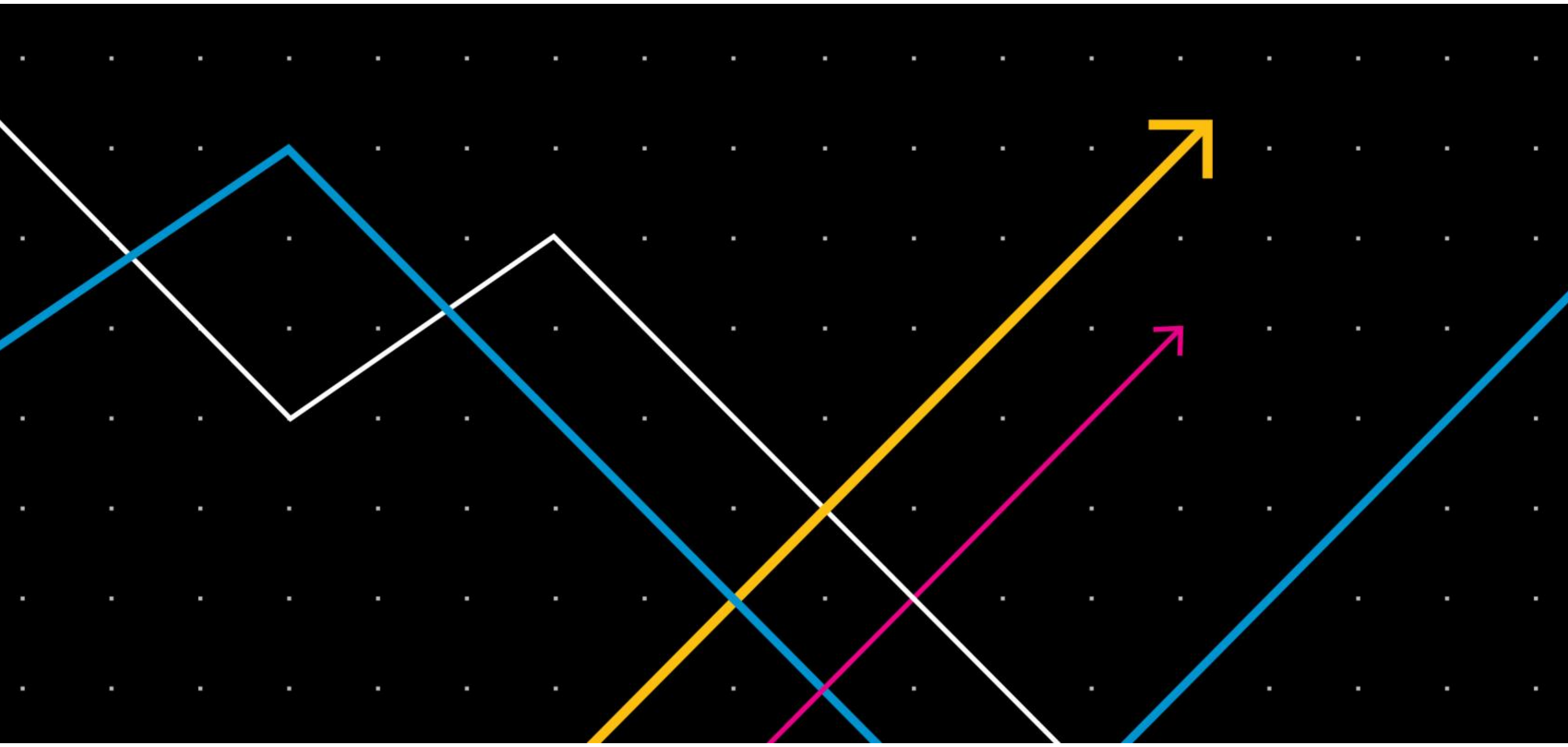

RESEARCH REPORT

# NeighborWorks America's Homeownership Education and Counseling: Who Receives It and Is It Effective?

*Wei Li* *Bing Bai* *Laurie Goodman* *Jun Zhu*

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# Executive Summary

This report answers three important questions about NeighborWorks America's homeownership education and counseling program:

1. Who uses the program?
2. Where could the program be of greatest use?
3. How effectively does the program improve loan performance?

NeighborWorks' nationwide network of affiliates offer homeownership education and counseling program throughout the country. NeighborWorks organizations are required to provide a homeownership education and counseling program or establish a partnership with an organization that meets the minimum requirements of homeownership education and counseling, as defined by NeighborWorks America for its National Homeownership and Lending Programs. The requirements include using a specifically approved curriculum, an approved online provider or classroom setting, and providing 8+ hours of training and/or education (including a minimum of 1 hour of individual counseling). Organizations are required to provide details on their homebuyer education classes, including agendas and curricula, the length of classes (number of meetings, number of classroom hours) and attendance.

A 2013 report that examined loans made between 2007 and 2009 found that NeighborWorks homeownership education and counseling was correlated with a nearly one-third drop in the likelihood of serious mortgage delinquency. This report uses a similar although not identical methodology to extend and expand that analysis to loans originated after the financial crisis, from 2010 to 2012.

To complete the analysis, we use Home Mortgage Disclosure Act (HMDA) data to establish our control group, NeighborWorks data to establish the test group, and CoreLogic data to enhance the factors available for both groups. We also use a unique denial rate calculator to help determine where the program could be of greatest use.

## Who Uses NeighborWorks America's Homeownership Education and Counseling Program?

By comparing the characteristics of homebuyers who received NeighborWorks services with all homebuyers in HMDA, we determine that NeighborWorks clients who receive pre-purchase education and counseling services are more likely to be African American, Hispanic, low income, and female than the general population of home purchase borrowers. These groups of borrowers form the base of traditionally disadvantaged borrowers who have difficulty accessing mortgage credit or who are more likely to be prey to predatory lenders. More specifically, we find that the share of disadvantaged borrowers among NeighborWorks clients is almost twice as high as that among general home purchase mortgage applicants and borrowers.

The share of African American borrowers among NeighborWorks clients is almost three times as high as that among general home purchase mortgage applicants and borrowers, and the share of Hispanic borrowers is twice as high. The share of very-low-income borrowers among NeighborWorks clients is five times as high as that among general home purchase mortgage applicants and borrowers, and the share of low-income borrowers is twice as high. Finally, the share of female borrowers among NeighborWorks clients is 1.7 times that among general home purchase mortgage applicants and borrowers.

## Where Could the Program Be of Greatest Use?

To measure the market potential for NeighborWorks America's homeownership education and counseling services, we use, as a proxy, the number of mortgage applicants who are denied a home purchase mortgage application. We also use a more robust measure developed by the Urban Institute's Housing Finance Policy Center, the real denial rate (RDR), to calculate the denial rate.

We present our findings in three lists:

- the 50 metropolitan statistical areas (MSAs) with the most rejected home purchase mortgage applicants
- the 20 MSAs with the highest traditional denial rate
- the 20 MSAs with the highest real denial rate

After presenting and explaining these different lists, we suggest that counselors focus on locations with both a high RDR and a relatively good match between income and house prices rather than places where home prices make buying unaffordable to a very large proportion of the population, such as San Francisco.

## How Effectively Does the Program Improve Loan Performance?

Our research shows that buyers who receive homeownership education and counseling from NeighborWorks achieve significantly better loan performance than do comparable buyers without NeighborWorks services. Holding all other things equal, we find that the delinquency rates of 90 days or more (90+) for NeighborWorks loans are 16 percent lower than those rates for non-NeighborWorks loans. Various racial and income groups show no statistically significant difference, except Hispanic borrowers with very low incomes, who actually perform significantly better than the reference group. Loans made in the Middle Atlantic and West South Central census divisions perform significantly better than loans made in the Pacific census division. Loans of the South Atlantic census division perform better, but with only marginal significance. Other census divisions do not show any significant differences.

We note that although Mayer and Temkin (2013)'s analysis found a nearly one-third drop in the likelihood of serious mortgage delinquency when consumers receive pre-purchase counseling and education, that research was based on mortgage loans originated between 2007 and 2009, a time when the housing crisis had only begun to unfold and the credit box had begun to tighten. Because mortgage credit has tightened considerably since 2009, the impact is, not surprisingly, less dramatic for loans originated between 2010 and 2012. This report reveals, however, that NeighborWorks homeownership education and counseling program works even when it serves more disadvantaged homebuyers in a tight-credit, low-default housing market.

# Introduction

Homeownership counseling and education provide an opportunity for consumers who wish to buy a home to work with a housing counselor to develop a budget, strengthen their credit to maximize their chance of obtaining the lowest possible mortgage rate, set a realistic timeline for the purchase, connect with other experts such as real estate agents and home inspectors, and get the most out of all the professionals involved in the homebuying process. The ultimate goal is to increase the long-term sustainability of the consumer as a homeowner.

Through the 1968 Housing and Urban Development Act, the Department of Housing and Urban Development (HUD) was granted the authority to authorize public and private institutions to provide mortgage counseling services. Six years later, the 1974 Housing and Community Development Act authorized HUD to provide funding to counseling agencies. As a result of these laws and similar legislation, homeownership counseling has become an important aspect of many homebuying programs, particularly those targeted toward low-income, minority, immigrant, and other groups whose homeownership rates are below the national average.

Homeownership counseling varies significantly. It can be provided by different types of entities, including government agencies, lenders, mortgage insurers, and nonprofits. Counseling may also occur before the home purchase (pre-purchase counseling), during the home purchase, after the home purchase (postpurchase counseling), or at any combination of these times. Counseling can occur through a variety of mechanisms requiring different levels of time commitment. Finally, homeownership counseling programs vary in their scope, depth, and types of information covered.

Though variation among programs is great, the primary goals are generally to instill financial literacy, encourage budgeting and responsible financial behavior, provide information on the homebuying process, prepare buyers for the unique maintenance challenges associated with owning a home, and promote the long-term sustainability of homeownership.

