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Foreclosures: Relationship Lending in the Consumer Market and Its Aftermath

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Relationship lending theory suggests that lenders in close proximity to their borrowers might be the most efficient providers of screening and monitoring services, because the cost of collecting information declines with distance. In agreement with this theory, I present evidence that ties bank branch presence to borrower performance in the low-income housing market.

Keywords: Relationship lending, foreclosure, branch proximity

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1. Introduction

Banks are experts in lending to informationally opaque borrowers because banks specialize in establishing long-term relationships with customers and collecting soft (i.e. information that is difficult to express in hard numbers, such as honesty and diligence) information about them. This information allows banks to assess the creditworthiness of applicants who would not qualify for a loan if the decision was based solely on a credit score (Berger and Udell, 1995; Petersen and Rajan, 1994). In areas where informational opacity is a problem, the proximity of borrowers to the lender plays a crucial role in enhancing credit availability. Proximity is important because the costs of collecting information come down with declining distance, and this affects availability and terms of credit (Petersen and Rajan, 1994; Degryse and Ongena, 2005; Hauswald and Marquez, 2006; Agarwal and Hauswald, 2006). Ergungor (2006) extends the implications of this theory to the mortgage market for low-moderate income borrowers and finds that the presence of a bank branch in communities of low-moderate income is associated with greater access to home-purchase mortgages; namely, higher quantity and lower price.

In this paper, I go one step further and look at the aftermath of relationship lending. Do relationships make a difference in terms of loan performance? For example, if relationships improve the effectiveness of the screening process before lending, and the bank continues to monitor the loan after origination, one would expect to observe a lower foreclosure rate (number of foreclosures per housing unit with a mortgage).[1] Monitoring, in this case, would entail identifying any problems early on and renegotiating loan terms if necessary to avoid foreclosure, a process that entails substantial deadweight losses (Harding and Sirmans, 2002). To the extent that information-collection costs decline with declining distance to the lender, the structure of the banking market in low-income areas should matter. In this paper, I look for evidence that ties branch presence to borrower performance in the housing market. The main question of the paper is: does bank-branch presence in low-income communities have an impact on home foreclosure rates?

[1] Note that the *number* of foreclosures may increase with more lending. However, the foreclosure *rate* may still decline.

I find that in Ohio, county-level foreclosure rates are negatively correlated with the presence of bank branches in the low-moderate income neighborhoods of the county. Furthermore, I find that the distance between the branch and the community is important; the closer the branches are, the stronger is the effect on foreclosures.

This paper is closely related to the literature of two research areas. First, there is a rich literature in the area of real estate on the topics of mortgage defaults and foreclosures. Using individual mortgage data, researchers have identified some of the characteristics of borrowers, loans, and markets that seem to have a significant effect on the probability of default, the probability of foreclosure given default, and the amount of loss given foreclosure (Avery et al., 1996; Ambrose and Capone, 1998; Phillips and VanderHoff, 2004; Capozza and Thomson, 2005). Examples of each type of characteristic include whether or not borrowers are self-employed, the loan-to-value ratio of the mortgage, and the foreclosure laws of the state. Yet this literature has been quiet on the impact of the structure of the local lending market and the distance between borrowers and lenders on the foreclosure rates. This paper is the first to tackle these issues.

The other literature my paper is related to is the work on relationship lending. Small banks have long been recognized as an important supplier of credit to informationally opaque small businesses (Berger, Saunders, Scalise, and Udell, 1998; Peek and Rosengren, 1998, Strahan and Weston, 1998; Cole et al., 2004; Berger et al., 2005). The disappearance of a small bank from a market has been associated with increased use of expensive trade credit, but no long-term credit constraints have been found (Jayaratne and Wolken, 1999). More recently, however, DeYoung, Glennon, and Nigro (2006) examined small business loan defaults and found that loan default probabilities increase with the distance to the lender. In this paper, I provide further support for the relationship theory by confirming the importance, with respect to mortgage foreclosures, of bank presence and distance to the lender. I also find that lender size is important. My results are driven mainly by the presence of small banks (total assets less than $1 billion) in low-moderate income areas.

The rest of the paper is organized as follows. Section 2 provides the background for the analysis and presents the paper's main hypothesis. Section 3 describes the data. Section 4 explains the method. Section 5 presents the results. Section 6 concludes.

2. Background and Hypothesis

The presence of a bank branch in low-moderate income neighborhoods is associated with more abundant lending (Ergungor, 2006). The reason a branch presence is thought to make a difference is because banks specialize in lending to the informationally opaque borrowers that predominate in such neighborhoods. Credit score-based lending rules are often infeasible in these areas, where credit histories are tainted by past problems or simply nonexistent. Estimates for these types of consumers vary between 10 and 22 million households ("Innovations in Personal Finance for the Unbanked: Emerging Practices from the Field", Fannie Mae Foundation Case Studies, 2003).

The advantage banks have in such an environment comes from their ability to extract nonpublic information (referred to as soft information in this literature) about their customers from their multiple interactions with them (Berger, 1999; Degryse and Van Cayseele, 2000). For example, Mester, Nakamura, and Renault (1998) find that commercial borrowers' checking account transactions contain information that can be used to predict loan delinquencies. Banks can use such information to screen potential borrowers (Allen, 1990; Ramakrishnan and Thakor, 1984) and monitor them later on (Diamond, 1984; Gorton and Haubrich, 1987; Diamond, 1991; Winton, 1995; Gorton and Kahn, 2000). Such screening and monitoring work to alleviate the incentive distortions caused by asymmetric information and increase the likelihood of efficient project continuations (Von Thadden, 1992).

These principles that arise out of corporate finance studies may also apply to mortgage lending in low-moderate neighborhoods. A bank could glean useful information about a customer's creditworthiness from his transactions with the bank, such as how many checks he bounces every month, how many weeks he can go without using a payday loan, or how often he has to renegotiate the repayment schedule. Armed with this information, the bank might weed out excessively poor credit risks beforehand, offer loan products tailored to the borrower's needs, and if it is efficient to do so, avoid costly foreclosure by renegotiating the terms of the mortgage.

A major friction in this process, however, is information collection costs, and this is where the distance between the borrower and the lender becomes crucial. Geographic proximity lowers the cost of collecting soft information (e.g., for communication and transportation), which has been shown to be related to the finding that loan applicants close to their lenders are more likely to be approved and less likely to default (Petersen and Rajan, 2002; Brevoort and Hannan, 2004; DeYoung et al 2006).

The main hypothesis of this paper is based on the premise that soft information is important for screening and monitoring, and that lenders in close proximity to the borrower will be the most efficient providers of these services, because the cost of collecting information declines with distance. Therefore, I expect to observe declining foreclosure rates when there are banks present in low-moderate income neighborhoods. Note that this not to mean that the *number* of foreclosures will decline. As relationships generate more loans, a side effect might be an increase in the number of foreclosures. However, if the number of loans is increasing faster than foreclosures, the foreclosure *rate* may decline.

Hypothesis 1: *Foreclosure rates on housing loans to low-moderate income consumers will decline with increasing access to bank branches.*

The second hypothesis deals with the size of the banks that are physically present in the county. The small-business-lending literature suggests that small banks have an advantage over larger lenders in originating relationship loans. The source of their advantage is their organizational structure. Stein (2002) and Berger et al. (2005) explain that in a large financial institution with a hierarchical structure, a loan officer does not have an incentive to invest in soft information collection because he cannot easily transmit this information to his superiors. For example, a borrower's character (honesty, hard work) cannot be expressed in hard numbers to justify to the upper management why capital must be allocated to that borrower. Because the superiors---who may be located in a different city---have to base their capital allocation decisions on hard information, they may refuse to allocate capital to the loan officer. Anticipating that his efforts may go to waste, the loan officer does not invest in information collection in the first place. At the other extreme, in a small organization with a perfectly decentralized structure, the loan officer is his own CEO and has more freedom to allocate capital as he sees fit. This gives him a greater incentive to invest in soft information collection. The second hypothesis of the paper is based on small banks' advantage in processing soft information.

Hypothesis 2: *Foreclosure rates will decline more rapidly with increasing access to small-bank branches rather than large-bank branches.*

3. Data Description

I analyze the effect of bank-branch presence in low-moderate income neighborhoods on the foreclosure rates in Ohio's 88 counties. Admittedly, I do not know exactly in which income-level neighborhood the foreclosures have taken place. Yet it is not too farfetched to assume that they are more likely to occur in the lower-income areas of the county. Therefore, I expect to capture some correlation between branch presence in low-income areas and county-level foreclosures.

All information related to census tract characteristics comes from the 2000 Decennial Census. Information related to the mortgages that were originated within a county, such as quantity and price, comes from the Home Mortgage Disclosure Act (HMDA) Loan Application Register (LAR) data. The addresses I use to determine where bank branches are located come from the FDIC's Summary of Deposits file. In the remainder of this section, I will describe my data in greater detail.

