Beyond the Transaction: Depository Institutions and Reduced Mortgage Default for Low Income Homebuyers

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Abstract:

We evaluate the effects of the lending institution and soft information on mortgage loan performance for low income homebuyers. We find that even aftercontrolling for the propensity of a borrower to get a loan from a local bank based on observable characteristics, those who receive a loan from a local bank are significantly less likely to become delinquent or default than other bank or non-bank borrowers, suggesting an unobserved information effect. These effects are most pronounced for higher risk borrowers, who likely benefit more from informational advantages of local banks. These findings support previous research on information-driven lending, and provide additional explanation for observed differences in mortgage loan performance between bank and non-bank lenders.

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A growing body of research finds that lower income borrowers with mortgage loans originated by depository institutions are less likely to default on their mortgages than similar borrowers with loans originated by mortgage companies or brokers. Differences in loan characteristics between lender types explain some of this variation; however, studies have found significant differences in default even after controlling for loan and other observable borrower risk characteristics (Alexandar et al. 2002; Coulton et al. 2008; Ding et al. 2011; Laderman and Reid 2009; Moulton 2010). The primary explanation for this difference is the regulatory environment of banking institutions, with more scrutiny over loan quality, minimum capital requirements, and stronger incentives to screen loan applicants (Alexander et al. 2002; GAO Report to the Subcommittee on Oversight and Investigations, Committee on Financial Services, House of Representatives; April 2006-387).

While these studies call attention to the lower mortgage default rates of depository institutions, they do not systematically consider explanations beyond the stricter regulatory environment. Drawing from the literature on relationship lending, we consider the added influence of information-based lending technologies for local bank branches. Unlike mortgage companies that specialize in a single product, banks (meaning depository institutions hereafter) with branch presence in a market may interact with the potential borrowers *and* the community on both sides of their balance sheets and may have an important *informational* advantage over non-local banks and non-bank financial institutions. This advantage may enable local banks to screen loans to higher risk borrowers more accurately based on unobservable soft information, thereby resulting in better loan outcomes (in a small business lending setting, see Agarwal and Hauswald, 2010; Brevoort and Hannan, 2006; Degryse and Ongena 2005; DeYoung et al 2007; Petersen and Rajan, 2002).

To verify our claims, we ask: do information-based lending technologies play a role in mortgage performance? If information-based lending technologies provide an added influence to regulatory effects, we would expect to find that homebuyers with mortgages from local bank branches are less likely to become delinquent or default on their mortgages, compared with homebuyers from non-local bank branches. However, if it is simply the bank regulatory environment that drives lending outcomes, then we will not find a significant difference between local and non-local bank branch originations. The presence (or absence) of an information effect has important implications for regulatory lending policy post the subprime mortgage boom and bust. While regulation may be a necessary condition to encourage careful screening, information-based lending technologies may provide an important added influence to reduce mortgage default, particularly for otherwise higher risk borrowers.

In line with previous research, we find that low-income borrowers with loans from banks are indeed less likely to become delinquent or default, indicative of a regulatory effect; however, we also find evidence of an information effect. Borrowers with a higher propensity to receive a mortgage from a local branch are significantly less likely to become delinquent or default on their mortgages. Even after controlling for propensity to select a particular lender type, *local* bank borrowers are still less likely to fall behind on their mortgage payments, indicative of soft information. With regard to default, local and nonlocaldifferences are most apparent among individuals with credit scores less than 660, who likely benefit more from soft information-based lending (Ergungor 2010; Moulton 2010). Further, for both delinquency and default, local and non-local differences are most statistically robust for larger banks, where mortgages originated from non-local large bank branches are *not* associated with better loan performance. These findings suggest that small banks and large *local* bank branches may be more capable of distinguishing between creditworthy and uncreditworthy borrowers, particularly among those with blemished credit histories. What makes this conclusion unique is the fact that it goes against the common belief in the literature that mortgages are not relationship loans, in part because of the lenders' reliance on credit scoring (Stein, 2002, p. 1892). Nevertheless, we show that there appears to be a group of borrowers who may benefit from the assistance of a lender willing to invest in the collection of soft information.

We employ a unique dataset, which consists of more than 20,000 low and moderate income first-time homebuyers participating in a statewide affordable mortgage program in Ohio. Unlike other loan performance datasets, the design of the affordable mortgage program holds constant loan characteristics and loan servicer, allowing us to isolate the selection of borrowers to particular types of lending institutions and their subsequent probability of mortgage default. We employ comprehensive data on borrower risk characteristics (such as credit score, income, debt burden, loan to value ratio), purchase characteristics, geographic location (previous and new address of the borrower) and neighborhood characteristics to (1) estimate the propensity for a borrower to select a particular type of lending institution, and (2) evaluate both the propensity to select a bank and direct bank effect on mortgage delinquency (defined as ever 60 days delinquent) and default. Rather than collapsing all banks into one category, we distinguish between banks with a local branch presence in the borrower's market (defined as a bank with a branch located within 2 miles of the borrower's previous or new address), and banks without a local branch presence. This allows us to further explore the extent to which the bank effect is due to the regulatory structure alone (where banks in general would be more cautious lenders than non-banks and local branch presence would not matter), or the added influence of information (where local branch presence would be significant).

This paper proceeds as follows. Section I provides a background review of the literature on lending institution type and mortgage performanceand the potential importance of information, concluding with testable implications. Section II describes our data and analytical approach. Section III provides the findings from our analysis, and Section IV concludes with policy and research implications.

I. Background Literature & Testable Hypotheses

There is growing evidence that banks may play an important role in reducing mortgage default, particularly for higher risk borrowers. In an analysis of subprime loans serviced by one large national lender, Alexander et al. (2002) found that loans originated by third party originators (such as mortgage brokers) are more likely to default, holding observable borrower and loan characteristics constant. They view the poor loan quality as an agency problem, that while third parties originate the loans, they are not responsible for the performance of the loans. Ding et al. (2011) employ propensity score matching techniques to compare different characteristics predicting mortgage default for low income borrowers receiving two different types of loan products: affordable mortgages and high cost mortgages. In addition to finding a significant relationship between different loan products (cost and terms) and default, they find that regardless of the loan product, low-income borrowers with mortgages originated by brokers are three to five times more likely to default than borrowers with non-broker originated mortgages.

In a working paper, Coulton et al. (2008) explore the relationship between higher cost lending (as reported under HMDA) and foreclosures (per county foreclosure records in Cleveland, Ohio), and find that a handful of large mortgage companies (not local banks) were responsible for the high cost lending activity in the area, and such mortgage company originated loans are significantly associated with increased foreclosure. In a more in depth analysis, Laderman and Reid (2009) merge HMDA data with proprietary Lender Processing Services (LPS) data, allowing for more robust controls for individual risk characteristics and more detailed data on loan performance. They find that mortgages originated by CRA regulated institutions were significantly less likely to foreclose than mortgages originated by independent mortgage companies, even after controlling for loan terms and borrower risk characteristics.

While these studies consistently find lower rates of delinquency and default for bank originated mortgages, they presume the effect is due to the regulatory environment of banking institutions. Ding et al. (2011) and Laderman and Reid (2009) note the importance of regulation, like the Community Reinvestment Act, to enable careful, affordable lending by depository institutions. Alexander et al. (2002) highlight potential principal agent problems with third party originations. Unlike depository institutions, third party originators lack the regulatory environment to be held accountable for longer term mortgage outcomes, and may even be incentivized (by upfront payment) to passively or actively game lenders and investors in the origination process (moral hazard). Without the regulative incentives in place, they may passively substitute quick turnaround for rigor in screening applicants, intentionally inflate measures of credit quality or property value, or target and place borrowers into subprime mortgages who may have qualified for lower cost alternatives.

Thus, the institution effect due to regulation may make depository institutions more cautious lenders than their non-bank counterparts. However, there may be additional “informational advantages” that help explain reduced default, particularly for banks with a local branch presence. Information used to evaluate creditworthiness can be separated into “hard information” that is readily observable and easy to evaluate (such as credit score, income, debt levels) and “soft information” that is not readily observable, and is difficult to evaluate (such as a borrower’s commitment to make the mortgage payment, their understanding of their mortgage obligation, and the economic stability of the neighborhood). While access to hard information for mortgage lending has increased due to automated underwriting, soft information may play an important role for lower income borrowers. Similar to small businesses who lack the market signals of larger publicly traded firms, informational frictions inherent in lower income borrowers (such as marginal or lower credit scores) may reduce the accuracy by which a lender can evaluate the likelihood of repayment (Berger and Udell 1995; Brevoort and Hanan 2006; DeYoung et al. 2007; Ergungor 2010; Uzzi 1999; 2002). By collecting additional information about the borrower and the neighborhood where they live, banks can reduce the informational frictions and increase the likelihood of selecting a borrower who is more likely to repay their loan (Agarwal and Hauswald 2010; Agarwal, et al. 2010; Peterson and Rajan 2002; Norden and Weber 2010).

Lenders closer to their borrowers, and closer to their market, are more equipped to collect soft information through reduced transaction costs and repeated interactions. For example, borrowers located nearby a banking institution are more likely to have another type of account with the banking institution. Distance between the lender and borrower is thus a relatively good indicator of the potential for information-based lending, where borrowers closer to lenders are more likely to be approved for financing, at a lower cost, and are less likely to default (Petersen and Rajan, 1994; Degryse and Cayseele, 2000; Petersen and Rajan, 2002; Degryse and Ongena, 2005; Hauswald and Marquez, 2006; Brevoort and Hannan, 2006; Agarwal and Hauswald, 2010; DeYoung et al 2007; Bharat et al. 2011).

Our approach to relationship lending differs from the rest of the literature in one important aspect. Unlike the traditional relationship lending model that relies on an intimate knowledge of the borrower that makes it feasible for the bank to incur the cost of investing in the relationship now and tax the borrower later (hold-up problem), there are no taxable future relationships in the residential mortgage market. However, we postulate that a bank's advantage in this market is cost savings due to its ability to utilize the same information across multiple business units. That is, a bank can build a better understanding of economic opportunities in a community through its deposit taking, business and consumer lending operations and utilize that information at no additional cost in its residential mortgage lending business as well. Thus, the "relationship" is not limited to the borrower per se but with the entire community.

Understanding the economic challenges and opportunities faced by the loan applicants where they live can provide the local bank an edge against the competition.

