Big Banks, Household Credit Access, and Intergenerational Economic Mobility

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Abstract

Consolidation in the United States banking industry has led to larger banks. I find that low income households face reduced access to credit when local banks are large. This result appears to stem from large banks' comparative disadvantage using soft information, which is particularly important for lending to low income households. In contrast, the size of local banks has little or no effect on high income households' access to credit. Moreover, intergenerational economic mobility is lower in areas where banks are large, consistent with low income parents' additional credit constraints limiting their investment in their children's human capital.

The United States banking industry has experienced tremendous consolidation since states began removing barriers to bank expansion in the 1970s, leading to much larger banks. From the average U.S. household's perspective, the median-sized bank within 10 miles of their home is over 7 times larger today than it was in 1995. In this paper I test whether the size of banks affects households' access to credit, and through this channel, intergenerational economic mobility.

It is unclear whether we should expect larger banks to lead to more or less credit access for households. Stein (2002) predicts small banks will have a comparative advantage using soft information to reduce information asymmetries, which should increase credit access (Stiglitz and Weiss (1981)). On the other hand, large banks benefit from economies of scale, and from diversification that reduces the cost of delegated monitoring (Diamond (1984)) and allows banks to lend out a higher proportion of their capital (e.g., Demsetz and Strahan (1997)). If these benefits increase the supply of loanable funds enough to outweigh any effects of reduced soft information production, we might expect larger banks to improve households' access to credit, especially in cases where soft information is less important.

I find that borrowers of low economic status (i.e., low income, subprime credit score, and/or limited credit history) experience lower credit approval rates when local banks are large. In contrast, the size of banks has little or no effect on borrowers of high economic status. The evidence suggests that this asymmetric effect stems from the increased importance of soft information for lending to low income households. These findings naturally raise the question of whether consolidation in the banking industry contributes to economic inequality.

Equality of opportunity, the principle that an individual's success depends primarily on their abilities and work ethic rather than family circumstance, is characterized by intergenerational economic mobility. High mobility levels indicate that children from low income families have the opportunity to move up in the income distribution as adults. In theoretical models, credit access plays an important role in fostering mobility by allowing low income households to invest in their children's human capital (e.g., Becker and Tomes (1979, 1986)). Therefore, I test the hypothesis that having large banks reduces intergenerational mobility due to the additional credit constraints low income households face. I find evidence in support of this hypothesis using newly available data on mobility from Chetty et al. (2014). This finding constitutes the first evidence of a link between the characteristics of financial institutions and intergenerational mobility.

The first set of empirical tests examine household credit access using a nationally representative sample of credit bureau records that provide individuals' age, census tract, credit score, debt by category (mortgage, auto, etc.), credit application inquiries, and other financial variables. The baseline OLS regressions show that *Large Bank Market Share* — the fraction of bank branches within 10 miles of a borrower owned by banks with assets over $1 Billion — has a negative effect on credit approval rates for borrowers of low economic status. These regressions control for borrower credit scores and individual, census tract, and county level characteristics, as well as local banking competition and state-by-year fixed effects.

Despite the rich set of explanatory variables, this paper must address the challenges to identification that may arise from borrowers' credit applications not being randomly assigned to banks. The potential selection comes in two layers. First, borrowers can choose which banks to try when applying for credit. Importantly, we should expect this source of selection to work against finding that the composition of local banks affects credit access, because borrowers likely end up applying for credit at the type of bank most willing to lend to them (either knowingly, or through trial and error shopping).[1] The second layer of potential selection stems from the fact that the composition of local banks reflects large

[1] I measure credit approval based on the success rate of annual credit shopping attempts rather than individual applications. This approach is conservative because it allows borrowers to shop for credit and potentially try multiple lenders.

banks' location decisions. If large banks' location decisions are correlated with an unobservable component of borrower credit quality, it could generate an omitted variables problem. However, it is important to point out that if large banks systematically build/buy branches where they want to lend to local households, we should expect the resulting bias to work against the baseline OLS result that large banks reduce households' access to credit.

To avoid an omitted variables bias, I employ an instrumental variables approach that isolates exogenous variation in *Large Bank Market Share*. I exploit differences in state policies that restrict the ability of out-of-state banks (e.g., national banks) to enter local markets by building new branches or purchasing existing ones. I identify 36 state borders where one state has strong regulatory barriers to out-of-state bank branching, and the other state is open to entry. Unsurprisingly, branches in the state with barriers to out-of-state bank entry are owned by smaller banks. I select everyone in the credit bureau data living within 50 miles of these borders and use their location relative to the border to instrument for *Large Bank Market Share*. The differences in regulation make a person's position relative to the border an instrument for *Large Bank Market Share* even when comparing two people living in the same state. For example, a person living 11 miles towards the interior of the state with regulatory barriers and small banks will have a lower *Large Bank Market Share* than someone in the same state who lives near the border, because the neighboring state's banks are large.

The identifying assumption this approach makes is that for two borrowers in the same state during the same year, controlling for credit scores and individual, census tract, and county level characteristics, their distance to the state border affects credit approval only through its effect on *Large Bank Market Share*. The results from these instrumental variables tests show that a standard deviation increase in *Large Bank Market Share* decreases subprime borrowers' credit approval rates by 3.8 percentage points compared to their mean approval rate of 53.0%, whereas the effect on prime borrowers' credit approval is positive but statistically insignificant. The estimated effect of *Large Bank Market Share* is larger in the instrumental variables regressions than their OLS counterparts, suggesting that any omitted variables bias indeed works against the OLS results.

The second set of empirical tests use Home Mortgage Disclosure Act (HMDA) data on mortgage applications, where the lender's identity is directly reported. I test the hypothesis that low income households have better access to mortgage credit at small banks, and that small banks have a comparative advantage using soft information. I find that small banks approve a higher percentage of mortgage applications, consistent with these banks collecting soft information to price risks and ration credit less. I also find that as the distance from the property to the lender's nearest branch increases, the mortgage approval rate decreases, especially when the borrower has a low income and/or the bank is small. Following the interpretation in the literature that borrower-lender distance affects credit provision through soft information production (e.g., Petersen and Rajan (2002), DeYoung et al. (2008), Agarwal and Hauswald (2010)), these cross-sectional results indicate that soft information is especially important when lending to low income households, and that smaller banks incorporate more of this information into lending decisions. In addition, I find that conditional on loan characteristics, delinquency rates are similar for mortgages originated by large and small banks, despite small banks approving a higher percentage of loans. This finding suggests the higher approval rates at small banks reflect an advantage using soft information, rather than a tendency to originate "bad loans."

After establishing that low income households face tighter credit constraints when local banks are large, I test the hypothesis that large banks reduce intergenerational mobility. I use newly available mobility statistics computed at the county level by Chetty et al. (2014) from the IRS tax returns of children born in the early 1980s and their parents. Controlling for a broad set of covariates outlined in Chetty et al. (2014), plus additional controls, I find that the share of bank branches in a county owned by large banks has a negative effect on mobility levels.

To isolate plausibly exogenous variation in the size of local banks during the childhood of children in the Chetty et al. (2014) data, I use an instrumental variables approach that exploits the staggered removal of state regulations prohibiting interstate bank mergers. Prior to a state's decision to deregulate, out-of-state banks could not enter local markets. States removed these regulations from 1978 to 1997, and the number of years since the state deregulated serves as a powerful instrument for the fraction of branches owned by large banks. The instrumental variables results show that having larger banks leads to lower intergenerational mobility levels. Specifically, a standard deviation increase in the share of large bank branches in a county causes a 4.7 percentage point reduction in the probability that a child with parents in the bottom 40% of the income distribution ends up outside this bottom 40% as an adult, compared to a mean probability of 51.5%.

This paper is related to studies showing small banks are important providers of credit to small businesses, consistent with an advantage lending based on soft information.[2] Although recent work suggests soft information matters when lending to households (e.g., Agarwal et al. (2011) and Iyer et al. (2016)), evidence on whether small banks play a special role in this setting is limited.[3] My paper contributes to this literature by providing loan-level evidence that small banks incorporate more soft information when lending to households, and by showing that low income households are most affected by the size of local banks.

This paper is also connected to studies on the effects of banking deregulation and consolidation. These studies typically examine deregulation's effect on economic growth, or on firms.[4] Recent work also finds mixed evidence on the net effect of banking deregulation and consolidation on households' access to bank accounts (Celerier and

[2]See for example Berger et al. (2005), Berger and Udell (2002), Berger and Black (2011), Berger et al. (2001), Cole et al. (2004), Carter and McNulty (2005), and Strahan and Weston (1998).

[3]Notably, Loutskina and Strahan (2011) show that banks operating primarily in one metropolitan area are more active in the jumbo mortgage market, consistent with an advantage using soft information.

[4]For the effect on economic growth, see e.g., Jayaratne and Strahan (1996) and Berger et al. (2017). For the effects on firms, see e.g., Rice and Strahan (2010), Cetorelli and Strahan (2006), and Chava et al. (2013).

Matray (2017) and Bord (2017)). In contrast, my paper is the first to examine the effects on the distribution of credit across households, and on economic mobility.

My work is also closely related to papers examining the effect of credit constraints on intergenerational mobility. Several studies using household survey data find that constraints reduce mobility (Gaviria (2002) and Mazumder (2005)). However, Black and Devereux (2011) review this literature and point out that it relies on small samples and struggles to address endogeneity issues that arise from using wealth as a proxy for credit constraints. I contribute to this literature by showing credit constraints reduce mobility using plausibly exogenous variation in low income households' constraints based on banking deregulation and the size of local banks. This paper's findings also provide the first evidence of a link between the structure of the banking industry and intergenerational mobility.

1. Regulatory Restrictions on Bank Expansion

Banks in the United States have faced restrictions on geographic expansion since the Constitution gave states the right to charter and regulate banks (see Kroszner and Strahan (2014)). Prior to the Civil War, this authority remained with the states, and few banks established branches either within their home state (intrastate branching) or across state lines (interstate branching) (see Johnson and Rice (2008)). The McFadden Act of 1927 formalized states' authority to regulate all bank branching activity within their borders.

Prior to 1970, most states restricted intrastate branching. Then, throughout the 1970s and 1980s, states removed these restrictions and allowed the banks in their state to build branches and to convert subsidiaries and new acquisitions into branches. This intrastate banking deregulation started the process of banking consolidation that has led to larger banks. Figure 1 shows the continued consolidation from 1995-2015 from the average U.S. household's perspective by plotting the fraction of branches owned by small banks and the median size of banks who own branches within 10 miles of the household.

[Insert Figure 1 Here]

The states also historically used their authority to limit banks' expansion across state borders by prohibiting cross-state ownership of banks (interstate banking) and bank branches (interstate branching). The process of removing barriers to interstate banking began in 1978, when Maine decided to allow out-of-state banking companies to acquire its banks, as long as the acquirer's home state reciprocated and gave banks in Maine the right to acquire banks in their state. Other states began to pass similar laws starting in 1982, and by 1993 every state except Hawaii allowed interstate banking (see Table A.1 for the years that states deregulated). I use these staggered interstate deregulation events to isolate plausibly exogenous variation in the size of banks as of 1995 in order to study the effect of local banks' size on intergenerational mobility.

Although states opened their borders to bank acquisitions throughout the 1980s, only a few states allowed out-of-state banks to establish branches in their state prior to the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) in 1994. The IBBEA removed remaining federal barriers and allowed bank holding companies (BHCs) to engage in interstate banking and branching. However, the IBBEA also gave states the power to erect barriers to limit the entry of out-of-state banks. States were allowed to restrict out-of-state bank entry with four regulatory provisions: (1) the minimum age of the target institution in an interstate bank merger, (2) de novo interstate branching, (3) the acquisition of individual branches, and (4) a statewide deposit cap. I follow Rice and Strahan (2010) and construct an index describing states' policies toward out-of-state bank entry that ranges from 0 to 4. The index takes a value of 0 for states most open to out-of-state bank entry, and 4 for states that use all 4 possible regulatory barriers to make it more difficult for out-of-state banks to establish branches. Specifically, I add one to the index if the state sets the minimum age requirement for target banks in an interstate merger at 3 years or more, if the state prohibits out-of-state banks from building new branches within its borders (de novo branching), if the state prohibits the acquisition of individual bank branches, and if the state sets their statewide deposit cap for banks at less than 30% (the initial limit set by the IBBEA).

I use state borders where states have large differences in interstate branching policies to study the effect of the size of banks on household credit access using credit bureau data from 2010-2015. The Dodd-Frank Act effectively eliminated states' ability to restrict de novo branching starting in July 2010. Therefore, I assign each state its value of the branching restriction index based on the state laws as of the start of 2010. This method ensures that states that prevented de novo branching from 1994-2010 are classified as having been more difficult for out-of-state banks to enter than states that allowed de novo branching during this period. The reduced amount of de novo branching since the financial crisis also makes states' historical de novo policies important to account for.

2. Data and Methods

2.1 Data Sources Overview

I use de-identified credit bureau records and Home Mortgage Disclosure Act (HMDA) data on mortgage applications in order to analyze approval rates on individuals' credit applications. To test whether large banks reduce intergenerational mobility by tightening low income households' credit constraints, I use county level statistics on mobility published by Chetty et al. (2014). These statistics are computed from Internal Revenue Service (IRS) tax returns.

The main explanatory variables of interest in this paper are the characteristics of local banks, or of the specific bank receiving the credit application, when this is directly observable (i.e., when using HMDA data). The locations of bank branches in terms of latitude and longitude are available from the Summary of Deposits data published by the Federal Deposit Insurance Corporation (FDIC). I match bank branches to the commercial banks who own them, and collect data on these banks' characteristics from the Reports of Condition and Income (Call Reports) published by the Federal Financial Institutions Examination Council (FFIEC).

In order to control for a broad set of characteristics describing a location, this paper uses county level and census tract level data from the U.S. Census Bureau. I also use county level data on unemployment rates and personal income from the Bureau of Labor Statistics (BLS) and the Bureau of Economic Analysis (BEA), respectively. The paper also uses additional county level control variables collected from the National Center for Education Statistics (NCES), the George W. Bush Global Report Card, the Association of Religion Data Archives (ARDA), and the Federal Bureau of Investigation. I also use county level statistics describing income inequality computed in Chetty et al. (2014), and the county level measure of social capital computed in Rupasingha et al. (2006) as controls.

2.2 Credit Bureau Data

This paper uses a panel dataset of anonymized individual credit bureau records. The data are a 1% representative sample of all U.S. residents with a credit history and social security number. Any individual who has an open credit account from a lender reporting to the credit bureaus (mortgage, auto loan, credit card, etc.), or who previously had an account that closed within the last 7 years has a credit history. Additionally, even individuals who have never used credit, but have a public record (bankruptcy, tax lien, court judgement, etc.) in the last 7-10 years (depending on the record type) will have a credit bureau file. For reference, 12% of the observations in the sample are individuals with no current open lines of credit or past due debt. These observations come from individuals who had accounts in the previous 7 years and closed them, or whose credit bureau file exists because of a public record.

The 1% sample of credit bureau data was constructed by selecting all individuals with social security numbers ending in an arbitrarily chosen final two-digits (for example, all social security numbers ending in 10). The Social Security Administration sequentially assigns the last 4 digits of social security numbers to new applicants, regardless of geographical location. Hence, the sampling procedure produces a random sample of individuals. This sampling method produces a panel that tracks individuals over time, and allows individuals to enter and exit the sample at the same rate as the target population, ensuring that the sample remains representative of the target population over time. This sampling design closely follows that of the Federal Reserve Bank of New York Consumer Credit Panel (see Lee and van der Klaauw (2010) for a detailed description of the sampling design and credit bureau data). The dataset in this paper includes annual observations for approximately 2.3 million individuals per year. The observations are based on data extracted from the credit file on December 31st each year.

The credit bureau data provide a complete credit history for each individual, including the individual's credit score, total debt, debt by category (mortgage, auto, credit card, etc.), past due debt, new sources of credit opened, and "hard" credit inquiries. These credit inquiries occur when a borrower applies for credit, and the lender checks their credit report. The data also provide the individual's age and the census tract they live in.