3.1 Foreclosures

County-level foreclosure data come from the Ohio Supreme Court's annual Ohio Courts Summary – Courts of Common Pleas General Division. I collect this data for each year from 1999 to 2005. The foreclosure rate for each county at year t, $Foreclose_t$, is the number of new foreclosure filings per owner-occupied housing unit with a mortgage. The number of owner-occupied housing units with a mortgage is based on data from the 2000 Census. The Census Bureau examines a sample of housing units in each county and reports the number of housing units with and without a mortgage. This gives a fraction of units with and without a mortgage that I assume is valid for the entire county. Multiplying this fraction by the total number of owner-occupied housing units in the county gives the *total* number of owner-occupied housing units in the county with a mortgage.

3.2 Branch Presence

Because my foreclosure data are at county level, I must create a county-level measure for the degree of bank branch presence in the low-income neighborhoods of the county, where a neighborhood is delineated by the census tract it is in.[2] I begin by measuring the branch presence at census tract level for each census tract, then I aggregate it to county level. In the following two sections I describe each step in detail.

3.2.1 Branch Presence at Census Tract Level

The FDIC's Summary of Deposits file provides the branch addresses of every FDIC-insured institution in the country. There were 3,886 bank branches in Ohio in 1999. Using CRAWiz, a geocoding software package, each address is matched to a latitude and longitude. About 92 percent of the addresses match automatically; because of spelling errors or incomplete addresses, the rest must be matched manually. For those, I search for the correct address on the Internet and replace the old address with the new one in CRAWiz. If that fails, there are a few other alternatives. If the address is an intersection, I can point to the intersection on the CRAWiz map, and the software will use the latitude and longitude of that point. If there is ambiguity about the directional qualifier (e.g., North vs. South Main Street), I use Google satellite pictures to determine where the branch is located; for example, if 123 North Main Street is a residence and 123 South Main Street is a business building, the branch is in the business building. Using this method, I determine the location of every branch of FDIC-insured institutions in the state.

To obtain a measure of branch presence in a census tract, I determine the distance of each branch to the census tract centroid using the Haversine Formula (Sinnott, 1984). Then, I take all the branches within 10 miles of the centroid and calculate the local branch access variable as:

[2] Census tracts are designed by the Census Bureau to be relatively homogeneous units in terms of population (about 4,000 inhabitants), population characteristics, economic status, and living conditions.

$$Branches_{co,ct} = \ln\left(1 + \sum_{k=1}^{n_b} \frac{1}{D_{ct,k}}\right) \tag{1}$$

where $Branches_{co,ct}$ is the branch access variable for census tract *ct* in county *co*, n_b is the number of branches within 10-mile radius of the centroid of census tract *ct*, $D_{ct,k}$ is the distance of branch *k* to the centroid of census tract *ct*. In accordance with the relationship literature, this construction assumes that the farther the branch is from the centroid, the less likely it is to improve the accessibility of banking services in the census tract. Five important issues about this variable are worth mentioning. First, this measure is better than counting only the branches inside a census tract because in urban areas, one could miss a branch across a street if the tract boundary is the street. Including all branches within a certain distance to the tract solves this problem. Second, the implicit assumption is that branches farther than 10 miles have no effect on branch access. Ergungor (2006) finds that including branches more distant than 10 miles increases the noise level in the measure; so, I stop at 10 miles. Third, I assume that bank branches can supply relationship services with perfect elasticity. So, if one branch falls within 10 miles of multiple census tracts, the quality of its service to each tract will be a function of its distance to the tract and not the number of tracts it has to serve. In other words, the *Branches* variable for different census tracts may include the same branch, as if the branch exclusively served each community alone. Fourth, the natural log captures the idea that the marginal contribution of each additional branch will decline in urban areas with a large number of bank branches. Fifth, if the branch is located exactly over the census tract centroid, $Branches_{co,ct}$ will go to infinity. In my sample, none of the branches is closer than 0.02 miles. But one could conceivably get extremely large $Branches_{co,ct}$ values. I investigate this issue further in robustness checks by winsorizing $Branches_{co,ct}$, and alternatively, by redefining $Branches_{co,ct}$ as

$$Branches_{co,ct}^{1-mile} = \ln\left(1 + \sum_{k=1}^{n_b} \frac{1}{\max\left(1, D_{ct,k}\right)}\right) \tag{1'}$$

which treats branches that are closer than 1 mile as if they were at exactly 1 mile.

3.2.2 Branch Presence at the County Level

The next task is to aggregate the census-tract-level measures up to the county level. I accomplish this task by taking a weighed average of individual census tracts in the county. More specifically, the county-level branch access variable, *BAccess*, is defined as

$$BAccess = \sum_{ct=1}^{n_{CO,CT}} \Psi_{co,ct} Branches_{co,ct} \tag{2}$$

where $Branches_{co,ct}$ is the tract-level access variable I calculated earlier for county *co* census tract *ct*, $n_{CO,CT}$ is the number of census tracts in county *co*, and $\Psi_{co,ct}$ is the weight of county *co*, census tract *ct*.

I use three weighting schemes in this aggregation. First, I take a simple average of all census tracts in the county ($\Psi^{EW}_{co,ct} = 1/n_{CO,CT}$; equal-weight scheme or Scheme EW). The branch access variable created by the weight $\Psi^{EW}_{co,ct}$ is $BAccess_{EW}$. Second, since I am interested primarily in branch presence in low-income census tracts where foreclosures are most likely to occur, I use a weighting scheme that emphasizes the branch presence in these areas (Scheme W)

$$\Psi^{W}_{co,ct} = \frac{\frac{1}{I_{co,ct}}}{\sum_{\forall c \text{ in } co} \frac{1}{I_{co,c}}} \tag{3}$$

where $I_{co,ct}$ is the median income of census tract *ct* in county *co* and the index *c* tracks all census tracts in the county *co*. The branch access variable created by the weight $\Psi^{W}_{co,ct}$ is $BAccess_{W}$. Note that the weight $\Psi^{W}_{co,ct}$ is *decreasing* in census tract median income. The denominator is a county-specific constant that makes the weights add up to one in each county. To see how the weighting scheme works, imagine two counties, X and Y, with two census tracts in each, x_1, x_2, y_1, and y_2. The median incomes for x_1 and x_2 are \$10 and \$20, respectively. The median incomes for y_1 and y_2 are \$100 and \$200, respectively. Under weighting scheme W, x_1 and y_1 get weighted by 2/3 and x_2 and y_2 get weighted by 1/3. In other words, the largest weight in the county goes to the census tract that has the lowest median income. As a result, counties that have greater access to bank branches in their *relatively* low-income areas will have a higher $BAccess_W$ variable. Put differently, I expect any given level of branch accessibility to be more effective in lowering foreclosures if it belongs to a low-moderate income census tract than a high-income tract. It is worth emphasizing that in calculating each tract's weight, the tract's income is compared to the other census tracts in its county (in the denominator), not all the other census tracts in the state. This strategy allows me to concentrate on the relatively low-income areas of each county where banks should make the greatest impact in reducing foreclosures in that county. Then, after controlling for the cross-county variation in foreclosures arising from cross-county differences in incomes, I expect the foreclosures to be negatively correlated with the presence of banks in low-income neighborhoods.

Third, to show that it is indeed the branch presence in low-income areas that matters most, I will use a weight that puts the emphasis on branch presence in high-income census tracts (inverse-weighting scheme or Scheme IW). With this scheme, I expect the negative correlation between *BAccess* and foreclosure rates to break down. In other words, foreclosure rates should not be lower in counties where banks are located in high-income areas at the expense of low-income areas. The weight on each census tract in Scheme IW is

$$\Psi^{IW}_{co,ct} = I_{co,ct} \Big/ \sum_{\forall c \text{ in } co} I_{co,c} \qquad (4)$$

The branch access variable created by the weight $\Psi^{IW}_{co,ct}$ is $BAccess_{IW}$. Note that the only difference between (3) and (4) is the inverted numerator (and the denominator adjusted accordingly).

3.3 HMDA

Under the Home Mortgage Disclosure Act of 1975, depository and nondepository financial institutions report all mortgage applications they receive in each census tract by disclosing the loan applicant's income, race, gender, the loan's amount and purpose (home purchase, refinancing, or purchase of renter-occupied property), whether the application was approved or denied and if it is denied, the reason for denial, and, starting for the first time with the 2004 data (reported in 2005), the spread of the loan price over the Treasury rate of a comparable maturity at the time of origination if the spread exceeds 3%.[3] The loan price includes the interest rate as well as points, fees, and premiums for private mortgage insurance.

I exclude refinancings and mortgages to purchase renter-occupied property from the analysis. I also exclude the data on mortgages purchased by financial institutions that were originated at an earlier time. This prevents double counting, once at origination and once at the time of sale. After this clean-up, I am left with 246,327 mortgage originations (>$17.3 billion) in Ohio in 2000.

Because a loan's interest spread is reported only if it is 3 percentage points above the Treasury rate, some mortgages are reported with a zero interest rate. In order to estimate the county-level mortgage interest rate, I fit a lognormal distribution over the reported spread data in each county, assuming that the distribution is left-censored at 3%. I accomplish this by estimating a censored regression model using only an intercept on the right-hand side. The intercept is the mean of the uncensored distribution, which I use in the analysis.

