
Acqtyp			0.000	0.000
			(0.001)	(0.001)
Coborrower			-0.002	-0.002
			(0.002)	(0.002)
Log (Back-End)		0.011***		0.011***
		(0.002)		(0.002)
Constant	0.011	0.007	0.009	0.003
	(0.059)	(0.058)	(0.059)	(0.058)
Observations	8,416	8,416	8,416	8,416
R-squared	0.383	0.384	0.383	0.385

Notes: FHA_INCOMECAT*UFM is average treatment effect of the policy, Real Income is the borrower's annual income in 2010 dollars, Rate is the fixed interest mortgage rate to a 30 year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrowers total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoGender is an indicator for the borrower's gender, BoAge is the borrower's age, Geog is indicator for whether the house is in a census tract classified as underserved, Acqtyp is an indicator for the type of acquisition (cash or credit enhancement) and Coborrower is an indicator for whether the borrower had a coborrower. The standard errors are clustered at the county level.

Table 2.23 Difference-in-Differences Regression Results Income Category Two (LTV<=0.95)

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.083***	0.082***	0.083***	0.082***
	(0.005)	(0.005)	(0.004)	(0.004)
FHA_INCOMECAT	0.013***	0.013***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
FHA_INCOMECAT*UFM	-0.014**	-0.015**	-0.014**	-0.015**
	(0.007)	(0.007)	(0.007)	(0.007)
Log (Real Income)	-0.009**	-0.009**	-0.010**	-0.009**
	(0.004)	(0.004)	(0.004)	(0.004)
Log (Rate)	0.029**	0.027**	0.030**	0.027**
	(0.012)	(0.012)	(0.012)	(0.012)
Log (Front-End)	0.006***		0.006***	
	(0.002)		(0.002)	
BoCredit	0.008	0.005	0.008	0.005
(620-660)	(0.012)	(0.012)	(0.012)	(0.011)
BoCredit	0.021*	0.019*	0.021*	0.018*
(661-700)	(0.011)	(0.011)	(0.011)	(0.011)
BoCredit	0.025**	0.023**	0.024**	0.022**
(701-760)	(0.011)	(0.011)	(0.011)	(0.011)
BoCredit	0.021*	0.021*	0.021*	0.020*
(>761)	(0.011)	(0.011)	(0.011)	(0.011)
BoGender	0.003*	0.003*	0.003*	0.003*
	(0.001)	(0.001)	(0.002)	(0.002)
Boage	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Geog			0.006	0.007
			(0.005)	(0.005)
Acqtyp			0.000	0.000
			(0.001)	(0.001)
Coborrower			-0.002	-0.002
			(0.002)	(0.002)
Log (Back-End)		0.012***		0.012***
		(0.002)		(0.002)
Constant	-0.008	-0.012	-0.012	-0.018
	(0.064)	(0.063)	(0.064)	(0.063)
Observations	7,738	7,738	7,738	7,738
R-squared	0.068	0.070	0.068	0.071

Notes: FHA_INCOMECAT*UFM is average treatment effect of the policy, Real Income is the borrower's annual income in 2010 dollars, Rate is the fixed interest mortgage rate to a 30 year loan term, Back-end is the borrower's non-mortgage debt to income ratio, front-end is the borrower's total debt to income ratio, BoCredit is an indicator for the borrower's credit rating, BoGender is an indicator for the borrower's gender, BoAge is the borrowers age, Geog is indicator for whether the house is in a census tract classified as underserved, Acqtyp is an indicator for the type of acquisition (cash or credit enhancement) and Coborrower is an indicator for whether the borrower had a coborrower. The standard errors are clustered at the county level.

Figure 2.3 Overlap Plots All Incomes Across Loan Type and Home Buyer Type

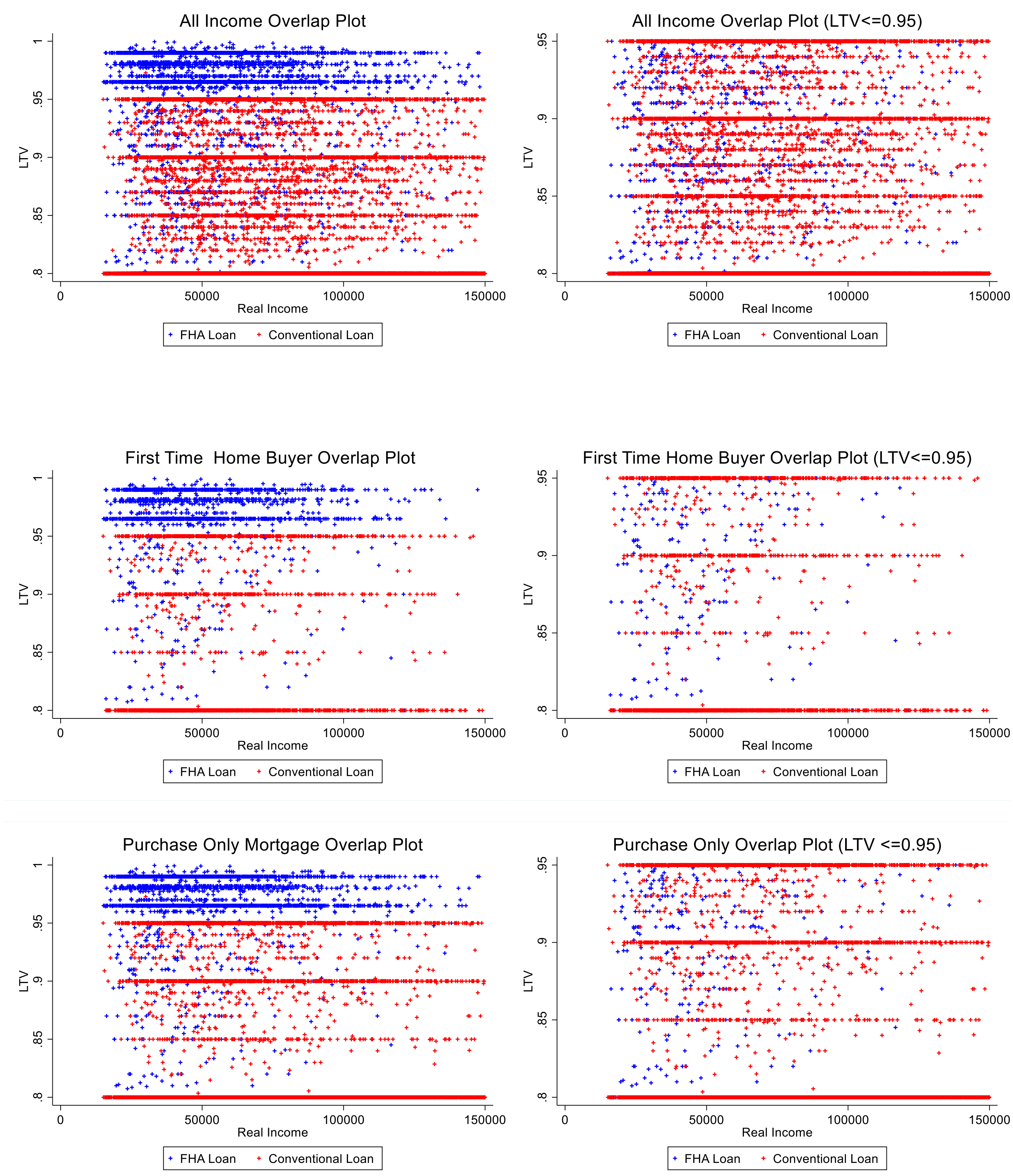

Figure 2.4 Overlap Plots All Incomes by Income Category for All Loan Types

Table 2.24 Combined Matching-DID Regression Results Across All Incomes

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.018***	0.013***	0.009*	0.015***
	(0.004)	(0.002)	(0.005)	(0.003)
FHA	0.149***	0.149***	0.152***	0.152***
	(0.003)	(0.003)	(0.003)	(0.003)
UFM*FHA	-0.024***	-0.019***	-0.015***	-0.021***
	(0.004)	(0.003)	(0.005)	(0.004)
Constant	-0.195***	-0.195***	-0.197***	-0.197***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	18,577	18,577	18,577	18,577
R-squared	0.529	0.620	0.642	0.650

Notes: The outcome variable is the mortgage loan-to-value ratio., The UFM is the time the policy took effect in this case it is 2011, FHA is an indicator variable representing whether the mortgage is FHA or conventional and UFM*FHA is the average treatment effect of the policy. The standard errors are clustered at the county level.

Table 2.25 Combined Matching-DID Regression Results Across All Incomes (LTV<=0.95)

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.016***	0.015***	0.020***	0.014***
	(0.003)	(0.003)	(0.002)	(0.003)
FHA	0.082***	0.082***	0.084***	0.084***
	(0.003)	(0.003)	(0.003)	(0.003)
FHA*UFM	-0.021***	-0.020***	-0.025***	-0.019***
	(0.005)	(0.005)	(0.005)	(0.005)
Constant	-0.199***	-0.199***	-0.201***	-0.201***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	15,762	15,762	15,762	15,762
R-squared	0.313	0.315	0.345	0.335

Notes: The outcome variable is the mortgage loan-to-value ratio., The UFM is the time the policy took effect in this case it is 2011, FHA is an indicator variable representing whether the mortgage is FHA or conventional and UFM*FHA is the average treatment effect of the policy. The standard errors are clustered at the county level.

Table 2.26 Combined Matching-DID Regression Results First Time Home Buyers

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.028***	0.017*	0.028***	0.025**
	(0.008)	(0.009)	(0.007)	(0.010)
FHA_FIRST	0.156***	0.147***	0.162***	0.153***
	(0.005)	(0.009)	(0.007)	(0.011)
FHA_FIRST*UFM	-0.042***	-0.031***	-0.042***	-0.039***
	(0.009)	(0.009)	(0.007)	(0.010)
Constant	-0.183***	-0.175***	-0.189***	-0.181***
	(0.005)	(0.008)	(0.006)	(0.010)
Observations	3,619	3,619	3,619	3,619
R-squared	0.610	0.545	0.586	0.590

Notes: The outcome variable is the mortgage loan-to-value ratio., The UFM is the time the policy took effect in this case it is 2011, FHA_FIRST is an indicator variable representing whether the mortgage borrower is utilizing a FHA loan or conventional loan and FHA_FIRST*UFM is the average treatment effect of the policy. The standard errors are clustered at the county level.

Table 2.27 Combined Matching-DID Regression Results First Time Home Buyers (LTV<=0.95)

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.026***	0.015**	0.034**	0.020**
	(0.006)	(0.006)	(0.015)	(0.009)
FHA_FIRST	0.072***	0.070***	0.074***	0.071***
	(0.008)	(0.007)	(0.009)	(0.009)
FHA_FIRST*UFM	-0.030***	-0.019*	-0.037**	-0.024*
	(0.011)	(0.011)	(0.018)	(0.014)
Constant	-0.184***	-0.181***	-0.186***	-0.182***
	(0.005)	(0.005)	(0.005)	(0.006)
Observations	2,093	2,093	2,093	2,093
R-squared	0.175	0.181	0.155	0.202

Notes: The outcome variable is the mortgage loan-to-value ratio., The UFM is the time the policy took effect in this case it is 2011, FHA_FIRST is an indicator variable representing whether the mortgage borrower is utilizing a FHA loan or conventional loan and FHA_FIRST*UFM is the average treatment effect of the policy. The standard errors are clustered at the county level.

Table 2.28 Combined Matching-DID Regression Results Purchase Only Mortgage

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.014***	0.012**	0.019***	0.013**
	(0.004)	(0.005)	(0.005)	(0.006)
FHA_PURCHASE	0.158***	0.158***	0.163***	0.164***
	(0.005)	(0.005)	(0.006)	(0.006)
FHA_PURCHASE *UFM	-0.029***	-0.027***	-0.033***	-0.027***
	(0.005)	(0.005)	(0.005)	(0.007)
Constant	-0.185***	-0.185***	-0.190***	-0.191***
	(0.004)	(0.004)	(0.005)	(0.005)
Observations	9,095	9,095	9,095	9,095
R-squared	0.553	0.595	0.654	0.634

Notes: The outcome variable is the mortgage loan-to-value ratio., The UFM is the time the policy took effect in this case it is 2011, FHA_PURCHASE is an indicator variable representing whether the mortgage borrower is utilizing a FHA loan or conventional loan and FHA_PURCHASE*UFM is the average treatment effect of the policy. The standard errors are clustered at the county level.

Table 2.29 Combined Matching-DID Regression Results Purchase Only Mortgage (LTV<=0.95)

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.019***	0.018***	0.022***	0.023***
	(0.005)	(0.005)	(0.004)	(0.004)
FHA_PURCHASE	0.081***	0.082***	0.084***	0.083***
	(0.006)	(0.006)	(0.006)	(0.006)
FHA_PURCHASE*UFM	-0.023***	-0.023***	-0.027***	-0.028***
	(0.009)	(0.009)	(0.009)	(0.009)
Constant	-0.190***	-0.191***	-0.193***	-0.192***
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	6,698	6,698	6,698	6,698
R-squared	0.241	0.262	0.276	0.240

Notes: The outcome variable is the mortgage loan-to-value ratio., The UFM is the time the policy took effect in this case it is 2011, FHA_PURCHASE is an indicator variable representing whether the mortgage borrower is utilizing a FHA loan or conventional loan and FHA_PURCHASE*UFM is the average treatment effect of the policy. The standard errors are clustered at the county level.

Table 2.30 Combined Matching-DID Regression Results Income Category One

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.007*	0.009**	0.013***	0.013***
	(0.004)	(0.004)	(0.004)	(0.004)
FHA_INCOMECAT	0.146***	0.145***	0.148***	0.148***
	(0.003)	(0.003)	(0.003)	(0.003)
FHA_INCOMECAT *UFM	-0.013***	-0.015***	-0.019***	-0.019***
	(0.005)	(0.005)	(0.005)	(0.004)
Constant	-0.191***	-0.191***	-0.193***	-0.193***
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	7,820	7,820	7,820	7,820
R-squared	0.617	0.610	0.618	0.619

Notes: The outcome variable is the mortgage loan-to-value ratio., The UFM is the time the policy took effect in this case it is 2011, FHA_INCOMECAT is an indicator variable representing whether the mortgage borrower is utilizing a FHA loan or conventional loan and FHA_INCOMECAT*UFM is the average treatment effect of the policy. The standard errors are clustered at the county level.

Table 2.31 Combined Matching-DID Regression Results Income Category One (LTV<=0.95)

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.021***	0.018***	0.025***	0.017***
	(0.005)	(0.004)	(0.005)	(0.004)
FHA_INCOMECAT	0.079***	0.079***	0.082***	0.082***
	(0.004)	(0.004)	(0.004)	(0.004)
FHA_INCOMECAT *UFM	-0.025***	-0.023***	-0.029***	-0.021***
	(0.007)	(0.006)	(0.007)	(0.005)
Constant	-0.197***	-0.197***	-0.201***	-0.201***
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	6,400	6,400	6,400	6,400
R-squared	0.284	0.268	0.334	0.334

Notes: The outcome variable is the mortgage loan-to-value ratio., The UFM is the time the policy took effect in this case it is 2011, FHA_INCOMECAT is an indicator variable representing whether the mortgage borrower is utilizing a FHA loan or conventional loan and FHA_INCOMECAT*UFM is the average treatment effect of the policy. The standard errors are clustered at the county level.

Table 2.32 Combined Matching-DID Regression Results Income Category Two

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.009**	0.002	-0.003	0.010***
	(0.004)	(0.003)	(0.007)	(0.003)
FHA_INCOMECAT	0.144***	0.144***	0.144***	0.145***
	(0.003)	(0.004)	(0.004)	(0.004)
FHA_INCOMECAT *UFM	-0.008	-0.001	0.004	-0.009**
	(0.005)	(0.005)	(0.008)	(0.004)
Constant	-0.194***	-0.194***	-0.194***	-0.195***
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	8,410	8,410	8,410	8,410
R-squared	0.627	0.650	0.664	0.644

Notes: The outcome variable is the mortgage loan-to-value ratio., The UFM is the time the policy took effect in this case it is 2011, FHA_INCOMECAT is an indicator variable representing whether the mortgage borrower is utilizing a FHA loan or conventional loan and FHA_INCOMECAT*UFM is the average treatment effect of the policy. The standard errors are clustered at the county level.