Since its inception, pre-purchase mortgage counseling has been credited with a number of positive outcomes, including more responsible mortgage shopping and selection, improved home maintenance, lower default rates, and even neighborhood stabilization. Indeed, a number of studies have corroborated these outcomes. Hirad and Zorn's (2001) study of 40,000 mortgages originated through Freddie Mac's Affordable Gold Program found that homeowners who received pre-purchase counseling were, on average, 19 percent less likely to become 90+ days delinquent. This finding was particularly true for participants who received individualized, one-on-one counseling. Such participants were, on average, 34 percent less likely to become seriously delinquent than peers who had not received counseling. Similarly, Mayer and Temkin (2013), in their analysis of the NeighborWorks program, found that counseling participants were one-third less likely to become 90+ days delinquent relative to their peers. Importantly, their findings were robust after a number of statistical controls designed to reduce the effect of unobserved differences between homeowners who participated in counseling and those who elected not to participate. Finally, Agarwal et al. (2010) found that homeownership counseling not only reduced delinquency, but also was most effective with borrowers with low incomes, low FICO (credit) scores, or both.

Importantly, these findings were further validated by a randomized experiment conducted by the Federal Reserve Bank of Philadelphia (Smith, Hochberg, and Greene 2014). Under this program, first-time homebuyers who received one-on-one counseling had significantly better loan performance than first-time homebuyers who received only a two-hour pre-purchase workshop and no other services.

Using loans originated between 1999 and 2003 in the Community Advantage Program for the home loan secondary market, Quercia and Spader (2008) observed the performance of these loans through the first quarter of 2006. They found that homeownership counseling increased the likelihood of prepayment but had no statistically significant effect on default rates. However, as the authors acknowledged, the study covered only a period during which strong housing appreciation and decreasing interest rates generated substantial refinancing activity, which highlights the importance of examining different study periods.

This report provides another case study, specifically of NeighborWorks America's pre-purchase counseling program, with a focus on loans in the program that originated after the financial crisis or between 2010 and 2012.

NeighborWorks America is a congressionally chartered nonprofit that supports a network of approximately 250 affiliated local and regional nonprofit housing and community development organizations that provide on-the-ground support to families and communities in every state, the District of Columbia, and Puerto Rico. These organizations develop affordable rental housing linked to services to address affordable housing needs; engage in community stabilization and community engagement activities to rebuild neighborhoods; and work to rebuild the path to improved credit, savings, and sustainable homeownership for low- to moderate-income families.

In 2015, NeighborWorks America helped 21,700 families become homeowners through services such as pre-purchase education, down-payment assistance, access to affordable mortgages, and construction or rehabilitation of affordable houses. In the pre-purchase stage, NeighborWorks housing counseling helps prospective homebuyers calculate which homes are affordable, keep finances on track, research neighborhoods, work with real estate agents, and help access down-payment assistance, either through NeighborWorks or through other sources such as local government programs. In the purchasing process, NeighborWorks helps homebuyers understand property taxes, obtain homeowners insurance, and obtain affordable, sustainable mortgages and home inspections. NeighborWorks ensures that its network remains a leader in providing comprehensive, high-quality homeownership services through regular assessments of each NeighborWorks organization's programs and by offering grants, technical assistance, topical webinars, and specific tools.

One of the useful aspects of studying NeighborWorks client is that the network organizations generally follow common sets of standards and requirements. NeighborWorks has approximately 187 affiliates offering homeownership education and counseling program throughout the country. NeighborWorks organizations are required to provide a homeownership education and counseling program or establish a partnership with an organization that meets the minimum requirements of homeownership education and counseling, as defined by NeighborWorks America for its National Homeownership and Lending Programs. The requirements include using a specifically approved curriculum, an approved online provider or classroom setting, and providing 8+ hours of training and/or education (including a minimum of 1 hour of individual counseling). Organizations are required to provide details on their homebuyer education classes, including agendas and curricula, the length of classes (number of meetings, number of classroom hours) and attendance.

NeighborWorks collects and manages a large amount of unique information on homebuyers, their mortgages, and services received. Mayer and Temkin (2013) analyzed the impact of pre-purchase counseling and education provided by NeighborWorks on the performance of counseled borrowers' mortgages. The study found a nearly one-third drop in the likelihood of serious mortgage delinquency when consumers received pre-purchase counseling and education. That research was based on approximately 75,000 mortgages originated from 2007 to 2009, when the housing crisis started to unfold and the credit box began to tighten. Of the loans in the study, 18,258 were made to clients who received pre-purchase counseling from NeighborWorks organizations at some point between October 2007 and September 2009 and who also purchased a home within this 24-month period. The other 56,298 loans were made to a comparison group of borrowers with observable characteristics similar to those of the NeighborWorks pre-purchase clients.

This report extends the preceding study by examining NeighborWorks loans originated from 2010 to 2012, when the housing market struggled to recover and many homes continued to lose equity. We test whether the positive impact of housing counseling services of NeighborWorks on the performance of its mortgages was sustained under economic conditions very different from those initially experienced by borrowers whose loans originated between 2007 and 2009.

In the next sections, we use Home Mortgage Disclosure Act (HMDA) data to compare the demographic profile of borrowers who received pre-purchase counseling services from NeighborWorks with that of the general population of borrowers who took out first-lien mortgages to purchase an owner-occupied property during the same period. This comparison will help us understand the consumer base for NeighborWorks services. We then review the reasons consumers seek these services and connect these reasons to a more rigorous measure of the market potential for pre-purchase counseling services. Finally, we construct two groups of borrowers with similar credit profiles: one group received NeighborWorks counseling services, and the other did not. We then use regression models to compare loan performance differences between the two groups.

# Who Uses the Program?

This section explores whether homebuyer services such as those provided by NeighborWorks tend to serve the most disadvantaged group of homebuyers. To evaluate this hypothesis, we contrast the characteristics of homebuyers who received NeighborWorks services with all homebuyers in the HMDA data.

Low-income and minority borrowers are more likely to seek pre-purchase counseling services or to be targeted by outreach efforts providing access to such services not only because they are often first-time homebuyers themselves, but also because they may have little family history of homeownership. Moreover, legislation has targeted homeownership counseling toward low-income, minority, immigrant, and other types of families that have historically lower homeownership rates. Some programs require borrowers to first complete counseling before obtaining a mortgage, such as Fannie Mae's HomeReady program. Unfortunately, the empirical evidence on the demographics of the clients of these services is scarce.

In 2009, HUD's Pre-Purchase Counseling Outcome Study (Turnham and Jefferson 2012) surveyed 573 people seeking pre-purchase counseling services from counseling agencies that were approved and funded by HUD. Of that 573, 52 percent were African American, 19 percent were Hispanic or Latino, and 72 percent were women. Clients had an annual average median income of $30,000, compared with $63,000 for all homeowner households and $30,000 for renter households nationwide in 2009. Unfortunately, Turnham and Jefferson were unable to assess whether their sample was random, given data limitations.

Another HUD study, the State of the Housing Counseling Industry report (Herbert, Turnham, and Rodgers 2008), presented demographic information on 1.7 million individuals who received housing counseling services in 2007. That study found that the clients were more likely to be minority: 35 percent were African American, and 19 percent were Hispanic.

In this section, we document the demographic profile of borrowers who received pre-purchase counseling services from NeighborWorks and compare those clients with the general population of borrowers.

# Data and Methods

## HMDA Data

HMDA data are considered the "universe" of mortgage loans because federal law requires that almost all mortgage originations, except originations by some small lenders, be reported in HMDA. See Avery, Brevoort, and Canner (2007) and McCoy (2007) for a detailed discussion of HMDA's coverage of residential mortgages. HMDA data contain information about mortgage applicants and the mortgages they applied for or received, including income, loan amount, race and ethnicity, and outcome of the application—denied, originated, or approved but not accepted. To make HMDA data comparable with the consumer base of NeighborWorks pre-purchase counseling services, we limit our analysis to borrowers who took out a first lien mortgage to purchase a one- to four-unit owner-occupied property. Moreover, loans purchased by a financial institution during the HMDA reporting year, but originated in an earlier year, are excluded from the analysis.

### BORROWER RACE AND ETHNICITY

We adopt a hierarchical approach to defining race and ethnicity jointly. From 1990 to 2003, an applicant's race and ethnicity were reported jointly in one of six possible categories: white, black, Hispanic, Asian or Pacific Islander, American Indian and Alaska Native, and "other." These categories are used directly for our definition. Since 2004, race and ethnicity have been reported separately; moreover, applicants are now allowed to choose more than one racial category. For HMDA data reported between 2004 and 2012, we adopted the approach used by Avery, Canner, and Cook (2005) and Avery, Brevoort, and Canner (2006): black supersedes Hispanic, Hispanic supersedes Asian, Asian supersedes "other minorities," and "other minorities" supersedes white, in any one of the five race fields and one ethnicity field. A coapplicant's race and ethnicity are ignored when defining an applicant's race and ethnicity. See Avery, Brevoort, and Canner (2007) for race and ethnicity definition issues.

### LOW-INCOME BORROWERS

We compared a borrower's income to the area median family income to identify low-income borrowers. If a borrower's income is at or below 40 percent of the metropolitan statistical area's (MSA's) median family income, he or she is described as an extremely low-income borrower. If a borrower's income is above 40 percent but at or below 70 percent of the MSA median family income, he or she is described as a low-income borrower. If a borrower's income is above 70 percent but at or below 110 percent of the

MSA median family income, he or she is described as a moderate-income borrower. If the borrower's income is above 110 percent of the MSA median family income, he or she is described as a high-income borrower. We use cutoffs for borrower income categories of 40, 70, and 110 percent of area median income (AMI); these cutoffs differ from those used by others, which typically are 50, 80, and 120 percent of AMI. NeighborWorks data report only family income of a borrower, whereas HMDA data report an individual borrower's income. To address this inconsistency, we used 50, 80, and 120 percent of AMI to define the income categories for NeighborWorks data and 40, 70, and 110 percent of AMI to define the income categories for HMDA data.

#### BORROWERS FROM A DISADVANTAGED GROUP

If a borrower's income is at or below 70 percent of the MSA median family income or the borrower is not a non-Hispanic white, the borrower is considered a disadvantaged borrower.