4. Method

I assess the impact of bank branch presence in 2000, *BAccess00*, on county foreclosure rates by estimating the following regression with OLS.[4]

[3] There are some exemptions to reporting requirements based on an institution's asset size or the size of its mortgage lending business. However, the reporting threshold is low enough that HMDA represents an accurate picture of the local lending market.

[4] I drop the weight subscripts to simplify the notation. They will be reintroduced when the discussion requires them.

$$Foreclose_t = f\,(BAccess00,\ Income00,\ BAccess00 \times Income00,\ \boldsymbol{X_1}) + \varepsilon_F \qquad (5)$$

where $Foreclose_t$ is the county foreclosure rate in each year from 2000 to 2005 (each year is estimated separately). I also estimate the regression using the mean foreclosure rate over the 6-year period, *M_Foreclose*. *Income00* is the natural log of the county median household income in 2000. The interaction term *BAccess00* x *Income00* captures the nonlinear impact of branch presence on foreclosure rates. Since I expect banking relationships to matter most in low-income areas, I expect to observe a negative coefficient for *BAccess00*, but the effect should weaken or disappear in high-income counties; so I expect to observe a positive coefficient for the interaction term.

$\boldsymbol{X_1}$ is a vector of control variables that comprises demographic, and loan-market specific factors, which I review below.

4.1 Demographic Factors

ChildInFamily00 is the share of children in the county who live in a two-parent household. Because single-parent households may be more cash-constrained, *ChildInFamily00* may be negatively associated with foreclosure rates.

Gini00 is a measure of income inequality among the census tracts of the county. A value of one would indicate complete inequality of distribution, while a 0 indicates no inequality. Keeping median incomes constant, I expect to see more foreclosures with increasing inequality.

HighSchool00 is the share of the population over 25 years of age whose educational achievement is a high school diploma or less.

PopDens00 is the population density of the county calculated as the population divided by the land area.

UrbanPop00 is the share of the population in the county that is classified as urban by the Census Bureau. Foreclosures may be higher in rural areas because of the dependence of the local economies on farming, a volatile sector of the economy.

Race00 is the share of the African American population in the total county population.

4.2 Loan-Market Specific Factors

CreditProblem00 is the share of mortgage applicants denied credit because of poor credit histories in 2000. As I do not have information on the credit quality of borrowers in each county, such as credit scores, I use *CreditProblem00* as a proxy for credit risk at the county level.

BankShare00 is the share of banks in mortgage originations in the county. This variable controls for the presence of institutions that are not insured by the FDIC (credit unions and nonbank mortgage lenders).

Foreclose99 is the initial value of *Foreclose* in 1999.

Herfindahl00 is the deposit market Herfindahl index, where the market is the county.

HomeValue00 is the natural log of the median house price in the county in 2000.

Origine00 is the dollar amount of mortgages originated in the county per household. A county where lenders originate many loans may see higher foreclosures in the future.

The descriptive statistics are presented in Table 1.

I also examine which of my three weighting schemes has the greatest explanatory power. I hypothesize that Scheme W is better than both EW and IW. I test this hypothesis by estimating the following regressions with OLS:

$$M\_Foreclose = f\,(BAccess00_{W}, BAccess00_{EW}, Income00, BAccess00_{W} \times Income00, BAccess00_{EW} \times Income00, \boldsymbol{X_1}) + \varepsilon_{F,\,W\text{-}EW} \qquad (6)$$

$$M\_Foreclose = f\,(BAccess00_{W}, BAccess00_{IW}, Income00, BAccess00_{W} \times Income00, BAccess00_{IW} \times Income00, \boldsymbol{X_1}) + \varepsilon_{F,\,W\text{-}IW} \qquad (7)$$

Note that (6) includes both $BAccess00_{W}$ and $BAccess00_{EW}$ and (7) includes both $BAccess00_{W}$ and $BAccess00_{IW}$ and their interactions with income.

To examine how the asset size of the bank owning the branch affects foreclosure rates, I use a model similar to (5):

$$Foreclose_t = f\,(SBAccess00, LBAccess00, Income00, SBAccess00 \times Income00, LBAccess00 \times Income00, \boldsymbol{X_1}) + \varepsilon_F \qquad (8)$$

where *SBAccess00* is the level of access to small-bank branches, and *LBAccess00* is the level of access to large-bank branches. A small bank is defined as a bank with total assets less than $1 billion. Both access measures are defined in a manner similar to *BAccess00* by defining *SBranches* and *LBranches* at census tract level (as in (1)) but by counting large and small banks separately.

There is one variable that I excluded from the analysis so far due to data limitations. While the level of interest rates in the market may be a strong determinant of foreclosures, the mortgage interest rate data from HMDA is only available in 2004. So, I develop a model that takes the endogeneity of spreads, and foreclosures into account. The limitation is that I can only work with one year of foreclosures, 2004.

In order to take into account the potentially endogenous relationships, I estimate the following system using GMM:

$$\begin{aligned} &Spread04 = f\,(\boldsymbol{Z_{1990}}, \boldsymbol{Z_{2000}}, Foreclose04, \boldsymbol{X_2}) + \varepsilon_S \\ &Foreclose04 = f\,(BAccess00, BAccess00 \times Income00, Spread04, Foreclose99, \boldsymbol{Z_{2000}}, \boldsymbol{X_2}) + \varepsilon_F \end{aligned} \tag{9}$$

where $\boldsymbol{Z_{2000}}$ includes *Income00* and *HomeValue00*. Foreclosures are identified by the assumption that while banks' pricing decisions depend on long-term trends in the local market, the decision to foreclose will depend on current conditions. So, the spread equation includes the instruments $\boldsymbol{Z_{1990}}$ but the foreclosure equation does not. $\boldsymbol{X_2}$ includes everything in $\boldsymbol{X_1}$, except *Foreclose99*, and *HomeValue00*. *HomeValue00* now appears in $\boldsymbol{Z_{2000}}$, and *Foreclose99* is included only in the foreclosure equation.

In my results, I will also report the R-square measure proposed by Windmeijer (1995), which is the squared-correlation of the observed and predicted dependent variables.

5. Results

Table 2 shows the effect of bank branch presence in 2000, *BAccess00*, on county foreclosure rates by estimating the model in (5). Weighing scheme EW, which puts equal weight on all census tracts, is in Panel A, scheme W, which emphasizes branch presence in low-income markets, is in Panel B, and scheme IW, which emphasizes branch presence in high-income markets, is in Panel C. Panel D compares scheme W to EW and IW to determine which scheme has greater explanatory power.

The results show that weighing schemes that ignore the relative income of the local market or put the weight on local markets that need relationships and branch access the least (EW and IW) capture little or no significant impact from branch presence on foreclosure rates (Panels A and C). However, when *BAccess00* focuses primarily on the relatively low-income census tracts of the counties (Panel B), my analysis reveals a somewhat different picture. Branch presence in 2000, $BAccess00_W$, is negatively correlated with foreclosures in all years except 2000, and the correlation disappears in higher-income counties (the positive and significant interaction term). However, these findings are economically weak and their statistical significance does not appear robust. In a low-income county, such as Meigs County, where the median household income is $27,287, a one-standard-deviation increase in $BAccess00_W$ is associated with an average annual decline of about 5% in county foreclosure rates (i.e, 5% of the annual mean foreclosure rate of 2% using the coefficients for *M_Foreclose*). Also, note that the branch variables lose their statistical significance in all years, except in 2004, 2005 and the six-year average, in the expanded specification that includes a wider set of demographic factors. Still, Panel D shows that weighting scheme W does a better job explaining foreclosures than the other two.

The results also show that, as expected, foreclosure rates are negatively correlated with incomes (*Income00*). Foreclosure rates are also negatively correlated with deposit market concentration (*Herfinahl00*). This finding is in line with the Petersen and Rajan's (1995) argument that banks must have market power to recoup their initial investment into the relationship from future profitable transactions with the borrower. Foreclosures are also lower if a larger share of mortgages are originated by banks (*BankShare00*). The extent of bank lending may be an indicator of the absence of the fringe financial sector that is often blamed for predatory lending practices. Home values are negatively correlated with foreclosure rates (*HomeValue00*). If the collateral is valuable and the mortgage is in arrears, a foreclosure may be avoided by selling the asset and paying back the lender. *ChildInFam00*, the share of children who live in a two-parent household, is negatively correlated with foreclosures. This is in line with my earlier claim that single-parent households may be more cash-constrained. Finally, *Race00* is uncorrelated with foreclosure rates.

The weak significance of $BAccess00_W$ in Panel B is mainly a result of treating large-bank and small-bank branches identically. Using Scheme W, Table 3 shows that the size of the institution present in the market is important. In fact, my earlier significant results are driven entirely by the branches of small banks. The only exception is 2000, which is an unusual year in the sense that the average foreclosure rate in 2000 is half of the later years in the sample. In other words, if economic conditions are such that overall foreclosure rates are low, branch access does not matter. In later years, a one–standard-deviation increase in the *SBAccess00* in a low-income county is associated with a decline in foreclosure rates that varies between 5% (2001) and 12% (2004). Overall, the evidence supports Hypotheses 1 and 2.