Table 2.33 Combined Matching-DID Regression Results Income Category Two (LTV<=0.95)

Variables	Model (1)	Model (2)	Model (3)	Model (4)
UFM	0.007***	0.009**	0.011***	0.006
	(0.002)	(0.004)	(0.003)	(0.004)
FHA_INCOMECAT	0.083***	0.083***	0.083***	0.082***
	(0.005)	(0.005)	(0.005)	(0.005)
FHA_INCOMECAT*UFM	-0.012*	-0.014*	-0.015**	-0.011
	(0.007)	(0.008)	(0.007)	(0.008)
Constant	-0.195***	-0.195***	-0.195***	-0.195***
	(0.002)	(0.002)	(0.003)	(0.003)
Observations	7,732	7,732	7,732	7,732
R-squared	0.349	0.340	0.358	0.361

Notes: The outcome variable is the mortgage loan-to-value ratio., The UFM is the time the policy took effect in this case it is 2011, FHA_INCOMECAT is an indicator variable representing whether the mortgage borrower is utilizing a FHA loan or conventional loan and FHA_INCOMECAT*UFM is the average treatment effect of the policy. The standard errors are clustered at the county level.

Chapter 3

Capital Targets, Liquidity and Lending in US Agricultural Banks

3.1 Introduction

This research attempts to address pertinent issues in the US agricultural banking sector which revolve around the lending process. Primarily, the key objective it is to elaborate on the independent contribution of tier 1 risk-based capital-ratio gap and bank liquidity-ratio and structure of their interaction in the provision of loans. Important questions to answer include: does the bank liquidity-ratio and risk-based capital-ratio gap jointly enhance each other in the provision of loans? Is this interaction homogenous across agricultural banks of different asset classes? Thirdly, if agricultural banks pursue a target risk-based capital ratio, how does liquidity and the risk-based capital-ratio gap independently impact loan provision? and how does their interaction manifest itself when these banks are operating above or below the target capital-ratio (state of capital-surplus or capital-deficit)? Some authors had addressed the interaction between the capital-ratio and liquidity. Kim and Sohn (2017) and Thornton and Tommaso (2019) analyze the interaction between the liquidity-ratio and the capital-ratio in US banks and UK banks, respectively in times of economic prosperity and economic crises. They both find a positive relationship between the two variables. Others research, for instance, Berrospide and Edge (2010) and Francis and Osborne (2009) analyze the impact of the capital-gap (difference between target capital-ratio and actual capital ratio) on lending. They find that commercial bank with a capital surplus tend to have a higher credit growth compared to those in a state of capital deficit.

In the 2000s and especially post 2007 global financial crisis period, there have as well been significant reviews of the Basel Accords primarily focusing on liquidity and capital standards which commercial banks must adhere. This has led to research on the analysis of the impact of government regulation on bank behavior. Bonner and Clemens (2015) find that implementation of liquidity regulation in commercial banks in the Netherlands led to an increase in their investments in government bonds and reduction in loans. Bonner et al. (2013) find that in countries with more stringent bank liquidity regulation, the correlation between liquidity buffers and deposit liabilities tend to be stronger. Banerjee and Mio (2015) find that the implementation of liquidity regulation in UK banks did not reduce the amount of loans disbursed but instead find evidence of rebalancing of assets and liabilities and a shift towards better-quality liquid assets.

Analyzing the impact of the transition from Basel I to Basel II in French banks, Brun et al. (2013) find a statistically negative relationship between the increase in the capital requirements and the volume of lending. Francis and Osborne (2012) analyze banks in the UK and find that capital requirements have significant impact on their establishment of their target capital as well as adjustment of capital-ratios. Nacuer and Roulet (2017) argue that capital requirements act as a tax on commercial banks because capital is more expensive to raise as compared to deposits, this could then affect lending as it may lead banks to rebalance their portfolio.

This research differentiates itself from previous empirical work and contributes to the banking literature in the following ways: (1) Unlike other empirical studies mentioned earlier and others to be reviewed in the next section which have primarily analyzed commercial banks in general, this research chooses to analyze well capitalized agricultural banks which have been operational over the period right after the 2007 financial crisis and continue to be operational over the study period (2011-2019). (2) Kim and Sohn (2017) and Thornton and Tommaso (2019) which both analyze the interaction between the liquidity-ratio and the capital-ratio and its impact on lending. This research instead analyzes the interaction between the liquidity-ratio and the capital-ratio gap and its impact on lending. (3) Berrospide and Edge (2010) and Francis and Osborne (2009) analyze the impact of the capital-gap (difference between target capital-ratio and actual capital ratio) on lending. This study will build on their research. Like the two studies this research estimates the target capital-ratio, computes the capital-gap, and empirically investigates its role on lending. In addition, this research will now analyze the liquidity-ratio and the capital-gap interaction across the both states of the capital-gap (capital deficit and capital surplus) and the joint impact of these dynamics on lending.

To briefly preview the results. First discussing the partial adjustment model. It is found that the largest banks close about 42.4% of the capital-gap (gap between their target capital-ratio and current capital-ratio) within one year. In the case of small and medium sized banks, over a similar time-period, they close 36.1% and 28.6% of their capital-gap, respectively. Comparing the long-run impact of net-income across banks sizes, medium-sized banks report the largest impact of 1.20% while the smallest impact of 0.79% is reported in small banks. The coefficient for the ratio of loan allowance to loans which is a proxy for credit risk is statistically insignificant in small banks but is found to be statistically significant in medium-sized banks and large banks yielding positive magnitudes of 0.09% and 0.08% respectively.

In the case of the loan determinants regression model. Liquidity1(ratio of liquid assets to assets) is found to be statistically significant in medium-sized banks and large banks but with negative magnitudes of -0.013% and -0.048% respectively. This total effect of liquidity was analyzed at the means, the magnitudes illustrate a symmetric impact of liquidity on loan provision across capital-states (capital-surplus or capital-shortfall). It was as well only statistically significant in medium-sized agricultural banks and large agricultural banks. The interaction between liquidity1 and the capital-gap was only statistically significant in the existence of a capital deficit (capital shortfall). The result reported for small agricultural banks was -0.102. However, medium-sized agricultural banks and large agricultural banks both yielded positive magnitudes of 0.10 and 0.13, respectively. The total effect of the capital gap was as well evaluated at the means. The results indicate an asymmetric relationship across the capital-states in all the bank sizes considered. Moreover, in small agricultural banks the total effect was only statistically significant in the existence of a capital-shortfall and the reported magnitude was 0.207. However, in the case of medium-sized banks and large banks, the total effect of the capital-gap was only statistically significant in the existence of a capital-surplus. The reported magnitudes were 0.19 and 0.29 for medium-sized agricultural banks and large agricultural banks, respectively.

The rest of the paper is structured as follows. Section two provides a brief review of pertinent literature. Section three provides a brief description of the conceptual framework of the model and the methodology utilized to estimate the partial adjustment model, compute the capital-gap, to estimate the loan determinants and compute the marginal effects. Section four describes the properties of the agricultural banking data used in this study. The empirical findings and discussion of the results are provided in section five and the last section presents concluding remarks and comments.

3.2 Literature Review

There exists a vast literature on the determinants of commercial bank loans primarily focusing on the role of bank capital and liquidity on lending. For instance, Berrospide and Edge (2010) analyze US banks and report a significantly strong relationship between capital-ratio and loan growth. However, Carlson et al (2011) as well analyze US banks but find a much smaller impact of the capital-ratio. Jimenez et al. (2012) analyzing banks in Spain find that highly capitalized banks lend less compared to less capitalized banks. However, a positive relationship was obtained when the capital-ratio was interacted with macroeconomic variables. dipatti et al. (2012) examine commercial banks during the financial crisis and find that the decay of commercial bank capital negatively impacted the volume of lending. Carlson et al. (2013) find that the impact of capital on lending diminishes as a bank's capital-ratio rises. Labonne and Lame (2014) analyze banks over the period of the financial crisis. They find that both tier 1 capital and deposits increased lending over the crisis. They, however, find that tier 2 capital does not have any significant effect on lending. Gambacorta and Marquez (2011) find a positive effect of tier 1 capital on bank lending during the financial crisis. Olszak et al (2014) in their analysis to determine the role of capital in lending consider bank policy as a determining factor. They find that supply of loans in banks which engage in income smoothing are less sensitive to changes in the capital-ratio compared to banks which do not engage in a similar policy. Francis and Osborne (2009) take a different approach and analyze the impact of the capital-gap on lending in UK commercial banks. They first estimate the target capital-ratio using a partial adjustment model and the compute the capital-gap between observed capital-ratio and the target capital-ratio. The find that increases in the capital-gap led to less lending and as well show that banks with a surplus have a higher credit growth. Berrospide and edge (2010) as well estimate the target capital ratio in US commercial banks and compute the capital gap. They analyze the impact of the capital gap on both total loans and only commercial loans and find that in both cases capital surpluses positively influence their respective lending levels.

Berger and Bouwman (2009) highlight two key theoretical relationships between bank capital and liquidity creation. The first is the risk absorption theory which states that banks with higher bank capital engage in more liquidity creation as they have a higher risk bearing capacity. The second is the financial fragility-crowding out theory. This states that capital investors are less willing to supply funds to banks because unlike depositors they are unable to run on the banks. Even though these theories are not directly relating lending to capital they have however led to discussion and empirical analysis on (1) the structure of the relationship between capital and lending and (2) the relationship between capital and liquidity in the process of lending. For instance, Kim and Sohn (2017) analyzing US banks, in their loan growth model find that the interaction effect between capital and liquidity to statistically insignificant in small and medium-sized banks. However, they find that in large banks the effect of an increase in the capital-ratio on credit growth is negative when liquidity levels are low but find a statistically significant positive relationship at higher liquidity levels. Thornton and Tommaso (2019) utilizing a similar model, analyzes the determinants of loan growth and credit growth in European banks. They find that the interaction between capital and liquidity is positive and stronger especially in times of crisis. Calomiris et al. (2012) analyze the substitution between minimum regulatory capital and liquidity requirements. They articulate incentives for holding liquid assets which indicate the possibility of substitution. Distinguin et al. (2013) analyzing US and European publicly traded banks find that banks substitute their bank capital for liquidity. Deyoung et al. (2018) as well analyze the relationship between liquidity and capital, examining the impacts of deviations from capital targets. They discovered that when small banks fall below the capital target, the level of liquidity transformations declines.

Kashyap and Stein (2000) analyze US banks and find that the heterogenous and asymmetric responses to a monetary policy shock across banks is primary caused by the heterogeneity in liquidity positions. Matousek and Sarantis (2009) analyzing banks in emerging economies find that bank size and liquidity positions determine the severity of a bank reaction to a monetary policy shock. Alper et al. (2012) analyze the role of bank liquidity in lending in times of both high and low systemic liquidity in Turkish banks. They find that the impact of individual bank liquidity on lending is much higher in times of low systemic liquidity as compared to high systemic liquidity. Berrospide and Edge (2010) analyzing US banks, utilized a VAR model and illustrated how the commercial banks adjust their stock of securities to adjust to loan growth. Jimenez et al. (2012) analyzing Spanish banks empirically illustrates that the level of lending varies with liquidity positions.

Betubiza and Leatham (1995) find that in US commercial banks that agricultural lending declines when bank deposit volatility with respect to market rates increases. Nam et al. (2007) analyzing US banks find that bank assets and deposit growth increase agricultural lending but discover in their sample a negative relationship between agricultural lending and both liquidity measure (loan-to-deposit ratio) and capital adequacy measure (equity-to-asset ratio). Meinster (1997) Analyzing rural banks in the US, finds that bank balances increase agricultural lending as they provide a smoothing effect on seasonal deposits and loans. Settlage et al. (2009) Analyze the role of agricultural lending by US commercial banks on the probability of failure. They find a statistically insignificant effect of increasing the share of agricultural lending. In the bank sample analyzed an increase in the share of agricultural loans had neither a positive nor negative effect on bank survival. Kliesen and Gilbert (1996) find that small and medium-sized banks tend to hold a smaller percentage of cash as compared to non-agricultural banks. Lastly, Barry and Escalante (1998) illustrate that agricultural lending is a more viable and profitable niche for well capitalized banks. In the next section, the primary econometric techniques utilized in this study are discussed in detail.

3.3 Data

The dataset used in this study was obtained from the Federal Deposit Insurance corporation (FDIC). It consists of over 900 US agricultural commercial banks and covers a period of nine years (2011-2019). Commercial banks are considered agricultural banks when their combined share or agricultural and rural loans are greater than 20% of the total loan portfolio. It is also worth mentioning that the dataset only contains commercial banks which remained operational over the entirety of the study's period. All variables utilized in this analysis are as well adjusted to 2010 prices. The summary statistics of each variable utilized in this study are presented in table (3.1), table (3.2) and table (3.3).

Initially the bank sample was divided by size, which was proxied by the variable asset, which is the overall sum of the bank total assets. The choice of including different bank sizes is reasonable as substantive empirical literature for instance have successfully illustrated that bank behavior differs significantly across different asset classes.

Table (3.1) provides the summary statistics of the variables used in the study over the entire sample. As expected, the loan amounts and total assets increase by bank size. The Capital-Ratio variable represents the tier 1 risk-based capital ratio. The ratio ranges between 0.11 and 0.12 across the three asset classes. The expected sign of the capital-ratio coefficient is positive. This is because better capitalized banks can absorb market shocks more effectively which in turn permits them to hold larger loan portfolios. The reported liquidity1 levels in table (3.1) illustrate that the largest banks in the sample have the lowest levels of liquidity1 compared to smaller banks (review article on liquidity levels). In the case of liquidity1 which is the ratio of liquid assets to assets. The liquid assets include cash balances due from deposit institutions, federal funds sold and reverse purchases, US government securities and US treasury securities. The largest banks' report a ratio of 0.18 while the small banks report a ratio of 0.28. The large banks have a liquidity1 ratio which is 35.7% less than that of small banks. The medium-sized banks report a liquidity1 ratio of 0.22 which is 21.3% smaller than that of small banks in the sample. The case is not significantly different for liquidity2 levels across asset classes. Liquidity2 is the ratio of liquid assets to total deposits. Small banks once again report the largest ratios in the sample of 0.36 while medium-sized banks and large banks report ratios of 0.28 and 0.22, respectively. These values are 22.2% and 38.9% smaller ratios respectively compared to the reported liquidity2 ratio in small banks.

Table (3.1) also reports the commercial banks' unused commitments which is represented by the variable commitment. This is the ratio of unused commitments to total assets. An increase in unused commitments is expected to increase the likeliness of a commercial bank to extend a loan. From table (3.1), larger banks' unused commitments ratio is 0.13 which is about 62.5% larger than that of smaller banks and 30% larger than the ratio reported by medium sized commercial banks. Small banks and medium-sized banks report unused commitments ratios of 0.08 and 0.10, respectively. However, across the different bank sizes the variables ROA (return on assets), commercial (share of commercial loans in total loan portfolio) and NPL (share of non-performing loans) are roughly equal.

The variable Allow is the loan loss allowance to loans ratio. Table (3.1) provides 0.45 ratio in large banks, a 0.10 ratio in medium-sized banks and 0.03 ratio in small banks. An increase in this ratio indicates a drop in the loan portfolio quality which in turn makes commercial banks less probable to extend loans to their clients. The Net-Income variable are the banks' reported profits after tax. As expected, the larger banks record the largest net-income of 6.1$ billion while smaller banks report a net-income of 362.9$ million. The HHI-Loan is the Herfindahl loan portfolio diversification index. Table (3.1) illustrates that larger banks are slightly more diversified as compared to smaller banks. Small banks report an index of 0.41, medium-sized banks report an index of 0.45 and large banks report an index of 0.48.