If proximity to lending institutions facilitates relationship lending, then it would stand to reason that mortgage brokers and third party originators in close proximity to their borrowers might also have relationships with borrowers, leaving the observed difference in mortgage default between bank and non-bank originations largely unexplained. However, third party originators lack the technology, incentives and discretion to collect and employ soft information in lending decisions. They exist to facilitate the mortgage transaction, not to provide checking or savings accounts to their customers, offer other lines of credit, or assist with overall financial planning. Neither do they have lending or deposit relationships with businesses in a community, which potentially puts them at an informational disadvantage relative to banks that are better informed about the economic prospects of their region. Thus, the banks' information advantage should be viewed in addition to (not a substitute for) the regulatory institution effect.

The information and regulatory effects have two testable implications. First, if the regulatory effect is valid, then we would expect the loans originated by both local and non-local banks to perform better than those originated by non-bank financial institutions. There is already some evidence in the literature that supports this claim but we anticipate that our unique dataset, which we describe below, will give us a more accurate measure of the impact of institutional factors after accounting for lender selection. Second, under the information effect, we expect local banks to be more successful at selecting creditworthy borrowers than nonlocal banks even after controlling for various observable measures of creditworthiness and borrower selection to type of lending institution. We primarily expect informational advantages from bank branch presence in a borrower's market, but we also consider bank size, as smaller banks may have more local discretion and better knowledge of their local market than large non-local banks (Stein, 2002; Cole et al., 2004; Berger et al., 2005).

A corollary of this hypothesis is that the information effect will be most powerful within a subsample of opaque borrowers with lower credit scores (below 660), who may benefit more from soft information-based lending. We thus expect that the bank effect on delinquencies and defaults will be less significant for higher credit quality borrowers, as there is less expected gain from relationship lending.

II.Sample, Data and Method

A. Sample Description

Our sample dataset for this analysis is drawn from one of the largest publicly-subsidized affordable homeownership programs nationwide serving low- and moderate-income homebuyers, a state administered Mortgage Revenue Bond (MRB) program in Ohio. MRBs are tax-exempt securities issued by state or local housing finance agencies (HFAs). HFAs use the proceeds to provide reduced or affordable interest rate mortgages, to low- and moderate- income first time homebuyers (households with incomes below 115 percent of area median income).[1] Increasingly, HFAs couple the reduced interest rate financing with other forms of borrower assistance, including downpayment subsidies, second mortgages, reduced private mortgage insurance, or homebuyer education (Goldberg and Harding 2003; Moulton 2010). While HFAs fund the mortgages, they are often originated through a network of private lenders (including bank and non-bank originators). Each state sets its own policies for administering its program.

In Ohio, the Ohio Housing Finance Agency (OHFA) administers the program through a network of more than 100 participating lenders. MRB mortgages are originated through private banks or mortgage companies and are guaranteed by the Federal Housing Administration (FHA), Fannie Mae or Freddie Mac. This program provides an ideal opportunity to isolate the influence of the originating lender, as loan terms that would typically vary by originator are held constant; *all* of the OHFA subsidized mortgages are 30 year, fixed-rate mortgages with the same interest rate at any given point in time (these terms cannot vary by originator). Further, while there are different lenders that originate OHFA mortgages, all OHFA mortgages are purchased within 60 days of closing by a single Master Servicer based on the same underwriting criteria, and originating lenders are compensated a set fee for loans

[1]MRB subsidized mortgages are currently restricted by Congress to first time homebuyers (who have not purchased a home in the past three years), earning less than area median income, or less than 115 percent of area median income for families of three or more, or less than 140 percent of area median income in targeted underserved areas. Further, the price of homes to be purchased with MRBs is limited to 90 percent of the average purchase price. In 2006, the median income of borrowers assisted with MRB mortgages nationwide was $31,703, which is 65 percent of the national median of $48,451. The average purchase price was $132,939, 62 percent of the national median purchase price of $222,000 (NCSHA, National Council of State Housing Finance Agencies. 2010. Housing Bonds. http://www.ncsha.org/advocacy-issues/housing-bonds (accessed 7 October 2010)).

meeting the established criteria[2]. After closing, loans are serviced (payments collected) by the same Master Servicer, reducing the potential for variation in servicing,such as preemptive modifications by some servicers, that might influence observed loan performance(Stegman et al. 2007). The originator's only discretion is whether to approve the loan or not; it is this discretion, holding constant loan terms, underwriting, originator compensation, and servicing, that we exploit in this analysis.

The discretion to originate a loan may be exercised by varying reliance on hard or soft information, and may be a signal to borrowers (and/ or their realtors) about which types of lenders are more likely to (quickly) approve a loan[3]. If loan terms, originator compensation, and servicing are held constant in this program, what would motivate a participating lender to collect soft information regarding the transaction, and subsequentlyoriginate loans with a lower probability of default? We suggest a few possible motivating factors. First, while the Master Servicer assumes the primary credit risk for mortgages in this program, participating lenders may be required to "buy back" mortgages from the Master Servicer if they become delinquent within a set period of months after closing (and the originator cannot provide sufficient documentation of due diligence at the time of origination). This re-purchase provision was rarely enforced from 2005-2008, although it began increasing towards the latter part of 2008 and in subsequent years. As a further discipline mechanism, OHFA requires participating lenders to be approved by Fannie Mae, Freddie Mac and/or FHA to originate mortgages through the program. Lenders with originations that are of consistently poor quality may lose their secondary market approval, and thus may be removed from the program and/or forced out of business entirely. Finally, we contend that the soft information that a bank acquires by being present in a market is,to some extent,the natural outcome of the many different ways the bank engages with the community. In other words, the bank aggregates its

[2]During the time of this study (2005-2010), originating lenders in OHFA's MRB program were compensated as follows: (1) up to 1 percent origination fee assessed at closing (per the lender's discretion), and (2) a 1 percent servicing release premium upon successful transfer of the loan to the Master Servicer.

[3]In a related study (Moulton 2011), interviews with participating lenders confirm that different types of lenders view this discretion differently. For example, a non-bank originator reported that they are "paid to originate the loan", and if a borrower meets the minimum underwriting criteria, it is their "obligation" to originate the loan- not doing so would be bad for their business. On the other hand, a small local bank lender commented that they tell their originators to "not even look at the credit score" until after they have met with the borrower and discussed their commitment and ability to repay the mortgage. They view themselves as having a "long term" relationship with the borrower, and report that many of their borrowers trust them and will wait and come back at a later time when they are more prepared for home purchase.

information as a result of its interactions with businesses, consumers, and local governments. The information is not collected exclusively for MRB lending but can be used across many different functions. A mortgage broker does not interact with its community the same way. Therefore, building relationships would require an extra costly effort for the broker and may not be worth the compensation through the program.

From 2005 through 2008, Ohio's MRB program subsidized 28,033 purchases, of which origination data could be linked to monthly servicing data on loan performance for 95 percent (26,665) of the transactions[4]. Of those, all data, including geographically identifiable information for both previous and new address (using ARC GIS), was available and clean for 21,128 observations (75 percent of the entire population, and 79 percent of the matched population). We further limit the data to those purchases located within Metropolitan Statistical Areas (MSAs), producing a final sample of 18,370 borrowers.

B. Lending Institution Data

We identify the type of originating institution for the borrowers (bank or non-bank) by hand coding the name of the originating institution (provided in the origination file) according to the Home Mortgage Disclosure Act (HMDA) Loan Application Register (LAR) and Transmittal Information Sheet (TIS). We code originating institutions as "non-bank" if the originating institution is listed under HMDA as "independent and regulated by HUD" or if it does not have a deposit taking bank branch located within Ohio[5]. We derive our measures for bank branch locations from the bank branch addresses in the FDIC's Summary of Deposits file. The FDIC's Summary of Deposits file provides the branch addresses of every FDIC-insured institution in the country. There were 3,962 bank branches in Ohio in 2005, 3,920 in 2006, 4,052 in 2007, 4,046 in 2008, and 4,033 in 2009. Using a geocoding software package, each branch address is matched to a latitude and longitude. About 95 percent of the addresses match automatically; because of spelling errors or incomplete addresses, the rest must be matched manually.

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[4]Both sources of data were provided to the researchers by OHFA; however, the servicing data is reported to OHFA by the Master Servicer, while the origination data is provided to OHFA by the originating lender. Both have unique identifiers that do not coincide; address and original loan amount was used to match observations between the two files.

[5]There are 3 lenders in our sample who are regulated as banks under HMDA, but who do not have any deposit taking bank branches in the state of Ohio. These lenders are considered "non-banks" for the purposes of our analysis.

We further separate bank originations into those originated by institutions with and without local branches, based on whether or not there is a branch of the bank within 2 miles of the borrower's previous or new address (which we defined as a local branch). Based on this definition, 29 percent of originations in our sample were made by local bank branches, 17 percent were made by non-local bank branches and 54 percent were made by non-bank entities, as indicated in Table I. As an alternative specification, we consider local bank branch originations as those with a branch presence within 5 miles of the new or previous address. Under this specification, 9 percent of all originations were made by non-local bank branches.

[Insert Table I Here]

C. Borrower & Loan Data

Borrower level data employed in this analysis consists of origination and servicing data. The key outcome variables of interest are mortgage delinquency and default; however, it is important to include the competing outcome of loan prepayment that may also result in mortgage termination. Monthly servicing data from January 1, 2005- February 28, 2011 is used for this analysis, which includes flags for loans that are 60 days (or more) late, in foreclosure or loss mitigation, or prepaid as of the end of each month. We code a loan as ever delinquent if the loan was ever 60 days past due on a monthly payment.[6] We code loans as in default if they were in the foreclosure process or foreclosure was complete as of February 28, 2011. In alternative specifications (survival models), we also identify the month after origination when the loan first became 60 days delinquent , or when the loan first defaulted (stopped making payments prior to foreclosure filing). We identify a loan as "prepaid" if the borrower paid their loan in full, which could be an indication of refinancing or of home sale (we cannot determine which in our data).

Table I provides summary statistics for both the servicing and origination variables used in this analysis. For borrowers in our sample (loans originated between 2005-2008), 78 percent were still making mortgage payments as of February, 2011. By contrast, 11.55 percent of borrowers had their mortgage

[6] Our dataset has an indicator for 60 day delinquency and the filing of foreclosure. It does not allow us to experiment with alternative measures of delinquency such as 90+ day past-due.

foreclosed or were in the foreclosure process, 10.36 percent had prepaid their mortgages, and about 26 percent had been ever 60 days delinquent since the time of origination. There are significant differences in loan performance by type of originating institution; for example, nearly 30 percent of non-bank loans had been ever 60 days delinquent, compared with just over 20 percent of bank loans from a local branch, with bank loans from a non-local branch falling in between at about 26 percent.