Next, I consider the impact of the price of mortgages originated in the market on foreclosures. When I take the level of spreads into account (9), Table 4 shows that the results are very strong when the emphasis is on low-income markets ($BAccess00_W$). Using the median household income of Meigs County as an example, a one-standard-deviation increase in $BAccess00_W$ is associated with a one-percentage-point drop in foreclosures in 2004; that is, the foreclosure rate drops by 43 percent relative to the mean foreclosure rate of 2.3 percent. These findings support Hypothesis 1. Table 4 also shows a positive correlation between mortgage spreads and foreclosures, as expected.

Also note that when I segregate the access variable into small and large-bank access, I find once again that, in support of Hypothesis 2, the results are driven by small banks. Even though the large-bank access appears economically significant, its effect is statistically zero.

5.1 Robustness Checks

I subject my results to two robustness checks. For the sake of brevity, I will present the results for the six-year average foreclosure rate, *M_Foreclose*, and weighing scheme W alone.

First, given the small sample size, I make sure that my results are not driven by a few outliers. I accomplish this by winsorizing $BAccess00_W$, $SBAccess00_W$, and $LBAccess00_W$ at 1% and 99% levels. In other words, any observation that is below the 1st percentile or above the 99th percentile of the sample is reset to the 1st percentile and 99th percentile values. The winsorized variables are named $BAccess00_{W,W}$, $SBAccess00_{W,W}$, and $LBAccess00_{W,W}$. The results in Table 5 show that my conclusions are not affected by outlier observations.

I also reduce the impact of potential outliers by redefining the branch access variable using $Branches_{co,ct}^{1-mile}$ (1'). The new variable is named $BAccess00_{W,1M}$. $SBAccess00_{W,1M}$ and $LBAccess00_{W,1M}$ are defined similarly. Those results are in Table 6. Panel A shows the OLS estimates, and Panel B shows the GMM estimates with endogenous mortgage spreads. My conclusions are not affected by outliers.

Second, by design, $Branches_{co,ct}$ in (1) assumes that the impact of a branch on foreclosure rates declines with its distance to the market. If this assumption is correct, disregarding the distance and simply counting the bank branches in and around a neighborhood should weaken the results by adding noise to the measure. To test this hypothesis, I redefine $Branches_{co,ct}$ as $Branches_{co,ct}^{ND} = \ln(1+n_b)$ and recalculate the branch access variable $BAccess00_{W,ND}$. Table 7 shows the results. If I ignore the distance and treat all branches in and around the neighborhood the same, the economic and statistical significance of the new access variable $BAccess00_{W,ND}$ declines. To make sure that $BAccess00_W$ is the superior measure compared to $BAccess00_{W,ND}$, I include them both into the regression including their interactions with income (Panel C). The results confirm that $BAccess00_W$ is the superior variable as the significance of $BAccess00_{W,ND}$ disappears when both variables are included into the regressions. Thus, considering the distance between a neighborhood and lenders is important in estimating the impact of lender presence on foreclosures.

6. Conclusion

Banks specialize in screening and monitoring informationally opaque borrowers. Ergungor (2006) shows that mortgage originations rise with increased bank branch presence in a low-income market because the proximity to the borrower reduces the distance-related frictions in the information gathering process. In this paper, I examine the success of such lending. If there is more lending in the low-income area that have more bank branches, it would not be surprising to see more loan defaults and foreclosures. Yet I find that foreclosures are not higher in these areas; on the contrary, I observe a significant decline in foreclosure rates when there are more branches present in the low-income communities of a county.

I also find that the size of the institution operating the branch in the market is important. Small banks are the institutions that drive the results of the paper. While the small sample size necessitates caution in interpreting these results, this paper provides support for the hypothesis that bank-borrower relationships are indispensable in low-income communities.

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Table 1: Descriptive Statistics

	Mean	Std Dev	Median	Minimum	Maximum
Endogenous Variables					
Spread04	1.316	0.328	1.288	0.511	2.389
Foreclose00	0.013	0.004	0.012	0.003	0.024
Foreclose01	0.017	0.005	0.016	0.005	0.031
Foreclose02	0.021	0.007	0.020	0.010	0.037
Foreclose03	0.023	0.007	0.022	0.011	0.040
Foreclose04	0.023	0.007	0.023	0.011	0.040
Foreclose05	0.024	0.007	0.024	0.008	0.045
Exogenous Variables					
BAccess00_{W}	0.172	0.109	0.137	0.050	0.674
BAccess00_{EW}	0.144	0.082	0.121	0.049	0.544
BAccess00_{IW}	0.318	0.236	0.275	0.128	2.019
$\text{BAccess00}_{W,\ ND}$	0.325	0.169	0.293	0.137	1.385
$\text{BAccess00}_{W,\ 1M}$	0.106	0.045	0.093	0.050	0.338
SBAccess00_{W}	0.093	0.091	0.070	0.003	0.580
LBAccess00_{W}	0.078	0.065	0.065	0.000	0.369
$\text{SBAccess00}_{W,\ ND}$	0.159	0.097	0.140	0.017	0.480
$\text{LBAccess00}_{W,\ ND}$	0.166	0.148	0.121	0.000	0.906
$\text{SBAccess00}_{W,\ 1M}$	0.054	0.033	0.049	0.003	0.156
$\text{LBAccess00}_{W,\ 1M}$	0.052	0.037	0.049	0.000	0.213
BankShare00	0.709	0.078	0.708	0.395	0.844
ChildInFam00	0.709	0.060	0.708	0.574	0.893
CreditProblem00	0.372	0.058	0.370	0.214	0.515
Foreclose99	0.012	0.004	0.011	0.005	0.023
Gini00	0.105	0.057	0.091	0.012	0.255
Herfindahl00	0.156	0.081	0.127	0.073	0.454
HighSchool00	0.188	0.053	0.179	0.071	0.485
HighSchool90	0.268	0.061	0.258	0.156	0.531
HomeValue00	11.432	0.240	11.404	10.986	12.149
HomeValue90	11.083	0.246	11.065	10.597	11.773
Income00	10.592	0.191	10.608	10.179	11.193
Income90	10.404	0.201	10.437	9.918	10.872
Origine00	0.790	0.692	0.810	-0.897	2.777
Race00	0.043	0.055	0.023	0.002	0.282
Urban00	0.511	0.241	0.517	0.022	0.992

Table 2: The Effect of Branch Presence on Foreclosure Rates – OLS Estimates

This table shows the effect of bank branch presence in 2000 on county foreclosure rates by estimating the following regressions with OLS:

$Foreclose = f\,(BAccess00_{EW}, Income00, BAccess00_{EW} \times Income00, \boldsymbol{X_1}) + \varepsilon_{F,\,EW}$ (Panel A)
$Foreclose = f\,(BAccess00_{W}, Income00, BAccess00_{W} \times Income00, \boldsymbol{X_1}) + \varepsilon_{F,\,W}$ (Panel B)
$Foreclose = f\,(BAccess00_{IW}, Income00, BAccess00_{IW} \times Income00, \boldsymbol{X_1}) + \varepsilon_{F,\,IW}$ (Panel C)

where $BAccess00_{EW}$ is the equally-weighted access variable, $BAccess00_{W}$ is the access variable calculated using the weighting scheme in (3), $BAccess00_{IW}$ is the access variable calculated using the weighting scheme in (4). $\boldsymbol{X_1}$ is a vector of control variables, which I add to the regression in small steps due to their high correlation with *Income00*. *Foreclose* is the county foreclosure rate in each year from 2000 to 2005. *M_Foreclose* is the mean foreclosure rate over the 6-year period.

Panel D shows that $BAccess00_{W}$ has greater explanatory power than $BAccess00_{EW}$ or $BAccess00_{IW}$ by estimating the following regressions with OLS:

$M\_Foreclose = f\,(BAccess00_{W}, BAccess00_{EW}, Income00, BAccess00_{W} \times Income00, BAccess00_{EW} \times Income00, \boldsymbol{X_1}) + \varepsilon_{F,\,W\text{-}EW}$
$M\_Foreclose = f\,(BAccess00_{W}, BAccess00_{IW}, Income00, BAccess00_{W} \times Income00, BAccess00_{IW} \times Income00, \boldsymbol{X_1}) + \varepsilon_{F,\,W\text{-}IW}$

t-statistics are in parenthesis.