The Fund variable is the ratio of non-deposit liabilities to total assets. Small banks, medium-sized banks, and large banks report ratios of 0.03, 0.04 and 0.06, respectively. The expected sign of this variable's coefficient varies by bank size. Large banks are expected to yield a positive coefficient because they can source funds from the market while small banks would report a negative Fund coefficient because they do not have access to such facilities. Lastly, as expected, large banks hold the highest amount of deposits amounting to over $300 billion while smaller banks hold an average of $32.8 billion.

To consider the potential effects of excess capital or capital deficits on lending and to effectively illustrate how liquidity and capital gaps interact in the loan production process, two more tasks were carried out. The first was to estimate a dynamic model to obtain the target capital-ratio and determine the speed of capital adjustment in agricultural commercial banks. Having obtained the target capital-ratio the next task was to decompose the entire bank sample into those agricultural banks which held excess capital and those agricultural banks which were experiencing a capital deficit.

Table (3.2) reports the means and standard deviations of variables of agricultural banks which were in a state of capital surplus. These banks had their actual capital-ratios greater than their target capital-ratios. On the other hand, table (3.3) reports the means and standard deviations of variables of agricultural banks which were experiencing a capital deficit. From table (3.2) and table (3.3) in the case of medium-sized banks and large banks which experienced a capital deficit had loan portfolios which were 4.3% and 42% less respectively. However, the amount of loans supplied by smaller banks rose by 10.8%. Agricultural banks experiencing a capital shortfall also had a smaller capital ratio compared to their counterparts. For instance, small banks experiencing a capital deficit have a 28.8% lower capital-ratio while medium-sized banks have a 16.7% and 9.1% lower ratio, respectively. This means that these banks are more susceptible to market shocks compared to their counterparts.

In the case of liquidity1, the largest difference occurs in medium-sized banks and large banks. The liquidity ratios are 26.9% and 52.4% smaller than the agricultural banks facing a capital surplus. A similar feature can be observed in the case of liquidity2. However, in this case the differences are much smaller. Once again, medium-sized banks and large banks have the largest differences of 7.7% and 14.3% respectively, while the difference in small banks is only 3.1%.

The ROA (return on assets) and NPL (ratio of non-current loans to loans) is roughly the same across all bank sizes and capital state (surplus or deficit). In the case of commercial loans, small banks and large banks with a capital deficit had a 7.7% and 14.3% smaller share, respectively. Medium-sized agricultural banks had roughly the same share of commercial loans across both capital states. In the case of unused commitments banks with a capital deficit had larger ratios compared to those with a capital surplus. Smaller banks reported the largest difference of 14.3% while medium-sized banks and large banks reported differences of 11.11% and 8.3%, respectively.

The ratio of loan allowance to loans, Allow, was significantly lower in banks with a capital deficit compared to their counterparts across all bank sizes. Small agricultural banks and medium-sized agricultural banks reported 0.3% and 2.8% smaller ratios. The larger banks report the largest difference in the loan allowance to loan ratio of 45.5%. Net-Income and deposits values reported are significantly smaller in banks in a capital deficit state as compared to those experiencing a capital surplus. However, in the case of the variables Fund and HHI-Loan variables, the values are roughly similar across both bank samples.

3.4 Methodology

As mentioned earlier, the primary objectives of this research are to determine how liquidity and bank capital-gaps in agricultural banks interact in the loan generation process, the impact of the capital-state (capital surplus or capital shortfall) and capital-gap on lending, and finally how the capital-state of the agricultural banks can influence the interaction between liquidity and capital-gap. To achieve these objectives, an empirical analysis must be carried out in two stages. In this section, the primary empirical techniques applied in this research are discussed.

The first step of the estimation process is to determine the target tier 1 risk-based capital-ratio. This step focuses on empirically evaluating the link between the target capital-ratio and the agricultural banks' balance sheet items and other variables which proxy for risk and loan diversification. Like Flannery and Rangan (2006), Maurin and Toivanen (2012), Hovakimian and Li (2012), Elsas and Florysiak (2015) and Bakkar et al. (2019) a dynamic partial adjustment model is utilized to determine the target capital-ratio. An added advantage of this model is that through minor algebra, the speed of adjustment and long-run impacts of the balance sheet items on the target capital-ratio across different agricultural banks classified by asset size are easily obtained. Due to the dynamic nature of the model to be estimated, and like the previously mentioned studies above the two-step general method of moments (GMM) estimation technique is utilized. The standard errors are corrected for heteroscedasticity.

The target tier 1 risk-based capital-ratio (K_{it}^{*}) of an agricultural bank (i) at time (t) is empirically determined jointly by a vector of agricultural banks' balance sheet items and other characteristics (X_{it}). This vector includes Net-Income, Deposits, Assets, ROA (Return on Assets), Commercial (Share of commercial loans on total loans), NPL (Ratio of non-current loans), HHI-Loan (Herfindahl Loan portfolio diversification index) and Allow (ratio of loan allowance to loans). This estimation will produce a coefficient vector (β_i) and its equation is presented below.

$$K_{it}^* = X_{it-1}\beta \tag{1}$$

For agricultural banks setting a tier 1 capital-ratio target (K_{it}^*) the coefficient vector (β_i) should comprise of statistically significant coefficients. As mentioned earlier this is a dynamic partial adjustment model and will take the structure presented below. The variable (K_{it}^*) is the target capital-ratio, (K_{it}) is the observed capital-ratio and (ε_{it}) is the error term.

$$K_{it} - K_{it-1} = \lambda(K_{it}^* - K_{t-1}) + \varepsilon_{it} \tag{2}$$

The equation above states that over one financial period, agricultural banks would close a proportion (λ) of the gap between their actual capital-ratio and their desired capital-ratio. The next step is to substitute the right-hand side of the target capital-ratio in equation (1) into equation (2) and rearrange the partial adjustment model whose final structure is presented below.

$$K_{it} = (1 - \lambda)K_{it-1} + \lambda(X_{it-1}\beta) + \varepsilon_{it} \tag{3}$$

The model specification above implies two key properties. The first is that if statistical significance is obtained in ($X_{it-1}\beta$) then agricultural banks' actual tier 1 capital-ratio (K_{it}) converges to its target capital-ratio (K_{it}^*). Secondly, all agricultural banks of the same asset class size will have the same speed of adjustment. Rewriting equation (3) above to include the variables to be utilized in the estimation yields the equation below.

$$\begin{aligned} CapitalRatio_{it} &= \beta_0 + \beta_1 CapitalRatio_{it-1} + \beta_2 NetIncome_{it-1} + \beta_3 Deposit_{it-1} + \\ &\beta_4 Asset_{it-1} + \beta_5 ROA_{it-1} + \beta_6 Commercial_{it-1} + \beta_7 NPL_{it-1} + \beta_8 HHILoan_{it-1} + \\ &\beta_9 Allow_{it-1} + \varepsilon_{it} \end{aligned} \tag{4}$$

The next stage of the analysis is to obtain the capital-gap. Based on the estimated model presented in equation (1) – equation (4), the target tier 1 risk-based capital-ratio (K_{it}^*) is computed for each agricultural bank. The capital-gap is therefore the difference between the target capital-ratio and the actual capital-ratio observed by the agricultural banks. The capital-gap provides information on whether the agricultural bank is in a state of capital surplus or capital deficit. The target capital ratio (K_{it}^*) and observed capital (K_{it}) are identified in equation (3) above. Following, Osborne et al. (2012) the agricultural banks' capital-gap is computed as (K_{it}^*/K_{it}) An agricultural bank in a state of capital surplus will have a capital gap of less than one while an agricultural bank experiencing a capital shortfall will have a capital gap of greater than one. An indicator variable on capital-state is then computed. This indicator variable will equal one when the bank is experiencing a capital deficit (shortfall) and will equal zero when the agricultural bank is experiencing a capital surplus (Excess capital).

Now, having estimated the partial adjustment model, computed the target capital-ratio, and determine the capital states across the agricultural banks, the next step is to evaluate the lending behavior across the agricultural banks using a fixed effects regression model. The two primary objectives of this research are to (1) empirically analyze the relationship between liquidity and the capital-gap and (2) determine whether the relationship varies depending on whether the bank is experiencing a capital surplus or a capital shortfall. To analyze (1) the variables representing the capital-gap and the liquidity are interacted and to analyze (2) we interact the indicator variable representing capital state, with the variables representing the capital-gap and agricultural bank liquidity. The structure of the equation is provided below.

$$Loan_{it} = \beta_0 + \beta_1 Loan_{it-1} + \beta_2 Asset_{it-1} + \beta_3 Fund_{it-1} + \beta_4 Commitment_{it-1} + \beta_5 NPL_{it-1} + \beta_6 Allow_{it-1} + \beta_7 ROA_{it-1} + \beta_8 NetIncome_{it-1} + \beta_9 CapitalRatio_{it-1} + \beta_{10} Liquidity_{it-1} + \beta_{11} Capitalgap_{it-1} + \beta_{12} Capitalstate * Liquidity_{it-1} * Capitalgap_{it-1} + \beta_{13} Capitalstate + \varepsilon_{it} \quad (5)$$

The main coefficient of interest is coefficient (β_{12}) which represents the estimated impact of the interaction between the capital-gap, bank liquidity and the banks' capital status (capital-surplus or capital shortfall). The coefficient will be conditioned on the indicator variable ($capitalstate$) which equals one if the bank is experiencing a shortfall and equals zero if the bank has capital surplus. This means the coefficient (β_{12}) will be examined when banks have a capital surplus or are experiencing a capital shortfall.

To obtain the total effect of bank liquidity on lending in agricultural banks. The first derivative of equation (5) is respect computed with to ($Liquidity_{it-1}$) and is examined across the two possible capital states represented by indicator variable ($capitalstate$). The equation representing the first derivative is presented below.

$$\frac{\partial E[Loan|X_{it-1}]}{\partial Liquidity_{it-1}} = \beta_{10} + \beta_{12} Capitalstate * Capitalgap_{it-1} \quad (6)$$

In similar fashion, to obtain the total effect of the capital gap on loan production in agricultural banks. The first derivative of equation (5) is computed with respect to ($CapitalGap_{it-1}$) and is as well analyzed across both capital states. The equation representing the first derivative is presented below.

$$\frac{\partial E[Loan|X_{it-1}]}{\partial Capitalgap_{it-1}} = \beta_{10} + \beta_{12} Capitalstate * Liquidity_{it-1} \tag{7}$$

These derivatives of both liquidity and the capital gap above are evaluated at both their respective means and percentiles. The regression results to partial adjustment model presented in equation (4) and the loan determinants model presented in equation (5), the computed liquidity and capital-gap marginal effects presented in equation (6) and (7) are discussed in the next section.

3.5 Empirical Results

In this section the regression results obtained from the partial adjustment model, loan determinants model and the computed marginal effects are discussed.

Table (3.4) reports the results to the target capital partial adjustment model. Taking a quick glance, different capital-ratio coefficients are reported, this is an indication of different speeds of adjustment across bank sizes. For instance, in small banks the reported coefficient is 0.64. (This is (1-λ) reported in equation (4)). Therefore, the speed of adjustment in small banks is 0.34 (1-0.64). This means that small banks on average manage to reduce 34% ((1-0.64) *100) of their capital gap within one financial year. On the other hand, medium-sized banks reduce their capital gap by 29% while large banks on average reduce their capital gap by 42% respectively, over a similar period.

The coefficients to the other variables reported in table (3.1) are the short-run impacts of these variables on tier 1 risk-based capital-ratio. For instance, in the case of small banks a 1% increase in net-income will increase the capital ratio by 0.28%. In the case of medium-sized banks and large banks, a 1% increase in net-income will increase tier 1 risk-based capital-ratio by 0.34% and 0.39%, respectively. The long-run impact is obtained by dividing the estimated coefficient by the speed of adjustment ($\hat{\beta}/\lambda$). In the case of small banks, the long-run impact of income is 0.79, while that of medium-sized bank and large banks is 1.20 and 0.93, respectively. It is clear from the information provided above that in the short-run large banks experienced the greatest the percentage increase in their capital-ratio of 0.39% from income but in the long-run medium-sized banks experience the largest percentage increase of 1.20%.

The impact of deposits on the capital-ratio was statistically insignificant in both small and large agricultural banks. However, in the case of medium-sized banks the coefficient statistically significant at a 95% confidence interval. The short-run magnitude reported was 0.19 and the computed long-run impact was 0.65. In the short-run 1% percentage increase in deposits will increase the capital-ratio by 0.19%, while in the long-run, a similar percentage increase deposits will increase the capital-ratio by 0.65%.

As expected, the increase in assets leads to a decline in the tier 1 risk-based capital-ratio. In addition, its coefficient is statistically significant across all bank sizes. The reported results indicate that large banks experience the least decline of 0.52% from a 1% increase in total assets while the medium-sized banks experience the greatest decline of 0.69% in their capital-ratio from a similar percentage increase in total assets. This pattern holds as well in the long-run across the samples. Small banks report a 1.81% decline in capital-ratio from a 1% increase in assets while medium-sized banks and large banks report a 2.24% and 1.22% increase from a 1% increase in total assets. However, in the case of ROA (Return on Assets), the trend in the magnitude across banks sizes is different. The largest impact of ROA is reported in large banks. A percentage increase in ROA leads to a 0.34% decline in their capital-ratio. In the case of small banks and medium-sized banks, a similar percentage increase in ROA leads to a 0.27 and 0.33 decline in capital-ratio. In the long-run, however, medium-sized banks experience the largest percentage decline in capital-ratio of 1.14% from a percentage increase in ROA while small banks and large banks experience a 0.25% and a 0.79% decline in their respective capital-ratio.

Turning now to NPL (Ratio of non-performing loans to loans) and Allow (Ratio of loan allowance to loans). The coefficient for NPL is only statistically significant in large banks and at a 90% confidence interval. The reported coefficients indicates that a percentage increase in NPL will lead to a 0.005% increase in the capital-ratio in the short-run while in the long-run a percentage increase in the NPL leads to 0.01% decline in the capital-ratio. In the case of the variable Allow, its coefficients are positive across all bank sizes but statistically significant in only medium-sized banks and large banks. The reported short-run coefficients indicate 0.09% and 0.08% increase in the capital-ratio in medium-sized banks and large banks respectively while the computed long-run percentage impact is 0.32% and 0.18% in medium-sized and large banks, respectively.

At this stage, the partial adjustment models for each bank size category have been estimated, the capital gap in each bank and the capital-state indicator variable computed. These are then utilized in the loan determinants regression whose results are presented in table (3.5) – table (3.8).

Table (3.5) reports the main results to the loan determinants regression. The coefficient to the variable Fund (Ratio of non-deposit liabilities to total assets) is only statistically significant in small banks. Moreover, it is negative as expected with a magnitude of -0.006. This means in small banks a 1% increase in the Fund ratio leads to a 0.006% decline in total loan supplied. This negative relationship in small banks exists because smaller banks ability to source for outside capital is limited. The coefficient to the variable Commitment (Ratio of unused commitments to assets) as expected is positive across all bank sizes. However, it is only statistically significant in small and medium-sized banks. A percentage increase in unused commitments will lead to an increase of 0.02% and 0.03% in small banks and medium-sized banks, respectively.

In the case of NPL (Ratio of non-performing loans) and Allow (Ratio of loan allowance to loans) across all the bank sizes, the coefficient estimates are statistically significant and negative across all bank sizes. The NPL coefficient ranges between -0.005 and -0.009, with small banks and large banks experiencing the greatest percentage decline. The total loan supply is more responsive to Allow across all agricultural banks. A percentage increase in the loan allowance ratio leads to a -0.023% and 0.055% decline in total loans supplied in the case of small and medium- sized banks, respectively. Large banks reported a -0.049% decline in total loans, which is slightly less than what was reported in medium-sized banks.