### NeighborWorks Data

NeighborWorks collects borrower and loan information from its participating network of housing counseling agencies. This study limits the scope to loans originated during and after 2010 to complement the Mayer and Temkin (2013) study, which covers loans originated between 2007 and 2009.

## Findings

Our results show that clients of NeighborWorks pre-purchase counseling services are more likely to be African American, Hispanic, low income, or female than is the general HMDA population of home purchase borrowers (figure 1 and table 1). These groups of borrowers form the base of traditionally disadvantaged borrowers who have difficulty accessing mortgage credit or who are more likely to be prey to predatory lenders. This finding is not surprising, given that pre-purchase counseling's mission (both at NeighborWorks and more generally) is to focus on the more credit-constrained borrowers purchasing a home.

FIGURE 1

**Comparing the Demographic Profile of NeighborWorks Clients and HMDA Home Purchase Borrowers**

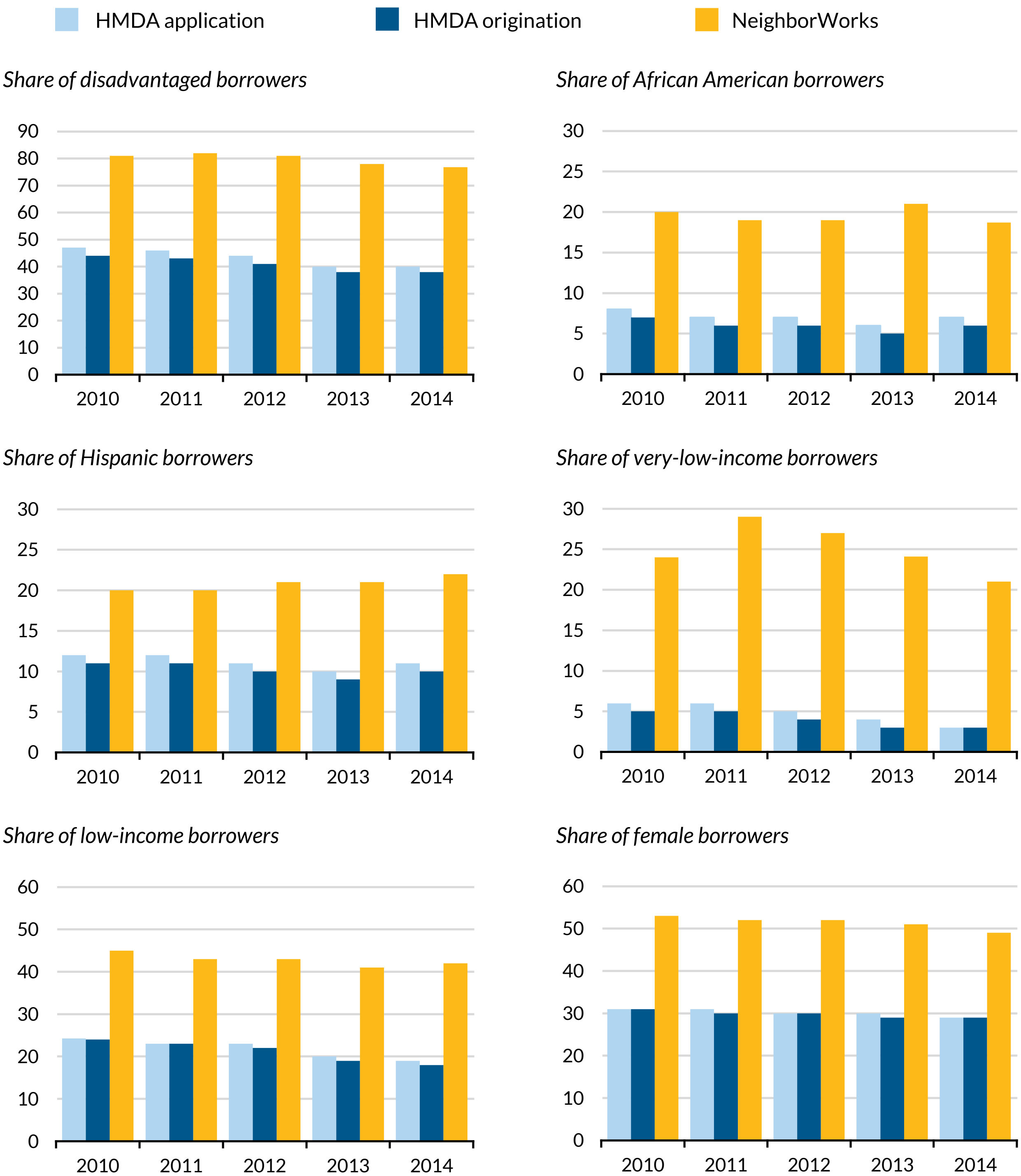

TABLE 1

**Comparing the Demographic Profile of NeighborWorks Clients and HMDA Borrowers**

| | HMDA Application | | | HMDA Origination | | | NeighborWorks | | |
|---|---|---|---|---|---|---|---|---|---|
| Year | Total | Target groups | % | Total | Target groups | % | Total | Target groups | % |
| | | | | **Share of disadvantaged borrowers** | | | | | |
| 2010 | 2,623,896 | 1,230,350 | 47 | 1,918,045 | 844,112 | 44 | 15,062 | 12,182 | 81 |
| 2011 | 2,444,884 | 1,114,293 | 46 | 1,794,933 | 767,874 | 43 | 12,561 | 10,316 | 82 |
| 2012 | 2,739,943 | 1,205,659 | 44 | 2,045,805 | 843,587 | 41 | 13,906 | 11,220 | 81 |
| 2013 | 3,154,474 | 1,275,589 | 40 | 2,355,554 | 887,978 | 38 | 19,637 | 15,250 | 78 |
| 2014 | 3,253,121 | 1,301,624 | 40 | 2,468,521 | 926,329 | 38 | 19,014 | 14,611 | 77 |
| 2015 | | | | | | | 13,463 | 10,249 | 76 |
| | | | | **Share of African American borrowers** | | | | | |
| 2010 | 2,623,896 | 200,909 | 8 | 1,918,045 | 128,682 | 7 | 15,062 | 3,029 | 20 |
| 2011 | 2,444,884 | 172,861 | 7 | 1,794,933 | 109,969 | 6 | 12,561 | 2,436 | 19 |
| 2012 | 2,739,943 | 182,033 | 7 | 2,045,805 | 116,106 | 6 | 13,906 | 2,675 | 19 |
| 2013 | 3,154,474 | 195,160 | 6 | 2,355,554 | 125,389 | 5 | 19,637 | 4,213 | 21 |
| 2014 | 3,253,121 | 217,179 | 7 | 2,468,521 | 144,185 | 6 | 19,014 | 3,557 | 19 |
| 2015 | | | | | | | 13,463 | 2,514 | 19 |
| | | | | **Share of Hispanic borrowers** | | | | | |
| 2010 | 2,623,896 | 310,715 | 12 | 1,918,045 | 203,006 | 11 | 15,062 | 2,986 | 20 |
| 2011 | 2,444,884 | 288,799 | 12 | 1,794,933 | 191,889 | 11 | 12,561 | 2,514 | 20 |
| 2012 | 2,739,943 | 300,055 | 11 | 2,045,805 | 203,319 | 10 | 13,906 | 2,944 | 21 |
| 2013 | 3,154,474 | 328,397 | 10 | 2,355,554 | 222,437 | 9 | 19,637 | 4,061 | 21 |
| 2014 | 3,253,121 | 360,856 | 11 | 2,468,521 | 253,471 | 10 | 19,014 | 4,245 | 22 |
| 2015 | | | | | | | 13,463 | 2,906 | 22 |
| | | | | **Share of very-low-income borrowers** | | | | | |
| 2010 | 2,623,896 | 155,886 | 6 | 1,918,045 | 91,846 | 5 | 15,062 | 3,570 | 24 |
| 2011 | 2,444,884 | 144,116 | 6 | 1,794,933 | 86,638 | 5 | 12,561 | 3,664 | 29 |
| 2012 | 2,739,943 | 150,080 | 5 | 2,045,805 | 90,584 | 4 | 13,906 | 3,763 | 27 |
| 2013 | 3,154,474 | 124,298 | 4 | 2,355,554 | 71,290 | 3 | 19,637 | 4,735 | 24 |
| 2014 | 3,253,121 | 108,789 | 3 | 2,468,521 | 63,328 | 3 | 19,014 | 3,902 | 21 |
| 2015 | | | | | | | 13,463 | 2,553 | 19 |
| | | | | **Share of low-income borrowers** | | | | | |
| 2010 | 2,623,896 | 636,641 | 24 | 1,918,045 | 452,340 | 24 | 15,062 | 6,765 | 45 |
| 2011 | 2,444,884 | 570,555 | 23 | 1,794,933 | 406,484 | 23 | 12,561 | 5,458 | 43 |
| 2012 | 2,739,943 | 624,002 | 23 | 2,045,805 | 450,512 | 22 | 13,906 | 6,023 | 43 |
| 2013 | 3,154,474 | 621,370 | 20 | 2,355,554 | 444,307 | 19 | 19,637 | 7,969 | 41 |
| 2014 | 3,253,121 | 603,292 | 19 | 2,468,521 | 438,675 | 18 | 19,014 | 8,023 | 42 |
| 2015 | | | | | | | 13,463 | 5,797 | 43 |
| | | | | **Share of female borrowers** | | | | | |
| 2010 | 2,623,896 | 826,271 | 31 | 1,918,045 | 593,721 | 31 | 15,062 | 7,942 | 53 |
| 2011 | 2,444,884 | 753,053 | 31 | 1,794,933 | 542,267 | 30 | 12,561 | 6,589 | 52 |
| 2012 | 2,739,943 | 828,847 | 30 | 2,045,805 | 607,125 | 30 | 13,906 | 7,238 | 52 |
| 2013 | 3,154,474 | 933,042 | 30 | 2,355,554 | 685,546 | 29 | 19,637 | 10,018 | 51 |
| 2014 | 3,253,121 | 959,240 | 29 | 2,468,521 | 718,025 | 29 | 19,014 | 9,361 | 49 |
| 2015 | | | | | | | 13,463 | 6,641 | 49 |

## Disadvantaged Borrowers

The share of disadvantaged borrowers among NeighborWorks clients is almost twice as high as that among HMDA home purchase mortgage applicants and borrowers (upper-left chart in figure 1 and first section of table 1). For loan applications between 2010 and 2014, HMDA data showed 40 to 47 percent of applicants as disadvantaged, as were 38 to 44 percent of borrowers. In contrast, 76 to 82 percent of NeighborWorks clients were disadvantaged.