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

(Table on next page)

Panel A – BAccess00$_{EW}$

	Foreclose00		Foreclose01		Foreclose02		Foreclose03		Foreclose04		Foreclose05		M_Foreclose	
BAccess00$_{EW}$	-0.0072	-0.0791	-0.3764	-0.1816	-0.3846	-0.1960	-0.3883	-0.2710	-0.6781	-0.5448	-0.5270	-0.3635	-0.3936	-0.2727
	(-0.04)	(-0.45)	(-1.69) *	(-0.82)	(-1.25)	(-0.61)	(-1.26)	(-0.88)	(-2.10) **	(-1.72) *	(-1.60)	(-1.09)	(-1.79) *	(-1.25)
BAccess00$_{EW}$ x Income00	0.0010	0.0079	0.0357	0.0171	0.0369	0.0190	0.0369	0.0260	0.0644	0.0515	0.0499	0.0343	0.0375	0.0259
	(0.06)	(0.47)	(1.70) *	(0.82)	(1.27)	(0.63)	(1.27)	(0.89)	(2.11)	(1.71)	(1.60)	(1.09)	(1.80) *	(1.26)
CreditProblem00	-0.0027	-0.0014	0.0053	0.0035	-0.0066	-0.0069	0.0065	0.0092	0.0062	0.0042	-0.0106	-0.0094	-0.0003	-0.0001
	(-0.62)	(-0.31)	(0.88)	(0.61)	(-0.79)	(-0.83)	(0.77)	(1.17)	(0.71)	(0.51)	(-1.19)	(-1.09)	(-0.05)	(-0.02)
Foreclose99	0.6954	0.6916	0.8149	0.6080	0.9640	0.7297	1.0350	0.7882	0.8661	0.6217	0.8202	0.6202	0.8659	0.6766
	(9.25) ***	(8.03) ***	(7.92) ***	(5.69) ***	(6.79) ***	(4.70) ***	(7.28) ***	(5.30) ***	(5.79) ***	(4.05) ***	(5.40) ***	(3.85) ***	(8.50) ***	(6.40) ***
BankShare00	-0.0071	-0.0050	-0.0120	-0.0105	-0.0111	-0.0076	-0.0127	-0.0072	-0.0159	-0.0088	-0.0136	-0.0056	-0.0121	-0.0075
	(-2.28) **	(-1.45)	(-2.81) ***	(-2.48) **	(-1.88) *	(-1.24)	(-2.15) **	(-1.21)	(-2.56) **	(-1.44)	(-2.15) **	(-0.88)	(-2.85) ***	(-1.78) *
Herfindahl00	-0.0041	-0.0029	-0.0134	-0.0108	-0.0169	-0.0156	-0.0152	-0.0135	-0.0140	-0.0140	-0.0187	-0.0181	-0.0137	-0.0125
	(-1.10)	(-0.73)	(-2.63) **	(-2.20) **	(-2.41) **	(-2.20) **	(-2.16) **	(-1.99) **	(-1.89) *	(-2.00) **	(-2.48) **	(-2.47) **	(-2.72) ***	(-2.59) **
Income00	-0.0047	-0.0024	-0.0111	0.0104	-0.0157	0.0083	-0.0121	0.0133	-0.0176	0.0112	-0.0203	0.0047	-0.0136	0.0076
	(-1.34)	(-0.46)	(-2.30) **	(1.56)	(-2.36) **	(0.86)	(-1.81)	(1.43)	(-2.52) **	(1.17)	(-2.84) ***	(0.47)	(-2.85) ***	(1.15)
Origine00	0.0006	-0.0004	0.0010	0.0018	0.0019	0.0022	0.0022	0.0012	0.0028	0.0026	0.0034	0.0023	0.0020	0.0016
	(0.70)	(-0.41)	(0.89)	(1.53)	(1.30)	(1.27)	(1.48)	(0.76)	(1.77) *	(1.52)	(2.10) **	(1.32)	(1.84) *	(1.40)
Race00	0.0192	0.0087	0.0160	0.0001	0.0134	-0.0067	0.0071	-0.0232	0.0215	-0.0041	0.0256	0.0002	0.0171	-0.0041
	(2.23) **	(0.85)	(1.36)	(0.01)	(0.82)	(-0.36)	(0.44)	(-1.31)	(1.26)	(-0.22)	(1.47)	(0.01)	(1.47)	(-0.33)
PopDens00	0.0001	0.0003	-0.0001	0.0000	0.0008	0.0018	-0.0001	0.0023	-0.0004	-0.0002	0.0007	0.0011	0.0002	0.0009
	(0.20)	(0.38)	(-0.13)	(0.02)	(0.69)	(1.11)	(-0.11)	(1.44)	(-0.31)	(-0.11)	(0.56)	(0.65)	(0.20)	(0.81)
ChildInFam00		-0.0137		-0.0212		-0.0332		-0.0535		-0.0324		-0.0452		-0.0332
		(-1.60)		(-1.99) **		(-2.14) **		(-3.61) ***		(-2.11) **		(-2.82) ***		(-3.16) ***
Urban00		-0.0033		-0.0001		-0.0044		-0.0111		-0.0048		-0.0047		-0.0047
		(-1.16)		(-0.02)		(-0.86)		(-2.24) **		(-0.94)		(-0.88)		(-1.35)
Gini00		0.0116		0.0139		0.0102		0.0080		0.0410		0.0173		0.0170
		(1.11)		(1.07)		(0.54)		(0.44)		(2.20) **		(0.88)		(1.32)
HomeValue00		0.0018		-0.0150		-0.0131		-0.0092		-0.0144		-0.0061		-0.0093
		(0.53)		(-3.70) ***		(-2.21) **		(-1.62)		(-2.46) **		(-1.00)		(-2.33) **
HighSchool00		0.0005		0.0189		0.0258		0.0212		0.0523		0.0427		0.0269
		(0.07)		(0.21)		(0.20)		(0.17)		(0.40)		(0.31)		(0.30)
Adj. R-Square	0.78	0.78	0.73	0.78	0.66	0.69	0.65	0.69	0.62	0.68	0.65	0.70	0.76	0.80

Panel B – BAccess00$_W$

	Foreclose00		Foreclose01		Foreclose02		Foreclose03		Foreclose04		Foreclose05		M_Foreclose	
BAccess00$_W$	-0.0677	-0.1214	-0.4652	-0.2710	-0.5028	-0.2911	-0.5548	-0.3935	-0.8039	-0.6274	-0.6676	-0.4885	-0.5103	-0.3655
	(-0.49)	(-0.80)	(-2.50) **	(-1.44)	(-1.94) *	(-1.06)	(-2.15) **	(-1.51)	(-2.97) ***	(-2.35) **	(-2.41) **	(-1.73) *	(-2.78) ***	(-1.99) **
BAccess00$_W$ x Income00	0.0067	0.0119	0.0443	0.0256	0.0481	0.0279	0.0528	0.0377	0.0763	0.0592	0.0633	0.0463	0.0486	0.0347
	(0.51)	(0.83)	(2.51) **	(1.44)	(1.96) *	(1.07)	(2.16) **	(1.53)	(2.98) ***	(2.34) **	(2.42) **	(1.73) *	(2.80) ***	(1.99) **
CreditProblem00	-0.0026	-0.0010	0.0055	0.0035	-0.0068	-0.0070	0.0067	0.0098	0.0057	0.0033	-0.0107	-0.0092	-0.0003	-0.0001
	(-0.58)	(-0.23)	(0.94)	(0.62)	(-0.82)	(-0.85)	(0.82)	(1.25)	(0.67)	(0.41)	(-1.22)	(-1.08)	(-0.06)	(-0.02)
Foreclose99	0.6993	0.7071	0.8129	0.6136	0.9558	0.7403	1.0309	0.8132	0.8459	0.6153	0.8072	0.6325	0.8587	0.6870
	(9.28) ***	(8.16) ***	(8.04) ***	(5.71) ***	(6.79) ***	(4.72) ***	(7.36) ***	(5.46) ***	(5.76) ***	(4.02) ***	(5.38) ***	(3.92) ***	(8.63) ***	(6.52) ***
BankShare00	-0.0068	-0.0046	-0.0110	-0.0101	-0.0098	-0.0068	-0.0114	-0.0063	-0.0141	-0.0077	-0.0121	-0.0048	-0.0109	-0.0067
	(-2.17) **	(-1.34)	(-2.62) **	(-2.38) **	(-1.67) *	(-1.11)	(-1.95) *	(-1.08)	(-2.32) **	(-1.28)	(-1.95) *	(-0.76)	(-2.63) **	(-1.62)
Herfindahl00	-0.0039	-0.0027	-0.0134	-0.0113	-0.0176	-0.0165	-0.0155	-0.0137	-0.0154	-0.0160	-0.0196	-0.0188	-0.0142	-0.0132
	(-1.02)	(-0.68)	(-2.62) **	(-2.29) **	(-2.47) **	(-2.28) **	(-2.19) **	(-2.00) **	(-2.08) **	(-2.26) **	(-2.58) **	(-2.54) **	(-2.83) ***	(-2.71) ***
Income00	-0.0053	-0.0039	-0.0131	0.0074	-0.0181	0.0050	-0.0153	0.0089	-0.0214	0.0063	-0.0239	-0.0002	-0.0162	0.0039
	(-1.45)	(-0.71)	(-2.69) ***	(1.07)	(-2.66) ***	(0.50)	(-2.27) **	(0.93)	(-3.03) ***	(0.64)	(-3.30) ***	(-0.02)	(-3.37) ***	(0.58)
Origine00	0.0005	-0.0005	0.0009	0.0017	0.0019	0.0021	0.0021	0.0010	0.0029	0.0027	0.0033	0.0022	0.0019	0.0015
	(0.60)	(-0.57)	(0.84)	(1.47)	(1.30)	(1.23)	(1.44)	(0.61)	(1.86) *	(1.63)	(2.14) **	(1.25)	(1.86) *	(1.33)
Race00	0.0186	0.0093	0.0148	0.0004	0.0139	-0.0043	0.0060	-0.0225	0.0228	-0.0006	0.0255	0.0007	0.0169	-0.0028
	(2.18) **	(0.93)	(1.29)	(0.03)	(0.87)	(-0.24)	(0.37)	(-1.31)	(1.37)	(-0.03)	(1.50)	(0.04)	(1.50)	(-0.23)
PopDens00	0.0001	0.0003	0.0000	0.0001	0.0007	0.0016	0.0000	0.0023	-0.0004	-0.0004	0.0007	0.0012	0.0002	0.0008
	(0.20)	(0.34)	(-0.01)	(0.10)	(0.65)	(1.03)	(-0.01)	(1.56)	(-0.38)	(-0.28)	(0.67)	(0.78)	(0.25)	(0.82)
ChildInFam00		-0.0133		-0.0202		-0.0316		-0.0522		-0.0295		-0.0435		-0.0317
		(-1.56)		(-1.91) *		(-2.04) **		(-3.56) ***		(-1.95) *		(-2.73) ***		(-3.05) ***
Urban00		-0.0033		-0.0004		-0.0041		-0.0113		-0.0044		-0.0052		-0.0048
		(-1.18)		(-0.12)		(-0.82)		(-2.40) **		(-0.90)		(-1.01)		(-1.43)
Gini00		0.0095		0.0146		0.0094		0.0058		0.0426		0.0174		0.0166
		(0.91)		(1.12)		(0.49)		(0.32)		(2.29) **		(0.89)		(1.29)
HomeValue00		0.0029		-0.0143		-0.0117		-0.0070		-0.0135		-0.0047		-0.0080
		(0.87)		(-3.41) ***		(-1.92) *		(-1.21)		(-2.26) **		(-0.74)		(-1.96) *
HighSchool00		-0.0008		0.0171		0.0245		0.0178		0.0509		0.0395		0.0249
		(-0.11)		(0.19)		(0.19)		(0.14)		(0.37)		(0.29)		(0.28)
Adj. R-Square	0.79	0.78	0.74	0.79	0.67	0.70	0.67	0.70	0.64	0.69	0.66	0.70	0.78	0.81