The ROA (Return on Assets) coefficient is negative and statistically significant across all bank sizes. The negative sign in the coefficient could be because of the agricultural banks choice to improve the quality of assets and rebalancing their assets portfolio by decreasing their loan supply. The greatest percentage decline is observed in medium-sized banks. A percentage increase in the ROA leads to a 0.17% decline in total loans supplied. The magnitudes to the ROA coefficients reported for small banks and larger banks are slightly less at -0.13% and -0.16%, respectively.

As expected, Net-Income has a positive impact on the total loan supplied, moreover, the magnitude of the impact increases with banks size. A percentage increase in net Net-Income experienced in small banks will increase the provision of loans by 0.14%. However, in medium-sized banks and large banks a percentage increase in Net-Income will increase the provision of loans by 0.17% and 0.18%, respectively.

The Capital-Ratio coefficient as expected is positive across all bank sizes, but it is only statistically significant in large banks. One percentage increase in the tier 1 risk-based capital-ratio leads to a 0.13% increase in total loans. The interaction variable between the liquidity and capital-gap is only statistically significant when the banks are experiencing a capital deficit. The interaction coefficients vary widely across the bank sizes with small banks yielding a negative coefficient of -0.10, while medium banks and large banks report positive coefficients of magnitude 0.1 and 0.13, respectively.

Table (3.6) reports the marginal effects of both liquidity1 and the capital-gap defined earlier in equation (6) and equation (7). It as well reports the coefficients to the capital-state indicator variable. In addition, the marginal effects are evaluated at the means and across both states of capital deficit and capital surplus.

Now, considering the marginal effects of liquidity1 (Ratio of liquid assets to assets). It can be seen from table (3.6) that the marginal effects are only statistically significant in medium-sized banks and large banks. Another key piece of information is the symmetric marginal effects across both capital-states (Capital Deficit and Capital Surplus). In medium-sized banks, a percentage increase in liquidity reduces the total loan supplied by 0.013% irrespective of the capital-state. In the case of large banks experiencing a capital surplus, one percentage increase in liquidity1 reduced total loan supply 0.049% which is approximately 0.05%. A similar magnitude is reported in large banks experiencing a capital shortfall.

In the case of the capital-gap marginal effects there are two main noticeable differences. The first, the reported results are asymmetric. Secondly, the marginal effect of the capital-gap is only statistically significant in only one of the capital-states. The reported marginal effect in small banks is only statistically significant when the banks are experiencing a capital deficit while the medium-sized banks' and the large banks' marginal effects are only statistically significant when they are experiencing a surplus. The reported marginal effect in small banks is 0.207. This means that an increase in the capital-gap by 1% will increase the total loan supplied by 0.21%. However, in medium-sized banks and large banks the reported marginal effects are 0.19 and 0.29. This means that a percentage increase in the capital-gap will increase the total loans supplied by 0.19% and 0.29% respectively.

Table (3.6) as well reports the coefficients obtained for the capital-state indicator variable. This variable equal one when banks are experiencing a capital deficit and zero when banks are experiencing a capital surplus. The results reported indicate that banks in a state of deficit supply more loans than those in a state of surplus. This can be restated as banks holding excess capital supplied less loans compared to their counterparts. The greatest difference is observed in small banks, with banks in a state of capital deficit supplying 7.8% more loans than their counterparts. On the other hand, medium-sized banks and large banks experiencing a capital deficit supplied 4.8% and 2.7% more loans than banks in their class sized holding excess capital.

Table (3.7) reports the linear predictions of total loans over different levels of liquidity1. The liquidity levels range from 5% percentile to 95% percentile across the entire sample and respective sub-samples, In the case of small banks, the total loan supplied mildly increases as the liquidity1 ratio increases. This increase is experienced in both capital states. Recall from table (3.5) the reported liquidity coefficient in small banks was positive. However, in the case of medium-sized banks and large banks, increasing liquidity1 levels leads to a decline in the total loan supplied. The reduction in medium-sized banks is mild while large banks experience a sharp decline in total loans supplied. Figure (3.1) provides a graphical analysis of the results presented in table (3.7). The first visible trait in the graph is the difference in slopes of the declines in the case of medium-sized banks and large banks and slightly ascending slopes in the case of small banks. The second visible trait in the graphs in each of the bank categories is the parallel slopes in the curves across capital-states. Recall from table (3.5), the computed marginal effects were symmetric across capital-states.

Table (3.8) reports the marginal effects of capital across different liqudity1 levels. Once again, the liquidity levels are from 5% percentile to 95% percentile across the entire sample and respective sub-sample. The results in table (3.8) are in line with marginal effects results reported in table (3.6). In the case of small banks, the capital-gap is only statistically significant when these banks are in a capital-deficit state. Secondly, the impact of the capital declines as the level of liquidity1 rises. These results explain that as the level of liquidity1 rises in small banks, the effect of a percentage increase in the capital-gap declines on total loans supplied. The range of the marginal effects is between 0.428 (low liquidity levels) and 0.148 (high liquidity levels). In medium-sized banks, the marginal effect of the capital-gap is statistically significant at all liquidity1 levels when the banks are in a state of capital surplus and the marginal effects range between 0.245 (low liquidity levels) and 0.173 (high liquidity levels). The marginal effect of the capital-gap in the state of capital deficit is only statistically significant at one point at which is the highest liquidity level. It should as well be noted that in the case of medium-sized banks in the state of capital surplus, the impact of one percentage increase in the capital-gap increases at higher liquidity1 levels. However, in the case of a deficit, the impact of a percentage increase in the capital-gap declines at higher liquidity1 levels. A similar phenomenon is observed in large banks. The only difference is that the marginal effects of the capital-gap are only statistically significant when the banks are in a state of capital surplus and are of greater magnitude and range between 0.508 (low liquidity levels) and 0.206 (high liquidity levels).

Table (3.10) reports the marginal effects of liquidity1 at different capital-gap levels. The capital-gap levels range from 5^{th} percentile to the 95^{th} percentile across the entire sample and sub-sample. In the case of small banks, majority of the marginal effects are statistically insignificant. Only at one point with a very small capital-gap and in a state of capital deficit is the marginal effect statistically significant. The results reported indicate that a 1% increase in liquidity1 would increase the total loan supplied by 0.015%. In medium-sized banks the marginal effect of liquidity is statistically significant in both states of capital. However, in the state of capital deficits, the marginal effects of liquidity on total loans supplied increases as the capital-gap increased while the marginal effect declines as the capital gap is increased when the banks are in a state of capital surplus. The marginal effects of liquidity1 when in a state of capital deficit range between -0.036 (high capital-gap) and -0.006 (low capital-gap). When the banks are in capital-surplus state the marginal effects range between -0.003 (low capital-gap) and -0.017(high capital-gap). The same phenomenon is observed in large banks, however, the marginal effects reported are of greater magnitude. In the case where banks are in a state of capital deficit the marginal effect range is between -0.051 (high capital-gap) and -0.048 (low capital-gap) while the range when the banks are in a state of capital surplus the range is between -0.004 (low capital-gap) and -0.061 (high capital-gap).

3.6 Robustness Check

A robustness check is performed by replacing the liquidity1 variable (ratio of liquid assets to total assets) with a common alternative liquidity proxy is the ratio of loans to deposits. In this study it is referred to as Liquidity2. The empirical results are presented in table (3.11) to table (3.16).

Table (3.1) reports the results to the loan determinants regression model. The reported results are within a feasible range when compared to the main regression results reported in table (3.5). For instance, the variable Fund is once again only statistically significant in the small banks sample and as well yields a similar coefficient of -0.006. The commitment variable is once again only statistically significant in the small banks and medium-sized banks. The only observed change is the 0.001 decline in the medium-sized banks' coefficient estimate. Turning to the NPL (Ratio of non-performing loans to total loans) and Allow (ratio of the loan allowance to total loans). In both the variables the results reported are identical to the main regression results reported in table (3.5).

In the case of the ROA (Return on Assets) there is a slight increase across all bank sizes. In small banks there was a 3.8% increase from -0.133 to -0.128. In medium-sized banks there is a 1.8% decline from -0.170 to -0.167. In the large banks there is a 1.2% decrease from -0.161 to 0.159. The net-income is still statistically significant across all bank samples. Moreover, there is a 3.6% and a 1.7% decline in the estimated coefficients for small and medium-sized banks, respectively. Once again, the capital-ratio is positive across all bank samples but is only statistically significant in the large banks sample. However, the coefficient estimate is 0.128 which is 2.4% larger than the estimate reported in the main regression. Figure 7(a) and figure 7(b) provide coefficient plots which compare the obtained coefficients from the main model and the robustness check.

Table (3.12) reports the marginal effects of Liquidity2 and the capital-gap as well as the percentage difference in total loans supplied by the banks across the capital-states. First, the marginal effects of Liquidity2 are only statistically significant in medium-sized banks and large banks. Secondly, like the main model the marginal effects are symmetric. In the case of medium-sized banks the marginal effects declined from -0.013 to -0.015 which is a 15.4% decline. However, in large banks the marginal effects increase from -0.048 to -0.043. This is a 10.4% increase in the marginal effects.

The marginal effects for the capital gap are once again statistically significant in one of the two capital-states and asymmetric across the states. For instance, in small banks, like the main model, the marginal effect is only statistically significant in the capital-deficit state. The reported marginal effect is 0.200. This is a 3.4% decline from the marginal effect computed in the main model. In the case of medium-sized banks there is no change in the marginal effects reported. The reported marginal effect is 0.190 and is statistically significant at the 99% confidence interval. However, in large banks the computed marginal effect increases by 2.7% from 0.291 reported in the main model to 0.299. The coefficient estimates for the capital-state indicator variable are equivalent to those computed and reported in the main model.

The capital-state indicator variable is once again positive and statistically significant. This is an indication that banks operating with excess capital above the capital target (state of capital surplus) supply less loans. The results reported are equivalent to those reported in the main model. The Small banks in capital deficit supplied 7.7% more loans than their counterparts while medium-sized banks and large banks supplied 4.8% and 2.7% more loans than their counterparts, respectively.

Table (3.12) reports the linear predictions of total loans over different levels of liquidity2. First, the ranges of the predictions computed are proximate to those computed from the main model. Secondly, like the main model's computed predictions, total loan supplied in small banks increases as the level of liquidity2 rises. The opposite applies in the case of medium-sized banks and large banks. Figure (3.4) provides a good representation of these predictions. Once again parallel curves are obtained due to the symmetry in the marginal effects. Therefore, the curves of the prediction plots based on liquidity2 have similar attributes to those obtained in the main model.

Table (3.15) reports the marginal effects of the Capital-Gap on loan provision across capital states at different liquidity levels. In small banks, the marginal effects are only statistically significant in the capital-deficit state. In addition, the magnitude of the marginal effects declines at higher Liquidity2 levels. The marginal effect range was between 0.465 and 0.233. In medium-sized banks and large banks the marginal effects are only statistically significant in the capital-surplus state. They as well decline the higher the liquidity2 level and range between 0.258 and 0.168. Large banks present a similar pattern but with higher marginal effects ranging between 0.541 and 0.215. A graphical analysis is presented in figure (3.5). The graphs are of similar attributes to those representing the marginal effects of the capital-gap in the main model.

The marginal effects of Liquidity2 at different capital-gap level are reported in table (3.16). In small banks, the marginal effects are positive and are only statistically significant in the state of capital deficit and at a more negative capital-gap level. The marginal effect range was between 0.062 and -0.025. In medium-sized banks the marginal effect of liquidity2 is statistically significant in both capital states. However, in the capital-deficit state the impact of liquidity increases (becomes less negative) at a more positive capital-gap while in the capital-surplus state the impact of the liquidity decreases (becomes more negative). The marginal effects range in the capital-surplus state and capital-deficit state range between -0.002 and -0.019 and between -0.042 and -0.007 respectively. In large banks, the marginal effects are statistically significant in both capital states. In the capital-surplus state, the marginal effect of liquidity declines (becomes more negative) and ranges between 0.004 and -0.057. On the other hand, in the capital-deficit state the marginal effect of liquidity increases (becomes less negative) as the capital-gap becomes more positive. The graphical analysis to these marginal effects is provide in figure (3.6) and the curves to the respective bank sizes present similar attributes to those representing the marginal effect computed from the main model.

3.7 Conclusion

This paper examined the effects of liquidity and the capital-gap on lending. This paper adds to the banking literature in that it analyzes the single effects of liquidity and the capital-gap as well as their interaction effect on lending. Secondly, because of the incorporation of the capital partial adjustment model which enabled the computation of the capital state, permitted the investigation of both effects across capital-surplus and capital-deficit states.

The impact of liquidity on lending evaluated at the mean, yielded symmetric marginal effects across both capital states. Small banks reported a statistically insignificant marginal effect. Medium-sized banks and large banks reported negative statistically significant results. On the other hand, the impact of the capital-gap was positive across all bank samples, but statistical significance varied by capital-state. In small banks, the marginal effect was statistically significant only in the capital-deficit state. However, in medium-sized banks and large banks the marginal effect was statistically significant only in the capital-surplus state. Secondly, the interaction effect was statistically significant only in the capital-deficit state. In small banks the interaction effect coefficient was negative (liquidity and the capital-gap were substitutes) while in medium-sized banks and large banks the interaction coefficient was positive (liquidity and the capital-gap were complements). Lastly, the marginal effect of the capital-gap in the case of medium-sized banks and large banks yielded some interesting results. When these banks were in a capital-deficit state, the impact of reducing the capital-gap on lending was larger at higher liquidity levels. However, when the banks were in a capital-surplus state, the impact of excess capital on lending was lower at higher liquidity levels. A similar pattern was observed in the case of the marginal effect of liquidity at different capital-gap magnitudes and across capital-deficit and capital-surplus states.

The results on the effects of the capital-gap suggest mild evidence that the risk absorption hypothesis applies across bank sizes. In the case of small banks, increased lending from reducing the capital deficit and in the case of medium-sized banks and large banks increased lending from increasing the capital surplus. However, this requires further investigation: (1) These phenomena are not based on the banks' actual capital but on a capital-gap built on an assumption that banks set a target capital-ratio and (2) the fact that the effect of the capital-gap varies across capital-deficit and capital-surplus states warrants new discussions into when the risk absorption hypothesis is best applicable.

The statistical significance of the interaction effect as well as the marginal effects of liquidity, highlight the importance of synchronized and codependent liquidity and capital management in US agricultural banks. Optimal levels of both capital and liquidity must be jointly determined to avoid offsetting effects on total lending. Secondly, because the costs of raising capital exceed those of raising liquidity, the heterogenous marginal effects of both the capital-gap (at different liquidity levels) and liquidity (at different capital-gap magnitudes) across capital-deficit and capital-surplus states highlight the potential of discordance between profit maximizing and lending. This as well suggests a possibility that some agricultural banks may deem it sustainable to operate in one capital-state over the other.

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Table 3.1 Summary Statistics Across Bank Samples

Variable	Full Sample	Small Banks	Medium Banks	Large Banks
Loan	129,228.18	21,814.99	70,187.95	300,627.00
	(205,153.42	(9,159.73)	(28,929.41)	(317,996.39)
Asset	197,877.46	38,761.45	113,252.78	446,467.00
	(284,668.83)	(10,851.14)	(35,619.64)	(432,741.22)
Capital-Ratio	0.11	0.12	0.11	0.11
	(0.03)	(0.04)	(0.03)	(0.02)
Liquidity1	0.22	0.28	0.22	0.18
	(0.13)	(0.16)	(0.13)	(0.09)
Liquidity2	0.27	0.36	0.28	0.22
	(0.16)	(0.19)	(0.16)	(0.11)
Commitment	0.11	0.08	0.10	0.13
	(0.06)	(0.06)	(0.06)	(0.06)
ROA	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.00)	(0.00)
Commercial	0.12	0.12	0.12	0.13
	(0.06)	(0.07)	(0.06)	(0.06)
NPL	0.01	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.01)
Loan Allowance	19.12	3.30	10.03	45.19
	(33.50)	(2.23)	(5.44)	(53.28)
Net Income	2,540.18	362.93	1,322.88	6,053.00
	(4,500.29)	(240.15)	(728.61)	(7,148.69)
HHI-Loan	0.45	0.41	0.45	0.48
	(0.10)	(0.09)	(0.10)	(0.11)
Fund	0.04	0.03	0.04	0.06
	(0.05)	(0.04)	(0.05)	(0.05)
Deposit	165,291.12	32,815.07	95,481.06	371,130.70
	(236,600.29)	(9,473.69)	(30,581.09)	(360,071.97)
Observations	6,276	1,021	3027	1,760

Notes: This table reports the summary statistics of the variables used in the regression models. Loan is the sum of agricultural loans, commercial loans, consumer loans & real estate loans, Asset is the total bank assets, Capital-Ratio is the tier-1 risk-based capital ratio, Liquidity1 is the ratio of liquid assets to total assets, Liquidity2 is the ratio of liquid assets to deposits, Commitment is the total unused bank commitments, ROA is the return on assets, Commercial is the share of commercial loans, NPL this is the ratio of non-current loans to loans, Loan Allowance is the loss allowance to loan, Net Income is the after tax revenue, HHI-Loan is the Herfindahl index of loan portfolio diversification, Fund is the ratio of non-deposit liabilities to total assets and Deposits are total domestic deposits.