D. Estimation Strategy

We use an estimation technique that consists of two stages: (1) selection to a local bank branch, a nonlocal bank branch, or a non-bank MRB lender; and (2) competing risks of delinquency (or default) and prepayment. The estimated propensities from the first stage (selection to a particular type of lender) are included in the second stage regression, in addition to the direct effect of the local bank branch, non-local bank branch and non-bank indicators on loan performance.

Stage 1: Local Bank, Non-Local Bank or Non-Bank

For the first stage, we regress our lender type variable (BANKLOAN$\in${LOCAL, NONLOCAL, NONBANK}) on a vector of explanatory variables, X_1, consisting of borrower characteristics for each borrower, as well as a vector of geography-specific variables, and our vector of instruments, Z_1, which we describe below. Our estimation technique is multinomial logit. The probability of each outcome is given by:

$$\Pr(BANKLOAN_i = j) = \frac{\exp(X_{1,i}\delta_j + Z_{1,i}\beta_j)}{1+\sum_{k\neq NONBANK}\exp(X_{1,i}\delta_k + Z_{1,i}\beta_k)} \text{ for } j \in \{LOCAL, NONLOCAL\} \qquad (1)$$

and $\Pr(BANKLOAN_i = NONBANK) = \dfrac{1}{1+\sum_{k\neq NONBANK}\exp(X_{1,i}\delta_k + Z_{1,i}\beta_k)}$

Exclusion Restrictions & Instrumental Variables

As with any instrumental variable technique, the exclusion restrictions are critical. Recall that due to the nature of the program, all MRB loans offered by all lenders at any given point in time are identical. If the borrower is to receive the same loan from any lender, the important aspect of the lender selection that is orthogonal to loan performance is market structure. In our estimation strategy, market structure is defined geographically as the location of the lenders participating in the MRB program relative to where borrowers live. Market structure is indicative of both borrower preference to select more local lenders (convenience) and the physical availability of local lenders within the borrower's purchase area.

We capture market structure using a measure of access to branches of MRB banks, within a 2 mile radius of the borrower's previous rental address and new purchase address. Both geographic areas are included, as the borrower may be more familiar with lenders located in the previous renter geographic area, while the realtor may be more familiar with the new purchase geographic area. Thus, the selection of a type of lender may be influenced by market structure in both geographic areas. Following Ergungor (2010), we measure bank access using the distance of the address of the borrower *i* to each MRB bank branch *j* in existence in the year *Y* that the loan was originated in, $D_{i,j}^{Y}$, which is determined using the Haversine Formula:

$$D_{i,j}^{Y} = 3{,}956\left(2\arcsin\left[\min\left[1,\left(\sin^2\left(\Delta Lat_{i,j}/2\right)+\cos\left(Lat_i\right)\cos\left(Lat_j\right)\sin^2\left(\Delta Lon_{i,j}/2\right)\right)^{1/2}\right]\right]\right)$$

where *Lat* and *Lon* are the latitude and longitude of the addresses in radians. Then, all the MRB branches within 2 miles of the borrower's previous address are used to calculate the branch-access variable as:

$$PA_i = \ln\left(1+\sum_{j=1}^{n_b}\frac{1}{D_{i,j}^{Y}}\right) \qquad (2)$$

where PA_i is the branch access variable for borrower *i*, and n_b is the number of branches within a 2-mile radius of his previous address in the year the loan was originated. MRB access around the new address, (NA_i) is defined similarly using the bank branches within 2 miles of the new address. This construction assumes that the farther the branch is from the address, the less likely it is to improve the accessibility of banking services (a measure of convenience). We also include a count of the number of MRB bank branches within 2 miles of the previous and new addresses as a control variable to more precisely identify the effect of proximity to banks (not just number of banks). Access to MRB bank branches is expected to influence the selection of the type of lending institution (stage 1), but is orthogonal to loan performance (stage 2), and thus is included in stage 1 to identify stage 2. However, we include control variables for access to, and count of, ALL bank branches (not limited to MRB bank branches) in stage 2, as overall access to banks may influence prepayment (and thus loan performance).

As demonstrated on Table I, there are considerable differences in bank branch access by originating lender type; as expected, borrowers who receive their mortgages from non-local bank branches have the least access to branches, and those who receive their mortgages from local bank branches have the most access, with those loans from non-banks in between.

Stage 2: Loan Performance

In the second stage, we model the competing risk of delinquency (or default) jointly with the risk of prepayment. This analysis follows Quercia.et al. (2007) and Rose (2008) and estimates the competing risks using a multinomial logit model. The use of the multinomial logit model is appropriate because the outcome is polytomous and the structure of the multinomial logit directly controls for competing risks, as the sum of the probabilities of all possible outcomes is equal to one. Further, it offers advantages over the proportional hazards model in that it does not assume proportionality and that it is easily estimated (Quercia et al. 2007). The primary disadvantage of the multinomial logit is the assumption that the alternatives are independent, or the Independence from Irrelevant Alternatives (IIA) assumption (Danis and Pennington Cross 2008). However, Hausmann tests are estimated for each of the models in this analysis, and confirm that the IIA assumption has not been violated.

In the second stage, loan performance indicators (PERFORM $\in$ {DELINQUENT, PREPAID, CURRENT}) are regressed on the same vector of explanatory variables, $X_{1,i}$, in the first stage. In addition, we include an access variable to all banks at the *new* address---which we expect will capture the potential for refinancing---, estimated propensities from stage 1 for local bank branch and nonlocal bank branch to control for the selection effect, and two direct dichotomous indicators of whether or not the borrower received his loan from a local bank branch or a nonlocal bank branch (where non-bank is the excluded category). After controlling for selection based on observable characteristics, the direct bank branch indicators are where we expect to see the effect of local and non-local branch originations, indicative of a soft informational advantage, on loan performance. Finally, we add an exposure variable (months since purchase, logged) that measures the amount of time since origination for each borrower. The shorter the exposure time, the less likely we are to observe a delinquency or prepayment event. In addition to modeling delinquency as "ever 60 days delinquent", we consider default (foreclosure filing) as an alternative specification for loan performance. We employ the same specification as before, but replace the outcome DELINQUENT, with DEFAULT[7].

E. Borrower & Geographic Control Variables

Characteristics of the lending environment are included in both Stage 1 and Stage 2, as controls. First, to control for geographic variation in the screening rigor of particular types of lenders, we include the denial rates of first-lien, owner-occupied, home purchase mortgage applications by banks and non-banks, as reported in HMDA, observed at the borrower's previous and new census tracts but in the year *preceding* the year of origination. The assumption is that if banks (or non-banks) in the area deny a large share of its applicants in one year, borrowers will tend seek loans from non-banks (or banks) in the following year (Stage 1). Further, with regard to loan performance (Stage 2), denial rates may capture unobserved systematic differences by geography in borrower risk that may lead to higher delinquency or default rates for borrowers in a particular geography.

In addition to denial rates, market competitiveness may influence a borrower's selection of a particular type of lending institution, and the probability of prepayment (refinance). We calculate the lending market Herfindahl index in the census tract of both the previous and new address using HMDA data, to measure the lending market competition (Ergungor 2010). We also include the total number of first lien mortgage applications in the previous and new census tracts as control variables for overall demand.

We control for borrower characteristics at origination including those that are typically associated with default risk in the contingent claims literature (see, for example, Kau et al, 1992; Kau et al, 1993;

[7]We also estimate a survival model, taking advantage of the time until the event (default, delinquent or censored/survive). However, the multinomial logit model provides a better estimation of competing risks that are simultaneously determined, and is thus our primary specification. See Appendix A for results of the survival analysis for Stage 2.

Kau et al, 1995). We expect borrower characteristics to influence both the selection of a particular lender type (stage 1) as well as loan performance (stage 2). For example, borrowers with increased risk for default based on observable characteristics may be more likely to be approved for a mortgage from a broker, and they may be more likely to self-sort into broker channels (for evidence of self-sorting into mortgage products, see Pennington-Cross and Nichols 2000). The indicators for observable risk include credit score, income, and housing and debt ratios (where the housing ratio is the proportion of monthly income spent on principle, interest, taxes, insurance and private mortgage insurance, and the debt ratio includes housing debt in addition to other monthly financed debt as a percent of monthly income). Demographic indicators include race, ethnicity, gender, age, and household size. Loan indicators include the loan to value ratio (ltv), interest rate, receipt of downpayment assistance (DPA) from OHFA in the form of a grant or a loan, and whether or not the loan was FHA or VA insured. Finally, we include indicators for the year of origination and the days since purchase.

As indicated on Table II, there are noticeable differences by type of lending institution. Borrowers with their mortgages from bank (local or non-local branch) tend to have higher credit scores, higher incomes, lower housing and debt ratios, slightly smaller household size, and less likely to receive downpayment assistance or an FHA/VA insured mortgage.

To control for geographic variables that might influence loan performance and/or be systematically associated with selection to a bank, we include an array of census tract, mobility and Metropolitan Statistical Area (MSA) indicators. Census tract indicators for both previous renter and new purchase tracts are derived from the 2000 US Census files, and include population density (measured as the population in the tract divided by the square miles in the tract), a dummy variables indicating whether or not 95% or more of the tract is considered urban (by the Census Bureau), the proportion of households in the tract employed in manufacturing jobs, the median home value in the tract, the tract income as a percent of the county or MSA income (% County AMI), the proportion of residents completing at least high school, and the proportion of residents that commute more than 30 miles to work. The distance moved in miles (logged) from the previous address to the new address is included to measure mobility, where an increase in distance moved may signal an increase in mobility and thus an increase the probability of moving again (prepayment). We also include dummy variables for each of the 8 MSAs in Ohio based on the location of purchase, as mortgage markets may differ significantly by MSA. Summary statistics for the geographic indicators are provided in Table II.

[Table II Here]

III. Results

A. Stage 1: Lender Type

Table III presents the coefficients from the multinomial logistic regression model predicting whether or not borrowers receive their loans from a local bank branch, a non-local bank branch, or non-bank lender, as well as the impact on predicted probabilities for interpretation. Because the coefficients from a multinomial logistic regression are not directly interpretable, the predicted probabilities are calculated as the change in the probability of the outcome category for a one standard deviation change (continuous variables) or one unit change (binary variables) in the respective independent variable, holding all other independent variables at their mean (continuous variables) or modal (binary variables) values ($\Delta\sigma$ or $\Delta 1$).