For example, in 2014, of 3,253,121 HMDA applications, 1,301,624 (40 percent) were from disadvantaged applicants. In the same year, of 19,014 NeighborWorks clients who obtained loans, 14,611 (77 percent) were disadvantaged. This pattern is consistent across all years studied.

We do not have data on the larger population of clients who received NeighborWorks pre-purchase counseling services but did not ultimately purchase a home. A comparison of clients who purchased a home with those who did not would be valuable. A reasonable expectation would be that an even higher percentage of those who received the service but did not purchase a home were disadvantaged. Indeed, one benefit of counseling is that potential borrowers may conclude that they need to save for a few more years to generate the resources necessary to purchase, or they may conclude that they cannot afford the home they really want and decide not to purchase.

## Minority Borrowers

Among these disadvantaged consumers, NeighborWorks clients were more likely to be minorities than the HMDA population.

The share of African American borrowers among NeighborWorks clients is almost three times as great as that among HMDA home purchase mortgage applicants and borrowers (upper-right chart in figure 1 and table 1). For loan applications made between 2010 and 2014, HMDA reports that 6 to 8 percent of applicants were African American, as were 5 to 7 percent of borrowers. In contrast, 19 to 21 percent of NeighborWorks clients who received loans were African American.

For example, in 2014, 217,179 (7 percent) of HMDA applicants were African American. In the same year, 3,557 (19 percent) of NeighborWorks clients who received loans were African American. These patterns are consistent across all study years.

Similarly, NeighborWorks clients are more likely to be Hispanic than was the HMDA population (center-left chart in figure 1 and middle of table 1). The share of Hispanic borrowers among

NeighborWorks clients is twice as high as that among HMDA home purchase mortgage applicants and borrowers. For loan applications between 2010 and 2014, HMDA data show that 10 to 12 percent of applicants were Hispanic, as were 9 to 11 percent of borrowers. In contrast, 20 to 22 percent of NeighborWorks clients who got loans were Hispanic.

In 2014, 360,856 (11 percent) of HMDA applicants were Hispanic. In the same year, 4,245 (22 percent) of NeighborWorks clients who got loans were Hispanic. These patterns are consistent in all years examined.

## Low-Income Borrowers

NeighborWorks clients tend to have lower incomes than the HMDA population.

The share of very-low-income borrowers among NeighborWorks clients is five times as high as that among HMDA home purchase mortgage applicants and borrowers (middle-right chart in figure 1 and middle of table 1). HMDA data show that between 2010 and 2014 only 3 to 6 percent of applicants were very low income, as were 3 to 5 percent of borrowers. In contrast, 21 to 29 percent of NeighborWorks clients who obtained loans were very low income.

For example, in 2014, only 108,789 (3 percent) of HMDA applications were from very-low-income applicants. In the same year, 3,902 (21 percent) of NeighborWorks clients who received loans were very-low-income borrowers. These patterns are consistent in all study years.

Similarly, NeighborWorks clients were more likely to be low income than was the HMDA population (lower-left chart in figure 1 and bottom of table 1). The share of low-income borrowers among NeighborWorks clients is twice as high as that among HMDA home purchase mortgage applicants and borrowers. For loan applications between 2010 and 2014, HMDA showed that 19 to 24 percent of applicants were low income, as were 18 to 24 percent of borrowers. For NeighborWorks, 41 to 45 percent of the clients who obtained loans were low income.

For example, in 2014, 603,292 (19 percent) of HMDA applicants were low income. In the same year, 8,023 (42 percent) of NeighborWorks clients who received loans were low income. These patterns are consistent in all study years.

## Female Borrowers

NeighborWorks clients are more likely to be women than the HMDA population.

The share of female borrowers among NeighborWorks clients is 1.7 times that among HMDA's home purchase mortgage applicants and borrowers (lower-right chart in figure 1 and bottom of table 1). For loan applications between 2010 and 2014, on the HMDA side, women accounted for about 30 percent of applicants and borrowers. But 49 to 53 percent of NeighborWorks borrower clients were women.

For example, in 2014, 959,240 (29 percent) of HMDA applications were from women. In the same year, 9,361 (49 percent) of NeighborWorks clients who received loans were women. These patterns are consistent in all study years.

# Where Can the Program Be of Greatest Use?

The previous section shows sharp demographic differences between borrowers who received NeighborWorks homeownership education and counseling services and the HMDA population of borrowers. NeighborWorks borrowers are much more likely to be African American, Hispanic, low income, or female. However, the number of borrowers who receive NeighborWorks counseling services constitutes only a small proportion of all disadvantaged borrowers. For example, in 2014, of 926,329 disadvantaged HMDA borrowers who purchased a one- to four-unit owner-occupied property with a first lien mortgage, 14,611 (1.6 percent)[1] received NeighborWorks education and counseling (top of table 1). Of course, not all disadvantaged borrowers need pre-purchase counseling, and other borrowers who are not disadvantaged may seek counseling. So this section provides a more rigorous measure of the market potential for those services.

To help the pre-purchase counseling industry measure the market potential of their services, we have to understand the reasons consumers seek or could benefit from these services.

The HUD Pre-Purchase Counseling Outcome Study summarizes the reasons for seeking pre-purchase counseling. (People indicate more than one reason.) From most frequent to least frequent, 58 percent seek any assistance program to help purchase a home, 58 percent are specifically looking to obtain down payment or closing-cost assistance or to qualify for a specific loan program, 44 percent want to find the most appropriate mortgage, 41 percent seek help in determining how much house they can afford, 33 percent are looking for help with the final stages of buying a house, 32 percent want help improving their credit or getting out of debt, 30 percent are looking for help finding the right house, 28 percent want to learn how to avoid high-cost or predatory loans, 26 percent seek help in deciding whether to buy a house, and 24 percent are looking for help with financial education or money management.

To measure the market potential for pre-purchase counseling services, ideally we have to ask whether a consumer has any of the foregoing needs. These data are hard to collect. But most of the reasons are related to housing finance issues: consumers seeking pre-purchase counseling services are concerned with obtaining the right mortgage to finance their home purchase. This observation enables us to use a proxy to measure the demand for these pre-purchase counseling services: the number of mortgage applicants who are denied a home purchase mortgage application. With pre-purchase education and counseling, rejected applicants might be able to improve their readiness, obtain appropriate mortgages and become successful homeowners.

Using that proxy, we can determine the places with the highest number of mortgage applicants who are denied by lenders; these are places where housing counseling can be of most help. In this section, we rank the major metropolitan areas by a few measures related to mortgage application outcomes that can help the pre-purchase counseling industry better allocate its resources.

# Data and Methods

## Measuring Applicants Who Are Denied for a Mortgage

HMDA contains information on the outcome of applications for a mortgage. Starting in 2004, HMDA data began including additional outcomes for loan applications associated with certain types of requests for preapproval of home purchase loans; see Avery, Canner, and Cook (2005) for details. In this paper, outcomes of a preapproval request and loan application are combined. The potential outcomes of a loan application are categorized as follows: if an application or preapproval request is denied, the application is considered denied; if an application or preapproval request is approved but not accepted or a loan is originated, the application is considered approved. Applications withdrawn by the applicant, files closed for incompleteness, and loans purchased by a financial institution during a HMDA reporting year but originated in a prior year are excluded from the analysis.

The traditional denial rate does not account for changes in the composition of the applicant pool or the relative tightness of credit standards (Li and Goodman 2014a). Higher denial rates can be the result of either a tighter credit environment or an increase in applications by weaker-credit borrowers. For example, denial rates were much higher in 2007 than they are now in the aftermath of the financial crisis. If interpreted literally, this finding would suggest that credit was tighter in 2007 than it is today. We know that is not the case. In 2007, more applicants with weaker credit applied for mortgages; the higher demand from lower-credit borrowers resulted in a higher denial rate than in years since.

We use the methodology in  Li and Goodman (2014a) to calculate a better measure: the real denial rate, or RDR. We divide applicants into two categories: high credit profile (HCP) and low credit profile (LCP). HCP applicants have strong-enough credit profiles that their mortgage applications are unlikely to be denied. Thus, by definition, HCP applicants have a denial rate of zero. Eliminating those applicants from the calculation enables us to calculate the RDR: the total number of denied applicants divided by the number of LCP applicants. By eliminating those whose mortgage applications are unlikely to be denied and focusing exclusively on those with weaker credit records, the RDR provides a much more accurate picture of credit access than the traditional denial rate.

In addition to traditional and real denial rates, for each of the 364 major MSAs in the United States, we calculate the following measures using the 2014 HMDA data:

- number of mortgage applicants
- number of applicants with weak credit profiles
- number of applicants denied by lenders
- percentage of all applicants denied by lenders (traditional denial rate)
- percentage of weak applicants denied by lenders (RDR)

The analysis is limited to first lien, one- to four-unit, owner-occupied home purchase mortgage applications. The borrower credit profile distributions by MSA are calculated using CoreLogic's mortgage data. All other information is calculated using 2014 HMDA data.

# Findings

In this section, we measure the market potential for pre-purchase counseling programs in geographic areas in which credit-constrained borrowers are concentrated and potentially can receive the greatest benefit from additional pre-purchase counseling services.

## Number of Rejected Applicants

Home purchase loan applications that are rejected by lenders are an indicator of the market potential for pre-purchase counseling services. With pre-purchase counseling, rejected applicants might be able to improve their readiness, obtain appropriate mortgages and become successful homeowners.