2.3 Mortgage Application Data

The Home Mortgage Disclosure Act requires all banks with total assets above $44 million (2016 threshold) and at least one branch in a Metropolitan Statistical Area (MSA) to report detailed information on all mortgage applications they receive, and their credit approval decision. The HMDA data include loan size, whether the application is a joint application, the applicant(s) income, and the race and ethnicity of the applicant(s). The data also contain information on the purpose of the loan (home purchase, refinancing, or home improvement), and whether the loan would be secured by a first or second lien. The location of the real property the mortgage would be on is reported at the census tract level.

In order to construct the sample of mortgage applications for this paper I merge lenders in the HMDA data to banks in the Call Report data based on federal agency identifiers common to both databases, and based on names for the remaining unmatched banks as in Loutskina and Strahan (2009). I select all mortgage applications received by commercial banks that are required to report HMDA data. I then exclude applications that the lender did not make a decision on due to the application being incomplete or withdrawn. Next, I require the application to be for a conventional mortgage (excludes applications related to programs run by the Federal Housing Administration, Veterans Administration, Farm Service Agency, or Rural Housing Service). I limit the sample to first-lien home purchase mortgage applications that are for loan amounts below the Government Sponsored Entities' securitization limits (excludes "jumbo" loans). Finally, I require the property the mortgage would be on to be located within an MSA, because this is where HMDA data are the most comprehensive. This process results in a sample of just over 4.7 million conventional mortgage applications between 2010 and 2015.

2.4 Intergenerational Mobility Data

I use county level data on intergenerational mobility published by Chetty et al. (2014). The authors obtained access to records from the Social Security Administration and Internal Revenue Service, and were able to link children to their parents based on parents claiming their children as dependents on tax returns. The authors collect information on children born from 1980-1982 and their parents. Parental household income is measured as the average combined income of parent(s) from 1996-2000 (i.e., when the child is 15-19 years old), and the children's income is measured at age 26 (i.e., 2006-2008). The authors' sample includes 9.9 million children matched to their parents.

Based on these administrative data, Chetty et al. (2014) construct county level intergenerational mobility statistics. Specifically, the authors provide estimates of the slope coefficient from a regression of child income rank on parent income rank for the people in a given county. This parent-child income slope is the coefficient from a rank-rank regression of child income distribution centile on parent income distribution centile (using the national income distribution). The authors also report transition matrices that describe the probabilities a child ends up in each quintile of the income distribution, based on which quintile of the distribution their parents were in. The two measures of mobility I use are the parent-child income slope, and the probability that a child with parents in the bottom 40% of the income distribution moves out of this bottom 40% as an adult. I also examine the sensitivity of children's college attendance to their parent's income using data provided by Chetty et al. (2014).

3. The Effect of Large Banks on Household Credit Access

3.1 Baseline OLS Results

In this section I examine whether the size of local banks affects households' access to credit. To estimate the effect of having large local banks on households' credit access I regress an individual's *Credit Approval* on *Large Bank Market Share*. *Credit Approval* measures an individual's access to credit by taking a value of 1 during years the person successfully opens a new line of credit, and a value of 0 when the person applies for credit during the year but does not open any new credit lines. I exclude credit card applications and credit lines when constructing *Credit Approval* because credit card lending is dominated by a few national banks and is less likely to depend on local branches. *Large Bank Market Share* is defined as the fraction of bank branches within 10 miles of the census tract the individual lives in that are owned by banks with greater than $1 Billion in assets (2010 dollars).

In order to test whether large banks have a heterogeneous effect on borrowers of high versus low economic status, I interact *Large Bank Market Share* with indicators for the borrower having a low income, subprime credit score, or limited credit history. *Low Income* indicates the borrower's *Estimated Income* from the credit bureau's proprietary model at the end of the prior year was below the median. This model is developed by the credit bureau based on a large sample of individuals' reported incomes on IRS tax returns and all of the individual attributes the credit bureau has on file, and it is re-verified annually. *Subprime* indicates the borrower's *Vantage Score* at the end of the prior year was less than or equal to 660, the cutoff defined by the credit bureau as subprime (approximately 43% of borrowers are subprime). *Limited Credit History* indicates the borrower had below the median number of open credit lines at the end of the prior year (2 or fewer).

The regressions of *Credit Approval* on *Large Bank Market Share* also include individual characteristics as of the end of the prior year, census tract characteristics, county level variables, and state-year fixed effects. Panel A of Table 1 presents summary statistics describing the outcome variables from the credit bureau data, as well as the individual and location-based control variables. The credit bureau dataset contains approximately 2.3 million annual observations per year from 2010-2015. Panel B of Table 1 summarizes how often individuals apply for various types of credit.

[Insert Table 1 Here]

To allow for nonlinearities in the regressions of *Credit Approval* on *Large Bank Market Share* I control for several of the individual characteristics using fixed effects based on binned values. The bins are based on 10 point intervals for *Vantage Score*, 5 percent ventiles for *Estimated Income*, and on each unique value for *Number of Credit Lines* and *Age*. These fixed effects for *Vantage Score*, *Estimated Income*, and *Number of Credit Lines* eliminate the need to control for the direct effect of *Subprime*, *Low Income*, and *Limited Credit History* when interacting these indicator variables with *Large Bank Market Share*, because the indicator is a direct linear combination of the fixed effects for the variable it is based on. The remaining individual characteristics control for the amount of total debt and delinquent debt the person has. The census tract variables describe the local population where the person lives, and proxy for non-financial personal characteristics. The county level variables control for local economic conditions. Finally, the state-year fixed effects are important because they control for differences in state policies that might affect credit supply (e.g., bankruptcy exemptions, foreclosure laws, or debt collection laws).

Table 2 presents the baseline OLS results. The regression in Column 1 shows that a standard deviation increase in *Large Bank Market Share* leads to a 0.43 percentage point decrease in *Credit Approval* across all borrowers, compared to the mean *Credit Approval* of 68.4%. The regressions in Columns 2-4 show that this result from Column 1 is driven by a much larger reduction in credit access for individuals of low economic status, whereas borrowers of high economic status are relatively unaffected. For instance, Column 3 shows that a standard deviation increase in *Large Bank Market Share* leads to a -0.11 percentage point decrease in *Credit Approval* for borrowers with prime credit scores, whereas it leads to a -0.80 percentage point decrease in *Credit Approval* for subprime borrowers whose mean *Credit Approval* is 53%. A similar pattern is seen in the results in Columns 2 and 4 when *Low Income* and *Limited Credit History* are used to define borrowers of low economic status.

[Insert Table 2 Here]

Figure 2 shows the heterogeneity in the effect of *Large Bank Market Share* on borrowers of high versus low economic status by plotting residual *Credit Approval* against residual *Large Bank Market Share* for prime and subprime borrowers separately. The residual versions of the two variables are computed by regressing each variable on all of the control variables in the regressions in Table 2, except for *Large Bank Market Share*. These plots implement the Frisch-Waugh theorem to show visually how the unique variation in *Large Bank Market Share*, net of the other controls, predicts *Credit Approval*. The striking difference between the plots shows that having large local banks leads to a much larger reduction in credit access for subprime borrowers than prime borrowers.

[Insert Figure 2 Here]

3.2 Identification Issues and OLS Results for Subsamples

At this point it is important to discuss potential reasons why the causal effect of large banks on household credit access might differ from the baseline OLS estimates presented in Table 2. In particular, an omitted variables problem could contribute to the relationship if *Large Bank Market Share* is negatively correlated with a component of low income borrowers' credit quality that is not captured by credit scores or the other control variables.

It is useful to think of *Large Bank Market Share* primarily as a function of where large banks choose to locate branches because as recently as the early 1970s, the vast majority of banks were small. The differences in *Large Bank Market Share* that have developed across geographic areas since then are the result of both regulatory barriers to bank expansion (discussed in Section 1), and large banks' decisions of where to acquire the local small banks and/or build branches. Therefore, it is important to discuss how we might expect the OLS results to be affected by the fact that large banks choose where to locate their branches.

The expected sign of the correlation between *Large Bank Market Share* and the unobservable component of borrower credit quality depends on how large banks choose where to put their branches. If large banks put branches where they intend to lend to households, potentially based on household characteristics that are difficult to control for, then we should expect *Large Bank Market Share* to be positively correlated with the unobserved component of borrower credit quality. This positive correlation would bias the OLS estimate of the effect of *Large Bank Market Share* on *Credit Approval* upwards, which would work against the baseline OLS finding that large banks reduce household credit access.

Despite the borrower, census tract, and county level controls, one aspect of borrower credit quality that might be difficult to control for is the expected future economic conditions where the person lives. We might expect large banks to put branches in areas where they expect the local economy to improve. If on average the economic growth in these areas improves the ability of low income borrowers to repay loans in the future (i.e., improves their credit quality today), we should expect a positive correlation between *Large Bank Market Share* and the unobserved component of borrower credit quality. This correlation would also bias the OLS results against finding that *Large Bank Market Share* reduces household credit access.

On the other hand, large banks may decide where to locate their branches primarily based on the expected profits from lending to local businesses, or based on where they expect to receive inexpensive financing through deposits from wealthy households. If the profitability of lending to local businesses and/or attracting wealthy households as customers is negatively correlated with an unobserved component of low income borrowers' credit quality, then the resulting omitted variables bias could contribute to the relationship found in the baseline OLS results. Although it does not seem particularly likely that the profitability of lending to businesses, or the deposits from wealthy households, are negatively correlated with the profitability of lending to households of low economic status, it may be more plausible in some areas than others. For instance, in urban areas and places with high levels of income inequality, the fates of businesses and households of high economic status may be less closely tied to the fates of households of low economic status. Therefore, I split the sample based on these dimensions and repeat the regressions from Table 2 on the subsamples in order to examine whether the negative effect of *Large Bank Market Share* on *Credit Approval* is restricted to, or driven by a certain type of location.

Table 3 presents the results of regressions of *Credit Approval* on *Large Bank Market Share*, its interaction with *Subprime*, and the control variables. Columns 1 and 2 split the sample into urban and rural areas based on whether the person lives in a Metropolitan

Statistical Area (MSA). The table also shows the results when the sample is split above/below the median level of income inequality (Columns 3 and 4), and minority population share (Columns 5 and 6). The sample split on minority population share is motivated by the literature on discrimination in lending (see e.g., Munnell et al. (1996)). The results show that in each of the 6 subsamples, *Large Bank Market Share* has a negative effect on *Credit Approval* for individuals with subprime credit scores. The effect on borrowers with prime credit scores is significantly less negative in each subsample, and the effect on these borrowers is insignificantly different from zero or positive in several subsamples. This finding that the baseline OLS results hold in each of the subsamples shows that the effect of *Large Bank Market Share* on *Credit Approval* is not driven by a certain type of location, and requires alternative explanations for the results to be applicable in each subsample.

[Insert Table 3 Here]

3.3 Instrumental Variables Approach

I use an instrumental variables approach to isolate exogenous variation in *Large Bank Market Share* and avoid any omitted variables bias resulting from large banks choosing where to locate their branches. The approach exploits the differences in state policies toward interstate bank branching that are described in detail in Section 1. These policies directly affect the ability of out-of-state banks (e.g., national banks) to enter local markets through building new branches or purchasing existing ones. I follow Rice and Strahan (2010) and use an index that describes the number of regulatory restrictions that out-of-state banks face when they consider establishing a branch in a state. The index ranges from 0 to 4 and increases by one if the state restricts the ability of out-of-state banks to build de novo branches or purchase individual branches of an existing bank. The index also increases by one if the state requires target banks in an interstate merger to have less than a 30% share of the state's deposits, or to be at least 3 years old.

Based on the index of regulatory restrictions I identify 36 state borders where one state has strong barriers to out-of-state bank branching (3 or 4 barriers), and the other state is open to out-of-state bank entry (0 or 1 barrier). I find that these regulatory barriers affect *Large Bank Market Share*; bank branches in the states with strong barriers are owned by smaller banks. In order to exploit this variation in *Large Bank Market Share* I select everyone in the credit bureau data living within 50 miles of these borders and use their location relative to the border to instrument for *Large Bank Market Share*. Figure 3 presents a map of the continental United States with the census tracts in these border areas highlighted.

[Insert Figure 3 Here]

The instrumental variable I use, *Position Relative to Border*, ranges from -50 in the interior of states with strong regulatory barriers, to 50 in the interior of states that are open to out-of-state bank entry. *Position Relative to Border* has a positive effect on *Large Bank Market Share* because banks in the states with barriers to entry are smaller than their counterparts in the neighboring state that is open to out-of-state bank entry. The top left plot in Figure 4 shows the relationship between a census tract's *Position Relative to Border* and the residual fraction of the bank branches in the tract that are owned by banks with assets greater than $1 Billion (2010 dollars). These residuals are from a census tract level regression of the large bank share in the tract on tract characteristics and year fixed effects. The plot shows that conditional on census tract characteristics, large banks own a higher percentage of branches in states that are open to out-of-state bank branching.

[Insert Figure 4 Here]

The bottom left and bottom right plots in Figure 4 show how *Credit Approval* varies across state borders for borrowers with prime and subprime credit scores respectively. These figures plot the residual *Credit Approval* from an individual level regression, against the person's *Position Relative to Border*. The individual level regression includes all of the controls from the previous regressions in Tables 2 and 3 except *Large Bank Market Share* and the state-year fixed effects. The figures suggest that both prime and subprime borrowers experience greater credit access when local banks are small, but the effect appears to be larger for subprime borrowers. The ensuing instrumental variables regressions formalize this approach.

Table 4 presents the first stage regressions for the instrumental variables approach. Column 1 shows the results when *Large Bank Market Share* is regressed on *Position Relative to Border* and individual, census tract, and county level controls, as well as state-year fixed effects. Because this paper tests whether the effect of *Large Bank Market Share* is different for households of low economic status, I also instrument for the interaction between *Large Bank Market Share* and indicators of low economic status (*Low Income*, *Subprime*, and *Limited Credit History*). Columns 2-4 show the first stage regressions for these interaction terms. I instrument for the interaction between the low economic status indicator and *Large Bank Market Share* with the indicator's interaction with *Position Relative to Border*. The results show that *Position Relative to Border* is a strong predictor of *Large Bank Market Share* even after controlling for characteristics of the local population as well as state-year fixed effects. The interactions with *Position Relative to Border* also predict the interactions with *Large Bank Market Share* in Columns 2-4. The instruments' power comes from the fact that the regulatory barriers make it more costly for large out-of-state banks to enter local markets in one state. The identifying assumption necessary to satisfy the exclusion restriction is that, for two borrowers in the same state during the same year, controlling for credit scores and individual, census tract, and county level characteristics, their distance to the state border affects *Credit Approval* only through its effect on *Large Bank Market Share*.

[Insert Table 4 Here]

Table 5 presents the main instrumental variables regressions and their OLS counterparts. Panel A shows the results for the primary outcome variable *Credit Approval*. In the OLS regressions in Column 1-4, the same pattern in the coefficients of interest emerges as in the baseline OLS results; when estimated across all borrowers, *Large Bank Market Share* has a negative effect on *Credit Approval*, but this effect is driven almost entirely by the effect on borrowers of low economic status. This pattern is even more striking in the instrumental variables results in Columns 5-8. For instance, the results in Column 7 show that a standard deviation increase in *Large Bank Market Share* actually increases prime borrowers' *Credit Approval* by 0.92 percentage points compared to a mean of 80.9%. In contrast, for subprime borrowers a standard deviation increase in *Large Bank Market Share* reduces *Credit Approval* by 3.78 percentage points (0.92 - 4.70), compared to their mean *Credit Approval* of 53.0%. The results in Panel A of Table 5 show that having large local banks reduces credit access for borrowers of low economic status, whereas borrowers of high economic status continue to receive credit and may even experience increased credit access. This pattern holds when borrowers of low economic status are defined as those with low incomes, low credit scores, or limited credit histories.