[Table III Here]

The Stage 1 model allows us to extract the propensities for borrowers to receive their mortgages from particular type of lenders given observable risk, market structure, lending and geographic characteristics. First, it may be that more sophisticated borrowers, with higher credit scores, are more likely to have an ongoing relationship with a bank, and thus select a local bank for their loan. Indeed, a one standard deviation increase in logged-credit score is associated with a 16 percent increase in the probability of going to a local bank (4.42% increase relative to base probability of 26.97%). Other indicators of "hard information" about credit risk, including, lower mortgage debt (Housing ratio) and lower loan to value ratio (LTV), are significantly associated with receipt of mortgage by a bank (local or non-local), relative to a non-bank lender. Income is not significantly associated with a particular lender type (although it is important to keep in mind that all borrowers in this sample have incomes below 115% of area median, and thus there is less heterogeneity than in the general population of homebuyers). Demographics including age (younger), household size (smaller), race (black) and ethnicity (Hispanic) are significantly associated with to the receipt of a mortgage by a local bank branch. Borrowers with FHA or VA mortgages are significantly more likely to receive a mortgage from a non-bank lender.

Aside from borrower sophistication, the selection of lender type in the MRB program may be influenced by the market structure , as measured by access to bank branches originating MRB loans, and the overall nature of the lending environment (competition and ease of approval) at both the previous and new address. As expected, an increase in MRB bank branch access, an increase in the non-bank denial rate and decrease in the bank denial rate is associated with an increased probability of selecting a local branch, whereas an increase in bank branch access is associated with a decrease in the probability of selecting a non-local bank branch, or a non-bank lender.

Finally, selection of bank type may be influenced in part by geographic characteristics of the neighborhood (at either the previous or new address). In particular, banks may be less likely to lend in neighborhoods with weaker housing and labor markets, whereas non-bank lenders may be more active in such areas. We find some evidence of this; an increase in manufacturing employment is associated with a decreased probability of receiving a loan from a bank (local or nonlocal), and an increase in the income of the tract (relative to the county area median income) is associated with an increased probability of receiving a loan from a bank (local or nonlocal), whereas previous tract characteristics are significantly associated with selection of a local bank, and new tract characteristics are significantly associated with selection of a non-local bank. Further, borrowers in urban tracts are more likely to receive their mortgage from a non-bank lender. Finally, the selection of bank varies significantly by MSA in Ohio, suggesting that local mortgage market conditions are an important factor determining lending outcomes[8].

B. Stage 2: Loan Performance

Tables IV and V present the coefficients and predicted probabilities from the multinomial logistic regression models for mortgage delinquency, prepayment or current (Table IV), and mortgage default, prepayment or current (Table V). The primary variables of interest in the stage 2 models are dichotomous

[8]The coefficients for the MSA indicators and the year indicators are not included in the table for sake of brevity; however, all eight of the MSA dummy variables (ninth category for out of state MSA excluded) were statistically significant (with varying signs).

variables for local bank branch (Bank branch ≤ 2 miles) and non-local bank branch (Bank branch > 2 miles), (where non-bank lender is the reference category), after controlling for the selection of local bank branch (≤ 2 miles) and non-local bank branch (> 2 miles) through the estimated propensities from the stage 1 selection model.

[Tables IV& V Here]

There is evidence of both a selection and a direct bank (regulatory) effect where borrowers with mortgages from banks (local or non-local branches) are significantly less likely to be ever delinquent (Table IV) than borrowers with loans from non-bank lenders. The predicted probability of delinquency is 2.36% lower for borrowers with loans from local branches, compared with 1.32% lower for borrowers with loans from non-local branches, suggesting potential informational advantages. However, Wald tests do not confirm that the coefficients for local and non-local branches are statistically different from each other. In the default equation (Table V), only local branch originations are significantly less likely to default (again, indicative of an information effect); however, the coefficients for local and nonlocal branch originations are once again not statistically different from each other. In addition to direct bank effects, selection to a local bank is associated with reduced probability of delinquency (Table IV) and default (Table V), where a one standard deviation increase in the propensity to select a local bank is associated with a 4.41% and 2.10% reduction in the probability of delinquency and default, respectively. Across both models, the selection coefficients are more robust and economically substantial (confirmed by Wald tests) for local bank branch originations than non-local bank branch originations.

Aside from the bank indicators, many of the borrower and geographic variables are also significantly predictive of delinquency and default. As would be expected, an increase in credit risk (lower credit score, higher housing ratio and higher debt ratios and LTV) are associated with an increased probability of delinquency and default (those with lower LTVs may be able to sell their home to exit if they become delinquent without defaulting on their mortgage). In addition, borrowers who receive downpayment assistance (in the form of a grant or second mortgage) are more likely to be delinquent, while those with the second mortgage form are also more likely to default. With regard to demographic characteristics, age (younger), race (black), and household size (large) are significantly associated with increased probability of delinquency and default. Finally, as would be expected, those who have been in their home longer (months since purchase) are more likely to have ever been delinquent on their mortgage due to longer exposure time.

In general, geographic characteristics of the census tract are more significantly associated with the probability of prepayment than delinquency or default. In particular, borrowers purchasing homes in urban tracts, with higher home values are more likely to prepay their mortgage, likely due to a more robust housing market. Also, an increase in the distance between the previous and new address of the borrower is associated with an increased probability of prepayment, as it is likely indicative of increased mobility of the household.

C. Alternative Specifications

While we find evidence of a regulatory effect in the previous models (Tables IV&V), we do not find statistical evidence of a soft information effect; that is, while there is a difference between the coefficients for local and non-local bank originations, the difference is not statistically significant. However, one of the deficiencies of our previous specification is that large banks and small banks are treated equally. Because the information effect is expected to be tied in part to the discretion of the originator, we might expect that smaller banks have greater discretion (where decisions can be made more locally) than larger banks, and thus may be more likely to realize information effects (regardless of distance to the borrower). Therefore, we repeat our two stage estimations, but divide banks into small and large[9], and local and non-local branches, resulting in four bank categories, plus one non-bank category. While the full models are estimated, for brevity, Table VI, Panel A presents the instrumental variables (access and denial rates) from the stage 1 model for selection of bank type, while Panel B presents the bank and selection coefficients of the stage 2 models for loan performance.

[Table VI: Panels A&B Here]

[9]We define banks as small or large based on asset size. Small community banks are generally defined as institutions with less than $10 Billion in assets.

The results of the stage 1 model for selection of bank type, by bank size, are consistent with expectations; an increase in access to small, local bank branches increases the probability of selecting a small local bank branch, and an increase in access to large, local bank branches increases the probability of selecting a large local bank branch (Panel A). In stage 2, there are strong (and statistically significant) differences between local and non-local large bank branch originations, where borrowers with loans from large local bank branches are 2.69 percent less likely to be delinquent and 1.38 percent less likely to default than other borrowers, and borrowers with loans from large non-local bank branches are not significantly less likely to default (and the coefficient is in the opposite direction). On the other hand, for borrowers with mortgages from small banks, both local and non-local branch originations are significantly less likely to be ever delinquent. This suggests that there is evidence of an information effect, but that the effect works differently for small and large banks; that is, local branches of large banks, and small banks (both local and non-local branches) may benefit from informational advantages over large, non-local bank branches when it comes to selecting creditworthy borrowers.

In addition to bank size, the precision of "hard information" for a borrower, as signaled by their credit score, may also influence the extent to which local bank branches benefit from informational advantages. That is, for higher credit score borrowers, their creditworthiness may be sufficiently signaled through their credit score. However, it is more difficult to distinguish between creditworthy borrowers with lower credit scores based on hard information alone, and thus soft information may play a more important role.

To explore this potential, we divide our sample into two groups; those with credit scores below 660 (7,140 borrowers), and those with credit scores equal to or above 660 (11,230 borrowers). We use 660 as a cutoff based on standard conventions for credit scoring that define borrowers with credit scores of 660 or greater as having lower credit risk. While we estimate the full model of both stage 1 and stage 2 (separately for high and low credit borrowers), we present the results of the bank and selection coefficients from stage 2 in Table VII, Panels A & B. The results of this specification suggest that informational advantages of local bank branches may indeed be more important for lower credit score borrowers (Panel A); however this is more statistically robust for default, where the local bank indicator is an insignificant predictor of default for higher credit score borrowers, but is a significant predictors of default for lower credit score borrowers. Importantly, when the sample is divided based on observed credit score (hard information), the selection variables are no longer statistically significant. This makes sense, as the division of the sample on credit score reduces the heterogeneity of observable risk within the two groups that would otherwise predict selection.

[Table VII: Panels A&B Here]

D. Robustness Checks & Data Limitations

While loan performance is most appropriately modeled within the competing risks framework (as through the multinomial logit specification), survival models are also commonly used to model loan performance (as the probability of survival, relative to default or prepayment). The weakness of the survival model is that survival includes both censored observations (who are current on their mortgage), and those who prepay their mortgage, which may be qualitatively different outcomes. The strength of the survival model is that it implicitly models the duration of exposure to an event (such as delinquency or default), which we can only control for (through the variable months since purchase) in the multinomial logistic regression. Our findings are robust under the survival model specification (presented in Appendix A). Both the direct effects of local and non-local bank branches as well as the selection effects are statistically significant for survival, relative to delinquency (Model A1) and default (Model A2), indicative of an institution effect. While the difference between local and non-local branch originations are not statistically different from one another in the base survival models (Models A1 and A2), they are statistically different under the alternative specifications accounting for bank size (Panel A1) and differences in borrower credit score (Panel A2).

Further, while our primary specification defines local bank branch originations based on a 2-mile radius around the previous and new address, we consider an alternative specification with a 5 miles radius around the previous and new address in both stage 1 and stage 2, to check for robustness. We would expect any informational effects from relationships to decrease as the distance radius increases. By extending the distance for the local bank branch originations to 5 miles, we expect that the non-local bank effect will weaken (to the point of non-significance). Appendix B presents the results of the 5 mile specification. While we still observe that bank loans, and selection to bank lenders, are associated with reduced probability of delinquency and default, the direct effect is only significant for local bank branches, and is not significant for those originations made by banks without a branch within 5 miles of the new or previous address.