Table 2 shows the 50 MSAs with the most rejected home purchase mortgage applicants. Although the ranking depends to some extent on the total number of applicants in the MSA, the number of applications is not perfectly correlated with the number of denials. For example, Houston-The Woodlands-Sugar Land, Texas, has more applications than Chicago-Naperville-Arlington Heights, Illinois, but the latter has more rejected applicants. The housing counseling industry can use this information to allocate its resources to areas with more rejected applicants.

TABLE 2

**Fifty MSAs with the Most Denied Mortgage Applications in 2014**

| MSA | Total | Weak applicants | Denied | % denied (ODR) | % weak denied (RDR) |
|---|---|---|---|---|---|
| Chicago-Naperville-Arlington Heights, IL | 77,945 | 22,809 | 11,671 | 15 | 51 |
| Houston-The Woodlands-Sugar Land, TX | 86,852 | 27,729 | 10,916 | 13 | 39 |
| Atlanta-Sandy Springs-Roswell, GA | 71,677 | 24,715 | 9,890 | 14 | 40 |
| Los Angeles-Long Beach-Glendale, CA | 59,181 | 17,273 | 8,398 | 14 | 49 |
| Washington-Arlington-Alexandria, DC-VA-MD-WV | 63,458 | 19,417 | 6,875 | 11 | 35 |
| Phoenix-Mesa-Scottsdale, AZ | 62,566 | 22,754 | 6,820 | 11 | 30 |
| Dallas-Plano-Irving, TX | 61,647 | 18,316 | 6,781 | 11 | 37 |
| Tampa-St. Petersburg-Clearwater, FL | 36,244 | 13,296 | 6,267 | 17 | 47 |
| Riverside-San Bernardino-Ontario, CA | 44,285 | 17,355 | 5,985 | 14 | 35 |
| Orlando-Kissimmee-Sanford, FL | 29,193 | 10,894 | 5,091 | 17 | 47 |
| Denver-Aurora-Lakewood, CO | 53,343 | 14,279 | 4,491 | 8 | 32 |
| Miami-Miami Beach-Kendall, FL | 18,342 | 7,150 | 4,260 | 23 | 60 |
| Charlotte-Concord-Gastonia, NC-SC | 35,908 | 10,842 | 4,231 | 12 | 39 |
| Seattle-Bellevue-Everett, WA | 40,595 | 10,466 | 4,214 | 10 | 40 |
| Minneapolis-St. Paul-Bloomington, MN-WI | 48,775 | 13,203 | 4,048 | 8 | 31 |
| Fort Lauderdale-Pompano Beach-Deerfield Beach, FL | 19,160 | 7,025 | 3,867 | 20 | 55 |
| San Antonio-New Braunfels, TX | 29,843 | 11,720 | 3,820 | 13 | 33 |
| Austin-Round Rock, TX | 32,976 | 9,732 | 3,790 | 12 | 39 |
| Jacksonville, FL | 20,497 | 7,678 | 3,414 | 17 | 45 |
| Newark, NJ-PA | 22,555 | 6,425 | 3,363 | 15 | 52 |
| Oakland-Hayward-Berkeley, CA | 28,113 | 7,205 | 3,346 | 12 | 46 |
| Las Vegas-Henderson-Paradise, NV | 25,843 | 10,130 | 3,263 | 13 | 32 |
| Nashville-Davidson-Murfreesboro-Franklin, TN | 29,642 | 9,255 | 3,222 | 11 | 35 |
| San Diego-Carlsbad, CA | 29,854 | 8,095 | 3,210 | 11 | 40 |
| St. Louis, MO-IL | 33,148 | 9,408 | 3,205 | 10 | 34 |
| Fort Worth-Arlington, TX | 29,883 | 9,841 | 3,179 | 11 | 32 |
| Sacramento-Roseville-Arden-Arcade, CA | 26,235 | 8,511 | 3,129 | 12 | 37 |
| Nassau County-Suffolk County, NY | 21,959 | 5,920 | 3,100 | 14 | 52 |
| Columbus, OH | 26,774 | 7,766 | 3,093 | 12 | 40 |
| Portland-Vancouver-Hillsboro, OR-WA | 33,328 | 8,452 | 2,989 | 9 | 35 |
| Cincinnati, OH-KY-IN | 26,103 | 8,104 | 2,960 | 11 | 37 |
| West Palm Beach-Boca Raton-Delray Beach, FL | 16,426 | 5,419 | 2,936 | 18 | 54 |
| Baltimore-Columbia-Towson, MD | 29,194 | 8,631 | 2,933 | 10 | 34 |
| Indianapolis-Carmel-Anderson, IN | 27,163 | 8,140 | 2,702 | 10 | 33 |
| Kansas City, MO-KS | 26,823 | 8,032 | 2,526 | 9 | 31 |
| Pittsburgh, PA | 23,254 | 6,355 | 2,268 | 10 | 36 |
| Cleveland-Elyria, OH | 20,184 | 5,977 | 2,227 | 11 | 37 |
| Cambridge-Newton-Framingham, MA | 25,292 | 4,525 | 2,157 | 9 | 48 |
| Louisville/Jefferson County, KY-IN | 16,714 | 5,587 | 2,151 | 13 | 39 |
| Detroit-Dearborn-Livonia, MI | 12,972 | 4,794 | 2,121 | 16 | 44 |
| Philadelphia, PA | 14,684 | 4,718 | 2,030 | 14 | 43 |
| Oklahoma City, OK | 18,559 | 6,015 | 1,919 | 10 | 32 |
| San Jose-Sunnyvale-Santa Clara, CA | 16,809 | 3,912 | 1,802 | 11 | 46 |
| Providence-Warwick, RI-MA | 14,286 | 4,381 | 1,753 | 12 | 40 |
| North Port-Sarasota-Bradenton, FL | 10,600 | 3,397 | 1,727 | 16 | 51 |
| Raleigh, NC | 20,771 | 5,171 | 1,712 | 8 | 33 |
| Virginia Beach-Norfolk-Newport News, VA-NC | 19,366 | 7,062 | 1,688 | 9 | 24 |
| Birmingham-Hoover, AL | 12,440 | 4,331 | 1,686 | 14 | 39 |
| Milwaukee-Waukesha-West Allis, WI | 15,600 | 3,845 | 1,642 | 11 | 43 |
| Cape Coral-Fort Myers, FL | 9,055 | 3,289 | 1,640 | 18 | 50 |

## Traditional and Real Denial Rates

This focus can be further refined by taking into account denial rates. We provide two rankings based on the percentage of rejected applicants: one based on the traditional denial rate, and the second based on the RDR. The lists both show substantial geographic variation in denial rates, but they are also quite different. The bottom-left section of table 3 shows the 20 MSAs with the highest traditional denial rate. At the top of the list are eight MSAs in which more than 20 percent of all owner-occupied, home purchase loan applications are rejected by lenders. In contrast, less than 6 percent of applicants are rejected in the eight MSAs with the lowest denial rates.

As we discussed previously, the traditional denial rate is not a perfect measure of mortgage accessibility because it omits consideration of the composition of the applicant pool. The large geographic variation in traditional denial rates in fact appears to reflect at least in part the geographic variation in the composition of the applicant pool. For example, in the top eight MSAs (with denial rates greater than 20 percent) 40 to 50 percent of applicants have weak credit profiles, whereas in the bottom eight MSAs (with denial rates under 6 percent) only 20 to 30 percent of applicants have weak credit. This composition of the applicant pool is another indicator of the demand for housing counseling.

## Weak Applicants and Real Denial Rate

The upper right section and lower half of table 3 show the top 20 MSAs by number of weak applicants, percentage of rejected applicants, and percentage of weak applicants that are rejected, respectively. In the 10 MSAs with the highest share of weak applicants, 46 to 54 percent of all owner-occupied home purchase mortgage applications are from applicants with weak credit profiles. In the bottom 10 MSAs, only 18 to 21 percent are weak applicants.

Once we consider this geographic variation in the composition of the applicant pool, we are able to calculate the RDR (appendix A). The order of MSAs ranked by RDR (bottom right of table 3) is very different from the rank based on the traditional denial rate (bottom left of table 3). In the 10 MSAs with the highest RDRs, 53 to 60 percent of weak applicants are rejected by lenders. In contrast, the RDR in the bottom 10 MSAs in appendix A is under 20 percent.

The pre-purchase homeownership counseling industry can use this information to better allocate resources to geographies in which a larger percentage (or number) of applicants with weak credit profiles has been unable to obtain mortgage credit. It might be more efficient for counselors to focus their work in locations with both a high RDR and a relatively good match between income and house prices rather than places where home prices make buying unaffordable to a very large proportion of the population (e.g., San Francisco).

TABLE 3

**Top 20 MSAs by Different Measures**

| By total applicants | By total applicants with weak credit |
|---|---|
| 1. Hinesville, GA | 1. Houston-The Woodlands-Sugar Land, TX |
| 2. Pine Bluff, AR | 2. Atlanta-Sandy Springs-Roswell, GA |
| 3. Valdosta, GA | 3. Chicago-Naperville-Arlington Heights, IL |
| 4. Albany, GA | 4. Phoenix-Mesa-Scottsdale, AZ |
| 5. Elizabethtown-Fort Knox, KY | 5. Washington-Arlington-Alexandria, DC-VA-MD-WV |
| 6. El Centro, CA | 6. Dallas-Plano-Irving, TX |
| 7. Laredo, TX | 7. Riverside-San Bernardino-Ontario, CA |
| 8. Fayetteville, NC | 8. Los Angeles-Long Beach-Glendale, CA |
| 9. Jacksonville, NC | 9. Denver-Aurora-Lakewood, CO |
| 10. Clarksville, TN-KY | 10. Tampa-St. Petersburg-Clearwater, FL |
| 11. Brownsville-Harlingen, TX | 11. Minneapolis-St. Paul-Bloomington, MN-WI |
| 12. Vineland-Bridgeton, NJ | 12. San Antonio-New Braunfels, TX |
| 13. Killeen-Temple, TX | 13. Orlando-Kissimmee-Sanford, FL |
| 14. Cumberland, MD-WV | 14. Charlotte-Concord-Gastonia, NC-SC |
| 15. Gadsden, AL | 15. Seattle-Bellevue-Everett, WA |
| 16. Lakeland-Winter Haven, FL | 16. Las Vegas-Henderson-Paradise, NV |
| 17. McAllen-Edinburg-Mission, TX | 17. Fort Worth-Arlington, TX |
| 18. El Paso, TX | 18. Austin-Round Rock, TX |
| 19. Morristown, TN | 19. St. Louis, MO-IL |
| 20. Lewiston-Auburn, ME | 20. Nashville-Davidson-Murfreesboro-Franklin, TN |