[Insert Table 5 Here]

The remaining panels of Table 5 present the OLS and instrumental variables estimates of the effect of *Large Bank Market Share* on several additional outcome variables. The tests in Panel B restrict the sample to individuals who had no mortgage as of the end of the prior year, and whose credit file indicates that a lender checked their credit score as part of a mortgage application during the current year. The credit bureau data does not require that the borrower complete the mortgage application process in order to classify them as having applied for a mortgage during the year. The advantage of this aspect of the data is that it will capture cases where, following a credit check, the bank either explicity or implicitly signals to the borrower that they are unlikely to receive credit. Measuring mortgage credit approval with the credit bureau data counts these cases as failed attempts to open a mortgage. This method of measuring mortgage credit approval results in considerably lower approval rates than those typically computed from HMDA application data. The difference arises because researchers using the HMDA data typically only examine applications that the lender reports making a final lending decision on, which excludes applications the lender reports as being withdrawn or having incomplete information, and these applications constituted 14% of HMDA applications in 2015. Reassuringly, I find that the inferences drawn from the credit bureau and HMDA data agree; large banks reduce low income households' access to mortgage credit. The results in Column 7 of Panel B show that for borrowers without an existing mortgage, a standard deviation increase in *Large Bank Market Share* has an insignificant effect on mortgage approval if you have a prime credit score, whereas it reduces the chances of mortgage approval by 2.56 (-.619 - 1.941) percentage points for borrowers with subprime credit scores.

The tests in Panels C and D of Table 5 use the share of a borrower's debt that is on credit cards, and an indicator for whether they have outstanding retail debt, as the outcome variables. Borrowing on credit cards or from retailers is typically more expensive than borrowing from a bank in the form of a mortgage, home equity line of credit, personal installment loan, etc. Therefore, if borrowers face credit rationing from local banks, these sources of credit may serve as more expensive substitutes. The instrumental variables results in Panel C show that a standard deviation increase in *Large Bank Market Share* has an insignificant effect on the share of debt that prime borrowers hold on credit cards, whereas it increases *Credit Card Debt Share* for subprime borrowers by 4.05% (.502 + 3.551). The results in Panel D show that borrowers of low economic status are also more likely to borrow from retailers when local banks are large. The finding that large local banks cause borrowers of low economic status to borrow using more expensive sources of debt provides further evidence that they face increased credit rationing from large banks.

4. Bank Size, Soft Information, and Lending to Households

4.1 Bank Size and Mortgage Credit Access

In this section I test the hypothesis that small banks incorporate more soft information into their lending decisions involving households than large banks do. I also examine whether soft information plays a larger role when banks evaluate low income borrowers than when they evaluate high income borrowers. If small banks do in fact incorporate more soft information into lending decisions, and this information is especially important when lending to low income borrowers, it could offer an explanation for the results in Section 3 showing that low income borrowers experience reduced credit access when local banks are large.

In order to evaluate the extent to which banks utilize soft information in their lending decisions, I examine the effect of borrower-lender distance on the likelihood that credit applications are approved. I interpret the extent to which credit approval rates decrease with borrower-lender distance as a measure of how much soft information is utilized in lending decisions. This approach follows the assumption in the literature that soft information collection is the main channel through which borrower-lender distance affects credit terms (e.g., Petersen and Rajan (2002), DeYoung et al. (2008), Agarwal and Hauswald (2010)).

I examine the role of soft information in banks' lending to households using data from the Home Mortgage Disclosure Act. The HMDA data include the identity of the lender receiving the mortgage application, their decision to approve or deny the application, and information on the applicant and the loan they requested. All banks with total assets above \$44 million (2016 threshold) and at least one branch in a Metropolitan Statistical Area are required to report HMDA data. Following the process described in Section 2, I construct a sample of just over 4.7 million conventional mortgage applications received by commercial banks between 2010 and 2015. Table 6 summarizes these mortgage application data and shows that small banks receive approximately 21% of conventional mortgage applications, that the median distance from the real property to the bank's nearest branch is 3.3 miles, and that the median loan amount applied for is $171,000.

[Insert Table 6 Here]

Figure 5 shows the relationship between mortgage approval rates and borrower-lender distance at small versus large banks. The left plot shows the results for low income applicants (reported incomes below the U.S. median household income). The plot shows that small banks approve a higher percentage of low income borrowers' applications than large banks, and that the likelihood of approval increases significantly at small banks when the real property is close to one of the bank's branches. On the other hand, borrower-lender distance does not appear to affect mortgage approval much at large banks. The right plot in Figure 5 shows the results for high income borrowers. These borrowers also have higher approval rates at small banks, but the relationship between borrower-lender distance and approval rates is less striking.

[Insert Figure 5 Here]

To formally test the hypothesis that borrower-lender distance has a larger effect on lending decisions at small banks, I regress an indicator for the mortgage application being approved on the distance to the bank's nearest branch, its interaction with *Small Bank* (indicates the bank has less than $1 Billion in assets), and control variables. The controls include borrower, census tract, and bank characteristics, as well as county-year fixed effects. The county-year fixed effects are included to capture across-county variation in borrower creditworthiness, local housing market conditions, and state policies that affect mortgage credit availability (e.g., foreclosure laws). The applicant characteristics work to control for any remaining variation in the creditworthiness of applicants within the same county-year applying to small versus large banks. These characteristics include the applicant's income, the loan amount, the loan to income ratio, and an indicator for joint applications (multiple applicants). I also include indicators for one or more of the applicants being a minority, given the literature on mortgage discrimination (e.g., Munnell et al. (1996)).

One disadvantage of the HMDA data is that it does not include the applicant's credit score. Unfortunately the credit bureau data can not be directly linked to all HMDA mortgage applications (in the next section I match the datasets for most originated loans). However, I am able alleviate concerns stemming from applicant credit scores being unavailable by controlling for the average credit score of residents in the census tract in which the applicant is trying to purchase a home. I also control for the ratio of the applicant's income, loan to income ratio, and loan amount, to the average of all applicants within the census tract that year. These variables are designed to capture whether the applicant is likely more or less creditworthy than the typical applicant in the census tract.

Table 7 presents the regressions showing the effect of borrower-lender distance on mortgage approval. Column 1 shows that for the full sample of borrowers and banks, each additional mile between the borrower and the bank reduces the chances of a mortgage being approved by 0.087 percentage points. Column 2 shows that the effect of distance on mortgage approval is over twice as large at small banks compared to large banks. Column 3 shows that the effect of distance is over 3 times as large for low income applicants compared to high income applicants. Columns 4 and 5 split the sample based on whether the applicant has a low or high income and show that in each case borrower-lender distance matters more at small banks. The positive estimated effect of *Small Bank* of approximately 1 percentage point in these regressions also confirms the observation from Figure 5 that small banks approve a higher percentage of mortgage applications than large banks.

[Insert Table 7 Here]

The results in Table 7 show that small banks utilize more soft information in their lending decisions than large banks and ration credit less. The results also show that soft information is utilized more heavily when lending to low income borrowers compared to high income borrowers. These findings suggest that large banks' comparative disadvantage at utilizing soft information is likely a driving force behind the results in Section 3; when local banks are large, less soft information is produced about local borrowers, and these borrowers experience reduced credit access. We should expect the reduction in credit access to be largest for borrowers for whom soft information is most important (e.g., low income borrowers), just as in the results in Section 3.

4.2 Bank Size and Mortgage Loan Performance

After documenting that small banks approve a higher percentage of mortgage applications, I test whether mortgages originated by small banks exhibit higher delinquency rates. Examining loan performance sheds light on whether the higher approval rates at small banks reflect a comparative advantage lending on soft information, or rather that small banks have looser lending standards and make more "bad loans." I examine the effect of bank size on delinquency rates using mortgages from a dataset that matches originated loans reported in HMDA data to loan performance information from the borrower's credit bureau file. I match the two data sources based on origination year, census tract, loan amount, and whether the mortgage is joint or belongs to a single borrower. Internet Appendix B outlines the matching process in detail and provides matching statistics. The matched sample consists of just over 30 thousand mortgages originated by commercial banks from 2010-2013.

I test whether mortgages originated by small banks exhibit higher delinquency rates by regressing an indicator for a mortgage becoming at least 60 days delinquent during the year of origination or the following two calendar years on an indicator for the originating bank being small. These regressions control for applicant and loan characteristics, as well as other characteristics of the bank, and county-year and origination month fixed effects. The results in Table 8 show that delinquency rates on loans originated by small banks are insignificantly different than those originated by large banks, conditional on their characteristics. The positive point estimates on the *Small Bank* coefficient are small in economic magnitude; the estimated effect for the full sample is 0.07 percentage points compared to a mean delinquency rate of 3.54%. These results suggest that the higher approval rates at small banks reflect these lenders' advantage at collecting soft information rather than a tendency to make "bad loans."

[Insert Table 8 Here]

5. Large Banks and Intergenerational Mobility

5.1 Intergenerational Mobility Overview

In this section I examine whether the structure of the banking industry affects economic inequality through its effect on the distribution of credit across households. The results in Section 3 show that when local banks are large, borrowers of low economic status experience reduced credit access whereas borrowers with high incomes/credit scores continue to receive credit. This asymmetric effect naturally suggests ties to inequality. Indeed, theory predicts that credit access plays an important role in fostering intergenerational mobility because it allows low income parents to invest in their children's human capital (e.g., Becker and Tomes (1979, 1986) and Solon (2004)). Therefore, I test whether having large local banks reduces intergenerational economic mobility.[5]

In practice, parental investments in a child's human capital come in many forms starting in early childhood and carrying through to age 18 and beyond. Quality day care, after

[5] In related work, Beck et al. (2010) show that *intrastate* banking deregulation, which allowed within-state consolidation and the formation of mid-sized community banks, led to reduced income inequality. In contrast, I examine the effect of national banks entering local markets following *interstate* deregulation on the turnover/mobility within the income distribution, rather than on the shape of the income distribution itself. While my results are not in direct conflict with Beck et al. (2010), income inequality and mobility do tend to be negatively correlated, suggesting that we are identifying separate economic mechanisms.

school programs and clubs, and private tutoring or schooling are obvious examples. Moving to a neighborhood with more positive peer influences, or a better school district, can also be viewed as an investment in children's human capital. As children approach adulthood, investments are likely required to optimally prepare for postsecondary education or training, and to pay for the education/training itself. Although government programs supplement and aid parental investment in several big ticket items (public schools, federal student loans, etc.), it is clear that a significant portion of investments in children are paid for by parents.

Parental investments in a child's human capital may be financed either directly or indirectly. For instance, a personal installment loan, second mortgage, or home equity line of credit could be used to raise capital directly for such an investment. On the other hand, being able to finance the purchase of an essential item like an automobile, rather than pay the full price up front, could indirectly finance continued investment in a child's human capital by smoothing the household's cash flows over time. The fungibility of various sources of finance suggests that households' overall access to external finance is likely most important for making sustained investments in their children's human capital.

Ideally, researchers would have administrative data linking parents and children, with information on parents' creditworthiness, their attempts to obtain credit, a source of exogenous variation in credit access, parents' investments in their children, and children's long-term outcomes. Unfortunately, these data are not available. Datasets linking parents and children over a long enough time period to evaluate children's earnings in adulthood are scarce and are usually based on household surveys. These datasets have small sample sizes and indirect measures of credit access and creditworthiness which make it difficult to identify the role of credit access or other determinants of intergenerational mobility. These data constraints have limited prior studies of the determinants of mobility.[6] However,

[6]Data constraints have forced most papers to focus on accurately measuring mobility at the national level, rather than on identifying the determinants of mobility. Notable exceptions include work on the role of returns to higher education (Blanden (2009)), and on government expenditures on public schools (Mayer and Lopoo (2008)).

research in this area is likely to expand given the newly available data on mobility published by Chetty et al. (2014). The authors obtained access to administrative IRS income tax records and were able to compute the first disaggregated (county level) statistics on intergenerational mobility in the United States.

I use these new county level mobility statistics, combined with county level measures of *Large Bank Market Share*, to evaluate the effect of having large local banks on intergenerational mobility. The statistics from Chetty et al. (2014) describe mobility levels within a county's population in two forms. First, the authors provide quintile transition matrices describing which quintile in the national income distribution children end up in, based on the quintile their parents were in. From these data I compute the probability that children with parents in the bottom 40% of the national income distribution transition out of the bottom 40% in terms of their incomes as adults. Second, the authors provide the slope coefficient from a regression of children's percentile rank in the national income distribution on their parent's percentile rank. A steeper *Parent-Child Income Slope* indicates lower intergenerational mobility levels in the county. I also use similar slope estimates provided by Chetty et al. (2014) describing the relationship between children's college attendance and their parent's rank in the income distribution. I use this intermediate outcome to more directly measure the sensitivity of human capital formation to parental income. These statistics are available for one cross section based on children born between 1980-1982. The parent's income is measured as the average household income from when the child is 15-19 years old, and the child's income is measured at age 26.

I collect county level covariates from various data sources describing the county's characteristics in the year 2000. To capture the type of banks their parents had access to as the children grew up, I measure *Large Bank Market Share* as of 1995 when children in the

Chetty et al. (2014) data were approximately 14 years old.[7] Table 9 summarizes the county level dataset and shows that the probability of transitioning out of the bottom 40% of the income distribution is 51.49%, the average *Parent-Child Income Slope* is 0.26, and on average, every percentile increase in parent's income rank increases the probability that their child attends college by 0.68 percentage points.

[Insert Table 9 Here]

5.2 The Effect of Large Banks on Upward Mobility

In order to estimate the effect of having large local banks on intergenerational mobility, I regress county level measures of mobility on *Large Bank Market Share*, a set of 15 correlates of mobility outlined in Chetty et al. (2014), and additional control variables. The 15 correlates outlined by Chetty et al. (2014) belong to 5 broad categories: race and segregation, income and inequality, family characteristics, kindergarten-12th grade education, and social capital. While these control variables represent the strongest correlates identified in Chetty et al. (2014), I add several additional control variables to reduce concerns about omitted variables. Specifically, I control for population density and the growth in per capita income in the county over the lifetime of the children in the Chetty et al. (2014) data (1980-2005).

Despite this effort to include a robust set of control variables, concerns may still remain that OLS regressions of intergenerational mobility on *Large Bank Market Share* will be biased due to an omitted variables problem arising from large banks choosing where to put their branches. It is also difficult to gauge which direction we should expect any omitted variables bias to work considering the limited literature on the determinants of intergenerational mobility. Therefore, to avoid an omitted variables bias I use an

[7] Comprehensive data on bank branches are not available from the FDIC prior to 1994. I find similar results if I measure *Large Bank Market Share* based on any year from 1994-2000, which covers the time period these children were in grades 6-12.

instrumental variables approach that exploits the staggered relaxation of state laws prohibiting interstate bank mergers from 1978 to 1997. Before the IBBEA took effect in 1997, there was essentially no bank branching across state lines, so bank mergers were the primary way for banks to expand across state lines. Maine was the first state to open its borders to out-of-state bank entry in 1978, and by 1993 every state except Hawaii had followed suit (see Table A.1 for the years that states deregulated).

In the instrumental variables approach, I use the number of years since a state opened its borders to interstate bank mergers as an instrument for *Large Bank Market Share* as of 1995. Table 10 shows the first stage regressions for the instrumental variables approach. The results show that counties in states that opened their borders to out-of-state bank entry earlier had significantly higher *Large Bank Market Share* in 1995 than counties in states that deregulated later. This instrumental variables approach is similar in spirit to the approach employed in Berger et al. (2005), where the authors use the fraction of the prior 10 years that a state has been deregulated to instrument for local bank size.[8] The identifying assumption this instrumental variables approach makes is that conditional on the county level control variables, the timing of a state's interstate banking deregulation during the 1978-1997 period influences intergenerational mobility for children turning 26 in 2006-2008 only through its effect on the size of local banks.