Finally, while we have been careful to appropriately estimate and test our model specifications, it is important to keep in mind the limitations of our data and thus our findings. First, our data is drawn from a specific affordable loan program (the MRB program) operating in one state during a tumultuous mortgage market cycle. Additional extensions of this type of analysis to other mortgage programs are important to increase the generalizability of our findings. Second, while our study is able to uniquely leverage address level data to calculate distance as an approximation of informational advantages for banks (patterned after small business lending literature), we do not observe whether or not banks do indeed have ongoing relationships or repeated interactions with borrowers. Future research should consider the extent to which repeated interactions with borrowers, as measured by bank accounts or other transactions with the lending institution, has a similar informational effect on loan performance, particularly for lower credit borrowers. Finally, while we include selection to type of lender in our model, we do not measure the extent to which this selection is driven by the borrower or the lender. Doing this would require full information about the borrower's search process and previous loan applications and denials (if any), prior to selecting the originating lender. However, the purpose of our selection equation is not to isolate borrower versus bank selection, but rather to control for selection to a type of lender based on observable hard information, allowing us to investigate the potential influence soft information on loan performance in stage 2.

IV. Conclusions

In line with previous research, we find that low and moderate income borrowers with loans from depository institutions are significantly less likely to default on their mortgage or be ever seriously delinquent than borrowers with the "same" mortgage from a non-depository mortgage company or broker.

Unlike most other studies that also include variation in loan product and/or servicing, our dataset allows us to isolate the effect of the originating lender by holding constant loan terms and servicing through the mortgage program. Our primary contribution to this literature is to incorporate the added role of soft information to the bank (regulatory) effect on loan performance.

Building on the literature on relationship lending to small businesses, and in particular Ergungor's (2010) recent extension to mortgage markets, we find evidence in support of relationship lending in mortgage markets. In particular, we find evidence that selection and soft information prior to purchase are significantly associated with reduced delinquency and default. And, in line with relationship lending, we find that this effect is most pronounced for borrowers with compromised credit (credit scores below 660), who likely benefit the most from soft information in the lending relationship. This suggests that for lower-income borrowers, relationship with a bank may be about more than the mortgage transaction.

There are at least two notable policy implications from our analysis. First, while arm's-length lending certainly has an important place in the mortgage market, and has led to efficiency gains overall,bank-borrower relationships may still be critical for those lower income and higher risk borrowers with more opaque risk characteristics. In such cases, there may be a danger in overreliance on hard information, such as credit score, for lower income, higher risk borrowers. While on average, credit score is still significantly predictive of mortgage default and delinquency for these borrowers, credit score alone is not sufficient. There may be soft information about motivation and commitment to mortgage performance that cannot be captured in a score, that more completely informs the likelihood of mortgage sustainability.

Second, while the institutional landscape for mortgage lending has shifted considerably over the past few decades, the recent mortgage crisis may provide an opportunity to reconsider the importance of institutional structures. In particularly, depository institutions may play an important role in not only extending access to credit, but also in ensuring the sustainability of credit to lower income, higher risk borrowers. On this note, one surprising result in our paper is the local large banks' ability to reduce delinquencies almost as effectively as small banks. In small business lending literature, it is always the latter that gets credited for possessing soft information-based lending technologies. In the mortgage market, however, this result could be one positive consequence of the Community Reinvestment Act of 1977 (CRA), which may have encouraged large banks to develop relationships in areas where they have branches so that they can meet the Act's requirement to meet the credit needs of low-income communities in their branch footprint. In the absence of any study on the economic efficiency of CRA, we abstain from specific recommendations built on this approach.

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Table I. Descriptive Statistics, Loan Performance, Bank and Lending Characteristics

	All Observations (N=18,370)				Non-Bank (N=9,999)	Non-Local Branch (N=3,063)	Local Branch (N=5,376)
	Mean	Std Dev	Min	Max	Mean	Mean	Mean
Type of Originator							
Local Bank branch ≤ 2 miles	28.89		0	1			
Bank branch >2 miles & ≤ 5 miles	7.95		0	1			
Non-Local Bank branch > 5 miles	9.13		0	1			
Non-Bank	54.03		0	1			
Loan Performance							
Current (No Default)	78.09%		0	1	77.08%	77.31%	79.77%
Default	11.55%		0	1	13.35%	11.24%	9.17%
Prepaid	10.36%		0	1	9.57%	11.45%	11.06%
Current (Never Delinquent)	63.47%		0	1	60.65%	62.90%	67.79%
Ever Delinquent 60 Days	26.17%		0	1	29.78%	25.65%	21.15%
Bank Branch Access at 2 Miles							
Prev Access MRB banks (log)[1]	1.73	0.92	0.00	5.59	1.71	1.48	1.90
Prev Count MRB banks[1]	6.23	4.63	0	29	6.128	5.10	7.079
New Access MRB banks (log)[1]	1.74	0.83	0.00	5.31	1.74	1.46	1.91
New Count MRB banks[1]	6.314	4.267	0	28	6.279	4.97	7.154
Access all banks (log)[2]	2.009	0.86	0.00	5.89	2.013	1.74	2.153
Count all banks[2]	8.587	5.72	0	40	8.650	6.86	9.442
Census Tract Lending Controls							
Prev Bank Denial Rate	0.133	0.09	0.00	1.00	0.136	0.136	0.127
Prev Non-Bank Denial Rate	0.184	0.13	0.00	1.00	0.180	0.195	0.187
New Bank Denial Rate	0.135	0.08	0.00	1.00	0.138	0.135	0.131
New Non-Bank Denial Rate	0.182	0.11	0.00	1.00	0.177	0.189	0.188
Prev Herfindahl	0.049	0.020	0.029	0.311	0.049	0.050	0.050
Prev Loan Applications	110.576	99.25	1.00	1532.00	109.80	115.18	109.28
New Herfindahl	0.049	0.02	0.03	0.31	0.049	0.050	0.050
New Loan Applications	117.950	108.18	1.00	1257.00	116.868	124.759	115.765

[1]Variable only included in Stage 1 (identifies Stage 2)

[2]Variable only included in Stage 2

Table II. Descriptive Statistics, Borrower and Geographic Characteristics

	All Observations (N=18,370)				Non-Bank (N=9,999)	Non-Local Branch (N=3,063)	Local Branch (N=5,376)
	Mean	Std. Dev.	Min	Max	Mean	Mean	Mean
Borrower Characteristics							
Credit Score	683.11	66.15	300	850	676.19	685.83	693.84
Monthly Income ($)	3,258.00	944.88	556.5	7387	3,249.56	3,301.23	3,244.64
Housing Ratio	0.282	0.08	0.056	0.679	0.285	0.279	0.280
Debt Ratio	0.401	0.10	0.072	0.699	0.404	0.399	0.396
Black (%)	0.108	0.31	0	1	0.107	0.096	0.123
Hispanic (%)	0.020	0.14	0	1	0.022	0.016	0.019
Female (%)	0.412	0.49	0	1	0.416	0.391	0.419
Age (Years)	31.75	10.07	18	91	31.97	31.50	31.58
LTV	0.976	0.06	0.246	1.199	0.980	0.973	0.971
Interest Rate[2]	5.859	0.45	4.500	7.500	5.846	5.869	5.877
DPA Grant (%)	0.197	0.40	0	1	0.212	0.182	0.175
DPA Second (%)	0.180	0.38	0	1	0.175	0.187	0.193
Household Size	1.93	1.18	1	11	2.00	1.95	1.81
FHA/VA Loan (%)	0.447	0.50	0	1	0.469	0.436	0.414
Days Since Purchase[2]	45.461	12.14	24	71	46.113	44.960	44.580
Closed 2005 (%)	0.139	0.35	0	1	0.159	0.125	0.110
Closed 2006 (%)	0.328	0.47	0	1	0.329	0.320	0.332
Closed 2007 (%)	0.271	0.44	0	1	0.264	0.284	0.280
Closed 2008 (%) (omitted)	0.262	0.44	0	1	0.251	0.271	0.278
Geographic Characteristics							
Prev Tract Density[1]	3,264.98	3,034.28	17.59	25,250	3,196.77	2,809.53	3,421.94
Prev Tract Urban[1]	0.735	0.442	0	1	0.722	0.635	0.773
Prev Tract % Manufacturing[1]	0.179	0.070	0	0.443	0.176	0.183	0.172
Prev Tract Home Value (log)[1]	11.57	0.36	9.21	13.82	11.57	11.57	11.56
Prev Tract % County AMI[1]	1.011	0.299	0.096	3.798	1.018	1.016	1.017
Prev Tract % High School[1]	0.844	0.091	0.319	0.996	0.846	0.840	0.848
Prev Tract % Commute >30 min.[1]	0.280	0.098	0.000	0.816	0.276	0.291	0.267
New Tract Density	3,430.25	2,697.34	17.59	24,820	3,294.99	2,854.69	3,545.47
New Tract Urban	0.777	0.416	0	1	0.754	0.670	0.804
New Tract % Manufacturing	0.183	0.066	0	0.434704	0.180	0.186	0.176
New Tract Home Value (log)	11.514	0.288	9.21024	13.320	11.51	11.53	11.50
New Tract % County AMI	0.98	0.24	0.10	3.18	0.988	0.999	0.980
New Tract % High School	0.838	0.081	0.377	0.993	0.839	0.836	0.841
New Tract % Commute >30 min.	0.280	0.095	0.073	0.816	0.278	0.296	0.267
Distance Move (miles)	8.80	20.73	0.00	323.65	8.67	9.58	8.12

[1]Variable only included in Stage 1 (identifies Stage 2)

[2]Variable only included in Stage 2

Table II. (continued)

	All Observations (N=18,370)				Non-Bank (N=9,999)	Non-Local Branch (N=3,063)	Local Branch (N=5,376)
	Mean	Std. Dev.	Min	Max	Mean	Mean	Mean
Akron (%)	7.9%	0.269261	0	1	6.7%	5.2%	7.4%
Canton (%)	3.7%	0.1899755	0	1	4.7%	4.0%	5.0%
Cincinnati (%)	21.7%	0.4122664	0	1	23.9%	26.8%	22.0%
Cleveland (%)	23.7%	0.4249805	0	1	17.8%	17.6%	17.7%
Columbus (%)	23.2%	0.4220433	0	1	23.4%	23.1%	23.3%
Dayton (%)	9.3%	0.2898317	0	1	13.6%	13.0%	15.0%
Toledo (%)	3.4%	0.1802819	0	1	1.9%	1.8%	1.8%
Youngstown (%)	1.7%	0.1310123	0	1	2.4%	1.6%	2.8%
Other MSA (%) (omitted)	5.5%		0	1	5.7%	6.8%	5.0%

[1]Variable only included in Stage 1 (identifies Stage 2)

[2]Variable only included in Stage 2

Table III. Stage 1, Multinomial Logistic Regression Predicting Lender Type (N=18,370)