| By share of applicants rejected (traditional denial rate) | By share of weak applicants rejected (real denial rate) |
|---|---|
| 1. Pine Bluff, AR | 1. Miami-Miami Beach-Kendall, FL |
| 2. Miami-Miami Beach-Kendall, FL | 2. Danville, IL |
| 3. Ocala, FL | 3. Gainesville, FL |
| 4. Albany, GA | 4. San Francisco-Redwood City-South San Francisco, CA |
| 5. Macon, GA | 5. Naples-Immokalee-Marco Island, FL |
| 6. Fort Lauderdale-Pompano Beach-Deerfield Beach, FL | 6. Fort Lauderdale-Pompano Beach-Deerfield Beach, FL |
| 7. Elizabethtown-Fort Knox, KY | 7. Bridgeport-Stamford-Norwalk, CT |
| 8. Danville, IL | 8. West Palm Beach-Boca Raton-Delray Beach, FL |
| 9. Gainesville, FL | 9. Ocala, FL |
| 10. Lakeland-Winter Haven, FL | 10. Punta Gorda, FL |
| 11. Punta Gorda, FL | 11. Napa, CA |
| 12. Gadsden, AL | 12. Nassau County-Suffolk County, NY |
| 13. Anniston-Oxford-Jacksonville, AL | 13. Newark, NJ-PA |
| 14. Mcallen-Edinburg-Mission, TX | 14. Chicago-Naperville-Arlington Heights, IL |
| 15. Charleston, WV | 15. North Port-Sarasota-Bradenton, FL |
| 16. Deltona-Daytona Beach-Ormond Beach, FL | 16. Macon, GA |
| 17. Atlantic City-Hammonton, NJ | 17. Wheeling, WV-OH |
| 18. Cape Coral-Fort Myers, FL | 18. Cape Coral-Fort Myers, FL |
| 19. Rocky Mount, NC | 19. Sebastian-Vero Beach, FL |
| 20. Hattiesburg, MS | 20. Trenton, NJ |

# How Effective Is the Program in Improving Loan Performance?

A hard-learned lesson from the Great Recession is that getting a mortgage and becoming a homeowner do not guarantee that homeownership will be sustained. During the recession, about 8 million homeowners lost their homes, according to CoreLogic, cutting the national homeownership rate by more than 5 percentage points. Making homeownership sustainable is as important as helping renters become homeowners, which is exactly the expected role of homeownership counseling. By helping potential homebuyers develop a budget, strengthen their credit to maximize their chance of getting the lowest possible mortgage rate, set a realistic timeline for the purchase, and connect with other needed experts, including real estate agents and home inspectors, the counseling services are expected to enable the borrowers to perform better than those who did not have the services. In this section, we use regression models to compare the loan performance of two groups of borrowers with similar credit profiles, one of which received NeighborWorks pre-purchase counseling services while the other one did not.

## Data and Methods

We first construct two groups of borrowers: borrowers who received NeighborWorks pre-purchase counseling services (treatment group) and borrowers who did not receive the services but are otherwise comparable (comparison group). We compare the performance of each group of loans while holding the risk profiles of the borrowers and loans constant. To compare the performance of the two groups, we developed logistic regressions where the dependent variable is a binary indicator that equals 1 if a loan has ever become 90+ days delinquent, including serious delinquencies in any stage of foreclosure and termination because of foreclosure.

### Data

Our primary data source is NeighborWorks client data. We constructed the treatment group by selecting the clients who received pre-purchase counseling from NeighborWorks and then purchased a single-family owner-occupied home with a 30-year fixed-rate mortgage in the 2010–2012 period. The

NeighborWorks data contain detailed information on borrowers and their mortgage loans at origination, but two challenges remain:

- NeighborWorks data do not have loan performance information.
- NeighborWorks data include only borrowers who received counseling; borrowers who obtained loans with no counseling are not included and thus cannot be used to construct the comparison group.

To overcome both challenges, we use a Home Mortgage Disclosure Act–CoreLogic (HMDA-CL) matched dataset, which covers the majority of the mortgage loan market. This dataset combines rich borrower demographic and income data from HMDA and mortgage origination and performance information from CoreLogic proprietary loan-level data, as will be described.

HMDA data contain most mortgage loans and include information on race or ethnicity and gender of the borrower and coborrower; income; year of origination; interest rate; loan amount; loan purpose (purchase, refinance, or home improvement); and census tract of the property. HMDA data also contain information on whether the unit is owner occupied and whether the loan is a government loan or a conventional loan.

However, HMDA data do not include any credit risk–related information such as the loan-to-value (LTV) ratio of the property or the borrower's credit score (FICO). Nor do HMDA data include any information on loan performance. By supplementing the HMDA data with proprietary loan-level data from CoreLogic, we can see all these data points and, thereby, obtain a more complete picture of the borrower at origination and observe the actual performance of the loan. CoreLogic covers the overwhelming majority of the mortgages we examined, because it contains both loans contributed by a large number of servicers and all mortgage loans contained in private label securitizations. The CoreLogic data contain extensive information on the loan, property, and borrower characteristics at the time of origination, as well as monthly updates on loan performance subsequent to origination. The procedure used to match the two databases is described in Li et al. (2014). In short, we match the two datasets by their origination year; loan amount; loan purpose (purchase or refinance); occupancy; lien; loan type (FHA, VA, or conventional); and geography.

## Matching Data to Create Treatment Group

By matching the NeighborWorks data with HMDA-CL data, we can obtain actual loan-specific performance information for each NeighborWorks loan in the treatment group. The common variables used to match loans in the two datasets include the census tract of the property (street addresses of NeighborWorks loans are geocoded to locate the property's census tract), origination year, borrower's race and ethnicity, gender, income, loan amount, interest rate, loan purpose, property type, loan product type, loan term, lien status, and occupancy status. As shown in table 4, the match created 6,224 NeighborWorks-counseled loans with loan performance measures, which formed the treatment group. In this group, 17 percent of the loans have become 90+ days delinquent.

## Selection of Comparable Loans

HMDA-CL loans that are not NeighborWorks loans form the control group. However, we cannot choose a random sample from this general pool. As discussed previously, compared to general homebuyers, those who obtained NeighborWorks counseling are more likely to be minorities and female and to have lower incomes. Therefore, our goal is to create a group of comparable loans that did not receive counseling but otherwise closely mimic the characteristics of those in the treatment group, such as borrower's FICO score, debt-to-income (DTI) ratio, LTV, race and ethnicity, income, and geographic location.

To achieve this goal, we adopted a two-step weighting approach in similar spirit to propensity score matching[2] to reduce the sample selection bias that arises from differences in observable characteristics between the counseled and noncounseled groups. More specifically, the selection of comparable loans is based on a combination of variables, including the state of the property, borrower's race and ethnicity, borrower's income relative to MSA median income, census tract median income relative to MSA median income, and borrower's FICO score, DTI, and LTV.

Table 4 shows 6,224 NeighborWorks loans in the treatment group. In the first step, we select comparable loans on the basis of the variables mentioned from the HMDA-CL loans that did not receive NeighborWorks counseling. Each borrower's FICO, DTI, and LTV are combined into a single measure called ex ante probability of default (EAPD), using a lookup table as shown in Li and Goodman (2014b). The difference in ex ante default risk between a NeighborWorks loan and its selected counterpart from the control pool should be less than 2.5 percent. Because many loans were missing DTI, we were able to calculate the front-end DTI of a loan by combining CoreLogic monthly payment and HMDA borrower monthly income, another advantage of using such a unique HMDA-CL matched dataset. The borrower's income and census tract income are first divided by MSA median income to create ratios. Both income ratios are transformed into ordinal variables before being used for selection.

The first step generated a total of 1,046,648 candidate loans for the comparison group, which is much bigger than the sample size of the treatment group. To make two groups with a comparable sample size, we created weights in the second step. We first put all loans (both treatment and comparison groups) into buckets defined by the combination of the variables used to select the control group of loans. Within each bucket, loan weights were calculated such that the sample size of the control group was approximately equal to the sample size of the treatment group.

As shown in table 4, the two-step sampling method successfully created a comparison group of 6,224 loans, identical in size to the treatment group, and the distribution of the two groups is very close to each other in all variables used for matching.

## Regression Analysis

We developed logistic regressions to compare the performance of the control and treatment loans. The dependent variable is a binary indicator that equals 1 if a loan is ever 90+ days delinquent or in any of the foreclosure stages, including termination because of foreclosure; it equals 0 if not. Table 5 shows the list of the independent variables included in the regression model, including a variable indicating the control or treatment group, the ex ante default risk, the year of origination, a categorical variable that combines borrower's race and ethnicity and income, a neighborhood income variable, and a census division variable.

Our analysis focused on the direct impact of pre-purchase counseling on loan performance: instilling financial literacy, encouraging budgeting and responsible financial behavior, providing information on the homebuying process, and preparing buyers for the unique maintenance challenges associated with owning a home—all of which help contribute to better loan performance and long-term sustainability of homeownership. Counseling could have an indirect impact through product choice. For example, counseling could help a borrower choose a property and mortgage product that result in lower LTVs, lower DTIs, or more favorable interest rates, which in turn could improve the loan performance. By controlling for DTI, LTV, and interest rates in selecting comparison group and logistic regression analysis, we estimate only the direct impact. The effect of counseling on product choices is an important topic for future research.