[Insert Table 10 Here]

Table 11 presents the results of OLS and instrumental variables regressions of *Transition out of Bottom 40%* on *Large Bank Market Share* and the control variables. This measure of intergenerational mobility captures upward mobility out of the bottom part of the income distribution (i.e., the households that I find face tighter credit constraints with large banks). Column 1 presents the full sample OLS results which show that a standard

[8]The authors' sample is set earlier than this paper's, so the authors use the earlier wave of intrastate rather than interstate deregulation events.

deviation increase in *Large Bank Market Share* leads to a 0.71 percentage point decrease in the probability that a child born to parents in the bottom 40% of the income distribution transitions out of this bottom 40% in adulthood, compared to a mean of 51.49%. The instrumental variables estimates in Column 4 show that a standard deviation increase in *Large Bank Market Share* causes a 4.73 percentage point reduction in this form of upward mobility. The larger estimated effect in the instrumental variables regressions suggests any omitted variables bias is likely working against the OLS findings. For instance, large banks may choose to put branches in areas where the local economy naturally exhibits high levels of mobility, and this may mask the fact that their presence actually lowers mobility levels. The results in the remaining columns of Table 11 show that the negative relationship between *Large Bank Market Share* and upward mobility exists in both the urban and rural subsamples. This finding adds to the robustness of the results because urban and rural areas differ on a wide range of characteristics, and the fact that the result holds in both subsamples suggests that differences in omitted variables across the urban/rural sample split are not driving the results.

[Insert Table 11 Here]

5.3 Large Banks and the Relationship Between Parental Income and Children's Income and Educational Attainment

The next tests examine the effect of the size of local banks on the relationship between parental income and two child outcomes: income and educational attainment. Panel A of Table 12 presents the results of OLS and instrumental variables regressions of *Log(Parent-Child Income Slope)* on *Large Bank Market Share* and the control variables. Column 1 presents the full sample OLS results which show that a standard deviation increase in *Large Bank Market Share* leads to a 1.98% increase in the magnitude of the *Parent-Child Income Slope*. The instrumental variables version of the regression presented in Column 4 shows a larger estimated effect; a standard deviation increase in *Large Bank Market Share* causes a 13.1% increase in the magnitude of the *Parent-Child Income Slope*. These results suggest that having large local banks leads to lower overall levels of intergenerational mobility.

[Insert Table 12 Here]

Next, I examine the effect of the size of local banks on the relationship between parental income and children's college attendance at age 19. This intermediate outcome offers a fairly direct measure of children's human capital attainment. The outcome variable in these tests is the natural log of *Parent Income-Child College Attendance Slope*, which is the slope coefficient from a regression of children's college attendance on their parent's rank in the national income distribution that is computed for the residents of a given county by Chetty et al. (2014). This slope coefficient measures the extent to which children's human capital attainment depends on their parent's income. The results in Table 12, Panel B, Column 4 show that a standard deviation increase in *Large Bank Market Share* causes a 15.4% increase in the magnitude of this slope coefficient. This finding suggests that human capital formation is indeed the channel through which large banks reduce intergenerational mobility, i.e., the additional credit constraints low income households face make human capital investment/attainment more sensitive to parental income. These results also show that a significant portion of large banks' negative effect on mobility can be seen in children before they enter the labor market, which is more consistent with banks influencing parental investments in children than an alternative explanation based on banks influencing local labor markets.

The results in this section provide evidence that having large local banks reduces intergenerational mobility by making human capital formation more dependent on parental income. The relationship holds in the OLS and instrumental variables results, and within the urban and rural subsamples. Moreover, the relationship is significant in economic terms, with a standard deviation increase in *Large Bank Market Share* causing a reduction in mobility levels comparable to approximately a 0.9 standard deviation increase in *Single Mother Households*.

6. Conclusion

This paper finds that when local banks are large, borrowers with low incomes, subprime credit scores, and/or limited credit histories experience reduced credit access. In contrast, borrowers of high economic status continue to receive credit. I find evidence that large banks utilize less soft information when lending to households, and that soft information is most important when lending to low income households. These findings suggest that large banks' comparative disadvantage utilizing soft information contributes to the reduction in credit access that borrowers of low economic status experience when local banks are large.

The finding that large banks lead to a disproportionate reduction in credit access for borrowers of low economic status leads this paper to examine whether large banks contribute to economic inequality. I find that having large local banks reduces intergenerational economic mobility, consistent with additional credit constraints reducing low income households' investment in their children's human capital. These results provide the first evidence of a link between the structure of the banking industry and mobility. Further exploration of the determinants of intergenerational mobility, including the role of credit constraints and financial institutions, is a promising avenue for future research.

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Tables

Table 1: Summary Statistics

This table presents summary statistics for the 1% national sample of individual credit bureau records used in this paper's first set of empirical tests. The sample includes approximately 2.3 million annual observations per year from 2010-2015. Panel A summarizes the credit bureau variables used as outcome variables, and the explanatory variables from the credit bureau data as well as the characteristics of the local banks, population, and economy where the individuals live. Columns 1-5 describe the full sample, and Columns 6-8 describe the sample used in the instrumental variables approach based on state borders where states have large differences in policies toward interstate bank branching. Panel B presents statistics describing how often borrowers apply for certain types of credit (all types, mortgage, auto, credit card). The application rates are reported for the full sample, borrowers with prime credit scores (Vantage Score $>$ 660), and borrowers with subprime credit scores (Vantage Score $\leq$ 660) in Columns 1,2, and 3 respectively.

Panel A: Summary Statistics

	Full Sample (N=13,833,955)					State Borders IV Sample (N=2,582,708)		
	Mean	Std. Dev.	P10	P50	P90	Mean	Std. Dev.	Norm. Diff.
Credit Bureau Outcome Variables								
Credit Approval	0.6840	0.4649	0	1	1	0.7108	0.4534	0.0413
Credit Approval (First Mortgage)	0.2237	0.4167	0	0	1	0.2463	0.4308	0.0376
Credit Card Debt Share	0.2729	0.3882	0	0.0415	1	0.2615	0.3825	-0.0209
Have Retail Debt	0.2939	0.4556	0	0	1	0.2946	0.4559	0.0011
Credit Bureau Characteristics								
Vantage Score$_{t-1}$	674	111	516	678	813	675	112	0.0056
Estimated Income $_{t-1}$	45561	25699	23000	39000	75000	43819	22970	-0.0505
Number of Credit Lines $_{t-1}$	4.14	4.22	0.00	3.00	10.00	4.04	4.16	-0.0167
Age	50	19	26	49	77	51	19	0.0084
Log(Total Debt $_{t-1}$)	7.05	4.84	0.00	8.76	12.29	6.97	4.85	-0.0105
Total Debt $_{t-1}$	65430	122127	0	6380	218206	59726	108684	-0.0349
Log(Past Due Debt $_{t-1}$)	2.52	3.62	0.00	0.00	8.33	2.52	3.58	-0.0011
Past Due Debt $_{t-1}$	1591	4796	0	0	4152	1450	4418	-0.0216
Have Delinquent Debt $_{t-1}$	0.2020	0.4015	0	0	1	0.1945	0.3958	-0.0132
Local Banks								
Large Bank Market Share	0.7698	0.2151	0.4667	0.8495	0.9498	0.6965	0.2299	-0.2329
HHI of Local Bank Branches	0.1356	0.1256	0.0656	0.1000	0.2222	0.1349	0.1268	-0.0044
Census Tract Characteristics								
Poverty (18-64)	0.1304	0.0976	0.0310	0.1050	0.2670	0.1328	0.0974	0.0173
Log(Population Density)	7.17	1.94	4.21	7.65	9.21	6.83	1.90	-0.1254
Minority Population Share	0.3475	0.2894	0.0470	0.2530	0.8430	0.2553	0.2479	-0.2420
Household Size	2.66	0.47	2.13	2.60	3.25	2.57	0.36	-0.1420
High School Diploma	0.8632	0.1069	0.7170	0.8920	0.9690	0.8648	0.0943	0.0111
Employed by Government	0.1476	0.0668	0.0720	0.1370	0.2370	0.1386	0.0616	-0.0992
County Characteristics								
Unemployment Rate	0.0761	0.0245	0.0467	0.0733	0.1090	0.0777	0.0229	0.0484
Personal Income Per Capita Growth	0.0329	0.0267	-0.0011	0.0341	0.0633	0.0316	0.0264	-0.0338

Panel B: Credit Application Rates

Credit Application Type	Fraction of Person-Years with Credit Applications		
	Full Sample	Prime Borrowers	Subprime Borrowers
All Types	0.5432	0.5279	0.5639
Mortgage	0.1349	0.1557	0.1068
Auto	0.1415	0.1311	0.1555
Credit Card	0.2738	0.2729	0.275
All Non-Credit Card	0.4563	0.4389	0.4796

Table 2: Large Bank Market Share and Household Credit Access: Baseline OLS Results

This table presents regressions of individuals' *Credit Approval* on *Large Bank Market Share* and individual, census tract, and county level characteristics as well as state-year fixed effects. *Credit Approval* takes a value of 1 when an individual successfully opens a new credit line, and a value of 0 when individuals apply for credit during the year but do not open any new credit lines. I exclude credit card applications and credit lines when constructing *Credit Approval* because credit card lending is dominated by a few national banks and is less likely to depend on local branches. *Large Bank Market Share* is the fraction of bank branches located within 10 miles of where the individual lives that are owned by banks with greater than $1 Billion in assets (2010 dollars). Column 1 presents the effect of *Large Bank Market Share* on *Credit Approval* for all borrowers. Columns 2, 3, and 4 interact *Large Bank Market Share* with indicators for the borrower having a low income, low credit score, or limited credit history, respectively. *Low Income* indicates the borrower's estimated income from the credit bureau's proprietary model is below the median. *Subprime* indicates the borrower has a *Vantage Score* $\leq$ 660, the cutoff defined by the credit bureau as subprime (43% of borrowers are subprime). *Limited Credit History* indicates the borrower had below the median number of open credit lines at the end of the prior year (2 or fewer). The base terms for the interaction between these 3 variables and *Large Bank Market Share* are omitted from the regressions because they are direct linear combinations of the fixed effects I already include to control for their direct effect (i.e. fixed effects based on *Vantage Score*, *Estimated Income*, and *Number of Credit Lines*). The sample includes all individual-years from 2010-2015 in the credit bureau dataset where the person applies for credit. All continuous explanatory variables are standardized to have a mean of 0 and a standard deviation of 1. Coefficients are reported in terms of percentage points, i.e. a coefficient of 1 indicates that a standard deviation increase in the explanatory variable results in a 1 percentage point increase in *Credit Approval*. The reported standard errors are clustered by census tract-year.

	(1)	(2)	(3)	(4)
Large Bank Market Share	-0.432***	-0.129***	-0.113***	-0.149***
	(0.0255)	(0.0289)	(0.0280)	(0.0271)
Large Bank Market Share X Low Income		-0.641***		
		(0.0340)		
Large Bank Market Share X Subprime			-0.688***	
			(0.0356)	
Large Bank Market Share X Limited Credit History				-0.790***
				(0.0372)
HHI of Local Bank Branches (10mi)	-0.0975***	-0.107***	-0.106***	-0.109***
	(0.0230)	(0.0230)	(0.0230)	(0.0230)
Individual Characteristics				
Vantage Score $_{t-1}$ 10 Point Bin FE	Yes	Yes	Yes	Yes
Estimated Income $_{t-1}$ Ventile FE	Yes	Yes	Yes	Yes
Number of Credit Lines $_{t-1}$ FE	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes
Log(Total Debt $_{t-1}$)	-1.711***	-1.729***	-1.711***	-1.708***
	(0.0484)	(0.0484)	(0.0484)	(0.0484)
Log(Past Due Debt $_{t-1}$)	-3.748***	-3.755***	-3.753***	-3.751***
	(0.0303)	(0.0303)	(0.0303)	(0.0303)
Have Delinquent Debt $_{t-1}$	-3.972***	-3.980***	-3.979***	-3.969***
	(0.0539)	(0.0539)	(0.0539)	(0.0539)
Census Tract Characteristics				
Poverty (18-64)	-0.0376	-0.0329	-0.0333	-0.0302
	(0.0276)	(0.0276)	(0.0276)	(0.0276)
Log(Population Density)	-1.157***	-1.170***	-1.176***	-1.174***
	(0.0302)	(0.0301)	(0.0301)	(0.0302)
Minority Population Share	-1.172***	-1.152***	-1.147***	-1.154***
	(0.0321)	(0.0322)	(0.0322)	(0.0321)
Household Size	0.914***	0.912***	0.917***	0.914***
	(0.0240)	(0.0240)	(0.0240)	(0.0240)
High School Diploma	-0.690***	-0.699***	-0.696***	-0.697***
	(0.0314)	(0.0314)	(0.0314)	(0.0314)
Employed by Government	0.928***	0.926***	0.927***	0.926***
	(0.0209)	(0.0209)	(0.0209)	(0.0209)
County Characteristics				
Unemployment Rate	0.406***	0.399***	0.399***	0.395***
	(0.0338)	(0.0338)	(0.0338)	(0.0338)
Personal Income Per Capita Growth	-0.198***	-0.200***	-0.201***	-0.201***
	(0.0246)	(0.0246)	(0.0246)	(0.0246)
State X Year FE	Yes	Yes	Yes	Yes
R^2	0.194	0.194	0.194	0.194
Observations	6240016	6240016	6240016	6240016

Table 3: Large Bank Market Share and Household Credit Access: OLS Results for Subsamples

This table presents regressions of individuals' *Credit Approval* on *Large Bank Market Share* and individual, census tract, and county level characteristics as well as state-year fixed effects. *Credit Approval* takes a value of 1 when an individual successfully opens a new credit line, and a value of 0 when individuals apply for credit during the year but do not open any new credit lines. I exclude credit card applications and credit lines when constructing *Credit Approval* because credit card lending is dominated by a few national banks and is less likely to depend on local branches. *Large Bank Market Share* is the fraction of bank branches located within 10 miles of where the individual lives that are owned by banks with greater than $1 Billion in assets (2010 dollars). I interact *Large Bank Market Share* with *Subprime*, which indicates the borrower has a *Vantage Score* $\leq$ 660, the cutoff defined by the credit bureau as subprime (43% of borrowers are subprime). The base term for the interaction (*Subprime*) is omitted from the regressions because it is a direct linear combination of the fixed effects for each 10 point bin of *Vantage Score*. The sample I start with includes all individual-years from 2010-2015 in the credit bureau dataset where the person applies for credit. I split this sample based on characteristics of the location where people live. Columns 1 and 2 split the sample into urban and rural areas (in a metropolitan statistical area or not). Columns 3 and 4 split the sample based on income inequality (above/below median gini coefficient from county level data published by Chetty et al. (2014)). Columns 5 and 6 split the sample based on the minority population share in the individual's census tract (above/below median). All continuous explanatory variables are standardized to have a mean of 0 and a standard deviation of 1. Coefficients are reported in terms of percentage points, i.e. a coefficient of 1 indicates that a standard deviation increase in the explanatory variable results in a 1 percentage point increase in *Credit Approval*. The reported standard errors are clustered by census tract-year.