		Bank branch ≤ 2 miles		Bank branch > 2 miles		Non-Bank
	Avg Δ	β	Δσ or *Δ1*	β	Δσ or *Δ1*	Δσ or *Δ1*
Borrower Characteristics						
Credit Score (log)	3.34%	2.512	4.42% **	1.326	0.59% **	-5.01%
Monthly Income (log)	0.72%	-0.153	-1.08%	0.166	0.71%	0.38%
Housing Ratio	0.84%	-0.790	-1.15% *	-0.367	-0.11%	1.26%
Debt Ratio	0.39%	-0.288	-0.59%	0.082	0.19%	0.41%
Black	5.66%	0.414	8.12% **	0.181	0.37%	-8.49%
Hispanic	3.80%	0.282	5.69%	0.052	-0.47%	-5.23%
Female	0.85%	-0.064	-1.18% *	-0.029	-0.10%	1.28%
Age (Years)	0.69%	-0.005	-0.85% *	-0.003	-0.17%	1.03%
LTV	1.75%	-1.889	-1.77% **	-1.944	-0.86% **	2.63%
DPA Grant	0.89%	-0.057	-0.94%	-0.054	-0.40%	1.33%
DPA Second	0.69%	-0.024	-0.19%	-0.087	-0.85%	1.04%
Household Size	1.02%	-0.063	-1.33% **	-0.035	-0.20% *	1.53%
FHA/VA Loan	2.30%	-0.160	-2.67%	-0.119	-0.77%	3.45%
Lending Environment Characteristics						
Prev Access MRB banks (log)	1.88%	0.126	2.81% **	-0.174	-2.14% **	-0.68%
Prev Count MRB banks	1.03%	0.016	1.54% ^	-0.008	-0.65%	-0.89%
New Access MRB banks (log)	2.07%	0.164	3.10% **	-0.154	-1.86% *	-1.24%
New Count MRB banks	1.22%	0.015	1.73%	-0.035	-1.82% ^	0.09%
Prev Tract Bank Denial Rate	0.97%	-0.779	-1.45% **	0.111	0.36%	1.10%
Prev Tract Non-Bank Denial Rate	0.64%	0.270	0.52%	0.386	0.43% *	-0.96%
New Tract Bank Denial Rate	1.06%	-1.001	-1.43% *	-0.491	-0.16%	1.58%
New Tract Non-Bank Denial Rate	0.93%	0.640	1.36% **	0.228	0.04%	-1.39%
PrevHerfindahl (Tract)	1.08%	3.670	1.27% ^	2.746	0.36%	-1.62%
New Herfindahl (Tract)	0.57%	-2.120	-0.73%	-1.238	-0.12%	0.86%
Prev Tract Loan Applications (log)	0.30%	0.023	0.45%	-0.043	-0.41%	-0.04%
New Tract Loan Applications (log)	0.25%	-0.011	-0.03%	-0.053	-0.35%	0.38%
Geographic Characteristics						
Prev Tract Density (log)	0.24%	0.011	0.21%	0.014	0.15%	-0.36%
Prev Tract Urban	1.62%	-0.028	0.24%	-0.214	-2.42% *	2.19%
Prev Tract % Manufacturing	1.18%	-1.187	-1.44% *	-0.815	-0.34%	1.78%
Prev Tract Home Value (log)	1.82%	-0.385	-2.73% **	0.034	0.60%	2.14%
Prev Tract % County AMI	1.71%	0.432	2.57% **	-0.027	-0.52%	-2.05%
Prev Tract % High School	0.62%	-0.549	-0.93%	-0.167	0.00%	0.93%
Prev Tract % Commute >30 min.	0.52%	0.087	0.40%	-0.697	-0.78% *	0.38%
New Tract Density (log)	0.47%	-0.002	0.17%	-0.055	-0.71%	0.54%
New Tract Urban	4.11%	-0.290	-5.42% *	-0.165	-0.75% ^	6.16%
New Tract % Manufacturing	1.32%	-0.845	-0.63%	-2.118	-1.35% *	1.98%

Table III. (continued)

		Bank branch ≤ 2 miles		Bank branch > 2 miles		Non-Bank
	Avg Δ	β	Δσ or *Δ1*	β	Δσ or *Δ1*	Δσ or *Δ1*
New Tract Home Value (log)	1.82%	-0.327	-1.33%	-0.544	-1.40%	2.73%
New Tract % High School	0.29%	0.110	0.30%	-0.457	-0.43%	0.13%
New Tract % Commute >30 min.	0.69%	-0.485	-1.04%	0.395	0.57%	0.47%
Distance Move (+1, logged)	0.81%	0.040	1.12% *	-0.099	-1.21% **	0.09%
Year Dummy Variables						
MSA Dummy Variables						
Constant	-5.443			-0.951		
Psuedo R2	0.067					
Pr(Y)			26.97%		12.51%	60.51%

Note: ^p<.10; *p<.05; **p<.01
Predicted probabilities (Δσ or *Δ1*) are calculated as the change in the probability of the outcome for a one standard deviation (continuous) or one unit (dummy) change in the independent variable, holding all other variables at their mean (continuous) or modal (dummy) values. Percent change can be calculated by dividing the predicted probability for a given variable by the base probability, Pr(Y).

Table IV. Multinomial Logistic Regression, Delinquent or Prepayment (N=18,370)

		Ever 60 Days Delinquent			Prepayment			Current
	Avg Δ	β	Δ σ | *Δ 1*		β	Δ σ | *Δ 1*		Δ σ | *Δ 1*
Borrower Characteristics								
Credit Score (log)	7.65%	-8.319	-11.48%	**	1.475	2.08%	**	9.40%
Monthly Income (log)	1.34%	-0.142	-0.94%		0.898	2.01%	**	-1.07%
Housing Ratio	1.81%	1.323	1.15%	**	2.961	1.56%	**	-2.72%
Debt Ratio	0.97%	1.056	1.46%	**	-0.129	-0.23%		-1.23%
Black	5.65%	0.491	8.48%	**	-0.408	-2.97%	*	-5.51%
Hispanic	1.04%	-0.026	-0.09%		-0.232	-1.48%		1.57%
Female	1.61%	-0.059	-0.44%	*	-0.260	-1.98%	**	2.42%
Age (Years)	1.19%	-0.006	-0.64%	*	-0.017	-1.15%	**	1.79%
LTV	1.05%	1.496	1.45%	^	-3.545	-1.57%	**	0.13%
Interest	3.35%	0.276	0.93%	**	1.325	4.09%	**	-5.02%
DPA Grant	1.24%	0.115	1.86%		-0.171	-1.27%	^	-0.59%
DPA Second	2.59%	0.223	3.88%	**	-0.495	-3.08%	**	-0.81%
Household Size	1.52%	0.132	2.28%	**	-0.085	-0.92%	**	-1.36%
FHA/VA Loan	2.33%	0.093	0.77%		0.348	2.72%	**	-3.49%
Months Since Purchase (log)	3.27%	1.122	4.15%	**	0.574	0.75%		-4.90%
Lending Environment Characteristics								
Bank branch ≤ 2 miles	1.57%	-0.184	-2.36%	**	-0.020	0.08%		2.28%
Bank Branch > 2 miles	0.92%	-0.102	-1.32%	*	-0.026	-0.06%		1.38%
Selection Bank ≤ 2 miles	3.02%	-2.620	-4.41%	**	-0.605	-0.12%		4.53%
Selection bank > 2 miles	1.72%	-2.008	-2.39%	*	-0.652	-0.19%		2.58%
Access all banks (log)	0.34%	0.036	0.50%		-0.069	-0.46%		-0.04%
Count all banks	0.33%	-0.002	-0.23%		0.012	0.49%	*	-0.26%
Prev Tract Bank Denial Rate	0.20%	-0.218	-0.27%		-0.095	-0.04%		0.30%
Prev Tract Non-Bank Denial Rate	0.36%	0.284	0.49%		0.108	0.05%		-0.55%
New Tract Bank Denial Rate	0.13%	0.109	0.15%		-0.335	-0.20%		0.05%
New Tract Non-Bank Denial Rate	0.39%	0.250	0.34%		0.337	0.24%		-0.58%
Prev Herfandahl (Tract)	0.64%	-2.201	-0.52%		-3.494	-0.45%	^	0.96%
Prev Tract Loan Applications (log)	0.10%	-0.007	-0.06%		-0.019	-0.10%		0.16%
New Herfandahl (Tract)	0.98%	4.471	1.11%	*	3.351	0.36%		-1.47%
New Tract Loan Applications (log)	0.30%	-0.020	-0.12%		-0.074	-0.33%	^	0.45%

Table IV. (Continued)

		Ever 60 Days Delinquent			Prepayment			Current
	Avg Δ	β	Δ σ | *Δ 1*		β	Δ σ | *Δ 1*		Δ σ | *Δ 1*
Geographic Characteristics								
Prev Tract Density (log)	0.26%	0.010	0.14%		0.029	0.25%		-0.38%
Prev Tract Urban	1.95%	-0.095	-0.93%		-0.282	-2.00%	**	2.93%
Prev Tract % Manufacturing	0.31%	0.084	0.16%		-0.923	-0.47%		0.30%
Prev Tract Home Value (log)	0.93%	-0.268	-1.26%	^	-0.097	-0.13%		1.39%
Prev Tract % County AMI	1.08%	0.259	0.92%		0.375	0.70%	*	-1.62%
Prev Tract % High School	0.29%	0.017	0.10%		-0.667	-0.43%		0.34%
Prev Tract % Commute >30 min.	0.60%	0.643	0.90%	**	-0.239	-0.25%		-0.65%
New Tract Density (log)	1.08%	-0.054	-0.71%	^	-0.116	-0.91%	*	1.62%
New Tract Urban	0.97%	-0.080	-1.39%		0.209	1.46%	*	-0.06%
New Tract % Manufacturing	0.28%	-0.060	0.02%		-0.908	-0.43%		0.40%
New Tract Home Value (log)	0.53%	-0.044	-0.31%		0.378	0.80%	^	-0.48%
New Tract % County AMI	0.50%	-0.215	-0.75%		0.174	0.36%		0.39%
New Tract % High School	0.36%	-0.262	-0.23%		-0.585	-0.31%		0.54%
New Tract % Commute >30 min.	0.26%	-0.298	-0.39%		0.034	0.06%		0.33%
Distance Move (+1, logged)	0.38%	-0.032	-0.53%		0.076	0.58%	*	-0.05%
Year Dummy Variables	Y							
MSA Dummy Variables	Y							
Constant		50.953	**		-26.37	**		
Psuedo R2		0.149	**					
Pr(Y)			16.45%			7.75%		75.79%

Note: ^p<.10; *p<.05; **p<.01
Predicted probabilities are calculated as the change in the probability of the outcome for a one standard deviation (continuous) or one unit (dummy) change in the independent variable, holding all other variables at their mean (continuous) or modal (dummy) values. Percent change can be calculated by dividing the predicted probability for a given variable by the base probability, Pr(Y).