# Findings

By helping potential homebuyers develop a budget, strengthen their credit to maximize their chance of getting the lowest possible mortgage rate, set a realistic timeline for the purchase, and connect with other needed experts, including real estate agents and home inspectors, counseling is expected to enable borrowers who receive it to perform better than those who did not receive counseling. Our research shows that, indeed, buyers who received NeighborWorks pre-purchase counseling achieve significantly better loan performance than do comparable buyers without NeighborWorks counseling. Holding all other things equal, we find that delinquency rates of 90+days for NeighborWorks loans are 16 percent lower than those rates for non-NeighborWorks loans. Note that the analysis are based on NeighborWorks mortgage loans originated between 2010 and 2012, when the housing market struggled to recover and mortgage credit became increasingly tight. The result shows that NeighborWorks education and counseling services work even in such a tight-credit, low-default housing market, as discussed in length in the discussion section.

To hold other aspects constant, we included major risk factors as independent variables, including the EAPD of a loan, which combines the borrower's FICO, DTI, and LTV into a single measure (Li and Goodman 2014b). The EAPD is developed on the basis of actual default experience of loans originated in 2001 and 2002 (pre-bubble years for normal scenario) and 2005–2006 (late-bubble years for stress scenario) for 360 different risk combinations of FICO, LTV, DTI, and product type. The combined index represents a more comprehensive measure of the potential risk compared to a simple linear relationship between the underlying credit factors (FICO, LTV, and DTI) if they were used separately instead. Also the index is exogenous to the loan performance outcomes because it is developed on the basis of loans originated in a period different from the 2010–2013 sample period. This index is highly statistically significant (table 5). A 1 percentage point increase in a loan's EAPD will increase the loan's actual baseline default rate by 4.6 percent.

To account for changes in economic conditions over time, we also include year fixed effects. Our reference year is 2010. Table 5 shows that loans originated in 2012 are performing significantly better than loans originated in 2010. The default rate of the 2012 cohort is 51 percent lower than that of the 2010 cohort. The 2011 cohort also performs better than the 2010 cohort, though the difference is only marginally significant. This outcome is expected, because the economy has been improving since 2010, with lower unemployment rates and a better housing market.

Bocian et al. (2011) show that a default rate variation exists on different racial and ethnic groups. To account for the effect of the borrower's race, ethnicity, and income on the default risk, we include a categorical variable that combined these variables (see table 5). Non-Hispanic white borrowers with high income are the reference category. However, after controlling for other risk factors, we find that compared to the reference category, the other racial and income groups have no statistically significant difference, except Hispanic borrowers with very low income, who actually perform significantly better than the reference group.

Previous literature documented a relationship between neighborhood and mortgage default (see, for example, Van Order and Zorn 2000). To account for neighborhood variations, we calculate a ratio by dividing census tract median income by MSA median income. Using this ratio, we put each census tract into low- to high-income neighborhoods and include this categorical variable in the regression. That is, if a census tract has a much lower income level than its MSA median income, we define it as very-low-income neighborhood. Low-, moderate-, and high-income neighborhoods are defined in the same way. Table 5 shows that, after controlling for other risk factors, neighborhood characteristics are not significant.

We also add a categorical variable indicating the census division of a loan. The Pacific census division is set as the reference area. Table 5 shows that loans of Middle Atlantic and West South Central census divisions perform significantly better than loans of the Pacific census division. Loans of the South Atlantic census division perform better, but with only marginal significance. Other census divisions do not show any significant differences.

# Limitations

Because random assignment is not an option for participation in NeighborWorks pre-purchase counseling, the study is subject to sample selection bias associated with self-selection of borrowers into the counseling services. The possibility of bias arises because the difference in loan performance between these two groups (counseled and noncounseled) may depend on characteristics that affected whether a borrower decided to receive counseling—not the effect of the counseling per se. In other words, if some combination of characteristics is correlated with the borrower's counseling participation decision as well as the loan performance for the borrower, the estimate of counseling's effect on loan performance will be biased.

We tried to address the selection bias in two ways. First, when selecting the comparison group, we adopted a two-step weighting approach to make it comparable to the treatment group on an extensive array of characteristics, including the state of the property, borrower's race and ethnicity, borrower's income relative to MSA median income, census tract median income relative to MSA median income, and borrower's FICO score, DTI, and LTV.

However, unobserved characteristics not available in our data could still cause some bias. In a similar NeighborWorks education and counseling study, Mayer and Temkin (2013) argued that one such unobservable could be the way people manage credit. They addressed this factor by using unique Experian data that contain measures of borrowers' credit practices and behaviors both at and prior to mortgage origination. Though we do not have the access to the same Experian data, the FICO score we included does control for borrowers' past credit history and behaviors to some extent. Moreover, Mayer and Temkin (2013) found that not controlling for borrowers' capability and approach to borrowing and repaying in the model does not create a false increase in perceived impact of counseling at all. In fact, they showed that the impact is slightly underestimated without the controls from Experian measures. If this is true and to the extent that our model does not fully control for the unobserved traits on credit management, NeighborWorks borrowers in our sample would actually perform better or benefit more from the counseling services than our estimation suggests.

Besides the selection bias, another potential bias arises from the fact that loans selected in the comparison group, which are HMDA-CL loans not matched to any NeighborWorks loans, might have received similar housing counseling services from providers outside the NeighborWorks network. If some of the loans from the comparison group did receive similar pre-purchase counseling services, then our observed baseline D90+ days delinquency rate, calculated using the current comparison group, would be expected to be higher than it would be without this contamination. In other words, without this bias, we would expect even better performance from NeighborWorks loans than from non-NeighborWorks loans.

# Discussion

Mayer and Temkin (2013) analyze the impact of pre-purchase education and counseling provided by the NeighborWorks network on the performance of counseled borrowers' mortgages. Their study finds a nearly one-third drop in the likelihood of serious mortgage delinquency when consumers receive pre-purchase counseling and education. That research is based on mortgage loans originated between 2007 and 2009, when the housing crisis started to unfold and the credit box began to tighten.

This report extends that study by examining NeighborWorks mortgage loans originated between 2010 and 2012, when the housing market struggled to recover and mortgage credit became increasingly tight. We find that the positive impact of NeighborWorks housing counseling services on mortgage performance was sustained: clients receiving pre-purchase education and counseling services from NeighborWorks are 16 percent less likely to become 90+ days delinquent. Note that this finding is lower than Mayer and Temkin (2013)'s estimate of 33 percent. This outcome is expected because mortgage credit became extremely tight, and the default rates for all loans have dropped dramatically since 2010. Urban Institute's Housing Credit Availability Index[3] declined from 14 percent in 2007 to 6 percent in 2012. Only the best borrowers are getting loans currently, and these loans are so thoroughly scrubbed and cleaned before they are made that hardly any of them end up going into default[4]. The report shows that NeighborWorks education and counseling services work even in a tight-credit, low-default housing market (table 4).

TABLE 4

**Comparing the Distribution between Non-NeighborWorks Loans and NeighborWorks Loans Used in the Regression Model**

| Variables | Not Weighted: Non-NeighborWorks N=1,046,648 | Not Weighted: NeighborWorks N=6224 | Weighted: Non-NeighborWorks N=6224 | Weighted: NeighborWorks N=6224 |
|---|---|---|---|---|
| **90 or more days delinquent, including foreclosures** | | | | |
| No | 80 | 83 | 80 | 83 |
| Yes | 20 | 17 | 20 | 17 |
| **Origination year** | | | | |
| 2010 | 39 | 23 | 32 | 23 |
| 2011 | 27 | 24 | 27 | 26 |
| 2012 | 34 | 53 | 41 | 51 |
| **Borrower race and ethnicity** | | | | |
| African-American | 11 | 28 | 25 | 26 |
| Hispanic | 25 | 18 | 21 | 19 |
| non-Hispanic White | 65 | 54 | 54 | 55 |
| **Borrower income** | | | | |
| Very Low | 8 | 20 | 20 | 21 |
| Low | 51 | 60 | 59 | 59 |
| Moderate | 31 | 19 | 19 | 18 |
| High | 9 | 2 | 2 | 2 |
| **Census division** | | | | |
| New England | 5 | 2 | 3 | 3 |
| Middle Atlantic | 14 | 11 | 13 | 13 |
| East North Central | 8 | 12 | 12 | 13 |
| West North Central | 7 | 9 | 9 | 10 |
| South Atlantic | 12 | 26 | 22 | 21 |
| East South Central | 6 | 5 | 6 | 6 |
| West South Central | 7 | 8 | 8 | 9 |
| Mountain | 14 | 17 | 14 | 16 |
| Pacific | 27 | 10 | 14 | 10 |
| **Census tract median income relative to MSA median income** | | | | |
| Very Low | 19 | 36 | 35 | 36 |
| Low | 20 | 22 | 21 | 21 |
| Moderate Low | 19 | 16 | 17 | 16 |
| Moderate High | 18 | 13 | 12 | 12 |
| High | 14 | 8 | 9 | 8 |
| Very High | 10 | 5 | 6 | 6 |
| **Borrower debt-to-income ratio at origination** | | | | |
| Missing | 0 | 1 | 1 | 1 |
| >=50 | 5 | 2 | 5 | 2 |
| [40,50) | 30 | 26 | 31 | 26 |
| [30,40) | 55 | 62 | 54 | 61 |
| (0,30) | 9 | 10 | 9 | 10 |
| **Borrower FICO at origination** | | | | |
| Missing | 3 | 2 | 3 | 2 |
| >740 | 34 | 26 | 34 | 29 |
| (700,740] | 19 | 18 | 20 | 19 |
| (660,700] | 23 | 26 | 24 | 24 |
| (620,660] | 19 | 24 | 18 | 23 |

| Variables | Not Weighted<br>Non-NeighborWorks<br>N=1,046,648 | <br>NeighborWorks<br>N=6224 | Weighted<br>Non-NeighborWorks<br>N=6224 | <br>NeighborWorks<br>N=6224 |
|---|---|---|---|---|
| (580,620] | 1 | 3 | 1 | 3 |
| <=580 | 0 | 0 | 0 | 0 |
| **Loan-to-value ratio at origination** | | | | |
| Missing | 0 | 0 | 0 | 0 |
| (0,68] | 5 | 3 | 5 | 5 |
| (68,78] | 4 | 5 | 4 | 5 |
| (78,82) | 10 | 8 | 12 | 10 |
| [82,90] | 6 | 10 | 7 | 11 |
| (90,95] | 8 | 10 | 10 | 11 |
| >95 | 66 | 65 | 63 | 58 |