Table 3.2 Summary Statistics for Banks Experiencing a Capital Surplus Across Bank Samples

Variable	Full Sample	Small Banks	Medium Banks	Large Banks
Loan	179,847.02	20,656.77	71,825.15	387,126.54
	(275,256.09)	(8,026.09)	(29,981.29)	(433,918.45)
Asset	281,364.41	41,260.05	125,496.00	593,984.00
	(378,038.62)	(9,879.06)	(34,873.26)	(581,716.91)
Capital-Ratio	0.12	0.14	0.12	0.11
	(0.03)	(0.05)	(0.03)	(0.02)
Liquidity1	0.24	0.32	0.26	0.21
	(0.14)	(0.17)	(0.14)	(0.10)
Liquidity2	0.31	0.41	0.33	0.26
	(0.18)	(0.21)	(0.18)	(0.12)
Commitment	0.10	0.07	0.09	0.12
	(0.06)	(0.05)	(0.06)	(0.06)
ROA	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.00)	(0.00)
Commercial	0.12	0.13	0.12	0.14
	(0.06)	(0.07)	(0.06)	(0.06)
NPL	0.01	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.01)
Loan Allowance	26.56	3.30	10.18	59.60
	(45.14)	(2.13)	(5.69)	(72.71)
Net Income	3,687.94	401.47	1,480.02	8,033.26
	(6,040.54)	(233.74)	(769.89)	(9,698.63)
HHI-Loan	0.46	0.41	0.47	0.47
	(0.11)	(0.10)	(0.11)	(0.11)
Fund	0.05	0.03	0.04	0.05
	(0.05)	(0.04)	(0.05)	(0.05)
Deposit	233,227.15	34,352.37	104,648.64	492,813.84
	(314,391.44)	(9,021.32)	(30,452.01)	(484,549.87)
Observations	3,029	477	1,392	823

Notes: This table reports the summary statistics of the variables used post-optimal capital estimation. Loan is the sum of agricultural loans, commercial loans, consumer loans & real estate loans, Asset is the total bank assets, Capital-Ratio is the tier-1 risk-based capital ratio, Liquidity1 is the ratio of liquid assets to total assets, Liquidity2 is the ratio of liquid assets to deposits, Commitment is the total unused bank commitments, ROA is the return on assets, Commercial is the share of commercial loans, NPL this is the ratio of non-current loans to loans, Allow is the loss allowance to loan, Net Income is the after tax revenue, HHI-Loan is the Herfindahl index of loan portfolio diversification, Fund is the ratio of non-deposit liabilities to total assets and Deposits are total domestic deposits.

Table 3.3 Summary Statistics for Banks Experiencing a Capital Deficit Across Bank Samples

Variable	Full Sample	Small Banks	Medium Banks	Large Banks
Loan	80,716.61	22,884.98	68,735.69	224,402.26
	(70,705.50)	(9,982.08)	(27,890.96)	(109,542.51)
Asset	117,856.14	36,453.23	102,392.50	316,472.74
	(92,978.34)	(11,199.79)	(32,635.28)	(134,789.62)
Capital-Ratio	0.10	0.10	0.10	0.10
	(0.02)	(0.02)	(0.02)	(0.01)
Liquidity1	0.20	0.25	0.19	0.15
	(0.12)	(0.13)	(0.11)	(0.08)
Liquidity2	0.25	0.31	0.24	0.18
	(0.14)	(0.15)	(0.13)	(0.09)
Commitment	0.11	0.08	0.11	0.13
	(0.06)	(0.06)	(0.06)	(0.06)
ROA	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.00)	(0.00)
Commercial	0.12	0.12	0.12	0.12
	(0.06)	(0.07)	(0.06)	(0.05)
NPL	0.01	0.01	0.01	0.01
	(0.01)	(0.02)	(0.01)	(0.01)
Allow	11.99	3.29	9.90	32.49
	(11.89)	(2.32)	(5.20)	(18.43)
Net-Income	1,440.01	327.33	1,183.48	4,307.96
	(1,489.60)	(240.69)	(659.50)	(2,606.17)
HHI-Loan	0.45	0.41	0.44	0.48
	(0.10)	(0.09)	(0.09)	(0.11)
Fund	0.04	0.04	0.04	0.06
	(0.05)	(0.04)	(0.05)	(0.05)
Deposit	100,175.57	31,394.90	87,349.00	263,901.63
	(78,954.91)	(9,665.13)	(28,318.45)	(112,098.31)
Observations	3,247	544	1,635	937

Notes: This table reports the summary statistics of the variables used post-optimal capital estimation. Loan is the sum of agricultural loans, commercial loans, consumer loans & real estate loans, Asset is the total bank assets, Capital-Ratio is the tier-1 risk-based capital ratio, Liquidity1 is the ratio of liquid assets to total assets, Liquidity2 is the ratio of liquid assets to deposits, Commitment is the total unused bank commitments, ROA is the return on assets, Commercial is the share of commercial loans, NPL this is the ratio of non-current loans to loans, Allow is the loss allowance to loan, Net Income is the after tax revenue, HHI-Loan is the Herfindahl index of loan portfolio diversification, Fund is the ratio of non-deposit liabilities to total assets and Deposits are total domestic deposits.

Table 3.4 Regression Results for Capital Partial Adjustment Model Across Bank Samples

	Bank Sample	Small Banks	Medium Banks	Large Banks
L. Capital Ratio	0.656***	0.639***	0.714***	0.576***
	(0.051)	(0.108)	(0.058)	(0.081)
L. Net Income	0.319***	0.284***	0.342***	0.393***
	(0.035)	(0.087)	(0.046)	(0.059)
L. Deposits	0.151*	0.169	0.188**	-0.014
	(0.078)	(0.124)	(0.086)	(0.119)
L. Asset	-0.579***	-0.653***	-0.691***	-0.517***
	(0.090)	(0.175)	(0.102)	(0.138)
L. ROA	-0.288***	-0.269***	-0.325***	-0.335***
	(0.036)	(0.089)	(0.047)	(0.060)
L. Commercial	-0.009	-0.038	-0.004	-0.020
	(0.012)	(0.023)	(0.015)	(0.025)
L. NPL	0.002*	0.003	0.001	0.005*
	(0.001)	(0.003)	(0.001)	(0.003)
L. HHI-Loan	0.030	-0.050	-0.025	0.054
	(0.045)	(0.090)	(0.053)	(0.095)
L. Allow	0.111***	0.037	0.091***	0.077**
	(0.028)	(0.032)	(0.028)	(0.033)
Constant	1.313***	1.641**	1.823***	1.555***
	(0.281)	(0.667)	(0.528)	(0.536)
Observations	7,702	1,483	3,797	2,105

Notes: Capital-Ratio is the tier-1 risk-based capital ratio, Net Income is the after-tax revenue, Deposits are total domestic deposits. Asset is the total bank assets, ROA is the return on assets, Commercial is the share of commercial loans, NPL this is the ratio of non-current loans to loans, HHI-Loan is the Herfindahl index of loan portfolio diversification and Allow is the loss allowance to loan. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

Table 3.5 Table Regression Results to Loan Determinants Regression Across Bank Samples

	Bank Sample	Small Banks	Medium Banks	Large Banks
L. Loan	0.633***	0.608***	0.663***	0.604***
	(0.027)	(0.044)	(0.030)	(0.054)
L. Asset	0.046	0.151**	-0.075*	0.052
	(0.044)	(0.071)	(0.044)	(0.072)
L. Fund	0.001	-0.006**	0.001	-0.005
	(0.002)	(0.003)	(0.002)	(0.005)
L. Commitment	0.029***	0.022**	0.033***	0.017
	(0.007)	(0.011)	(0.007)	(0.017)
L. NPL	-0.006***	-0.009***	-0.005***	-0.009***
	(0.001)	(0.002)	(0.001)	(0.003)
L. Allow	-0.046***	-0.023*	-0.055***	-0.049***
	(0.009)	(0.012)	(0.008)	(0.019)
L. ROA	-0.130***	-0.133*	-0.170***	-0.161***
	(0.036)	(0.072)	(0.038)	(0.055)
L.Net-Income	0.134***	0.140*	0.173***	0.176***
	(0.037)	(0.072)	(0.039)	(0.054)
L. Capital-Ratio	0.076***	0.070	0.015	0.125**
	(0.025)	(0.052)	(0.028)	(0.050)
L. Liquidity1	-0.030***	0.004	-0.013*	-0.048***
	(0.008)	(0.012)	(0.007)	(0.015)
L. Capital-Gap	0.129***	0.041	0.140***	0.055
	(0.045)	(0.103)	(0.045)	(0.116)
L. Liquidity1* L. Capital-Gap	-0.053*	-0.015	-0.030	-0.126
	(0.031)	(0.057)	(0.038)	(0.078)
Capital-State*L. Liquidity1* L. Capital-Gap	0.105***	-0.102**	0.096***	0.134***
	(0.037)	(0.047)	(0.033)	(0.048)
Capital-State	0.039***	0.077***	0.048***	0.027***
	(0.005)	(0.010)	(0.005)	(0.008)
Constant	1.992***	0.841*	2.433***	2.006***
	(0.256)	(0.504)	(0.314)	(0.333)
Observations	6,276	1,021	3,027	1,760
R-squared	0.717	0.591	0.715	0.761

Notes: L. Loan is the lag of the sum of agricultural loans, commercial loans, consumer loans & real estate loans, L. Asset is the lag of total bank assets, L. Fund is the lag of the ratio of non-deposit liabilities to total assets, L. Commitment is the lag of the total unused bank commitments, L. NPL is the lag of the ratio of non-current loans to loans, L. Allow is the lag of loss allowance to loan, L. ROA is the return on assets, L. Net-Income is the after tax revenue, L. Capital-Ratio is the lag of tier-1 risk-based capital ratio, L. Liquidity1 is the lag of the ratio of liquid assets to total assets, L. Capital-Gap is the lag of the difference between target capital and observed capital and Capital-State is a dummy variable which equals 1 if bank's current target capital is greater than observed current capital and equals 0 if bank's current target capital is less than observed current capital. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

Table 3.6 Marginal Effects Results Across Bank Samples

	L. Liquidity1	L. Capital-Gap	Capital-State
Overall Bank Sample			
Capital-State-Surplus	-0.030***	0.219***	
	(0.008)	(0.038)	
Capital-State-Deficit	-0.030***	0.043	0.039***
	(0.008)	(0.047)	(0.005)
Observations	6,276	6,276	6,276
Small Sized Banks			
	L. Liquidity1	L. Capital-Gap	Capital-State
Capital-State-Surplus	0.003	0.062	
	(0.012)	(0.061)	
Capital-State-Deficit	0.003	0.207***	0.078***
	(0.012)	(0.078)	(0.010)
Observations	1,021	1,021	1,021
Medium Sized Banks			
	L. Liquidity1	L. Capital-Gap	Capital-State
Capital-State-Surplus	-0.013*	0.190***	
	(0.007)	(0.047)	
Capital-State-Deficit	-0.013*	0.029	0.048***
	(0.007)	(0.034)	(0.005)
Observations	3,027	3,027	3,027
Large Sized Banks			
	L. Liquidity1	L. Capital-Gap	Capital-State
Capital-State-Surplus	-0.049***	0.291***	
	(0.015)	(0.097)	
Capital-State-Deficit	-0.048***	0.040	0.027***
	(0.015)	(0.059)	(0.008)
Observations	1,760	1,760	1,760

Notes: L. Liquidity1 is the lag of the ratio of liquid assets to total assets, L. Capital-Gap is the difference between target capital and observed capital and Capital-State is a dummy variable which equals 1 when a bank is facing a capital deficit (Positive Capital-Gap: Target capital is greater than observed capital) and equals 0 when a bank is having a capital surplus (Negative Capital-Gap: Target capital is less than observed capital). The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

Table 3.7 Linear Predictions at Different Liquidity1 Levels Across Bank Samples

	Bank Sample	Small Banks	Medium Banks	Large Banks
Liquidity Level 1- Capital Surplus	11.309***	9.820***	11.084***	12.487***
	(0.017)	(0.026)	(0.014)	(0.028)
Liquidity1 Level 1- Capital Deficit	11.349***	9.899***	11.133***	12.513***
	(0.016)	(0.024)	(0.014)	(0.027)
Liquidity1 Level 2- Capital Surplus	11.285***	9.822***	11.073***	12.448***
	(0.011)	(0.016)	(0.009)	(0.017)
Liquidity1 Level 2- Capital Deficit	11.325***	9.901***	11.122***	12.474***
	(0.010)	(0.015)	(0.008)	(0.015)
Liquidity1 Level 3- Capital Surplus	11.261***	9.825***	11.063***	12.409***
	(0.006)	(0.008)	(0.004)	(0.006)
Liquidity1 Level 3- Capital Deficit	11.301***	9.903***	11.111***	12.436***
	(0.004)	(0.007)	(0.003)	(0.005)
Liquidity1 Level 4- Capital Surplus	11.237***	9.828***	11.052***	12.370***
	(0.004)	(0.007)	(0.005)	(0.010)
Liquidity1 Level 4- Capital Deficit	11.276***	9.905***	11.101***	12.397***
	(0.004)	(0.008)	(0.005)	(0.010)
Observations	6,276	1,021	3,027	1,760

Notes: L. Liquidity1 is the lag of the ratio of liquid assets to total assets, Capital Surplus is experienced when the bank's target Capital-Ratio is less than observed Capital-Ratio while Capital Deficit is faced when the bank's target Capital-Ratio is greater than the observed Capital-Ratio. The bank sample liquidity1 range is from 0.058-0.65, the small banks' liquidity1 range is from 0.037-0.734, the medium banks' liquidity1 range is from 0.028-0.655 and the large banks liquidity1 range is from 0.028-0.463. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

Table 3.8 Marginal Effects of the Capital-Gap at Various Liquidity1 Levels Across Bank Samples

	Bank Sample	Small Banks	Medium Banks	Large Banks
Liquidity1 Level 1-Capital Surplus	0.320***	0.091	0.245**	0.508**
	(0.084)	(0.122)	(0.107)	(0.208)
Liquidity1 Level 1-Capital Deficit	-0.054	0.428***	-0.092	0.025
	(0.102)	(0.150)	(0.066)	(0.107)
Liquidity1 Level 2-Capital Surplus	0.278***	0.079	0.221***	0.408***
	(0.062)	(0.086)	(0.079)	(0.152)
Liquidity1 Level 2-Capital Deficit	-0.013	0.335***	-0.039	0.032
	(0.077)	(0.111)	(0.049)	(0.076)
Liquidity1 Level 3-Capital Surplus	0.235***	0.067	0.197***	0.307***
	(0.043)	(0.063)	(0.053)	(0.103)
Liquidity1 Level 3-Capital Deficit	0.028	0.242***	0.014	0.039
	(0.054)	(0.083)	(0.037)	(0.059)
Liquidity1 Level 4-Capital Surplus	0.192***	0.055	0.173***	0.206***
	(0.032)	(0.069)	(0.036)	(0.077)
Liquidity1 Level 4-Capital Deficit	0.069*	0.148*	0.067**	0.045
	(0.038)	(0.078)	(0.033)	(0.069)
Observations	6,276	1,021	3,027	1,760