Panel C – BAccess00$_{IW}$

	Foreclose00		Foreclose01		Foreclose02		Foreclose03		Foreclose04		Foreclose05		M_Foreclose	
BAccess00$_{IW}$	-0.0062	-0.0043	0.0113	0.0511	0.0208	0.0439	-0.0167	-0.0396	-0.0868	-0.0318	-0.1314	-0.1398	-0.0348	-0.0201
	(-0.09)	(-0.06)	(0.13)	(0.61)	(0.17)	(0.35)	(-0.13)	(-0.33)	(-0.65)	(-0.26)	(-0.98)	(-1.10)	(-0.39)	(-0.24)
BAccess00$_{IW}$ x Income00	0.0006	0.0004	-0.0013	-0.0049	-0.0021	-0.0042	0.0012	0.0035	0.0078	0.0028	0.0120	0.0128	0.0030	0.0017
	(0.09)	(0.07)	(-0.15)	(-0.63)	(-0.18)	(-0.37)	(0.11)	(0.32)	(0.63)	(0.24)	(0.97)	(1.08)	(0.36)	(0.22)
CreditProblem00	-0.0034	-0.0025	0.0051	0.0037	-0.0078	-0.0082	0.0063	0.0083	0.0053	0.0041	-0.0109	-0.0089	-0.0009	-0.0006
	(-0.76)	(-0.55)	(0.85)	(0.67)	(-0.93)	(-1.01)	(0.76)	(1.07)	(0.60)	(0.51)	(-1.22)	(-1.06)	(-0.14)	(-0.11)
Foreclose99	0.6817	0.6759	0.7934	0.5920	0.9254	0.6938	1.0032	0.7573	0.8474	0.5996	0.8136	0.6148	0.8441	0.6555
	(9.03) ***	(7.84) ***	(7.71) ***	(5.66) ***	(6.47) ***	(4.50) ***	(7.13) ***	(5.14) ***	(5.58) ***	(3.88) ***	(5.36) ***	(3.87) ***	(8.24) ***	(6.25) ***
BankShare00	-0.0070	-0.0047	-0.0130	-0.0119	-0.0120	-0.0084	-0.0136	-0.0077	-0.0166	-0.0101	-0.0138	-0.0058	-0.0127	-0.0081
	(-2.20) **	(-1.34)	(-3.01) ***	(-2.82) ***	(-1.99) *	(-1.35)	(-2.30) **	(-1.29)	(-2.60) **	(-1.62)	(-2.16) **	(-0.90)	(-2.94) ***	(-1.91)
Herfindahl00	-0.0054	-0.0038	-0.0127	-0.0096	-0.0178	-0.0163	-0.0154	-0.0150	-0.0141	-0.0128	-0.0190	-0.0190	-0.0141	-0.0127
	(-1.49)	(-0.97)	(-2.57) **	(-2.01) **	(-2.59) **	(-2.32) **	(-2.27) **	(-2.23) **	(-1.93) *	(-1.81) *	(-2.61) **	(-2.63) **	(-2.86) ***	(-2.66) ***
Income00	-0.0051	-0.0012	-0.0053	0.0143	-0.0100	0.0124	-0.0066	0.0159	-0.0103	0.0187	-0.0158	0.0059	-0.0089	0.0110
	(-1.59)	(-0.24)	(-1.21)	(2.35) **	(-1.66) *	(1.39)	(-1.12)	(1.86) *	(-1.60)	(2.09) **	(-2.47) **	(0.65)	(-2.05) **	(1.81) *
Origine00	0.0007	-0.0002	0.0016	0.0025	0.0027	0.0031	0.0029	0.0021	0.0034	0.0034	0.0037	0.0026	0.0025	0.0023
	(0.86)	(-0.19)	(1.40)	(2.13) **	(1.75) *	(1.78) *	(1.94) *	(1.26)	(2.07) **	(1.95) *	(2.24) **	(1.47)	(2.26) **	(1.91) *
Race00	0.0224	0.0116	0.0206	0.0038	0.0216	0.0011	0.0147	-0.0123	0.0304	0.0026	0.0331	0.0087	0.0238	0.0026
	(2.62) **	(1.10)	(1.77) *	(0.30)	(1.33)	(0.06)	(0.92)	(-0.68)	(1.77) *	(0.14)	(1.92) *	(0.45)	(2.05) **	(0.20)
PopDens00	-0.0001	-0.0001	-0.0006	-0.0004	0.0000	0.0008	-0.0009	0.0012	-0.0012	-0.0008	0.0000	0.0007	-0.0005	0.0002
	(-0.25)	(-0.15)	(-0.80)	(-0.37)	(-0.04)	(0.51)	(-0.82)	(0.82)	(-1.08)	(-0.51)	(0.00)	(0.45)	(-0.63)	(0.23)
ChildInFam00		-0.0134		-0.0182		-0.0294		-0.0504		-0.0316		-0.0455		-0.0314
		(-1.52)		(-1.71) *		(-1.87) *		(-3.35) ***		(-2.00) **		(-2.80) ***		(-2.93) ***
Urban00		-0.0022		0.0017		-0.0014		-0.0080		-0.0020		-0.0030		-0.0025
		(-0.80)		(0.50)		(-0.29)		(-1.67) *		(-0.39)		(-0.58)		(-0.73)
Gini00		0.0122		0.0097		0.0083		0.0012		0.0296		0.0048		0.0110
		(1.15)		(0.75)		(0.44)		(0.06)		(1.56)		(0.25)		(0.85)
HomeValue00		0.0011		-0.0155		-0.0142		-0.0098		-0.0153		-0.0059		-0.0099
		(0.35)		(-3.88) ***		(-2.41) **		(-1.74) *		(-2.60) **		(-0.97)		(-2.48) **
HighSchool00		0.0033		0.0205		0.0308		0.0251		0.0553		0.0428		0.0296
		(0.46)		(0.24)		(0.24)		(0.21)		(0.43)		(0.33)		(0.34)
Adj. R-Square	0.76	0.80	0.72	0.79	0.66	0.70	0.65	0.70	0.60	0.68	0.65	0.70	0.76	0.81

Panel D – BAccess00$_W$ vs. BAccess00$_{EW}$ and BAccess00$_W$ vs. BAccess00$_{IW}$