	Urban / Rural Split		Income Inequality Split		Minority Share Split	
	MSA	Non-MSA	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Large Bank Market Share	-0.185***	0.340***	-0.436***	-0.0187	-0.385***	0.141***
	(0.0388)	(0.0476)	(0.0580)	(0.0329)	(0.0550)	(0.0334)
Large Bank Market Share X Subprime	-0.365***	-0.857***	-0.913***	-0.734***	-0.939***	-0.925***
	(0.0513)	(0.0678)	(0.0682)	(0.0436)	(0.0637)	(0.0460)
HHI of Local Bank Branches (10mi)	-0.0730**	0.00394	-0.209***	0.0245	-0.142***	-0.0904***
	(0.0328)	(0.0338)	(0.0457)	(0.0270)	(0.0403)	(0.0281)
Individual Characteristics						
Vantage Score $_{t-1}$ 10 Point Bin FE	Yes	Yes	Yes	Yes	Yes	Yes
Estimated Income $_{t-1}$ Ventile FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of Credit Lines $_{t-1}$ FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes
Log(Total Debt $_{t-1}$)	-1.796***	-1.518***	-1.921***	-1.663***	-1.983***	-1.536***
	(0.0524)	(0.126)	(0.0701)	(0.0669)	(0.0705)	(0.0665)
Log(Past Due Debt $_{t-1}$)	-3.887***	-2.971***	-3.629***	-3.965***	-3.603***	-4.031***
	(0.0326)	(0.0812)	(0.0417)	(0.0440)	(0.0402)	(0.0461)
Have Delinquent Debt $_{t-1}$	-4.143***	-2.839***	-4.239***	-3.702***	-4.129***	-3.785***
	(0.0581)	(0.143)	(0.0761)	(0.0762)	(0.0735)	(0.0790)
Census Tract Characteristics						
Poverty (18-64)	-0.125***	0.0639	-0.222***	-0.0222	-0.0543	-0.0847*
	(0.0300)	(0.0722)	(0.0375)	(0.0409)	(0.0357)	(0.0444)
Log(Population Density)	-1.363***	0.0427	-1.509***	-0.407***	-1.391***	-0.738***
	(0.0352)	(0.0684)	(0.0505)	(0.0392)	(0.0498)	(0.0399)
Minority Population Share	-0.981***	-0.353***	-0.643***	-1.155***	-0.707***	-2.096***
	(0.0343)	(0.113)	(0.0428)	(0.0532)	(0.0479)	(0.127)
Household Size	0.903***	0.832***	0.983***	0.491***	1.026***	0.706***
	(0.0251)	(0.0945)	(0.0323)	(0.0369)	(0.0312)	(0.0402)
High School Diploma	-0.634***	-0.487***	-0.570***	-0.731***	-0.368***	-1.522***
	(0.0337)	(0.0943)	(0.0415)	(0.0501)	(0.0397)	(0.0593)
Employed by Government	0.920***	0.450***	0.925***	0.700***	0.972***	0.679***
	(0.0228)	(0.0543)	(0.0301)	(0.0294)	(0.0286)	(0.0309)
County Characteristics						
Unemployment Rate	0.395***	0.273***	0.363***	0.876***	0.274***	0.318***
	(0.0385)	(0.0788)	(0.0495)	(0.0506)	(0.0462)	(0.0509)
Personal Income Per Capita Growth	-0.263***	-0.0116	-0.225***	-0.0794**	-0.180***	-0.275***
	(0.0292)	(0.0502)	(0.0376)	(0.0352)	(0.0362)	(0.0337)
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.193	0.199	0.191	0.191	0.195	0.174
Observations	5419863	820153	3093706	3146039	3151257	3088759

Table 4: First Stage - Regressions of Large Bank Market Share on the Position Relative to the State Border

This table presents the first stage regressions for the IV/2SLS analysis that estimates the effect of *Large Bank Market Share* (abbreviated *LBMS* below) on households' credit access. The dependent variables in these first stage regressions are *Large Bank Market Share* (the fraction of bank branches located within 10 miles of a household that are owned by banks with greater than $1 Billion in assets) in Column 1, and its interactions with the indicators of low economic status (*Low Income*, *Subprime*, and *Limited Credit History*) in Columns 2-4. The sample includes all individual-years from 2010-2015 in the credit bureau data where the person applies for credit and lives within 50 miles of a state border where there is a large contrast in the two states' interstate bank branching policies (see Table A.2 for a list of these state borders). The instrumental variables are *Position Relative to Border* and its interaction with the indicators of low economic status. *Position Relative to Border* ranges from -50 to 50, with -50 representing census tracts that are 50 miles towards the interior of the state with strong branching restrictions, and positive values representing tracts toward the interior of the state that is open to out of state bank entry. The regressions also control for personal characteristics from the credit bureau data, and census tract and county level characteristics, as well as state-year fixed effects. Coefficients are reported in terms of percentage points, i.e. a coefficient of 1 indicates a 1 percentage point increase in *Large Bank Market Share*. The reported standard errors are clustered by census tract-year.

	LBMS	LBMS X Low Income	LBMS X Subprime	LBMS X Limited History
	(1)	(2)	(3)	(4)
Position Relative to Border	0.156***	0.145***	0.0952***	0.0821***
	(0.0145)	(0.0313)	(0.0294)	(0.0239)
Position Relative to Border X Low Income		0.346***		
		(0.0491)		
Position Relative to Border X Subprime			0.363***	
			(0.0486)	
Position Relative to Border X Limited Credit History				0.336***
				(0.0510)
HHI of Local Bank Branches (10mi)	-4.130***	-10.23***	-8.262***	-7.513***
	(0.256)	(0.572)	(0.524)	(0.444)
Individual, Census Tract, and County Controls	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes
R^2	0.570	0.275	0.254	0.206
Observations	1132847	1132847	1132847	1132847

Table 5: OLS and IV Estimates of the Effect of Large Bank Market Share on Household Credit Access

This table presents OLS and IV regressions of variables describing a person's credit access on *Large Bank Market Share* and individual, census tract, and county level characteristics as well as state-year fixed effects. The explanatory variable of interest, *Large Bank Market Share*, is the fraction of bank branches located within 10 miles of where the individual lives that are owned by banks with greater than $1 Billion in assets. I select all individual-years from 2010-2015 in the credit bureau data where the person lives within 50 miles of a state border where there is a large contrast in the two states' interstate bank branching policies (see Table A.2 for a list of these state borders). I instrument for *Large Bank Market Share* using a person's *Position Relative to Border*, which ranges from -50 to 50, with -50 and 50 representing census tracts 50 miles towards the interior of the state with strong or weak branching restrictions, respectively. I also interact *Large Bank Market Share* with indicators for the borrower having a low income (*Estimated Income* below median), low credit score (*Vantage Score* $\leq$ 660), or limited credit history (below median number of open credit lines). The IV regressions instrument for these interactions with the interaction between the indicator and *Position Relative to Border*. The base terms for these interactions are omitted from the regressions because they are direct linear combinations of the fixed effects already included to control for the direct effect (i.e. fixed effects based on *Vantage Score*, *Estimated Income*, and *Number of Credit Lines*). The results for the main outcome variable, *Credit Approval*, are presented in Panel A. This variable takes a value of 1 when an individual successfully opens a new credit line, and a value of 0 when individuals apply for credit during the year but do not open any new credit lines. Applications and new trade lines for credit cards are excluded when constructing *Credit Approval* because credit card lending is dominated by a few national banks and is less likely to depend on local branches. Panel B presents the results when *Credit Approval (First Mortgage)* is the outcome of interest. This variable measures mortgage credit approval for individuals who have no mortgage at the start of the year and attempt to open a mortgage during the year. Panels C and D present the results when an individual's share of total debt held on credit cards, and an indicator for having retail debt, are the dependent variables. The continuous explanatory variables are standardized to have a mean of 0 and a standard deviation of 1. Coefficients are reported in terms of percentage points, i.e. a coefficient of 1 indicates that a standard deviation increase in the explanatory variable results in a 1 percentage point increase in the outcome variable. The reported standard errors are clustered by census tract-year.

Panel A: Credit Approval

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Large Bank Market Share	-0.557***	-0.148**	0.0632	-0.117*	-1.176**	0.499	0.920*	0.559
	(0.0596)	(0.0675)	(0.0646)	(0.0629)	(0.495)	(0.508)	(0.497)	(0.499)
Large Bank Market Share X Low Income		-0.849***				-3.442***		
		(0.0773)				(0.410)		
Large Bank Market Share X Subprime			-1.410***				-4.704***	
			(0.0827)				(0.438)	
Large Bank Market Share X Limited Credit History				-1.239***				-4.978***
				(0.0846)				(0.456)
HHI of Local Bank Branches (10mi)	-0.131**	-0.145***	-0.136***	-0.147***	-0.228**	-0.279***	-0.239**	-0.294***
	(0.0521)	(0.0521)	(0.0520)	(0.0521)	(0.0930)	(0.0940)	(0.0934)	(0.0943)
Individual, Census Tract, and County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.196	0.196	0.197	0.196	-	-	-	-
Observations	1132847	1132847	1132847	1132847	1132847	1132847	1132847	1132847

Panel B: Credit Approval (First Mortgage)

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Large Bank Market Share	0.323*	0.946***	0.980***	0.484**	-1.561	-0.353	-0.619	-1.182
	(0.172)	(0.226)	(0.231)	(0.214)	(1.363)	(1.511)	(1.526)	(1.468)
Large Bank Market Share X Low Income		-1.145***				-2.201**		
		(0.232)				(1.079)		
Large Bank Market Share X Subprime			-1.306***				-1.941*	
			(0.227)				(1.063)	
Large Bank Market Share X Limited Credit History				-0.357				-0.893
				(0.221)				(1.021)
HHI of Local Bank Branches (10mi)	-0.245	-0.251*	-0.252*	-0.249	-0.533**	-0.533**	-0.524**	-0.512**
	(0.152)	(0.152)	(0.152)	(0.152)	(0.257)	(0.257)	(0.257)	(0.257)
Individual, Census Tract, and County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.167	0.167	0.167	0.167	-	-	-	-
Observations	130296	130296	130296	130296	130296	130296	130296	130296

Panel C: Credit Card Debt Share

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Large Bank Market Share	0.322***	-0.371***	-0.0739*	-0.104**	1.678***	-0.744**	0.502	-0.154
	(0.0395)	(0.0432)	(0.0442)	(0.0409)	(0.315)	(0.319)	(0.322)	(0.316)
Large Bank Market Share X Low Income		1.642***				5.694***		
		(0.0523)				(0.282)		
Large Bank Market Share X Subprime			1.231***				3.551***	
			(0.0512)				(0.267)	
Large Bank Market Share X Limited Credit History				1.401***				6.098***
				(0.0608)				(0.330)
HHI of Local Bank Branches (10mi)	0.176***	0.198***	0.179***	0.194***	0.388***	0.459***	0.391***	0.466***
	(0.0359)	(0.0359)	(0.0359)	(0.0360)	(0.0626)	(0.0637)	(0.0626)	(0.0641)
Individual, Census Tract, and County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.320	0.320	0.320	0.320	-	-	-	-
Observations	1821131	1821131	1821131	1821131	1821131	1821131	1821131	1821131

Panel D: Have Retail Debt

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Large Bank Market Share	-0.0207	-0.112**	-0.441***	-0.394***	0.263	-0.073	-1.595***	-0.194
	(0.0375)	(0.0510)	(0.0456)	(0.0514)	(0.309)	(0.353)	(0.330)	(0.355)
Large Bank Market Share X Low Income		0.161***				0.581**		
		(0.0496)				(0.249)		
Large Bank Market Share X Subprime			0.983***				2.609***	
			(0.0469)				(0.239)	
Large Bank Market Share X Limited Credit History				0.745***				1.081***
				(0.0484)				(0.236)
HHI of Local Bank Branches (10mi)	-0.244***	-0.241***	-0.239***	-0.233***	-0.313***	-0.321***	-0.302***	-0.312***
	(0.0326)	(0.0326)	(0.0326)	(0.0326)	(0.0581)	(0.0580)	(0.0582)	(0.0575)
Individual, Census Tract, and County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.330	0.330	0.330	0.330	-	-	-	-
Observations	2559406	2559406	2559406	2559406	2559406	2559406	2559406	2559406

Table 6: Summary Statistics for HMDA Mortgage Applications

This table presents summary statistics describing the sample of mortgage applications from the Home Mortgage Disclosure Act database. I collect all applications received by commercial banks for conventional mortgages (excludes applications related to programs run by the Federal Housing Administration, Veterans Administration, Farm Service Agency, or Rural Housing Service). I limit the sample to first-lien home purchase mortgage applications that are for loan amounts below the Government Sponsored Entities' securitization limits (excludes "jumbo" loans). I also require the real property to be located within an MSA, because this is where HMDA data are the most comprehensive. The sample includes just over 4.7 million mortgage applications between 2010 and 2015.

	Mean	Std. Dev.	P10	P50	P90
Mortgage Approval	0.8508	0.3562	0	1	1
Distance To Branch	12.99	18.42	0.70	3.30	51.00
Small Bank	0.2141	0.4102	0	0	1
Applicant and Loan Characteristics					
Log(Income)	11.38	0.69	10.49	11.39	12.25
Income	112038	90097	36000	88000	210000
Loan To Income Ratio	2.18	1.26	0.62	2.05	3.88
Log(Loan Amount)	11.95	0.78	10.92	12.05	12.87
Loan Amount	198038	126604	55000	171000	389000
Joint Application	0.4899	0.4999	0	0	1
African American	0.0353	0.1845	0	0	0
Hispanic	0.0699	0.2550	0	0	0
Census Tract Ratios and Averages					
Income / Tract Income	0.98	0.63	0.38	0.84	1.72
Loan To Income / Tract Loan To Income	0.99	0.52	0.33	0.95	1.66
Loan Amount / Tract Loan Amount	1.00	0.44	0.44	0.97	1.56
Average Vantage Score $_{t-1}$	689	39	634	693	736
Bank Characteristics					
Capital Ratio	0.1058	0.0328	0.0758	0.1068	0.1377
Real Estate Loans Ratio	0.4244	0.1709	0.2284	0.4080	0.6667
Profitability	0.0086	0.0082	0.0016	0.0102	0.0144

Table 7: The Effect of Borrower-Lender Distance on Mortgage Approval at Small vs. Large Banks

This table presents regressions of an indicator for a mortgage application being approved on the distance from the property to the bank's nearest branch, and this distance interacted with an indicator for the bank being small (assets less than 1 Billion in 2010 dollars) or the borrower having a low income (below the median U.S. household income), as well as control variables. Columns 1-3 present the results for the full sample, which includes all mortgage applications in the Home Mortgage Disclosure Act (HMDA) database that were received by commercial banks from 2010-2015 and intended for home purchase. I exclude non-conventional applications (e.g. FHA, VA) and applications for loan amounts above the limits set for securitization by the Government Sponsored Enterprises (i.e. "jumbo loans"). I also require the property to be located within a Metropolitan Statistical Area and for the distance from the property to the nearest branch to be less than 20 miles. Column 4 presents the results for the subsample of low income applicants, and Column 5 presents the results for applicants with incomes above the median U.S. household income. All specifications include county-year fixed effects, and the continuous explanatory variables are standardized to have a mean of 0 and a standard deviation of 1 except for *Distance To Branch*, which is in miles. All coefficients are reported in terms of percentage points, i.e. a coefficient of 1 indicates that a standard deviation increase in the explanatory variable results in a 1 percentage point increase in the dependent variable. The reported standard errors are clustered at the county-year level.