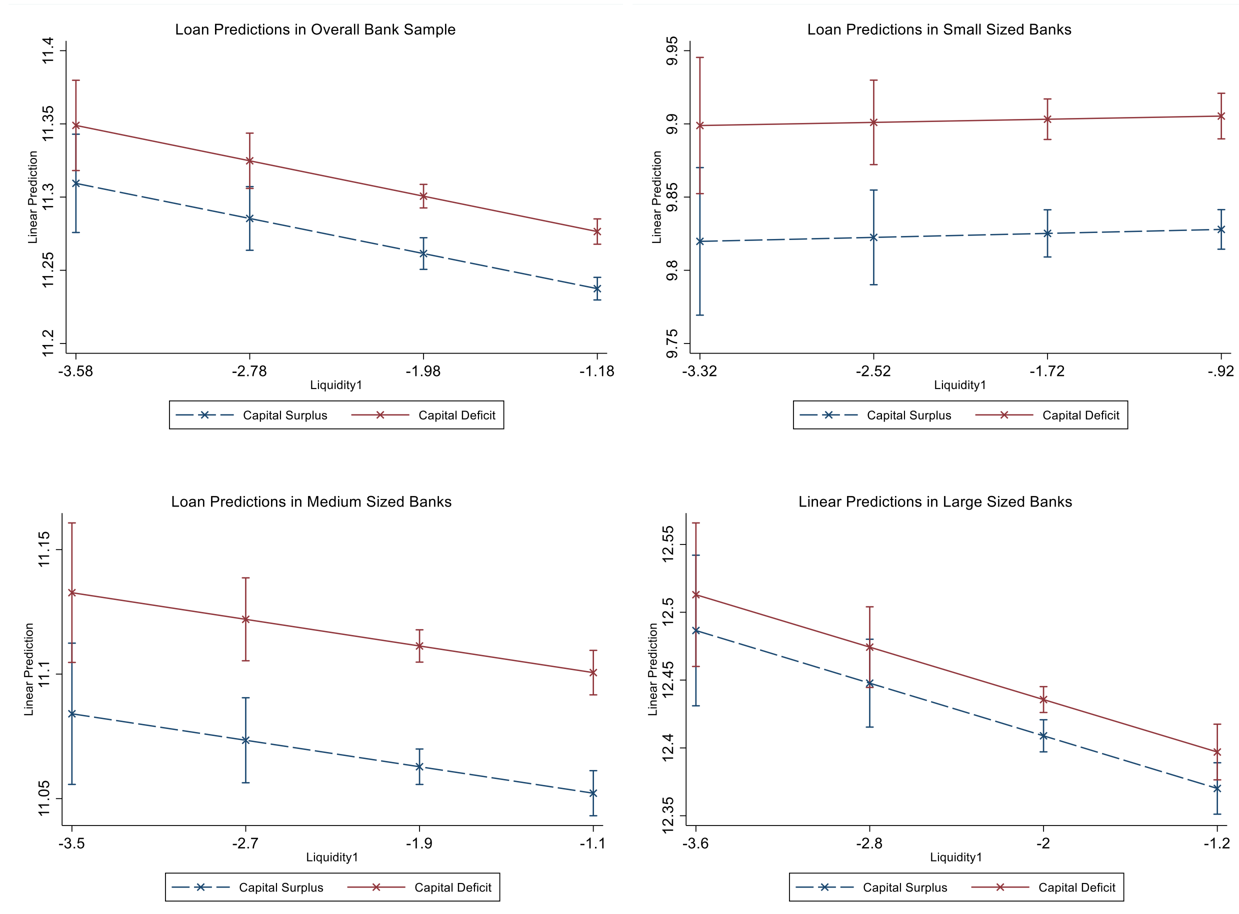
Notes: Liquidity1 is the lag of the ratio of liquid assets to total assets, Capital Surplus is experienced when the bank's optimal Capital-Ratio is greater than observed Capital-Ratio and Capital Deficit is faced when the bank's optimal Capital-Ratio is less than the observed Capital-Ratio. The bank sample liquidity1 range is from 0.058-0.65, the small banks' liquidity1 range is from 0.037-0.734, the medium banks' liquidity1 range is from 0.028-0.655 and the large banks liquidity1 range is from 0.028-0.463. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

Table 3.9 Marginal Effects of Liquidity1 at Different Capital-Gap levels Across Bank Samples

	Bank Sample	Small Banks	Medium Banks	Large Banks
Capital-Gap Level 1-Capital Surplus	-0.010	0.010	-0.003	-0.004
	(0.013)	(0.024)	(0.014)	(0.030)
Capital-Gap Level 1-Capital Deficit	-0.049***	0.051*	-0.036***	-0.051**
	(0.018)	(0.029)	(0.012)	(0.026)
Capital-Gap Level 2-Capital Surplus	-0.020**	0.007	-0.008	-0.023
	(0.009)	(0.016)	(0.009)	(0.020)
Capital-Gap Level 2-Capital Deficit	-0.039***	0.028	-0.026***	-0.050**
	(0.012)	(0.019)	(0.010)	(0.020)
Capital-Gap Level 3-Capital Surplus	-0.031***	0.004	-0.012*	-0.042***
	(0.008)	(0.012)	(0.007)	(0.015)
Capital-Gap Level 3-Capital Deficit	-0.029***	0.005	-0.016**	-0.049***
	(0.008)	(0.012)	(0.008)	(0.016)
Capital-Gap Level 4-Capital Surplus	-0.042***	0.001	-0.017*	-0.061***
	(0.011)	(0.017)	(0.009)	(0.018)
Capital-Gap Level 4-Capital Deficit	-0.019**	-0.019	-0.006	-0.048***
	(0.008)	(0.015)	(0.008)	(0.015)
Observations	6,276	1,021	3,027	1,760

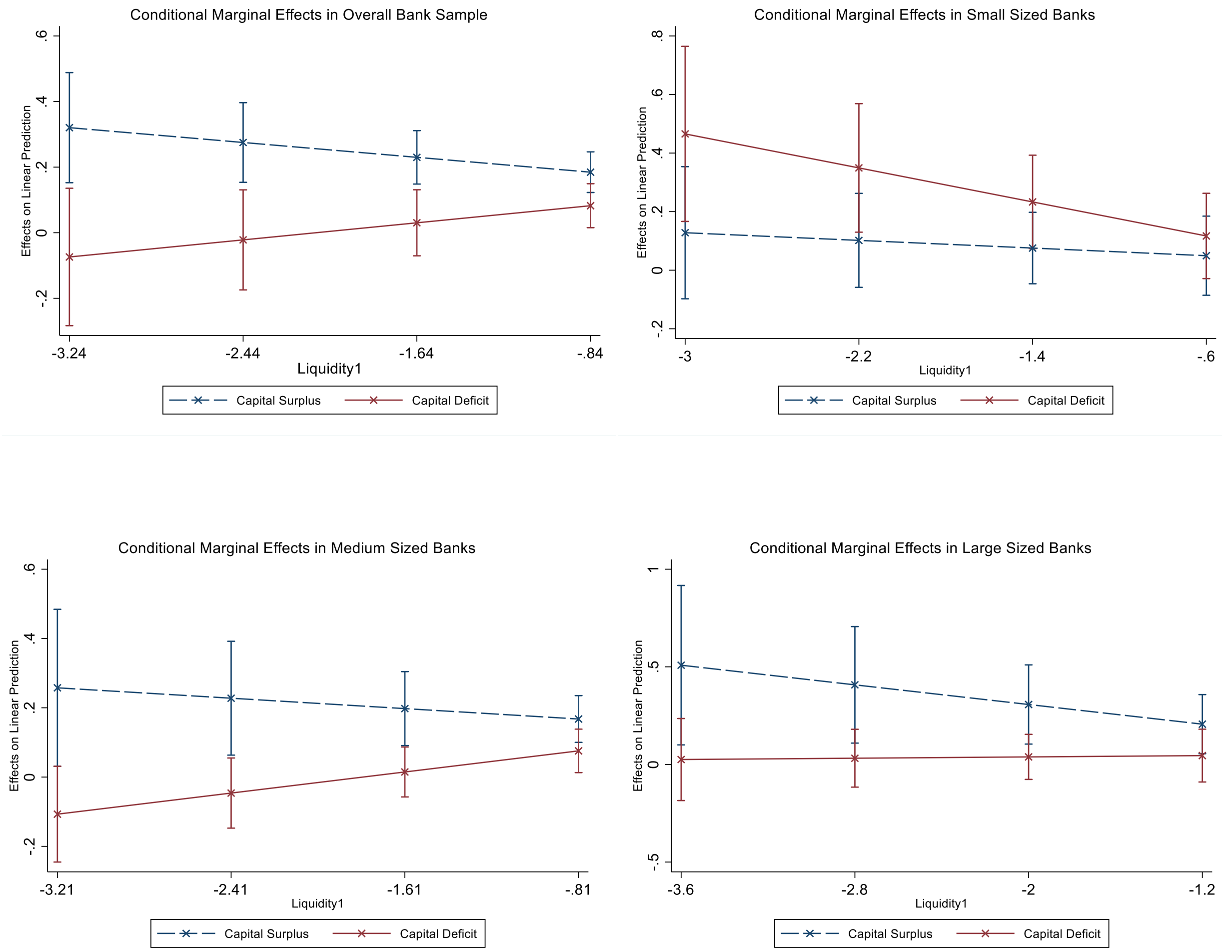
Notes: L. Liquidity1 is the lag of the ratio of liquid assets to total assets, Capital-Gap is the difference between target capital and observed capital, Capital Surplus is experienced when the bank's target Capital-Ratio is greater than observed Capital-Ratio and Capital Deficit is faced when the bank's target Capital-Ratio is less than the observed Capital-Ratio. The bank sample Capital-Gap range is from -0.38-0.287, the small banks' Capital-Gap range is from -0.41-0.32, the medium banks' Capital-Gap range is from -0.34-0.23 and the large banks Capital-Gap range is from -0.35-0.23. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

Figure 3.1 Graphs of Loan Predictions at different Liquidity Levels Across Bank Samples



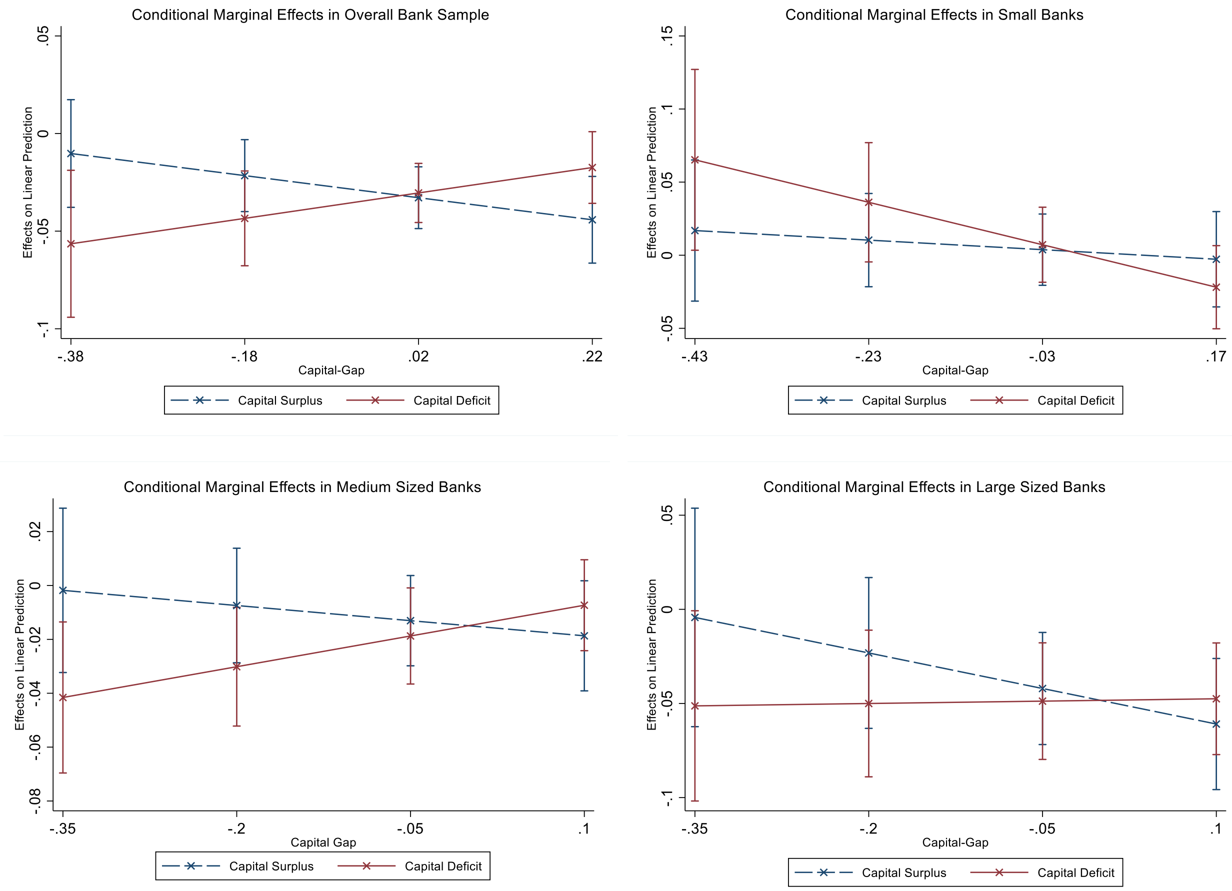
Notes: L. Liquidity1 is the lag of the ratio of liquid assets to total assets, Capital Surplus is experienced when the bank's optimal Capital-Ratio is greater than observed Capital-Ratio and Capital Deficit is faced when the bank's optimal Capital-Ratio is less than the observed Capital-Ratio. The bank sample liquidity range is from 0.058-0.65, the small banks' liquidity range is from 0.037-0.734, the medium banks' liquidity range is from 0.028-0.655 and the large banks liquidity range is from 0.028-0.463. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

Figure 3.2 Marginal Effects Graphs of Capital-Gap at different Liquidity1 Levels Across Bank Samples



Notes: L. Liquidity1 is the lag of the ratio of liquid assets to total assets, Capital Surplus is experienced when the bank's optimal Capital-Ratio is greater than observed Capital-Ratio and Capital Deficit is faced when the bank's optimal Capital-Ratio is less than the observed Capital-Ratio. The bank sample liquidity range is from 0.058-0.65, the small banks' liquidity range is from 0.037-0.734, the medium banks' liquidity range is from 0.028-0.655 and the large banks liquidity range is from 0.028-0.463. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

<u>Figure 3.3 Marginal Effects Graphs of Liquidity1 at Different Capital-Gap Levels Across Bank Samples</u>



Notes: L. Liquidity1 is the lag of the ratio of liquid assets to total assets, Capital-Gap is the difference between target capital and observed capital, Capital Surplus is experienced when the bank's target capital-ratio is greater than observed capital-ratio and capital deficit is faced when the bank's optimal capital-ratio is less than the observed capital-ratio. The bank sample capital-Gap range is from -0.38-0.287, the small banks' capital-Gap range is from -0.41-0.32, the medium banks' capital-Gap range is from -0.34-0.23 and the large banks capital-Gap range is from -0.35-0.23. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

Table 3.10 Robustness Check Results for Loan Determinants Model Across Bank Samples