Table V. Multinomial Logistic Regression, Default or Prepayment (N=18,370)

		Default			Prepayment			Current
	Avg Δ	β	Δ σ | *Δ 1*		β	Δ σ | *Δ 1*		Δ σ | *Δ 1*
Borrower Characteristics								
Credit Score (log)	2.95%	-6.128	-4.43%	**	3.024	2.33%	**	2.10%
Monthly Income (log)	1.25%	-0.126	-0.42%		0.902	1.87%	**	-1.45%
Housing Ratio	1.54%	1.887	0.94%	**	2.690	1.37%	**	-2.31%
Debt Ratio	0.14%	0.284	0.21%		-0.182	-0.14%		-0.07%
Black	1.84%	0.126	1.18%		-0.499	-2.76%	**	1.58%
Hispanic	1.07%	-0.074	-0.41%		-0.199	-1.20%		1.61%
Female	1.41%	-0.045	-0.15%		-0.265	-0.020	**	0.21%
Age (Years)	0.97%	-0.006	-0.34%	**	-0.017	-1.12%	**	1.46%
LTV	0.98%	2.411	1.09%	**	-3.611	-1.48%	**	0.39%
Interest	2.57%	0.050	-0.16%		1.284	3.86%	**	-3.70%
DPA Grant	0.85%	0.045	0.43%		-0.205	-1.28%	*	0.85%
DPA Second	1.95%	0.248	2.22%	*	-0.524	-2.92%	**	0.70%
Household Size	0.67%	0.089	0.82%	**	-0.119	-1.00%	**	0.19%
FHA/VA Loan	1.57%	-0.137	-1.08%	*	0.297	2.36%	**	-1.29%
Months Since Purchase (log)	1.11%	0.553	1.04%		0.375	0.62%		-1.66%
Lending Environment Characteristics								
Bank branch ≤ 2 miles	0.65%	-0.147	-0.97%	*	0.008	0.13%		0.85%
Bank Branch > 2 miles	0.46%	-0.099	-0.66%		-0.012	-0.03%		0.69%
Selection Bank ≤ 2 miles	1.67%	-2.438	-2.10%	*	-0.682	-0.40%		2.50%
Selection bank > 2 miles	1.23%	-2.508	-1.54%	*	-0.714	-0.31%		1.84%
Access all banks (log)	0.59%	0.141	0.88%	*	-0.061	-0.42%		-0.46%
Count all banks	0.55%	-0.020	-0.82%	*	0.011	0.50%	*	0.32%
Prev Tract Bank Denial Rate	0.05%	0.112	0.08%		-0.101	-0.07%		-0.01%
Prev Tract Non-Bank Denial Rate	0.09%	-0.142	-0.14%		0.072	0.07%		0.06%
New Tract Bank Denial Rate	0.15%	0.081	0.06%		-0.417	-0.22%		0.16%
New Tract Non-Bank Denial Rate	0.37%	0.395	0.29%		0.368	0.26%	^	-0.55%
Prev Herfandahl (Tract)	0.32%	-0.910	-0.10%		-2.900	-0.38%		0.48%
New Herfandahl (Tract)	0.06%	0.002	0.02%		-0.017	-0.09%		0.07%
Prev Tract Loan Applications (log)	0.64%	5.079	0.67%		2.616	0.29%		-0.95%
New Tract Loan Applications (log)	0.26%	-0.020	-0.07%		-0.073	-0.32%		0.38%

Table V. (continued)

		Default			Prepayment			Current
	Avg Δ	β	Δ σ | Δ 1		β	Δ σ | Δ 1		Δ σ | Δ 1
Geographic Characteristics								
Prev Tract Density (log)	0.17%	-0.019	-0.19%		0.028	0.25%		-0.06%
Prev Tract Urban	1.83%	-0.144	-0.87%		-0.276	-1.87%	**	2.74%
Prev Tract % Manufacturing	0.34%	-0.115	-0.02%		-1.051	-0.49%	^	0.50%
Prev Tract Home Value (log)	0.30%	-0.129	-0.31%		-0.070	-0.14%		0.45%
Prev Tract % County AMI	0.46%	-0.104	-0.27%		0.336	0.69%	*	-0.42%
Prev Tract % High School	0.29%	0.212	0.17%		-0.687	-0.43%		0.26%
Prev Tract % Commute >30 min.	0.18%	0.368	0.27%		-0.341	-0.24%		-0.03%
New Tract Density (log)	0.78%	-0.047	-0.32%		-0.109	-0.84%	*	1.16%
New Tract Urban	0.82%	-0.130	-1.07%		0.189	1.24%	*	-0.17%
New Tract % Manufacturing	0.66%	-1.261	-0.55%	^	-1.089	-0.44%	^	0.99%
New Tract Home Value (log)	0.47%	-0.326	-0.71%		0.328	0.69%	*	0.02%
New Tract % County AMI	0.40%	0.152	0.22%		0.251	0.38%		-0.60%
New Tract % High School	0.40%	-0.609	-0.32%		-0.566	-0.28%		0.60%
New Tract % Commute >30 min.	0.19%	-0.420	-0.28%		0.033	0.04%		0.24%
Distance Move (+1, logged)	0.45%	0.025	0.13%		0.085	0.55%	**	-0.68%
Year Dummy Variables	Y							
MSA Dummy Variables	Y							
Constant		40.072	**		-35.22	**		
Psuedo R2		0.104	**					
Pr(Y)			7.60%			7.24%		85.16%

Note: ^p<.10; *p<.05; **p<.01
Predicted probabilities are calculated as the change in the probability of the outcome for a one standard deviation (continuous) or one unit (dummy) change in the independent variable, holding all other variables at their mean (continuous) or modal (dummy) values. Percent change can be calculated by dividing the predicted probability for a given variable by the base probability, Pr(Y).

Table VI: Bank Size

Panel A: Stage 1, Bank Size and Branch Proximity (Multinomial Logit)

	Small Bank (Branch > 2 miles)			Large Bank (Branch > 2 miles)			Small Bank (Branch < 2 miles)			Large Bank (Branch < 2 miles)			Non-Bank
	β	Δ σ or *Δ 1*		β	Δ σ or *Δ 1*		β	Δ σ or *Δ 1*		β	Δ σ or *Δ 1*		Δ σ or *Δ 1*
PrevAccess Small MRB banks	0.05	0.31%		-0.03	-0.02%		0.47	2.16%	**	-0.19	-2.20%	*	-0.25%
PrevAccess Large MRB banks	-0.09	-0.92%	^	0.05	0.03%		-0.25	-1.69%	**	0.19	2.92%	**	-0.35%
New Access Small MRB banks	0.24	1.37%	*	0.12	0.04%		0.61	2.61%	**	-0.20	-2.57%	*	-0.72%
New Access Large MRB banks	-0.24	-1.87%	**	-0.09	-0.05%		-0.28	-1.57%	**	0.18	2.78%	**	-0.37%
Prev Count Small MRB banks	-0.15	-2.22%	**	-0.06	-0.07%		0.08	0.72%		0.11	2.29%	*	-1.44%
Prev Count Large MRB banks	0.02	0.92%	^	-0.28	-0.90%	**	0.00	-0.01%		0.01	0.36%		0.71%
New Count Small MRB banks	-0.18	-2.67%	**	-0.06	-0.06%		0.06	0.60%		0.09	2.19%		-0.05%
New Count Large MRB banks	0.01	0.35%		-0.22	-0.63%	**	0.03	0.64%		0.00	-0.14%		-0.21%
Pr(Y)		1.53%			0.76%			7.29%			17.49%		63.93%

Note: ^p<.10; *p<.05; **p<.01

Table VI. (continued)

Panel B: Stage 2, Predict Delinquency/Default or Prepayment

	Delinquency			Prepayment			Default			Prepayment		
	β	Δ σ or *Δ 1*		β	Δ σ or *Δ 1*		β	Δ σ or *Δ 1*		β	Δ σ or *Δ 1*	
Small Bank (Branch>2)	-0.16	-2.05%	**	-0.06	-0.21%		-0.10	-0.69%	^	-0.03	-0.15%	
Large Bank (Branch>2)	0.11	1.58%		-0.03	-0.33%		-0.06	-0.40%		-0.06	-0.36%	
Small Bank (Branch<2)	-0.19	-2.62%	**	0.11	1.01%		-0.13	-0.95%		0.14	1.03%	
Large Bank (Branch<2)	-0.21	-2.69%	**	-0.08	-0.28%		-0.21	-1.38%	**	-0.05	-0.22%	
Selection Small Bank > 2	-0.79	-0.50%		-1.99	-0.74%	^	-1.67	-0.64%		-2.06	-0.73%	^
Selection Large Bank > 2	-0.80	-0.78%		1.12	0.54%		-1.23	-0.58%		1.09	0.48%	
Selection Small Bank < 2	-0.43	-0.38%		-1.20	-0.64%	^	-0.66	-0.34%		-1.28	-0.66%	^
Selection Large Bank < 2	-1.85	-2.75%	**	-0.43	-0.07%		-1.26	-0.96%		-0.41	-0.21%	
Pr(Y)		16.81%			7.39%			7.79%			6.94%	

Note: ^p<.10; *p<.05; **p<.01

Table VII: Loan Performance and Bank (Selection), By Credit Score

Panel A: Stage 2, Credit Score < 660 (N=7,140)

	Delinquency			Prepayment		Default			Prepayment	
	β	Δ σ or *Δ 1*		β	Δ σ or *Δ 1*	β	Δ σ or *Δ 1*		β	Δ σ or *Δ 1*
Bank branch ≤ 2 miles	-0.18	-4.27%	**	-0.07	0.03%	-0.19	-3.06%	*	-0.03	0.06%
Bank Branch > 2 miles	-0.08	-2.02%		-0.01	0.14%	-0.06	-0.99%		0.02	0.15%
Selection bank > 2 miles	-1.86	-3.70%		-1.70	-0.36%	-1.48	-2.10%		-1.23	-0.37%
Selection Bank ≤ 2 miles	-2.12	-5.41%	^	-3.16	-1.27%	-1.23	-2.16%		-2.63	-1.32%
Pr(Y)		43.09%			5.04%		21.42%			4.90%