	Full Sample			Low Income	High Income
	(1)	(2)	(3)	(4)	(5)
Distance To Branch	-0.0871***	-0.0664***	-0.0556***	-0.139***	-0.0347***
	(0.0101)	(0.0126)	(0.00965)	(0.0224)	(0.0121)
Distance To Branch X Small Bank		-0.0818***		-0.102***	-0.0751***
		(0.0164)		(0.0333)	(0.0154)
Small Bank		1.058***		0.912***	1.291***
		(0.149)		(0.263)	(0.137)
Distance To Branch X Low Income			-0.129***		
			(0.0171)		
Low Income			3.055***		
			(0.124)		
Applicant and Loan Characteristics					
Log(Income)	53.27***	53.25***	65.21***	336.5***	25.61***
	(0.957)	(0.957)	(1.106)	(8.219)	(1.252)
Log(Income) ^{2}	-42.38***	-42.36***	-53.54***	-345.9***	-19.11***
	(0.978)	(0.978)	(1.109)	(8.991)	(1.217)
Loan To Income Ratio	27.00***	27.03***	26.93***	39.37***	17.57***
	(0.342)	(0.341)	(0.342)	(0.691)	(0.364)
Loan To Income Ratio^2	-19.71***	-19.73***	-19.62***	-27.52***	-13.23***
	(0.239)	(0.238)	(0.238)	(0.360)	(0.287)
Log(Loan Amount)	12.18***	12.20***	12.15***	-17.65***	12.01***
	(1.066)	(1.067)	(1.056)	(2.585)	(0.990)
Log(Loan Amount) ^{2}	-17.59***	-17.61***	-17.54***	7.879***	-13.38***
	(1.132)	(1.132)	(1.121)	(2.958)	(1.046)
Joint Application	-0.141***	-0.148***	-0.108**	-2.591***	0.923***
	(0.0514)	(0.0514)	(0.0513)	(0.119)	(0.0528)
African American	-7.921***	-7.914***	-7.933***	-9.132***	-7.389***
	(0.179)	(0.179)	(0.178)	(0.303)	(0.175)
Hispanic	-4.205***	-4.198***	-4.231***	-4.887***	-3.785***
	(0.151)	(0.151)	(0.151)	(0.247)	(0.170)
Census Tract Ratios and Averages					
Income / Tract Income	0.355***	0.353***	0.363***	-1.001***	0.373***
	(0.0633)	(0.0633)	(0.0631)	(0.276)	(0.0577)
Loan To Income / Tract Loan To Income	-2.008***	-2.009***	-1.992***	-2.270***	-1.756***
	(0.0870)	(0.0870)	(0.0865)	(0.153)	(0.0872)
Loan Amount / Tract Loan Amount	-0.944***	-0.941***	-0.972***	0.0207	-1.185***
	(0.0615)	(0.0615)	(0.0615)	(0.147)	(0.0622)
Average Vantage Score $_{t-1}$	1.153***	1.155***	1.152***	0.933***	1.277***
	(0.0477)	(0.0478)	(0.0477)	(0.0772)	(0.0538)
Bank Characteristics					
Capital Ratio	-0.438***	-0.427***	-0.441***	-0.105	-0.538***
	(0.0717)	(0.0716)	(0.0716)	(0.109)	(0.0699)
Real Estate Loans Ratio	4.196***	4.088***	4.195***	4.982***	3.814***
	(0.0677)	(0.0736)	(0.0677)	(0.111)	(0.0751)
Profitability	0.0268	0.0504	0.0312	-0.00237	0.113*
	(0.0600)	(0.0603)	(0.0600)	(0.0924)	(0.0604)
County X Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.087	0.087	0.087	0.122	0.056
Observations	3742920	3742920	3742920	910784	2832079

Table 8: Mortgage Delinquencies at Small vs. Large Banks

This table presents regressions of an indicator for a mortgage becoming at least 60 days delinquent in the two years following origination on an indicator for the loan being originated by a small bank (assets less than 1 Billion in 2010 dollars). The regressions control for borrower, loan, and bank characteristics, as well as county-year fixed effects. The mortgages in the sample are from a matched dataset with information from both HMDA and credit bureau data. The two data sources are matched based on origination year, census tract, loan amount, and whether the mortgage is joint or belongs to a single borrower. The matching process is outlined in detail in Internet Appendix B. Column 1 presents the results for the full sample, Column 2 presents results for the subsample of low income borrowers (below the U.S. median household income), and Column 3 presents the results for high income borrowers. All coefficients are reported in terms of percentage points, i.e. a coefficient of 1 indicates that a unit increase in the explanatory variable results in a 1 percentage point increase in delinquency. The reported standard errors are clustered at the county-year level.

	Full Sample (1)	Low Income (2)	High Income (3)
Small Bank	0.0721	0.1107	0.0599
	(0.2853)	(0.5715)	(0.3637)
Applicant and Loan Characteristics			
Vantage Score $_{t-1}$	-0.0298***	-0.0286***	-0.0273***
	(0.0027)	(0.0057)	(0.0031)
Number of Credit Lines $_{t-1}$	-0.0917***	-0.0342	-0.1083***
	(0.0303)	(0.0649)	(0.0364)
Age	0.0836***	0.0556***	0.0872***
	(0.0103)	(0.0204)	(0.0127)
Total Debt $_{t-1}$	0.0026***	0.0027	0.0026**
	(0.0010)	(0.0039)	(0.0010)
Past Due Debt $_{t-1}$	0.0001	0.0029**	-0.0000
	(0.0001)	(0.0011)	(0.0000)
Application Income	0.0013	-0.0116	-0.0004
	(0.0016)	(0.0327)	(0.0018)
Loan To Income Ratio	-0.0741	0.0360	-0.2372
	(0.0830)	(0.0600)	(0.1864)
Loan Amount	-0.0021	-0.0056	-0.0014
	(0.0013)	(0.0073)	(0.0017)
Joint Application	-0.2724	-0.1760	-0.2847
	(0.2331)	(0.5281)	(0.2886)
African American	-0.4108	-0.5703	-0.5892
	(0.7548)	(1.6672)	(0.8720)
Hispanic	1.0493*	2.0177	0.4969
	(0.5771)	(1.3358)	(0.6196)
Bank Characteristics			
Equity Capital Ratio	2.8731	-0.3812	4.5368
	(5.6850)	(11.5289)	(6.8382)
Real Estate Loans Ratio	0.5675	-1.8726	1.9562*
	(0.9726)	(2.4620)	(1.0859)
Profitability	-6.8191	8.5219	-9.9539
	(11.6920)	(25.8006)	(12.3644)
County X Year FE	Yes	Yes	Yes
Origination Month FE	Yes	Yes	Yes
R^2	0.145	0.293	0.155
Observations	30951	7198	22725

Table 9: Summary Statistics for Intergenerational Mobility and County Characteristics

This table presents summary statistics describing intergenerational mobility levels and county characteristics for U.S. counties. The intergenerational mobility statistics and measures of income inequality are computed from IRS tax returns and published by Chetty et al. (2014). The mobility statistics use children born from 1980-1982 and are computed based on their income at age 26 (i.e. 2006-2008) and their parents' income when the children were 15-19 years old. The remaining county characteristics describe counties as of the year 2000, except for *Large Bank Market Share* which measures the share of branches in a county owned by large banks in 1995, when the children in the Chetty et al. (2014) data were approximately 14 years old.

	Mean	Std. Dev.	P10	P50	P90	N
Intergenerational Mobility						
Transition out of Bottom 40%	0.5149	0.1115	0.3731	0.5117	0.6625	2,876
Parent-Child Income Slope	0.2642	0.0843	0.1551	0.2623	0.3745	2,873
Parent Income-Child College Attendance Slope	0.6817	0.1249	0.5093	0.6997	0.8230	3,012
Race and Segregation						
Black Population Share	0.0859	0.1407	0.0010	0.0165	0.3056	3,138
Racial Segregation	0.0745	0.0803	0.0040	0.0472	0.1876	3,138
Segregation of Poverty	0.0239	0.0273	0.0003	0.0132	0.0658	3,138
Commute Less Than 15min	0.4058	0.1382	0.2395	0.3870	0.6096	3,138
Income and Inequality						
Per Capita Income	32836	6709	25181	32244	40436	3,138
Gini Coefficient	0.3769	0.0846	0.2743	0.3689	0.4881	3,137
Top 1 Percent Income Share	0.0935	0.0437	0.0496	0.0834	0.1496	3,036
Family Characteristics						
Single Mother Households	0.1944	0.0656	0.1245	0.1825	0.2779	3,138
Fraction of Adults Divorced	0.0950	0.0189	0.0699	0.0955	0.1187	3,138
Fraction of Adults Married	0.5856	0.0571	0.5109	0.5965	0.6470	3,138
K-12 Education						
K12 Student Teacher Ratio	16.38	2.61	13.11	16.37	19.74	2,870
K12 Test Scores (Income Adjusted)	-0.01	8.94	-11.76	0.76	10.44	3,089
Social Capital						
Social Capital Index	-0.00	1.31	-1.65	-0.09	1.76	3,109
Religious Population Share	0.5299	0.1807	0.3097	0.5112	0.7794	3,136
Violent Crimes Per Capita	0.0014	0.0012	0.0002	0.0011	0.0030	2,961
Additional Covariates						
Large Bank Market Share	0.3881	0.3140	0.0000	0.3636	0.8286	3,114
Log(Population Density)	3.73	1.64	1.52	3.74	5.78	3,137
Per Capita Income Growth (1980-2005)	2.5303	0.6053	1.8885	2.4527	3.2220	3,126

Table 10: First Stage - Regressions of Large Bank Market Share on Years Since Interstate Deregulation

This table presents the first stage regression for the IV/2SLS analysis that estimates the effect of the share of large bank branches in a county on intergenerational mobility measures. The dependent variable in these first stage regressions is the share of large bank branches in a county. The sample includes the cross section of U.S. counties for which data on all of the covariates are available. Column 1 presents the results for the full sample and Columns 2 and 3 show the results for counties located inside and outside of metropolitan statistical areas, respectively. The instrumental variable is the years since the state removed its regulations preventing interstate bank mergers (*Years Since Interstate Deregulation*). The regression also controls for a broad set of county level characteristics measured as of the year 2000. All explanatory variables are standardized to have a mean of 0 and a standard deviation of 1, except for *Years Since Interstate Deregulation*, which is in years.

	Full Sample	MSA	Non-MSA
	(1)	(2)	(3)
Years Since Interstate Deregulation	0.0836***	0.0723***	0.0862***
	(0.00834)	(0.0150)	(0.0102)
Race and Segregation			
Black Population Share	-0.0872**	-0.195***	-0.0498
	(0.0384)	(0.0570)	(0.0531)
Racial Segregation	0.123***	0.0906**	0.114***
	(0.0217)	(0.0361)	(0.0300)
Segregation of Poverty	0.156***	0.102***	0.181***
	(0.0249)	(0.0308)	(0.0473)
Commute Less Than 15min	0.157***	0.215***	0.135***
	(0.0296)	(0.0583)	(0.0366)
Income and Inequality			
Per Capita Income	0.219***	0.206***	0.238***
	(0.0275)	(0.0462)	(0.0383)
Gini Coefficient	0.00298	0.0432	-0.0363
	(0.0361)	(0.0607)	(0.0466)
Top 1 Percent Income Share	-0.00690	-0.0549	0.0205
	(0.0294)	(0.0468)	(0.0373)
Family Characteristics			
Single Mother Households	0.00630	0.213***	-0.0489
	(0.0503)	(0.0770)	(0.0674)
Fraction of Adults Divorced	-0.0369	-0.0692*	-0.0386
	(0.0237)	(0.0388)	(0.0313)
Fraction of Adults Married	-0.0606*	-0.0366	-0.0514
	(0.0316)	(0.0532)	(0.0409)
K-12 Education			
K12 Student Teacher Ratio	0.190***	0.162***	0.218***
	(0.0210)	(0.0325)	(0.0284)
K12 Test Scores (Income Adjusted)	-0.00406	0.00254	-0.0148
	(0.0226)	(0.0362)	(0.0299)
Social Capital			
Social Capital Index	-0.0679***	-0.145***	-0.0607*
	(0.0263)	(0.0449)	(0.0339)
Religious Population Share	-0.138***	-0.0670	-0.166***
	(0.0223)	(0.0462)	(0.0252)
Violent Crimes Per Capita	0.0396**	-0.00207	0.0545**
	(0.0201)	(0.0312)	(0.0264)
Additional Controls			
Log(Population Density)	0.0948**	0.237***	0.0123
	(0.0398)	(0.0751)	(0.0480)
Per Capita Income Growth (1980-2005)	-0.0657***	-0.0230	-0.0649***
	(0.0212)	(0.0446)	(0.0242)
R^2	0.368	0.428	0.255
Observations	2417	856	1561

Table 11: Large Banks and the Probability of Moving out of the Bottom 40% of the Income Distribution

This table presents regressions of *Transition out of Bottom 40%* — the probability that a child with parents in the bottom 40% of the income distribution moves out of this bottom 40% as an adult — on the share of large bank branches in a county and control variables. *Transition out of Bottom 40%* is from county level data published by Chetty et al. (2014) who compute intergenerational mobility statistics from IRS income tax returns based on children born between 1980-1982 and their parents. The sample for this table's regressions is the cross section of U.S. counties for which data on all the covariates are available. Columns 1-3 present the OLS results for the full sample and the urban (MSA) and rural (Non-MSA) subsamples. Columns 4-6 present instrumental variables regressions that use the years since a state started allowing interstate bank mergers as an instrument for *Large Bank Market Share*. All explanatory variables are standardized to have a mean of 0 and a standard deviation of 1.

	OLS			IV		
	Full Sample	MSA	Non-MSA	Full Sample	MSA	Non-MSA
	(1)	(2)	(3)	(4)	(5)	(6)
Large Bank Market Share	-0.00712***	-0.0118***	-0.00632***	-0.0473***	-0.0781***	-0.0320***
	(0.00149)	(0.00248)	(0.00183)	(0.00861)	(0.0235)	(0.00913)
Race and Segregation						
Black Population Share	-0.0234***	-0.0442***	-0.0152***	-0.0276***	-0.0623***	-0.0166***
	(0.00315)	(0.00432)	(0.00378)	(0.00366)	(0.00846)	(0.00387)
Racial Segregation	-0.00318*	-0.00165	-0.00741***	0.00151	0.00653	-0.00539*
	(0.00188)	(0.00235)	(0.00245)	(0.00243)	(0.00449)	(0.00278)
Segregation of Poverty	-0.000757	-0.00541**	-0.00164	0.00448*	0.00185	0.00174
	(0.00201)	(0.00250)	(0.00340)	(0.00252)	(0.00431)	(0.00393)
Commute Less Than 15min	0.0123***	0.00781*	0.0155***	0.0172***	0.0259***	0.0171***
	(0.00220)	(0.00409)	(0.00274)	(0.00267)	(0.00829)	(0.00286)
Income and Inequality						
Per Capita Income	0.00777***	0.0214***	-0.000593	0.0167***	0.0407***	0.00415
	(0.00209)	(0.00350)	(0.00264)	(0.00304)	(0.00748)	(0.00346)
Gini Coefficient	-0.0262***	-0.0308***	-0.0275***	-0.0252***	-0.0263***	-0.0276***
	(0.00268)	(0.00440)	(0.00332)	(0.00309)	(0.00731)	(0.00346)
Top 1 Percent Income Share	0.0151***	0.0160***	0.0152***	0.0145***	0.0102	0.0154***
	(0.00224)	(0.00401)	(0.00261)	(0.00258)	(0.00641)	(0.00269)
Family Characteristics						
Single Mother Households	-0.0440***	-0.0108	-0.0498***	-0.0426***	0.0112	-0.0505***
	(0.00427)	(0.00680)	(0.00500)	(0.00474)	(0.0118)	(0.00501)
Fraction of Adults Divorced	-0.0174***	-0.0230***	-0.0149***	-0.0186***	-0.0292***	-0.0155***
	(0.00191)	(0.00283)	(0.00234)	(0.00218)	(0.00482)	(0.00244)
Fraction of Adults Married	-0.0109***	-0.0117***	-0.00718**	-0.0132***	-0.0142**	-0.00822**
	(0.00265)	(0.00435)	(0.00313)	(0.00306)	(0.00689)	(0.00327)
K-12 Education						
K12 Student Teacher Ratio	-0.00215	0.000107	-0.00295	0.00691***	0.0168***	0.00218
	(0.00156)	(0.00244)	(0.00200)	(0.00252)	(0.00545)	(0.00307)
K12 Test Scores (Income Adjusted)	-0.00172	-0.00170	0.000517	-0.000745	0.000274	0.000785
	(0.00191)	(0.00269)	(0.00238)	(0.00216)	(0.00425)	(0.00248)
Social Capital						
Social Capital Index	0.0147***	-0.000345	0.0179***	0.0102***	-0.0161**	0.0157***
	(0.00190)	(0.00339)	(0.00227)	(0.00239)	(0.00688)	(0.00250)
Religious Population Share	0.00909***	0.0150***	0.00532***	0.00355	0.00929*	0.00211
	(0.00165)	(0.00285)	(0.00197)	(0.00219)	(0.00525)	(0.00250)
Violent Crimes Per Capita	0.00413***	0.00672***	0.000943	0.00536***	0.00560	0.00191
	(0.00155)	(0.00226)	(0.00182)	(0.00173)	(0.00350)	(0.00189)
Additional Controls						
Log(Population Density)	-0.0195***	-0.0217***	-0.0228***	-0.0139***	0.00413	-0.0219***
	(0.00275)	(0.00446)	(0.00336)	(0.00352)	(0.0116)	(0.00349)
Per Capita Income Growth (1980-2005)	-0.00543***	-0.0118***	-0.00258	-0.00753***	-0.0120**	-0.00369*
	(0.00171)	(0.00307)	(0.00196)	(0.00205)	(0.00499)	(0.00214)
R^2	0.761	0.723	0.781	-	-	-
Observations	2420	857	1563	2420	857	1563

Table 12: Large Banks and the Relationship Between Parental Income and Children's Income and Educational Attainment

Panel A of this table presents regressions of *Log(Parent-Child Income Slope)* on the share of large bank branches in a county and control variables. The parent-child income slope is the coefficient from a rank-rank regression of child income centile on parent income centile. Chetty et al. (2014) compute these parent-child income slopes at the county level based on IRS income tax returns for children born between 1980-1982 and their parents. The dataset contains the cross section of U.S. counties for which data on all the covariates are available. Columns 1-3 present the OLS results for the full sample and the urban (MSA) and rural (Non-MSA) subsamples. Columns 4-6 present instrumental variables regressions that use the years since a state started allowing interstate bank mergers as an instrument for *Large Bank Market Share*. Panel B presents similar regressions using *Log(Parent Income-Child College Attendance Slope)* as the outcome variable. *Parent Income-Child College Attendance Slope* is the coefficient from a regression of an indicator for children's college attendance on their parent's rank in the national income distribution that is computed for the residents of a given county by Chetty et al. (2014). All explanatory variables are standardized to have a mean of 0 and a standard deviation of 1.