	Bank sample	Small Banks	Medium Banks	Large Banks
L. Loan	0.633***	0.607***	0.662***	0.616***
	(0.028)	(0.046)	(0.031)	(0.054)
L. Asset	0.052	0.159**	-0.070	0.046
	(0.042)	(0.072)	(0.047)	(0.074)
L. Fund	0.001	-0.006**	0.001	-0.004
	(0.002)	(0.003)	(0.002)	(0.005)
L. Commitment	0.029***	0.022**	0.032***	0.017
	(0.007)	(0.011)	(0.007)	(0.017)
L. NPL	-0.006***	-0.009***	-0.005***	-0.009***
	(0.001)	(0.002)	(0.001)	(0.003)
L. Allow	-0.044***	-0.023*	-0.055***	-0.049***
	(0.008)	(0.012)	(0.008)	(0.019)
L. ROA	-0.125***	-0.128*	-0.167***	-0.159***
	(0.035)	(0.072)	(0.039)	(0.055)
L. Net-Income	0.129***	0.135*	0.170***	0.175***
	(0.036)	(0.072)	(0.040)	(0.054)
L. Capital-Ratio	0.078***	0.072	0.015	0.128**
	(0.025)	(0.052)	(0.028)	(0.050)
L. Liquidity2	-0.032***	0.003	-0.015*	-0.043***
	(0.008)	(0.013)	(0.009)	(0.015)
L. Capital-Gap	0.137***	0.030	0.137***	0.074
	(0.041)	(0.089)	(0.041)	(0.103)
L. Liquidity2*L. Capital-Gap	-0.057*	-0.033	-0.038	-0.136*
	(0.033)	(0.054)	(0.042)	(0.082)
Capital-State*L. Liquidity2* L. Capital-Gap	0.122***	-0.112**	0.114***	0.157***
	(0.042)	(0.054)	(0.040)	(0.056)
Capital-State	0.039***	0.077***	0.048***	0.027***
	(0.005)	(0.010)	(0.004)	(0.008)
Constant	1.996***	0.820	2.428***	1.981***
	(0.253)	(0.497)	(0.314)	(0.333)
Observations	6,276	1,021	3,027	1,760
R-squared	0.717	0.591	0.715	0.760

Notes: L. Loan is the lag of the sum of agricultural loans, commercial loans, consumer loans & real estate loans, L. Asset is the lag of total bank assets, L. Fund is the lag of the ratio of non-deposit liabilities to total assets, L. Commitment is the lag of the total unused bank commitments, L. NPL is the lag of the ratio of non-current loans to loans, L. Allow is the lag of loss allowance to loan, L. ROA is the return on assets, L. Net-Income is the after tax revenue, L. Capital-Ratio is the lag of tier-1 risk-based capital ratio, L. Liquidity2 is the lag of the ratio of liquid assets to deposits, L. Capital-Gap is the lag of the difference between target capital and observed capital and Capital-State is a dummy variable which equals 1 if bank's current target capital is greater than observed current capital and equals 0 if bank's current target capital is less than observed current capital. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

Table 3.11 Marginal Effects Across Bank Samples

	L. Liquidity2	L. Capital-Gap	Capital-State
Entire Bank Sample			
Capital-State-Surplus	-0.032***	0.219***	
	(0.008)	(0.038)	
Capital-State-Deficit	-0.032***	0.043	0.039***
	(0.008)	(0.046)	(0.005)
Observations	6,276	6,276	6,276
Small Sized Banks			
	L. Liquidity2	L. Capital-Gap	Capital-State
Capital-State-Surplus	0.003	0.068	
	(0.013)	(0.061)	
Capital-State-Deficit	0.002	0.200***	0.078***
	(0.012)	(0.076)	(0.010)
Observations	1,021	1,021	1,021
Medium Sized Banks			
	L. Liquidity2	L. Capital-Gap	Capital-State
Capital-State-Surplus	-0.015*	0.190***	
	(0.009)	(0.048)	
Capital-State-Deficit	-0.015*	0.030	0.049***
	(0.009)	(0.034)	(0.004)
Observations	3,027	3,027	3,027
Large Sized Banks			
	L. Liquidity2	L. Capital-Gap	Capital-State
Capital-State-Surplus	-0.043***	0.299***	
	(0.015)	(0.098)	
Capital-State-Deficit	-0.043***	0.040	0.027***
	(0.015)	(0.060)	(0.008)
Observations	1,760	1,760	1,760

Notes: L. Liquidity2 is the lag of the ratio of liquid assets to deposits, L. Capital-Gap is the difference between target capital and observed capital and Capital-State is a dummy variable which equals 1 when a bank is facing a capital deficit (Positive Capital-Gap: Target capital is greater than observed capital) and equals 0 when a bank is having a capital surplus (Negative Capital-Gap: Target capital is less than observed capital). The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

Table 3.12 Linear Predictions at different Liquidity2 Levels Across Bank Samples

	Bank Sample	Small Banks	Medium Banks	Large Banks
Liquidity2 Level 1- Capital Surplus	11.310***	9.821***	11.086***	12.480***
	(0.016)	(0.026)	(0.017)	(0.030)
Liquidity2 Level 1- Capital Deficit	11.349***	9.901***	11.135***	12.507***
	(0.015)	(0.024)	(0.016)	(0.028)
Liquidity2 Level 2- Capital Surplus	11.284***	9.823***	11.075***	12.446***
	(0.010)	(0.016)	(0.010)	(0.018)
Liquidity2 Level 2- Capital Deficit	11.324***	9.902***	11.123***	12.472***
	(0.009)	(0.014)	(0.010)	(0.016)
Liquidity2 Level 3- Capital Surplus	11.259***	9.825***	11.063***	12.411***
	(0.005)	(0.008)	(0.004)	(0.007)
Liquidity2 Level 3- Capital Deficit	11.298***	9.904***	11.111***	12.438***
	(0.004)	(0.006)	(0.003)	(0.005)
Liquidity2 Level 4- Capital Surplus	11.234***	9.827***	11.051***	12.376***
	(0.005)	(0.008)	(0.005)	(0.009)
Liquidity2 Level 4- Capital Deficit	11.273***	9.905***	11.099***	12.403***
	(0.005)	(0.009)	(0.005)	(0.010)
Observations	6,276	1,021	3,027	1,760

Notes: L. Liquidity2 is the lag of the ratio of liquid assets to deposits, Capital Surplus is experienced when the bank's target Capital-Ratio is less than observed Capital-Ratio while Capital Deficit is faced when the bank's target Capital-Ratio is greater than the observed Capital-Ratio. The bank sample liquidity2 range is from 0.039-0.811, the small banks' liquidity2 range is from 0.048-0.943, the medium banks' liquidity2 range is from 0.039-0.818 and the large banks liquidity2 range is from 0.035-0.570. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

Table 3.13 Marginal Effects of Capital-Gap at Different Liquidity2 Levels Across Bank Samples

	Bank Sample	Small Banks	Medium Banks	Large Banks
Liquidity2 Level 1- Capital Surplus	0.320***	0.128	0.258**	0.541**
	(0.086)	(0.115)	(0.116)	(0.222)
Liquidity2 Level 1- Capital Deficit	-0.074	0.465***	-0.107	0.002
	(0.107)	(0.153)	(0.071)	(0.108)
Liquidity2 Level 2- Capital Surplus	0.275***	0.102	0.228***	0.432***
	(0.062)	(0.082)	(0.084)	(0.162)
Liquidity2 Level 2- Capital Deficit	-0.022	0.349***	-0.046	0.019
	(0.078)	(0.112)	(0.052)	(0.078)
Liquidity2 Level 3- Capital Surplus	0.230***	0.076	0.198***	0.323***
	(0.042)	(0.062)	(0.054)	(0.108)
Liquidity2 Level 3- Capital Deficit	0.030	0.233***	0.015	0.036
	(0.051)	(0.081)	(0.037)	(0.060)
Liquidity2 Level 4- Capital Surplus	0.185***	0.049	0.168***	0.215***
	(0.032)	(0.069)	(0.034)	(0.076)
Liquidity2 Level 4- Capital Deficit	0.082**	0.117	0.076**	0.053
	(0.034)	(0.074)	(0.032)	(0.067)
Observations	6,276	1,021	3,027	1,760

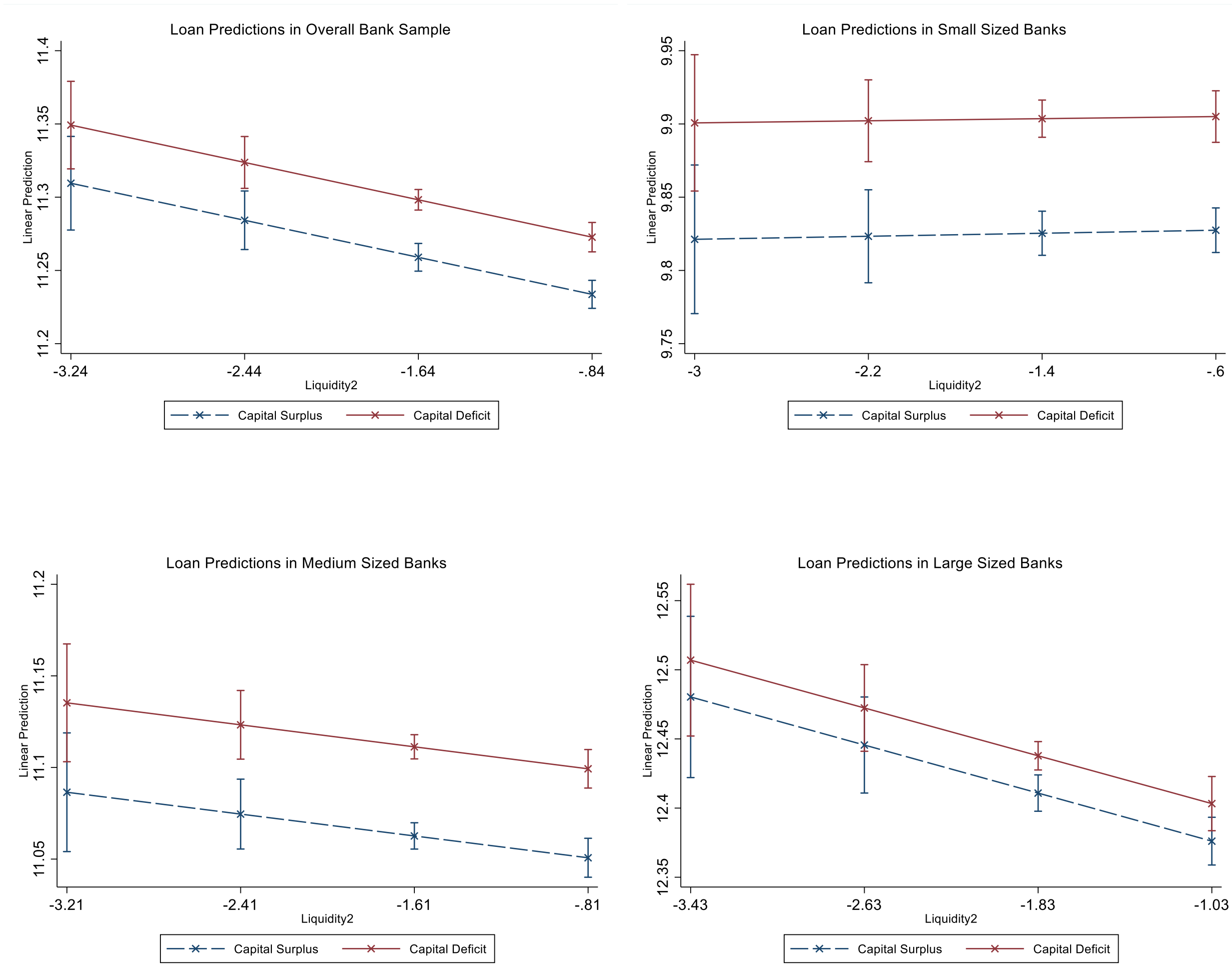
Notes: Liquidity2 is the lag of liquid assets to deposits, Capital-Gap is the difference between target capital and observed capital, Capital Surplus is experienced when the bank's optimal Capital-Ratio is greater than observed Capital-Ratio and Capital Deficit is faced when the bank's optimal Capital-Ratio is less than the observed Capital-Ratio. The bank sample liquidity2 range is from 0.039-0.811, the small banks' liquidity2 range is from 0.048-0.943, the medium banks' liquidity2 range is from 0.039-0.818 and the large banks liquidity2 range is from 0.035-0.570. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

Table 3.14 Marginal Effects of Liquidity2 at Different Capital-Gap levels Across Bank Samples

	Bank Sample	Small Banks	Medium Banks	Large Banks
Capital-Gap Level 1-Capital Surplus	-0.010	0.016	-0.002	0.004
	(0.014)	(0.024)	(0.016)	(0.031)
Capital-Gap Level 1-Capital Deficit	-0.056***	0.062**	-0.042***	-0.051**
	(0.019)	(0.030)	(0.014)	(0.026)
Capital-Gap Level 2-Capital Surplus	-0.022**	0.010	-0.007	-0.016
	(0.009)	(0.016)	(0.011)	(0.021)
Capital-Gap Level 2-Capital Deficit	-0.043***	0.033*	-0.030***	-0.047**
	(0.012)	(0.020)	(0.011)	(0.020)
Capital-Gap Level 3-Capital Surplus	-0.033***	0.003	-0.013	-0.036**
	(0.008)	(0.013)	(0.009)	(0.015)
Capital-Gap Level 3-Capital Deficit	-0.030***	0.004	-0.019**	-0.044***
	(0.008)	(0.013)	(0.009)	(0.016)
Capital-Gap Level 4-Capital Surplus	-0.044***	-0.003	-0.019*	-0.057***
	(0.011)	(0.017)	(0.010)	(0.018)
Capital-Gap Level 4-Capital Deficit	-0.017*	-0.025	-0.007	-0.041***
	(0.009)	(0.015)	(0.009)	(0.015)
Observations	6,276	1,021	3,027	1,760

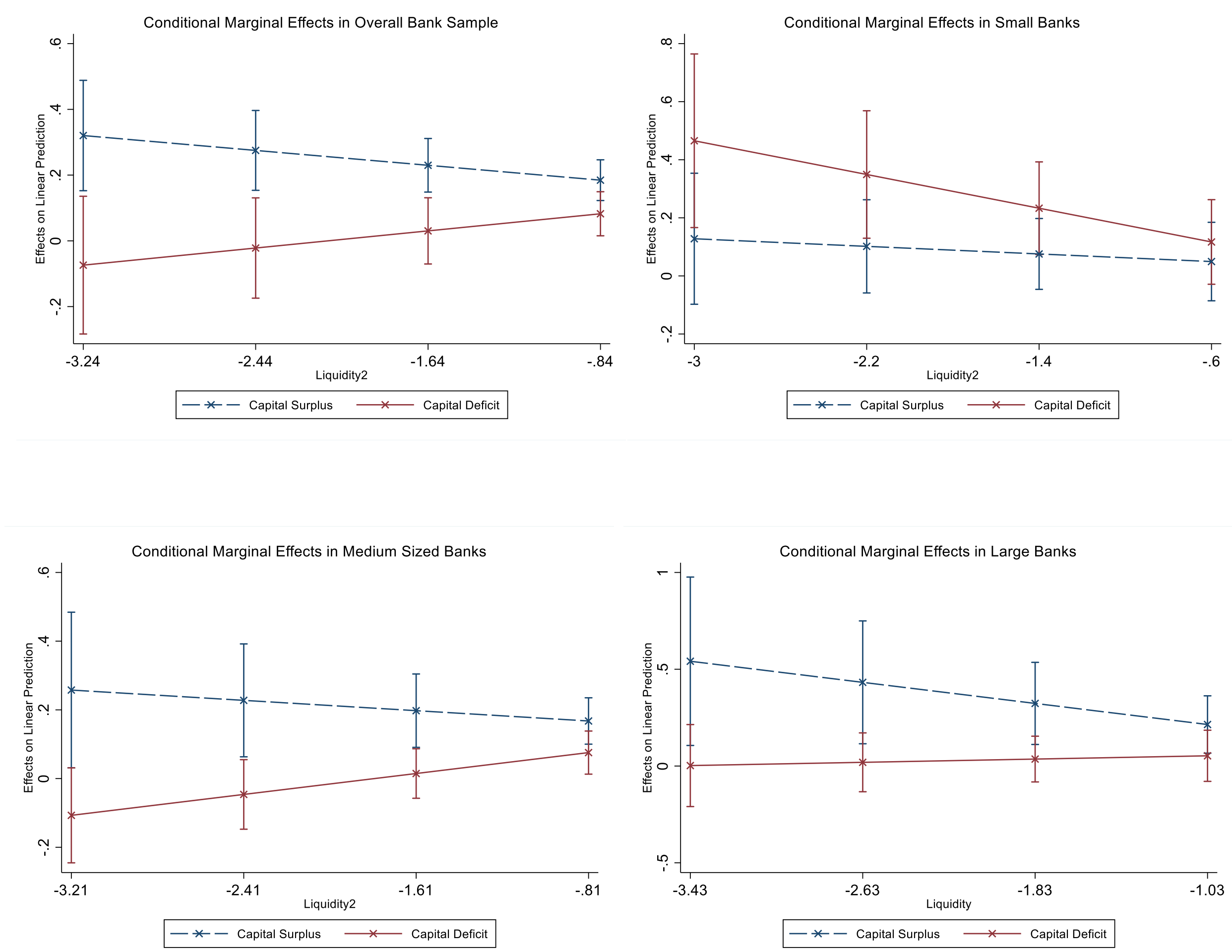
Notes: L. Liquidity2 is the lag of the ratio of liquid assets to deposits, Capital-Gap is the difference between target capital and observed capital, Capital Surplus is experienced when the bank's target Capital-Ratio is greater than observed Capital-Ratio and Capital Deficit is faced when the bank's target Capital-Ratio is less than the observed Capital-Ratio. The bank sample Capital-Gap range is from -0.38-0.287, the small banks' Capital-Gap range is from -0.41-0.32, the medium banks' Capital-Gap range is from -0.34-0.23 and the large banks Capital-Gap range is from -0.35-0.23. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