	M_Foreclose	
	W vs. EW	**W vs. IW**
BAccess00$_W$	-0.7681	-0.4124
	(-1.80) *	(-2.21) **
BAccess00$_W$ x Income00	0.0725	0.0394
	(1.80) *	(2.22) **
BAccess00$_{EW}$	0.5139	
	(1.04)	
BAccess00$_{EW}$ x Income00	-0.0482	
	(-1.04)	
BAccess00$_{IW}$		-0.0146
		(-0.17)
BAccess00$_{IW}$ x Income00		0.0011
		(0.14)
CreditProblem00	-0.0007	0.0008
	(-0.13)	(0.15)
Foreclose99	0.6743	0.6904
	(6.30) ***	(6.56) ***
BankShare00	-0.0065	-0.0072
	(-1.56)	(-1.72) *
Herfindahl00	-0.0136	-0.0137
	(-2.78) ***	(-2.80) ***
Income00	0.0036	0.0017
	(0.52)	(0.23)
Origine00	0.0018	0.0018
	(1.51)	(1.56)
Race00	-0.0014	0.0028
	(-0.11)	(0.22)
PopDens00	0.0008	0.0005
	(0.72)	(0.52)
ChildInFam00	-0.0306	-0.0285
	(-2.91) ***	(-2.69) ***
Urban00	-0.0043	-0.0038
	(-1.24)	(-1.13)
Gini00	0.0164	0.0114
	(1.25)	(0.84)
HomeValue00	-0.0082	-0.0069
	(-1.97) *	(-1.66)
HighSchool00	0.0247	0.0234
	(2.73) ***	(2.58) **
Adj. R-Square	0.81	0.81

Table 3: The Effect of Small vs. Large Bank Branch Presence on Foreclosure Rates – OLS Estimates

This table shows the effect of small-bank branch presence, $SBAccess00_W$ and large-bank branch presence in 2000, $LBAccess00_W$, on county foreclosure rates by estimating the following regression with OLS:

$$Foreclose = f\,(SBAccess00_W, LBAccess00_W, Income00, SBAccess00_W \times Income00, LBAccess00_W \times Income00, \boldsymbol{X_1}) + \varepsilon_F$$

where $\boldsymbol{X_1}$ is a vector of control variables. *Foreclose* is the county foreclosure rate in each year from 2000 to 2005. *M_Foreclose* is the mean foreclosure rate over the 6-year period.

t-statistics are in parenthesis.

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

(Table on next page)

	2000	2001	2002	2003	2004	2005	M
$SBAccess00_W$	-0.0943	-0.5605	-0.8641	-0.8022	-1.0264	-0.5824	-0.6550
	(-0.48)	(-2.30) **	(-2.48) **	(-2.38) **	(-2.95) ***	(-1.67) *	(-2.74) ***
$SBAccess00_W$ x Income00	0.0094	0.0535	0.0829	0.0768	0.0975	0.0551	0.0625
	(0.51)	(2.31) **	(2.50) **	(2.40) **	(2.94) ***	(1.66) *	(2.75) ***
$LBAccess00_W$	-0.5514	-0.0787	0.2775	0.1441	-0.2262	0.0620	-0.0621
	(-2.06) **	(-0.24)	(0.58)	(0.31)	(-0.47)	(0.12)	(-0.19)
$LBAccess00_W$ x Income00	0.0519	0.0069	-0.0266	-0.0134	0.0208	-0.0051	0.0057
	(2.06) **	(0.22)	(-0.59)	(-0.31)	(0.46)	(-0.11)	(0.19)
CreditProblem00	-0.0016	0.0054	-0.0031	0.0127	0.0061	-0.0081	0.0019
	(-0.35)	(0.95)	(-0.37)	(1.61)	(0.74)	(-0.94)	(0.34)
Foreclose99	0.7091	0.6394	0.7894	0.8468	0.6495	0.6357	0.7117
	(8.26) ***	(5.96) ***	(5.14) ***	(5.71) ***	(4.24) ***	(3.90) ***	(6.77) ***
BankShare00	-0.0038	-0.0113	-0.0097	-0.0086	-0.0097	-0.0060	-0.0082
	(-1.11)	(-2.66) ***	(-1.59)	(-1.45)	(-1.60)	(-0.93)	(-1.96) *
Herfindahl00	-0.0048	-0.0106	-0.0141	-0.0114	-0.0143	-0.0162	-0.0119
	(-1.18)	(-2.09) **	(-1.95) *	(-1.62)	(-1.98) *	(-2.11) **	(-2.40) **
Income00	-0.0054	0.0051	0.0013	0.0068	0.0038	0.0011	0.0021
	(-0.97)	(0.73)	(0.13)	(0.70)	(0.38)	(0.10)	(0.31)
Origine00	-0.0005	0.0017	0.0020	0.0009	0.0026	0.0021	0.0015
	(-0.55)	(1.45)	(1.21)	(0.58)	(1.61)	(1.22)	(1.31)
Race00	0.0094	-0.0014	-0.0078	-0.0249	-0.0030	0.0003	-0.0046
	(0.95)	(-0.12)	(-0.44)	(-1.46)	(-0.17)	(0.01)	(-0.38)
PopDens00	0.0005	0.0000	0.0013	0.0020	-0.0006	0.0010	0.0007
	(0.57)	(-0.01)	(0.85)	(1.38)	(-0.43)	(0.61)	(0.66)
ChildInFam00	-0.0141	-0.0187	-0.0283	-0.0496	-0.0272	-0.0423	-0.0300
	(-1.67) *	(-1.78) *	(-1.88) *	(-3.41) ***	(-1.81) *	(-2.64) **	(-2.91) ***
Urban00	-0.0026	-0.0001	-0.0037	-0.0113	-0.0041	-0.0059	-0.0046
	(-0.95)	(-0.02)	(-0.77)	(-2.41)	(-0.85)	(-1.14)	(-1.38)
Gini00	0.0071	0.0206	0.0220	0.0154	0.0514	0.0216	0.0230
	(0.66)	(1.53)	(1.14)	(0.83)	(2.68) ***	(1.06)	(1.75) *
HomeValue00	0.0015	-0.0127	-0.0080	-0.0040	-0.0109	-0.0027	-0.0061
	(0.45)	(-2.93) ***	(-1.29)	(-0.66)	(-1.76) *	(-0.41)	(-1.44)
HighSchool00	-0.0015	0.0148	0.0202	0.0151	0.0480	0.0397	0.0227
	(-0.20)	(0.16)	(0.16)	(0.12)	(0.37)	(0.29)	(0.25)
Adj. R-Square	0.79	0.79	0.71	0.71	0.69	0.70	0.81

Table 4: The Effect of Branch Presence on Foreclosure Rates – GMM Estimates

This table shows the effect of bank branch presence in 2000, $BAccess00_W$, under weighting scheme B, on county foreclosure rates by estimating the following system with GMM:

$$Spread04 = f\,(\mathbf{Z_{1990}}, \mathbf{Z_{2000}}, Foreclose04, \mathbf{X_2}) + \varepsilon_S$$

$$Foreclose04 = f\,(BAccess00_W, BAccess00_W \times Income00, Spread04, Foreclose99, \mathbf{Z_{2000}}, \mathbf{X_2}) + \varepsilon_F$$

where $\mathbf{X_2}$ is a vector of control variables. $\mathbf{Z_{1990}}$ are the instruments that identify *Foreclose04*. The analysis is also repeated separately for large and small banks.

R-square is the squared-correlation of the observed endogenous variable with its predicted value.

t-statistics are in parenthesis.

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

(Table on next page)

	Foreclose04	
$BAccess00_W$	-3.6853	
	(-2.38) **	
$BAccess00_W$ x Income00	0.3488	
	(2.38) **	
$SBAccess00_W$		-4.8065
		(-1.84) *
$SBAccess00_W$ x Income00		0.4552
		(1.84) *
$LBAccess00_W$		-9.5963
		(-1.10)
$LBAccess00_W$ x Income00		0.9010
		(1.10)
ChildInFam00	0.0023	0.0169
	(0.11)	(0.35)
Urban00	-0.0108	0.0047
	(-1.56)	(0.16)
Race00	0.0248	0.0620
	(0.90)	(0.60)
HomeValue00	0.0126	0.0119
	(1.95) *	(0.46)
Income00	-0.0700	-0.1231
	(-2.25) **	(-1.40)
CreditProblem00	0.0113	0.0058
	(1.02)	(0.26)
Foreclose99	0.7275	0.5606
	(3.34) ***	(1.13)
PopDens00	-0.0008	-0.0059
	(-0.41)	(-0.43)
Gini00	0.0528	0.0652
	(1.41)	(0.84)
BankShare00	0.0097	0.0271
	(0.77)	(0.69)
Herfindahl00	-0.0278	-0.0524
	(-2.25) **	(-1.37)
Origine00	0.0018	0.0061
	(0.69)	(0.78)
Spread04	0.0112	0.0214
	(1.87) *	(0.95)
R-Square	0.60	0.43

Table 5: The Effect of Branch Presence on the Foreclosure Rates: Winsorized Sample – OLS Estimates

This table shows the effect of bank branch presence in 2000, winsorized at 1 and 99%, $BAccess00_{W,W}$, on county foreclosure rates by estimating the following regression with OLS:

$M\_Foreclose = f\,(BAccess00_{W,W}, Income00, BAccess00_{W,W} \times Income00, \boldsymbol{X_1}) + \varepsilon_F$

where $\boldsymbol{X_1}$ is a vector of control variables. *M_Foreclose* is the mean foreclosure rate over the 6-year period.

The table also reports the results with banks segregated by size and access variables winsorized at 1 and 99%.