Note: ^p<.10; *p<.05; **p<.01

Panel B: Stage 2, Credit Score > 660 (N= 11,230)

	Delinquency			Prepayment		Default			Prepayment	
	β	Δ σ or *Δ 1*		β	Δ σ or *Δ 1*	β	Δ σ or *Δ 1*		β	Δ σ or *Δ 1*
Bank branch ≤ 2 miles	-0.18	-1.05%	**	0.00	0.12%	-0.07	-0.20%		0.02	0.20%
Bank Branch > 2 miles	-0.11	-0.64%		-0.04	-0.27%	-0.15	-0.37%		-0.03	-0.24%
Selection bank > 2 miles	-0.17	-0.11%		0.24	0.20%	0.19	0.04%		0.20	0.15%
Selection Bank ≤ 2 miles	-0.87	-0.66%		-0.12	-0.06%	-0.04	-0.01%		-0.12	-0.12%
Pr(Y)		6.71%			8.95%		2.86%			8.82%

Note: ^p<.10; *p<.05; **p<.01

Appendix A: Survival Models of Loan Performance (N=18,370)

	Model A1			Model A2		
	Survive or Prepay (Not Delinquent)			Survive or Prepay (Not Default)		
	β	e^β		β	e^β	
Borrower Characteristics						
Credit Score (log)	6.44	629.26	**	4.32	74.95	**
Monthly Income (log)	0.07	1.08		0.02	1.02	
Housing Ratio	-0.97	0.38	**	-1.21	0.30	**
Debt Ratio	-0.84	0.43	**	-0.46	0.63	*
Black	-0.26	0.77	**	-0.15	0.86	*
Hispanic	0.00	1.00		-0.03	0.97	
Female	0.01	1.01		0.00	1.00	
Age (Years)	0.00	1.00	*	0.00	1.00	*
LTV	-0.95	0.39	*	-1.77	0.17	**
Interest	-0.09	0.92		-0.08	0.92	
DPA Grant	-0.11	0.89	*	-0.02	0.98	
DPA Second	-0.17	0.84	**	-0.20	0.82	**
Household Size	-0.08	0.92	**	-0.05	0.95	**
FHA/VA Loan	-0.03	0.97		-0.04	0.97	
Months Since Purchase (log)	-0.06	0.94		0.23	1.26	
Lending Environment Characteristics						
Bank branch ≤ 2 miles	0.11	1.12	**	0.12	1.12	**
Bank Branch > 2 miles	0.07	1.07	*	0.09	1.09	*
Selection Bank ≤ 2 miles	1.50	4.48	**	1.85	6.39	**
Selection bank > 2 miles	1.38	3.97	*	1.77	5.89	*
Access all banks (log)	-0.03	0.97		-0.08	0.93	^
Count all banks	0.01	1.01		0.01	1.01	*
Prev Tract Bank Denial Rate	0.07	1.07		0.10	1.10	
Prev Tract Non-Bank Denial Rate	-0.03	0.97		0.01	1.02	
New Tract Bank Denial Rate	-0.07	0.94		-0.17	0.85	
New Tract Non-Bank Denial Rate	-0.19	0.82		-0.40	0.67	^
Prev Herfandahl (Tract)	1.04	2.82		-0.27	0.77	
New Herfandahl (Tract)	-2.11	0.12		-1.86	0.16	
Prev Tract Loan Applications (log)	0.02	1.02		0.00	1.00	
New Tract Loan Applications (log)	0.01	1.01		0.02	1.02	

Appendix A: (cont)

	Model A1			Model A2		
	Survive or Prepay (Not Delinquent)			Survive or Prepay (Not Default)		
	β	e^β		β	e^β	
Geographic Characteristics						
Prev Tract Density (log)	0.02	1.02		0.03	1.03	
Prev Tract Urban	-0.01	0.99		0.04	1.04	
Prev Tract % Manufacturing	-0.10	0.90		0.19	1.21	
Prev Tract Home Value (log)	0.17	1.18	^	0.09	1.09	
Prev Tract % County AMI	-0.13	0.88		0.03	1.03	
Prev Tract % High School	0.09	1.09		-0.07	0.93	
Prev Tract % Commute >30 min.	-0.46	0.63	**	-0.45	0.64	*
New Tract Density (log)	0.01	1.01		0.01	1.01	
New Tract Urban	0.12	1.13	*	0.14	1.15	^
New Tract % Manufacturing	0.17	1.19		0.47	1.59	
New Tract Home Value (log)	-0.08	0.92		0.14	1.15	
New Tract % County AMI	0.17	1.18	^	-0.14	0.87	
New Tract % High School	0.44	1.56	^	0.70	2.02	**
New Tract % Commute >30 min.	0.11	1.11		0.38	1.46	*
Distance Move (+1, logged)	0.02	1.02		0.00	1.00	
Year Dummy Variables	Y			Y		
MSA Dummy Variables	Y			Y		
Constant		-37.867	**		-25.18	**
/ln_gam		-0.356	**		-0.439	**
gamma		0.700			0.645	

^p<.10; *p<.05; **p<.01

Note: We use a loglogistic distribution for the hazard ratio, because the distribution violates the proportionality assumption for a proportional hazards model (Cox), and the loglogistic distribution represents the best fit with our data (minimizes the absolute value of the log likelihood). Robust standard errors are used to calculate significance.

Panel A1: Stage 2, Bank Size & Survival Models

	All Borrowers						Low Credit						High Credit					
	Not Delinquent			Not Default			Not Delinquent			Not Default			Not Delinquent			Not Default		
	β	e^β		β	e^β		β	e^β		β	e^β		β	e^β		β	e^β	
Small Bank (Branch>2)	0.08	1.09	*	0.09	1.09	**	0.04	1.04		0.03	1.03		0.15	1.16	^	0.17	1.19	*
Large Bank (Branch>2)	0.02	1.02		0.09	1.09		0.00	1.00		0.11	1.12		0.07	1.07		0.04	1.04	
Small Bank (Branch<2)	0.13	1.14	**	0.09	1.09		0.17	1.19	*	0.19	1.20	^	0.11	1.11	^	0.00	1.00	
Large Bank (Branch<2)	0.12	1.13	**	0.17	1.18	**	0.08	1.09	*	0.17	1.19	*	0.17	1.18	**	0.14	1.15	^
Selection Small Bank > 2	0.71	1.77		1.56	3.51	**	1.08	2.95		1.09	2.98		0.10	1.11		0.72	2.05	
Selection Large Bank > 2	0.39	1.56		0.91	2.51	^	0.81	2.26	^	0.85	2.34	^	-1.26	0.28		-0.67	0.51	
Selection Small Bank < 2	0.03	1.04		0.31	1.30		0.26	1.29		0.27	1.31		-0.87	0.42		-0.61	0.54	
Selection Large Bank < 2	1.05	2.77	**	1.32	3.13	**	1.21	3.35	^	1.24	3.46	*	-0.36	0.69		-0.47	0.63	
/ln_gam	-0.36	**		-0.44	**		-0.33	**		-0.42	**			-0.41	**		-0.50	**
gamma	0.6999			0.6449			0.7181			0.6592				0.662			0.60754	

Note: ^p<.10; *p<.05; **p<.01

Panel A2: Stage 2, Credit & Survival Models

	Low Credit						High Credit					
	Not Delinquent			Not Default			Not Delinquent			Not Default		
	β	e^β		β	e^β		β	e^β		β	e^β	
Bank branch ≤ 2 miles	0.09	1.10	*	0.14	1.15	*	0.12	1.13	**	0.07	1.07	
Bank Branch > 2 miles	0.03	1.03		0.05	1.05		0.12	1.13	^	0.15	1.16	^
Selection Bank ≤ 2 miles	0.71	2.04		1.02	2.78		0.12	1.13		-0.57	0.56	
Selection bank > 2 miles	0.87	2.38		0.78	2.17		-0.23	0.80		-0.54	0.58	
/ln_gam	-0.33	**		-0.42	**		-0.41	**		-0.50	**	
gamma	0.7184			0.659			0.6607			0.6084		

Note: ^p<.10; *p<.05; **p<.01

Appendix B: Branches Within 5 Miles

Panel B1: Stage 1, Predict Lender Type

		Bank branch ≤5 miles			Bank branch >5 miles			Non-Bank
	Avg Δ	β	Δ σ | Δ 1		β	Δ σ | Δ 1		Δ σ | Δ 1
Prev Access MRB banks (log)	1.57%	0.102	2.35%	*	-0.197	-1.58%	**	-0.77%
Prev Count MRB banks	0.47%	0.001	0.56%		-0.004	-0.70%		0.15%
New Access MRB banks (log)	2.27%	0.167	3.41%	*	-0.293	-2.15%	**	-1.26%
New Count MRB banks	0.26%	0.001	0.39%		-0.001	-0.21%		-0.18%
Pr(Y)			31.51%			8.68%		59.81%

Note: ^p<.10; *p<.05; **p<.01

Panel B2: Stage 2, Predict Delinquency or Prepayment

		Delinquency			Prepayment		Current
	Avg Δ	β	Δ σ | Δ 1		β	Δ σ | Δ 1	Δ σ | Δ 1
Bank branch ≤ 5 miles	1.22%	-0.154	-1.83%	**	0.007	0.22%	1.61%
Bank Branch > 5 miles	1.51%	-0.126	-1.36%		-0.152	-0.91%	2.27%
Selection Bank ≤ 5 miles	5.91%	-5.029	-8.76%	**	-0.915	-0.11%	8.87%
Selection bank > 5 miles	2.48%	-4.774	-3.72%	**	-0.199	0.25%	3.47%
Pr(Y)			14.65%			7.86%	77.49%

Note: ^p<.10; *p<.05; **p<.01

Panel B3: Stage 2, Predict Default or Prepayment

		Default			Prepayment		Current
	Avg Δ	β	Δ σ | Δ 1		β	Δ σ | Δ 1	Δ σ | Δ 1
Bank branch ≤ 5 miles	0.61%	-0.151	-0.92%	*	0.030	0.28%	0.64%
Bank Branch > 5 miles	0.70%	-0.047	-0.23%		-0.132	-0.82%	1.06%
Selection Bank ≤ 5 miles	3.38%	-5.164	-4.66%	*	-0.823	-0.41%	5.07%
Selection bank > 5 miles	1.55%	-5.787	-2.32%	**	0.015	0.19%	2.13%
Pr(Y)			6.86%			7.30%	85.84%

Note: ^p<.10; *p<.05; **p<.01