Figure 3.4 Graphs of Loan Predictions at different Liquidity2 Levels Across Bank Samples



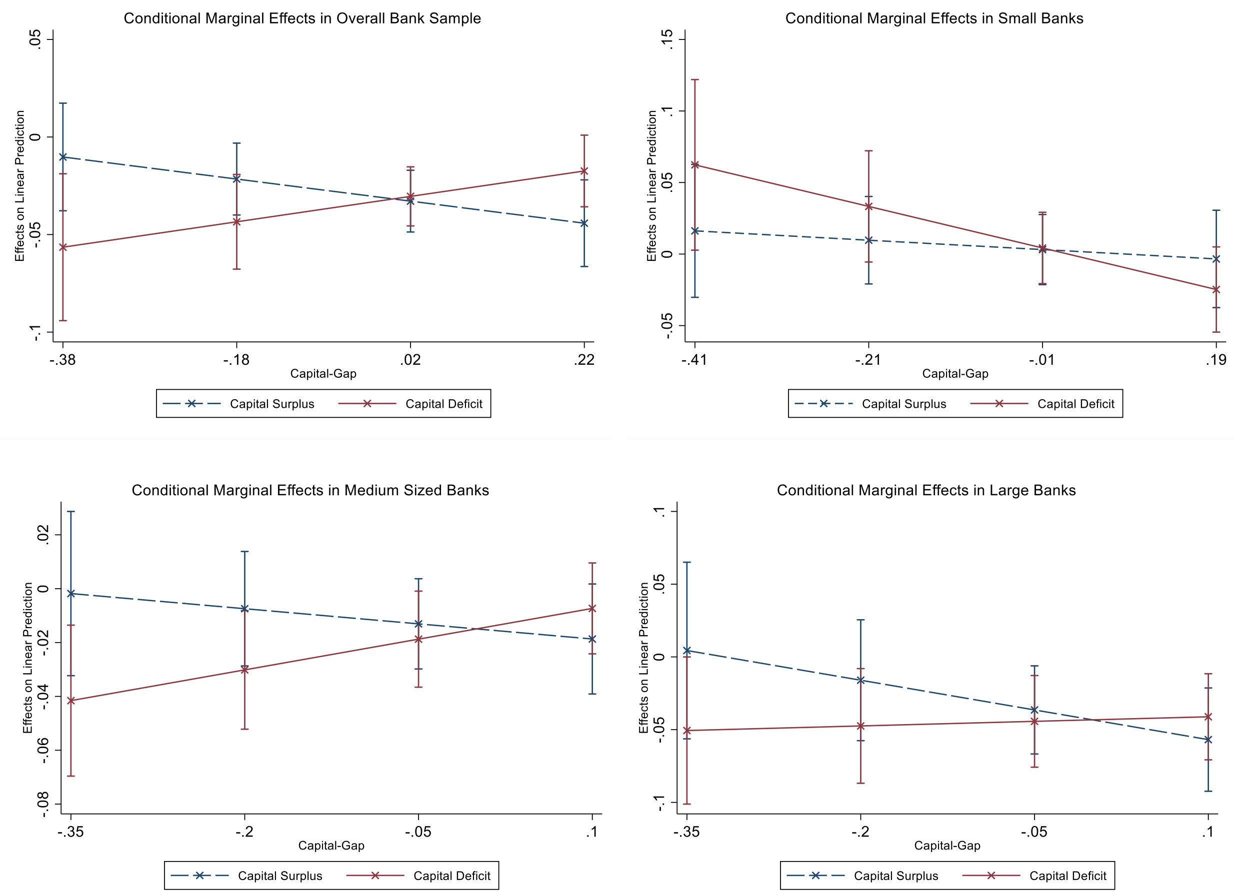
Notes: Liquidity2 is the lag of the ratio of liquid assets to deposits, Capital Surplus is experienced when the bank's target Capital-Ratio is less than observed Capital-Ratio while Capital Deficit is faced when the bank's target Capital-Ratio is greater than the observed Capital-Ratio. The bank sample liquidity2 range is from 0.039-0.811, the small banks' liquidity2 range is from 0.048-0.943, the medium banks' liquidity2 range is from 0.039-0.818 and the large banks liquidity2 range is from 0.035-0.570. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***$p<0.01$, **$p <0.05$ and *$p<0.1$ representing 99%, 95% and 90% confidence interval.

Figure 3.5 Marginal Effects Graphs of Capital-Gap at different Liquidity2 Levels Across Bank Samples



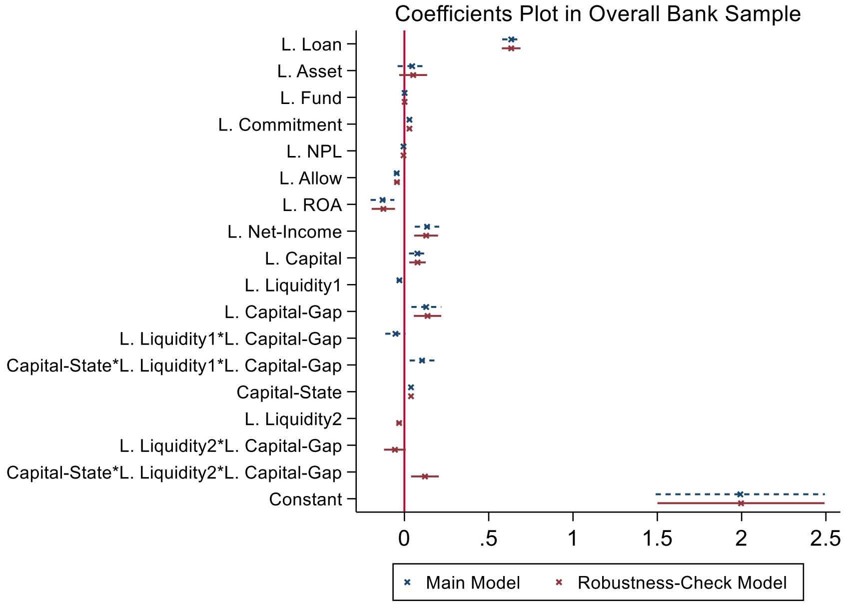
Notes: Liquidity2 is the lag of the ratio of liquid assets to deposits, Capital-Gap is the difference between target capital and observed capital, Capital Surplus is experienced when the bank's optimal Capital-Ratio is greater than observed Capital-Ratio and Capital Deficit is faced when the bank's optimal Capital-Ratio is less than the observed Capital-Ratio. The bank sample liquidity2 range is from 0.039-0.811, the small banks' liquidity2 range is from 0.048-0.943, the medium banks' liquidity2 range is from 0.039-0.818 and the large banks liquidity2 range is from 0.035-0.570. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

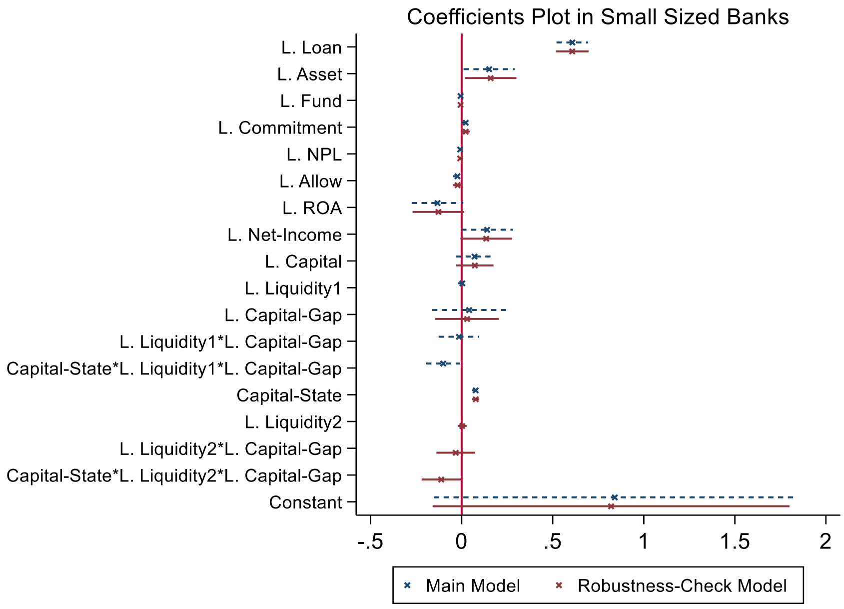
Figure 3.6 Marginal Effects Graphs of Liquidity2 at Different Capital-Gap Levels Across Bank Samples



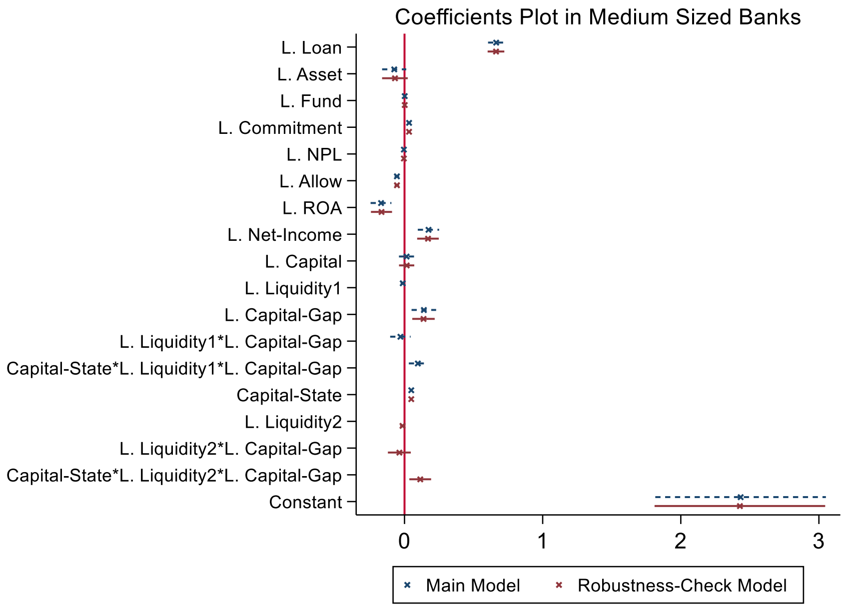
Notes: Liquidity2 is the lag of the ratio of liquid assets to deposits, Capital-Gap is the difference between target capital and observed capital, Capital Surplus is experienced when the bank's optimal Capital-Ratio is greater than observed Capital-Ratio and Capital Deficit is faced when the bank's optimal Capital-Ratio is less than the observed Capital-Ratio. The bank sample liquidity2 range is from 0.039-0.811, the small banks' liquidity2 range is from 0.048-0.943, the medium banks' liquidity2 range is from 0.039-0.818 and the large banks liquidity2 range is from 0.035-0.570. The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.

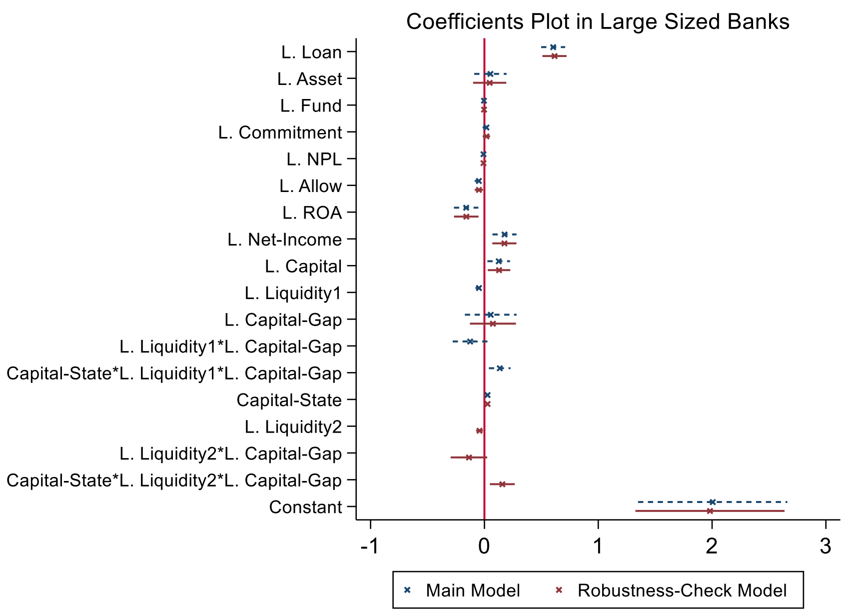
Figure 3.7 Coefficient Plots for Main Model and Robustness Check Across Bank Samples





Notes: L. Loan is the lag of the sum of agricultural loans, commercial loans, consumer loans & real estate loans, L. Asset is the lag of total bank assets, L. Fund is the lag of the ratio of non-deposit liabilities to total assets, L. Commitment is the lag of the total unused bank commitments, L. NPL is the lag of the ratio of non-current loans to loans, L. Allow is the lag of loss allowance to loan, L. ROA is the return on assets, L. Net-Income is the after tax revenue, L. Capital-Ratio is the lag of tier-1 risk-based capital ratio, L. Liquidity1 is the lag of the ratio of liquid assets to total assets, L. Capital-Gap is the lag of the difference between target capital and observed capital, Capital-State is a dummy variable which equals 1 if bank's current target capital is greater than observed current capital and equals 0 if bank's current target capital is less than observed current capital and L. Liquidity2 is the lag of the of liquid assets to deposits . The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.





Notes: L. Loan is the lag of the sum of agricultural loans, commercial loans, consumer loans & real estate loans, L. Asset is the lag of total bank assets, L. Fund is the lag of the ratio of non-deposit liabilities to total assets, L. Commitment is the lag of the total unused bank commitments, L. NPL is the lag of the ratio of non-current loans to loans, L. Allow is the lag of loss allowance to loan, L. ROA is the return on assets, L. Net-Income is the after tax revenue, L. Capital-Ratio is the lag of tier-1 risk-based capital ratio, L. Liquidity1 is the lag of the ratio of liquid assets to total assets, L. Capital-Gap is the lag of the difference between target capital and observed capital, Capital-State is a dummy variable which equals 1 if bank's current target capital is greater than observed current capital and equals 0 if bank's current target capital is less than observed current capital and L. Liquidity2 is the lag of the ratio of liquid assets to deposits . The standard errors are in the parentheses and are clustered standard errors at the bank level with ***p<0.01, **p <0.05 and *p<0.1 representing 99%, 95% and 90% confidence interval.