$M\_Foreclose = f\,(SBAccess00_{W,W}, LBAccess00_{W,W}, Income00, SBAccess00_{W,W} \times Income00,$
$LBAccess00_{W,W} \times Income00, \boldsymbol{X_1}) + \varepsilon_F$

t-statistics are in parenthesis.

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

(Table on next page)

	M_Foreclose	
$BAccess00_{W, W}$	-0.3655	
	(-1.99) **	
$BAccess00_{W, W}$ x Income00	0.0347	
	(1.99) **	
$SBAccess00_{W, W}$		-0.6550
		(-2.74) ***
$SBAccess00_{W, W}$ x Income00		0.0625
		(2.75) ***
$LBAccess00_{W, W}$		-0.0621
		(-0.19)
$LBAccess00_{W, W}$ x Income00		0.0057
		(0.19)
CreditProblem00	-0.0001	0.0019
	(-0.02)	(0.34)
Foreclose99	0.6870	0.7117
	(6.52) ***	(6.77) ***
BankShare00	-0.0067	-0.0082
	(-1.62)	(-1.96) *
Herfindahl00	-0.0132	-0.0119
	(-2.71) ***	(-2.40) **
Income00	0.0039	0.0021
	(0.58)	(0.31)
Origine00	0.0015	0.0015
	(1.33)	(1.31)
Race00	-0.0028	-0.0046
	(-0.23)	(-0.38)
PopDens00	0.0008	0.0007
	(0.82)	(0.66)
ChildInFam00	-0.0317	-0.0300
	(-3.05) ***	(-2.91) ***
Urban00	-0.0048	-0.0046
	(-1.43)	(-1.38)
Gini00	0.0166	0.0230
	(1.29)	(1.75) *
HomeValue00	-0.0080	-0.0061
	(-1.96) *	(-1.44)
HighSchool00	0.0249	0.0227
	(2.77) ***	(2.54) **
R-Square	0.81	0.81

Table 6: The Effect of Branch Presence on the Foreclosure Rates: Distance Adjusted to 1 Mile – OLS and GMM Estimates

This table shows the effect of various measures of bank branch presence in 2000, $BAccess00_{W,\,1M}$, $SBAccess00_{W,\,1M}$, and $LBAccess00_{W,\,1M}$ on county foreclosure rates by estimating the following regressions with OLS (Panel A):

$$M\_Foreclose = f\,(BAccess00_{W,\,1M}, Income00, BAccess00_{W,\,1M} \times Income00, \boldsymbol{X_1}) + \varepsilon_F$$

$$M\_Foreclose = f\,(SBAccess00_{W,\,1M}, LBAccess00_{W,\,1M}, Income00, SBAccess00_{W,\,1M} \times Income00, LBAccess00_{W,\,1M} \times Income00, \boldsymbol{X_1}) + \varepsilon_F$$

where $\boldsymbol{X_1}$ is a vector of control variables. *M_Foreclose* is the mean foreclosure rate over the 6-year period. $BAccess00_{W,\,1M}$, $SBAccess00_{W,\,1M}$, and $LBAccess00_{W,\,1M}$ are as defined in (2) using the alternative branch-access variable in (1′).

Panel B shows the GMM estimates from the following systems:

$$Spread04 = f\,(\boldsymbol{Z_{1990}}, \boldsymbol{Z_{2000}}, Foreclose04, \boldsymbol{X_2}) + \varepsilon_S$$

$$Foreclose04 = f\,(BAccess00_{W,\,1M}, BAccess00_{W,\,1M} \times Income00, Spread04, Foreclose99, \boldsymbol{Z_{2000}}, \boldsymbol{X_2}) + \varepsilon_F$$

and

$$Spread04 = f\,(\boldsymbol{Z_{1990}}, \boldsymbol{Z_{2000}}, Foreclose04, \boldsymbol{X_2}) + \varepsilon_S$$

$$Foreclose04 = f\,(SBAccess00_{W,\,1M}, LBAccess00_{W,\,1M}, SBAccess00_{W,\,1M} \times Income00, LBAccess00_{W,\,1M} \times Income00, Spread04, Foreclose99, \boldsymbol{Z_{2000}}, \boldsymbol{X_2}) + \varepsilon_F$$

R-square is the squared-correlation of the observed endogenous variable with its predicted value.

t-statistics are in parenthesis.

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

(Table on next page)

Panel A – OLS Estimates

	M_Foreclose	
$BAccess00_{W,1M}$	-0.2730	
	(-0.65)	
$BAccess00_{W,1M}$ x Income00	0.0255	
	(0.65)	
$SBAccess00_{W,1M}$		-1.3872
		(-2.39) **
$SBAccess00_{W,1M}$ x Income00		0.1316
		(2.40) **
$LBAccess00_{W,1M}$		0.5289
		(1.03)
$LBAccess00_{W,1M}$ x Income00		-0.0506
		(-1.05)
R-Square	0.80	0.81

Panel B – GMM Estimates

	Foreclose04	
$BAccess00_{W,1M}$	-7.2004	
	(-1.87) *	
$BAccess00_{W,1M}$ x Income00	0.6760	
	(1.87) *	
$SBAccess00_{W,1M}$		-12.6748
		(-2.27) **
$SBAccess00_{W,1M}$ x Income00		1.1962
		(2.27) **
$LBAccess00_{W,1M}$		-4.6806
		(-0.97)
$LBAccess00_{W,1M}$ x Income00		0.4357
		(0.96)
R-Square	0.44	0.49

Table 7: The Effect of Branch Presence on the Foreclosure Rates: Disregarding Distance – OLS Estimates

This table shows the effect of bank branch presence in 2000, $BAccess00_{W,\,ND}$, on county foreclosure rates by estimating the following regression with OLS (Panel A):

$M\_Foreclose = f\,(BAccess00_{W,\,ND}, Income00, BAccess00_{W,\,ND} \times Income00, \boldsymbol{X_1}) + \varepsilon_F$

where $BAccess00_{W,\,ND}$ is the inverse-income weighted average of the *number* of bank branches within 10-mile radius of each local market, irrespective of their distance to the census tract, $\boldsymbol{X_1}$ is a vector of control variables, *M_Foreclose* is the mean foreclosure rate over the 6-year period.

I also estimate the following system using GMM (Panel B):

$Spread04 = f\,(\boldsymbol{Z_{1990}}, \boldsymbol{Z_{2000}}, Foreclose04, \boldsymbol{X_2}) + \varepsilon_S$

$Foreclose04 = f\,(BAccess00_{W,\,ND}, BAccess00_{W,\,ND} \times Income00, Spread04, Foreclose99, \boldsymbol{Z_{2000}}, \boldsymbol{X_2}) + \varepsilon_F$

Panel C tests the hypothesis that $BAccess00_W$ is a superior measure compared to $BAccess00_{W,\,ND}$.

The regressions that include $SBAccess00_{W,\,ND}$ and $LBAccess00_{W,\,ND}$ are estimated similarly.

t-statistics are in parenthesis.

(***), (**), and (*) denote significant at 1%, 5%, and 10% level, respectively.

(Table on next page)

Panel A – OLS Estimates

	M_Foreclose	
$BAccess00_{W, ND}$	-0.1085	
	(-1.29)	
$BAccess00_{W, ND}$ x Income00	0.0098	
	(1.26)	
$SBAccess00_{W, ND}$		-0.4793
		(-3.33) ***
$SBAccess00_{W, ND}$ x Income00		0.0453
		(3.32) ***
$LBAccess00_{W, ND}$		0.1252
		(1.10)
$LBAccess00_{W, ND}$ x Income00		-0.0122
		(-1.16)
R-Square	0.80	0.81

Panel B – GMM Estimates

	Foreclose04	
$BAccess00_{W, ND}$	-0.7637	
	(-2.08) **	
$BAccess00_{W, ND}$ x Income00	0.0699	
	(2.06) **	
$SBAccess00_{W, ND}$		-3.2825
		(-2.15) **
$SBAccess00_{W, ND}$ x Income00		0.3096
		(2.14) **
$LBAccess00_{W, ND}$		-0.2684
		(-0.36)
$LBAccess00_{W, ND}$ x Income00		0.0220
		(0.31)
R-Square	0.44	0.49

Panel C – $BAccess00_{W}$ vs. $BAccess00_{W, ND}$

	M_Foreclose - OLS		Foreclose04 - GMM	
$BAccess00_{W}$	-0.3482		-2.4369	
	(-1.86) *		(-1.77) *	
$BAccess00_{W}$ x Income00	0.0335		0.2324	
	(1.89) *		(1.79) *	
$BAccess00_{W, ND}$	-0.1293		-0.9839	
	(-1.41)		(-1.25)	
$BAccess00_{W, ND}$ x Income00	0.0116		0.0903	
	(1.36)		(1.22)	
$SBAccess00_{W}$		-0.4426		-4.0784
		(-2.40) **		(-1.31)
$SBAccess00_{W}$ x Income00		0.0414		0.3833
		(2.38) **		(1.31)
$SBAccess00_{W, ND}$		-0.1910		4.1676
		(-0.66)		(0.67)
$SBAccess00_{W, ND}$ x Income00		0.0187		-0.3946
		(0.68)		(-0.66)
R-Square	0.82	0.83	0.59	0.46

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