Panel A: Large Banks and the Relationship Between Parent Income and Child Income

	OLS			IV		
	Full Sample	MSA	Non-MSA	Full Sample	MSA	Non-MSA
	(1)	(2)	(3)	(4)	(5)	(6)
Large Bank Market Share	0.0198***	0.0282**	0.0209**	0.131***	0.169**	0.104**
	(0.00665)	(0.0111)	(0.00815)	(0.0367)	(0.0736)	(0.0423)
Controls:						
Race and Segregation	Yes	Yes	Yes	Yes	Yes	Yes
Income and Inequality	Yes	Yes	Yes	Yes	Yes	Yes
Family Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
K-12 Education	Yes	Yes	Yes	Yes	Yes	Yes
Social Capital	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.512	0.507	0.540	-	-	-
Observations	2417	856	1561	2417	856	1561

Panel B: Large Banks and the Relationship Between Parent Income and Child College Attendance

	OLS			IV		
	Full Sample	MSA	Non-MSA	Full Sample	MSA	Non-MSA
	(1)	(2)	(3)	(4)	(5)	(6)
Large Bank Market Share	0.00392	0.0126**	0.00383	0.154***	0.191***	0.134***
	(0.00426)	(0.00635)	(0.00536)	(0.0254)	(0.0507)	(0.0292)
Controls:						
Race and Segregation	Yes	Yes	Yes	Yes	Yes	Yes
Income and Inequality	Yes	Yes	Yes	Yes	Yes	Yes
Family Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
K-12 Education	Yes	Yes	Yes	Yes	Yes	Yes
Social Capital	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.346	0.302	0.387	-	-	-
Observations	2533	864	1669	2533	864	1669

Figures

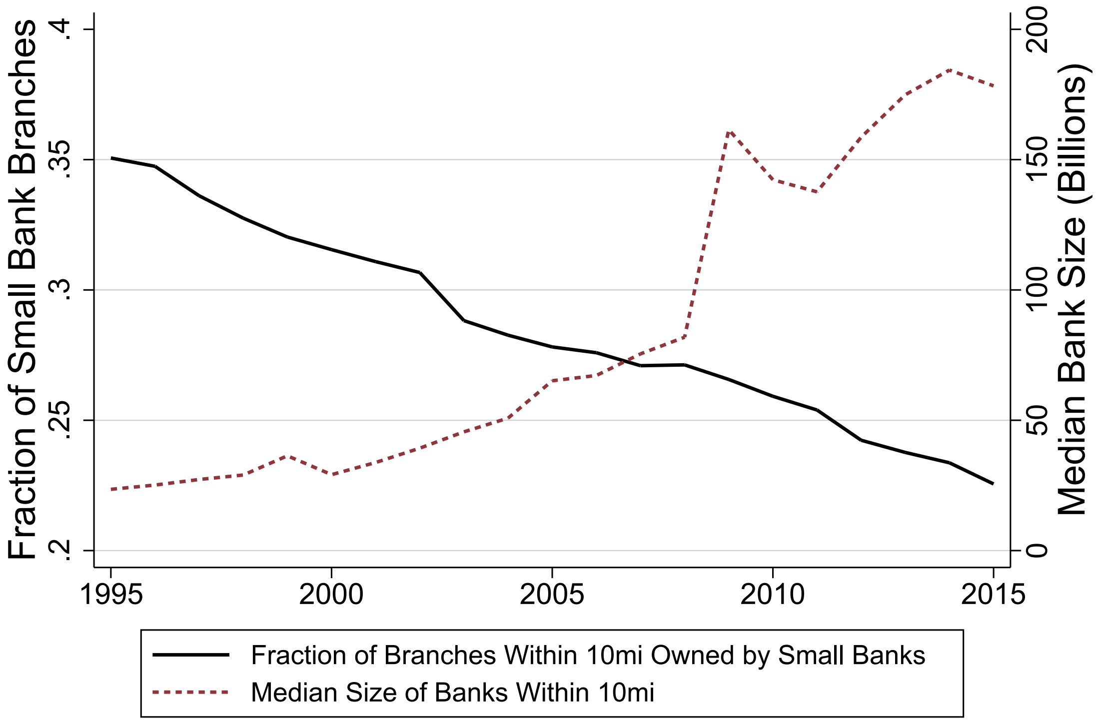

Figure 1
Banking Consolidation From U.S. Households' Perspective
This figure shows, from the average U.S. household's perspective, the fraction of local bank branches owned by small banks, and the median size of local banks. Local branches are defined as those within 10 miles of households, and small banks are those with less than 1 Billion in assets in 2010 dollars. If a bank is owned by a holding company, the size of the bank is set as the combined size of all banks in the holding company. The location of households is set as the centroid of the census tract they live in, and the locations of bank branches are specific longitude and latitude coordinates from the Summary of Deposits available from the Federal Deposit Insurance Corporation. Distances between households and bank branches are computed based on longitude and latitude using the Haversine formula.

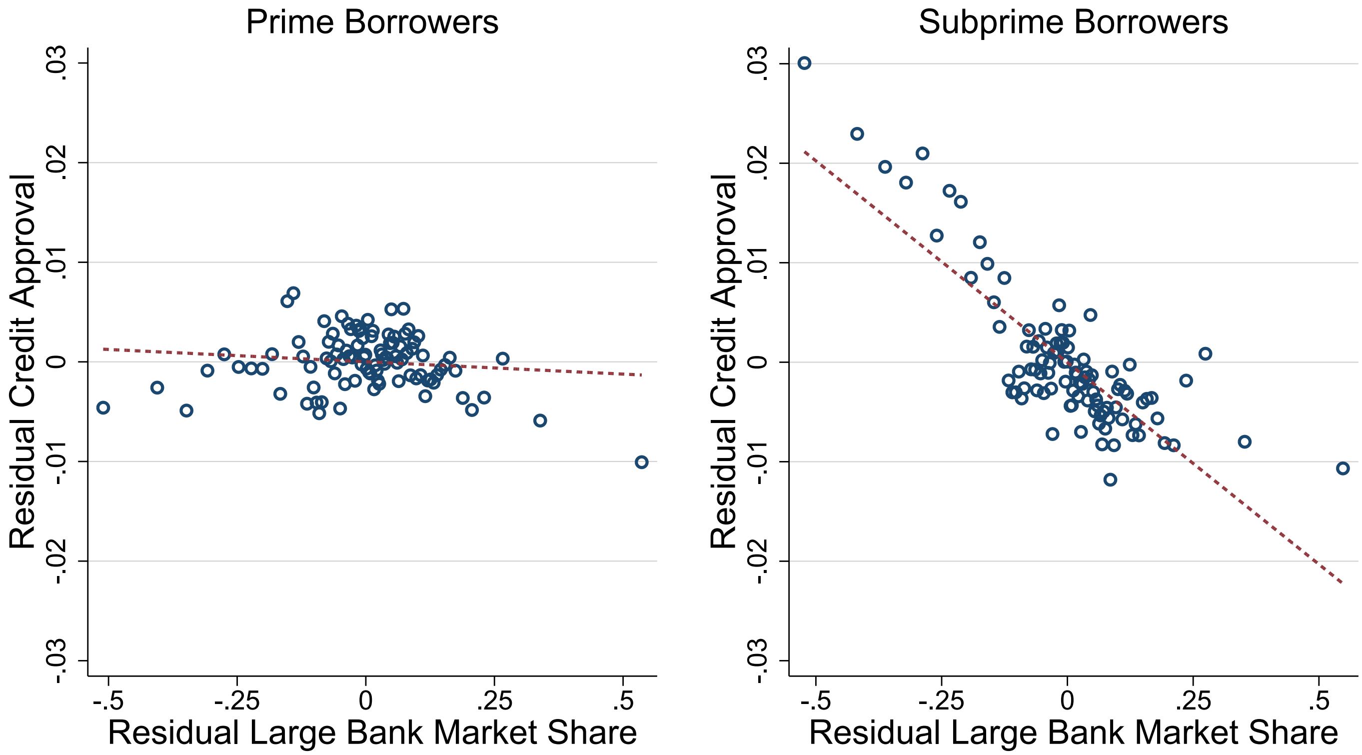

Figure 2
Large Bank Market Share and Household Credit Access
This figure plots *Residual Credit Approval* against *Residual Large Bank Market Share* for borrowers with prime and subprime credit scores. The two variables are residualized with respect to all the individual, census tract, and county level characteristics, as well as state-year fixed effects included in the baseline OLS results in Table 2 (except for *Large Bank Market Share* itself). This approach employs the Frisch-Waugh theorem to show how the unique variation in *Large Bank Market Share* explains variation in *Credit Approval*. The sample includes all individual-years from 2010-2015 in the credit bureau dataset where the person applies for credit.

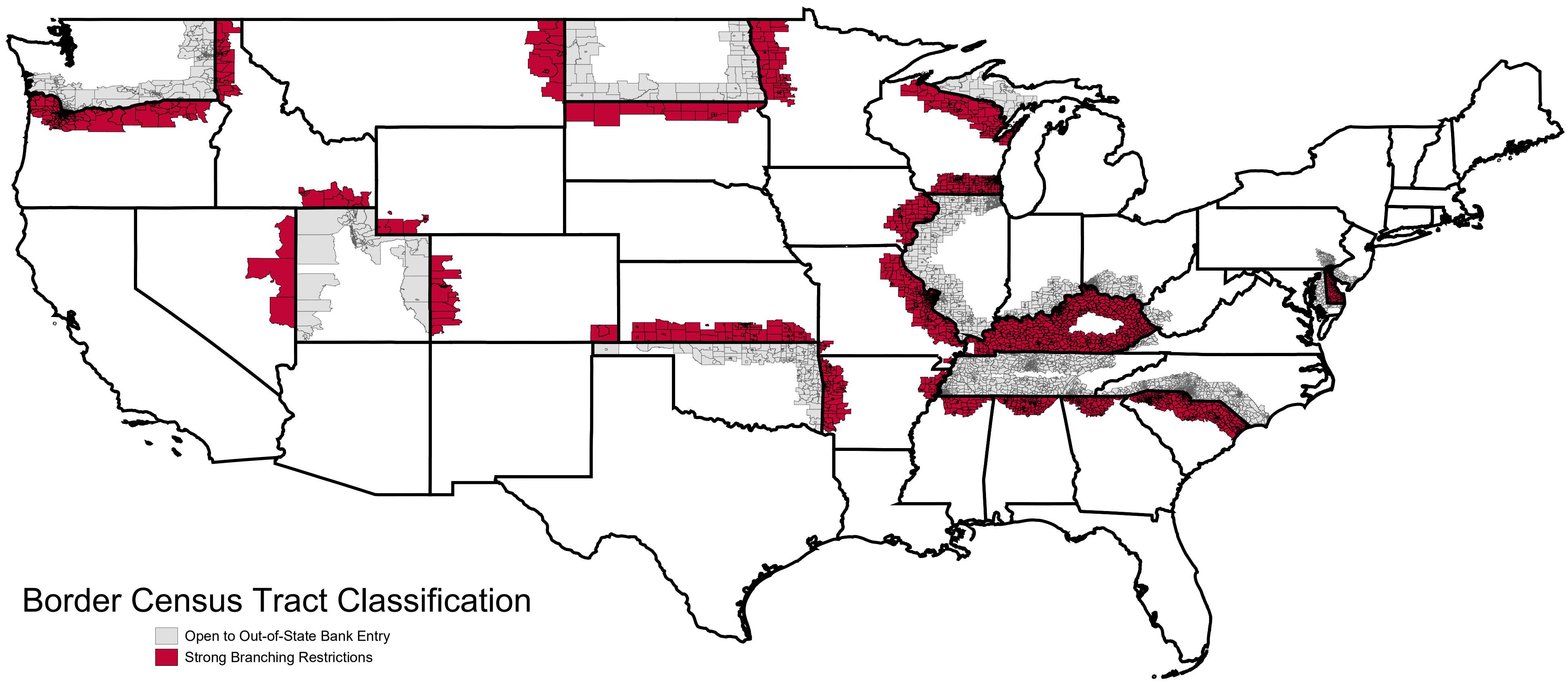

Figure 3
State Borders with a Large Contrast in Branching Restrictions
This figure shows the state borders where there is a large contrast in the two states' interstate bank branching policies. I use the index of branching restrictions developed in Rice and Strahan (2010), which ranges from 0 to 4, to define states with 3 or 4 restrictions as having strong restrictions, and to define states with 0 or 1 restriction as being open to out of state bank entry. This map shows the census tracts within 50 miles of the 36 state borders where one state has strong restrictions and the other state is open to out of state bank entry (see Table A.2 for a list of these state borders).

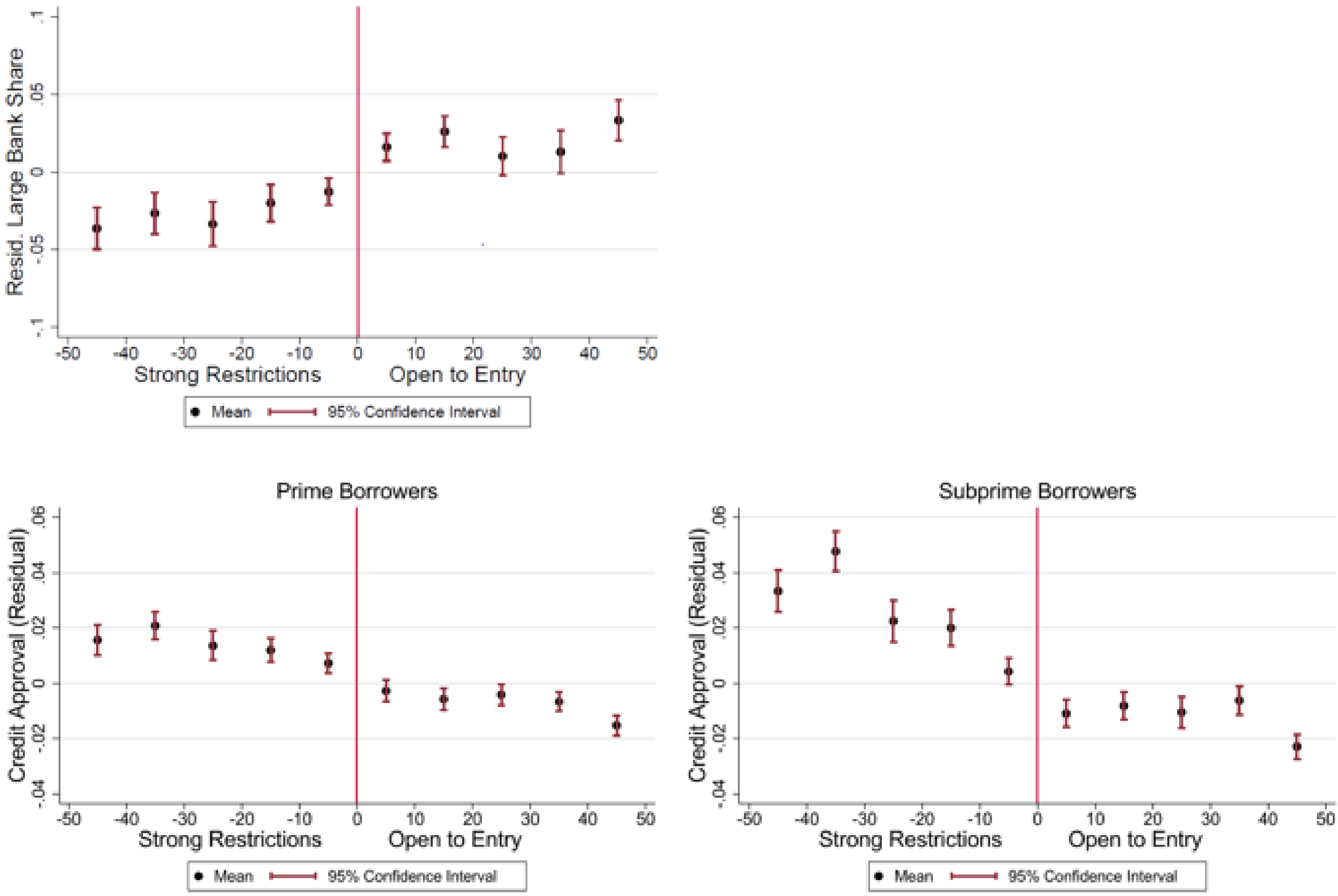

Figure 4
Bank Size and Household Credit Access Across State Borders with a Large Contrast in Interstate Bank Branching Policies
This figure shows how the size of banks and household credit access change around state borders where the two states have a stark contrast in interstate bank branching policies. I use the index of branching restrictions developed in Rice and Strahan (2010), which ranges from 0 to 4, to define states with 3 or 4 restrictions as having strong restrictions, and to define states with 0 or 1 restriction as being open to out of state bank entry. The top left plot shows the residual share of branches owned by large banks (assets greater than 1 Billion in 2010 dollars) in census tracts based on the tract's position relative to the border (measured in miles). These residuals are from a census tract level regression of the large bank share on tract characteristics and year fixed effects. The bottom left plot shows how residual credit approval varies across the relevant state borders for prime borrowers. Residual credit approval is obtained from an individual level regression of *Credit Approval* on the individual, census tract, and county level controls (see Table 2). The bottom right plot shows how residual credit approval varies across these borders for subprime borrowers.

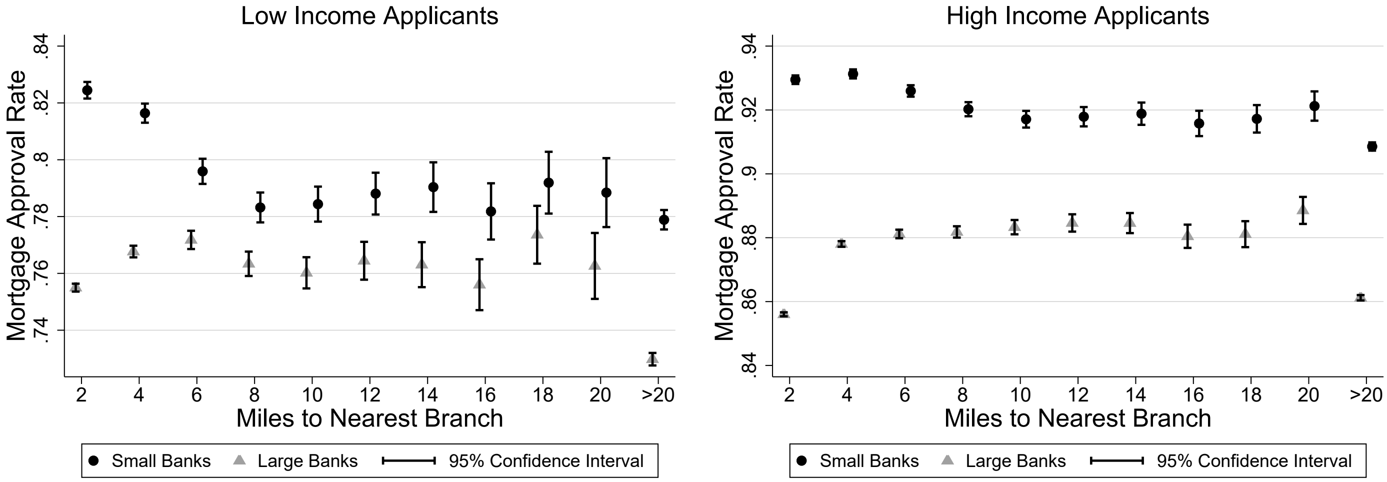

Figure 5

Mortgage Approval and Borrower-Lender Distance at Small vs. Large Banks

This figure shows the relationship between mortgage application approval rates and the distance from the property to the bank's nearest branch for applications received by commercial banks from 2010-2015. The left panel presents the results for low income applicants (below the median U.S. household income), and the right panel shows the results for all other applicants. The plots show the approval rates for small banks (assets less than 1 Billion in 2010 dollars), and large banks (all other banks). The sample consists of all mortgage applications intended for home purchase in the Home Mortgage Disclosure Act (HMDA) database, excluding non-conventional applications (e.g. FHA, VA) and applications for loan amounts above the limits set for securitization by the Government Sponsored Enterprises (i.e. "jumbo loans"). I also require the property to be located within a Metropolitan Statistical Area, because HMDA reporting requirements dictate that almost all loan applications in these areas are reported (small rural banks are sometimes exempt from HMDA). The distance from the property to the bank's nearest branch is computed using the Haversine formula which gives the distance between two sets of longitude and latitude coordinates. The coordinates of the property are defined as the centroid of the census tract it is in, and the coordinates for bank branches are available from the Federal Deposit Insurance Corporation.

For Online Publication

Internet Appendix A — Supplementary Tables

Table A.1: Interstate Banking Deregulation Years

This table presents the years that each state opened its borders to interstate banking by allowing interstate bank mergers.

State	Deregulation Year
Maine	1978
Alaska	1982
Connecticut	1983
Massachusetts	1983
Utah	1984
Kentucky	1984
Rhode Island	1984
North Carolina	1985
Nevada	1985
Virginia	1985
Idaho	1985
Ohio	1985
Georgia	1985
Tennessee	1985
Maryland	1985
District of Columbia	1985
Florida	1985
Minnesota	1986
New Jersey	1986
Michigan	1986
Missouri	1986
New York	1986
South Carolina	1986
Indiana	1986
Arizona	1986
Oregon	1986
Pennsylvania	1986
Illinois	1986
Wisconsin	1987
Texas	1987
Oklahoma	1987
Wyoming	1987
Louisiana	1987
Alabama	1987
New Hampshire	1987
California	1987
Washington	1987
South Dakota	1988
Colorado	1988
West Virginia	1988
Vermont	1988
Delaware	1988
Mississippi	1988
New Mexico	1989
Arkansas	1989
Nebraska	1990
Iowa	1991
North Dakota	1991
Kansas	1992
Montana	1993
Hawaii	1997

Table A.2: State Borders Where States Have a Large Contrast in Interstate Branching Policies

This table presents the state borders where the two states have a strong contrast in policies towards interstate bank branching as of the start of 2010. Columns 1 and 2 present the state with strong restrictions towards interstate branching and the value of the branching restrictions index developed in Rice and Strahan (2010). Columns 3 and 4 present the bordering state with fewer restrictions on interstate bank branching and its value of the restrictions index.

State with Strong Branching Restrictions	Restrictions Index	State Open to Entry	Restrictions Index
Alabama	3	Tennessee	1
Arkansas	4	Oklahoma	1
Arkansas	4	Tennessee	1
Colorado	4	Oklahoma	1
Colorado	4	Utah	1
Delaware	3	Maryland	0
Delaware	3	New Jersey	1
Delaware	3	Pennsylvania	0
Georgia	3	North Carolina	0
Georgia	3	Tennessee	1
Idaho	3	Utah	1
Idaho	3	Washington	1
Iowa	4	Illinois	0
Kansas	4	Oklahoma	1
Kentucky	3	Illinois	0
Kentucky	3	Indiana	1
Kentucky	3	Ohio	0
Kentucky	3	Tennessee	1
Kentucky	3	Virginia	0
Kentucky	3	West Virginia	1
Minnesota	3	Michigan	0
Minnesota	3	North Dakota	1
Mississippi	4	Tennessee	1
Missouri	4	Illinois	0
Missouri	4	Oklahoma	1
Missouri	4	Tennessee	1
Montana	4	North Dakota	1
Nevada	3	Utah	1
New Mexico	3	Oklahoma	1
New Mexico	3	Utah	1
Oregon	3	Washington	1
South Carolina	3	North Carolina	0
South Dakota	3	North Dakota	1
Wisconsin	3	Illinois	0
Wisconsin	3	Michigan	0
Wyoming	3	Utah	1

Internet Appendix B — Matching Credit Bureau Data and HMDA

This Appendix describes the process used to match mortgages in the credit bureau data to the Home Mortgage Disclosure Act (HMDA) database. This match allows information on the originating lender in the HMDA data to be combined with information on loan performance from the borrower's credit bureau record. There is no unique identifier to link the two datasets. Therefore, I match mortgages in the credit bureau data to originated mortgages in the HMDA data based on the year of origination, the census tract of the property, the loan amount, and whether the mortgage is joint or belongs to a single borrower. These variables are available in both databases and can be used to link the two datasets.

The Home Mortgage Disclosure Act requires almost all mortgage lenders to report detailed information on each loan application they receive and their decision to approve/deny the loan. Any depository institution must report HMDA data if it has at least one branch or office in a metropolitan statistical area (MSA), has at least $43 Million in assets (2014 threshold), and originated at least one mortgage in the previous year. Non-depository institutions with assets over $10 million must report HMDA data if their mortgage originations total at least $25 Million (or represent 10% of their loans), and they receive at least five mortgage applications from borrowers in MSAs. These requirements result in nearly all mortgage applications for properties in MSAs being reported to the HMDA database. Therefore, I match mortgages in the credit bureau data to HMDA when they are located within MSAs.

I require mortgages in the HMDA data to be unique based on the matching variables in order to be considered as potential matches (80.5% of conventional home purchase mortgages in HMDA are unique based on the matching variables). The ensuing tables and figures describe the success rate of this matching approach, and the characteristics of the matched and unmatched loans in the credit bureau data.

Table B.1: Summary of Credit Bureau to HMDA Match

This table summarizes the match between mortgages in the credit bureau data and Home Mortgage Disclosure Act data. The starting sample of credit bureau data contains conventional home purchase mortgages originated from 2010-2013, where the property is located within a metropolitan statistical area (MSA). The matching is done based on the origination year, the census tract of the property, the loan amount, and whether the mortgage is joint or belongs to a single borrower. Only mortgages in the HMDA data that are unique based on these matching variables are used as potential matches. Panel A shows the success rate of the matching approach. Panel B summarizes borrower-level and county-level characteristics of the matched and unmatched loans.

Panel A: Match Rate			
	Matched Loans	All Credit Bureau Loans	Match Rate
	71,159	114,305	62.25

Panel B: Summary Statistics			
	Matched Loans (N=71,159)	Unmatched Credit Bureau Loans (N=43,146)	Norm. Diff
Individual Characteristics			
Loan Amount	203.86	202.29	0.01
Joint Mortgage	0.53	0.54	-0.02
Age	43.61	46.25	-0.13
Vantage Score $_{t-1}$	754.32	751.16	0.04
Have Mortgage $_{t-1}$	0.42	0.53	-0.15
Auto Debt $_{t-1}$	6.39	6.38	0.00
Credit Card Debt $_{t-1}$	4.70	5.38	-0.06
Student Debt $_{t-1}$	5.24	4.43	0.03
County Characteristics			
High School Diploma	0.88	0.87	0.11
Poverty	0.13	0.13	-0.03
Minority Population Share	0.34	0.36	-0.08
Unemployment Rate	0.08	0.08	-0.10
Personal Income Per Capita	46.34	46.62	-0.01

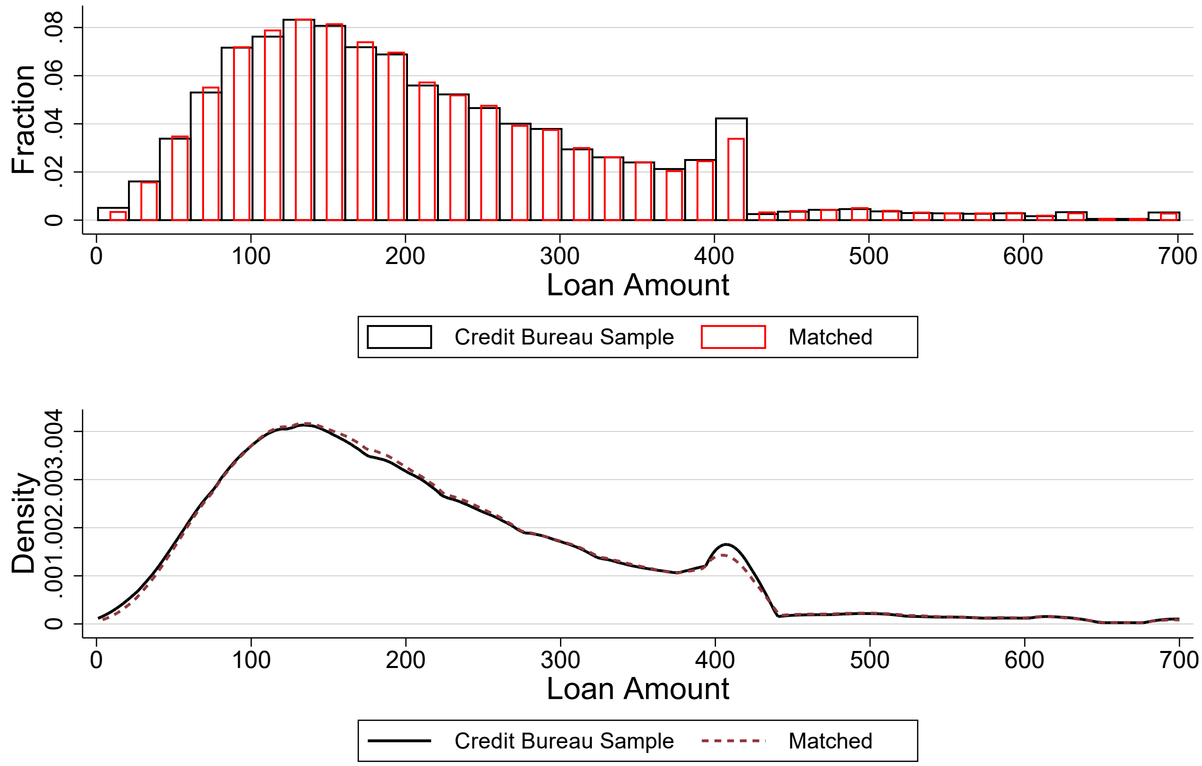

Figure B.1
Loan Amounts for Credit Bureau Mortgages and the Subset that Matched to HMDA
This figure shows the loan amount distribution for the sample of mortgages in the credit bureau data and for the subset of these mortgages that successfully matched to HMDA data. The starting sample of mortgages from the credit bureau data contains conventional home purchase mortgages originated from 2010-2013, where the property is located within a metropolitan statistical area (MSA). The matching is done based on the origination year, the census tract of the property, the loan amount, and whether the mortgage is joint or belongs to a single borrower. Only mortgages in the HMDA data that are unique based on these matching variables are used as potential matches.