TABLE 5

**Comparing Loan Performance between NeighborWorks Loans and Similar Non-NeighborWorks Loans**

*Logistic regression results*

| Independent Variables | | Estimate | t Value | Hazard |
|---|---|---|---|---|
| Intercept | | -1.04*** | -3.31 | -65% |
| **NeighborWorks Loans (compared to non-NeighborWorks loans)** | | **-0.17**** | **-2.52** | **-16%** |
| Ex-ante probability of default X 100 (Combines FICO, LTV and DTI) | | 0.0448*** | 10.3 | 4.6% |
| **Origination Year Dummy** | | | | |
| **(Compared to 2010)** | | | | |
| 2011 | | -0.16* | -1.93 | -15% |
| 2012 | | -0.71*** | -8.82 | -51% |
| **Borrower Race, Ethnicity and Income Dummies** | | | | |
| **(Compared to non-Hispanic White and high income borrowers)** | | | | |
| *Race and Ethnicity* | *Income* | | | |
| African American | High | -0.58 | -0.77 | -44% |
| | Low | -0.11 | -0.38 | -10% |
| | Moderate | -0.04 | -0.12 | -4% |
| | Very Low | -0.12 | -0.41 | -12% |
| Hispanic | High | 0.34 | 0.7 | 40% |
| | Low | -0.35 | -1.18 | -29% |
| | Moderate | -0.35 | -1.04 | -30% |
| | Very Low | -0.79** | -2.4 | -55% |
| Non-Hispanic white | Low | -0.21 | -0.74 | -19% |
| | Moderate | -0.09 | -0.3 | -8% |
| | Very Low | -0.26 | -0.88 | -23% |
| **Census Tract Median Income Relative to MSA Median Income** | | | | |
| **(Compared to very high income census tracts)** | | | | |
| High | | -0.17 | -0.99 | -16% |
| Low | | -0.17 | -1.17 | -16% |
| Moderate High | | -0.19 | -1.19 | -17% |
| Moderate Low | | -0.17 | -1.08 | -15% |
| Very Low | | -0.07 | -0.52 | -7% |
| **Census Division (compared to Pacific division)** | | | | |
| East North Central | | -0.10 | -0.68 | -9% |
| East South Central | | -0.03 | -0.15 | -2% |
| Middle Atlantic | | -0.42*** | -2.95 | -34% |
| Mountain | | -0.14 | -1.05 | -13% |
| New England | | -0.35 | -1.52 | -30% |
| South Atlantic | | -0.22* | -1.71 | -20% |
| West North Central | | 0.04 | 0.26 | 4% |
| West South Central | | -0.48*** | -2.93 | -38% |

**Note:** * $p \le 0.10$; ** $p < 0.05$; *** $p < 0.01$.

# Conclusion

A recent Urban Institute study, *Headship and Homeownership: What Does the Future Hold?* (Goodman, Pendall, and Zhu 2015), shows that the homeownership rate in the United States, which has been declining since the housing boom, will continue to decrease for at least the next 15 years. Moreover, it shows that the overwhelming majority of new households formed from 2010 to 2030 will be nonwhite and that the overwhelming majority of new homeowners will also be nonwhite. Taken together, these trends pose a great challenge to the nation's housing policy and cry out for measures that help new and struggling low-income and minority households sustainably become homeowners. Homeownership counseling services play an important role by helping potential homebuyers develop a budget, strengthen their credit to maximize their chance of getting the lowest possible mortgage rate, set a realistic timeline for the purchase, and connect with other needed experts, including real estate agents and home inspectors.

This study provides a comprehensive assessment of the pre-purchase homeownership education and counseling program by NeighborWorks America. The NeighborWorks network organizations are required to provide both homeownership education and counseling through the program, and to follow the same set of requirements that include using a specifically approved curriculum, an approved online provider or classroom setting, and providing 8+ hours of training and/or education (including a minimum of 1 hour of individual counseling). Organizations are required to provide details on their homebuyer education classes, including agendas and curricula, the length of classes (number of meetings, number of classroom hours) and attendance.

We compared the demographic profiles of borrowers who received NeighborWorks homeownership education and counseling services to those of the general population of borrowers who took out a first lien mortgage to purchase an owner-occupied property. We found that NeighborWorks borrowers are much more likely to be African American, Hispanic, low income, or female than the general population of borrowers. This finding confirms our hypothesis that these housing counseling services are predominantly serving disadvantaged homebuyers to help them realize the American dream.

We then reviewed the reasons consumers seek these services and connected those reasons to a more rigorous measure of the market potential of pre-purchase counseling services. We found that in many geographic areas, a high number of mortgage applicants are rejected, which provides good evidence for the housing counseling industry on how to allocate its resources.

Finally, we constructed two groups of borrowers with similar credit profiles: one group that received NeighborWorks counseling services and another that did not. When we compared the loan performance of the two groups, we found that borrowers who have undergone NeighborWorks pre-purchase counseling perform significantly better than those who do not. The default rates of NeighborWorks loans are 16 percent lower than those of non-NeighborWorks loans.

We note that although Mayer and Temkin (2013)'s analysis found a nearly one-third drop in the likelihood of serious mortgage delinquency when consumers receive NeighborWork education and counseling, that research was based on mortgage loans originated between 2007 and 2009, a time when the housing crisis had only begun to unfold and the credit box had begun to tighten. Because mortgage credit has tightened considerably since 2009, the impact is, not surprisingly, less dramatic for loans originated between 2010 and 2012. This report reveals, however, that NeighborWorks homeownership education and counseling program works even when it serves more disadvantaged homebuyers in a tight-credit, low-default housing market.

# Appendix A. Additional MSA Mortgage Application Results from 2014 HMDA

| MSA | Total applicants | Total weak applicants | Total denied | % denied | % weak denied |
|---|---|---|---|---|---|
| New Orleans-Metairie, LA | 11,863 | 3,958 | 1,636 | 14 | 41 |
| Charleston-North Charleston, SC | 12,183 | 4,009 | 1,499 | 12 | 37 |
| Camden, NJ | 11,063 | 3,814 | 1,484 | 13 | 39 |
| Richmond, VA | 14,848 | 4,620 | 1,482 | 10 | 32 |
| Grand Rapids-Wyoming, MI | 14,668 | 4,262 | 1,409 | 10 | 33 |
| Deltona-Daytona Beach-Ormond Beach, FL | 7,435 | 2,867 | 1,359 | 18 | 47 |
| Salt Lake City, UT | 16,089 | 4,809 | 1,357 | 8 | 28 |
| Tacoma-Lakewood, WA | 11,350 | 4,363 | 1,330 | 12 | 31 |
| Memphis, TN-MS-AR | 11,453 | 4,229 | 1,316 | 12 | 31 |
| Tulsa, OK | 11,730 | 4,117 | 1,280 | 11 | 31 |
| Columbia, SC | 9,284 | 3,574 | 1,269 | 14 | 36 |
| Lakeland-Winter Haven, FL | 6,321 | 2,878 | 1,200 | 19 | 42 |
| Bridgeport-Stamford-Norwalk, CT | 9,343 | 2,164 | 1,191 | 13 | 55 |
| Hartford-West Hartford-East Hartford, CT | 11,113 | 3,117 | 1,191 | 11 | 38 |
| Baton Rouge, LA | 9,641 | 3,990 | 1,190 | 12 | 30 |
| Knoxville, TN | 9,914 | 3,150 | 1,184 | 12 | 38 |
| Greenville-Anderson-Mauldin, SC | 10,433 | 3,423 | 1,167 | 11 | 34 |
| Palm Bay-Melbourne-Titusville, FL | 7,669 | 2,602 | 1,139 | 15 | 44 |
| Lake County-Kenosha County, IL-WI | 9,767 | 2,645 | 1,104 | 11 | 42 |
| Worcester, MA-CT | 9,644 | 2,939 | 1,103 | 11 | 38 |
| San Francisco-Redwood City-South San Francisco, CA | 10,815 | 1,948 | 1,076 | 10 | 55 |
| Albuquerque, NM | 8,820 | 2,981 | 1,030 | 12 | 35 |
| Omaha-Council Bluffs, NE-IA | 12,852 | 3,759 | 1,014 | 8 | 27 |
| Dayton, OH | 8,350 | 2,746 | 1,009 | 12 | 37 |
| Little Rock-North Little Rock-Conway, AR | 8,240 | 3,022 | 1,007 | 12 | 33 |
| Boise City, ID | 11,277 | 3,331 | 993 | 9 | 30 |
| Port St. Lucie, FL | 5,816 | 2,104 | 975 | 17 | 46 |
| Tucson, AZ | 10,441 | 3,570 | 962 | 9 | 27 |
| Allentown-Bethlehem-Easton, PA-NJ | 7,705 | 2,517 | 961 | 13 | 38 |
| Fayetteville-Springdale-Rogers, AR-MO | 7,333 | 2,376 | 933 | 13 | 39 |
| Fresno, CA | 7,680 | 2,911 | 932 | 12 | 32 |
| New Haven-Milford, CT | 6,551 | 2,004 | 924 | 14 | 46 |
| Des Moines-West Des Moines, IA | 10,019 | 2,871 | 911 | 9 | 32 |
| El Paso, TX | 6,648 | 2,948 | 903 | 14 | 31 |
| Buffalo-Cheektowaga-Niagara Falls, NY | 9,763 | 2,760 | 894 | 9 | 32 |
| Rochester, NY | 10,252 | 2,807 | 891 | 9 | 32 |
| Portland-South Portland, ME | 6,789 | 2,230 | 886 | 13 | 40 |
| Colorado Springs, CO | 12,104 | 4,265 | 879 | 7 | 21 |
| Myrtle Beach-Conway-North Myrtle Beach, SC-NC | 5,778 | 1,820 | 870 | 15 | 48 |
| Ogden-Clearfield, UT | 10,064 | 3,124 | 870 | 9 | 28 |
| Greensboro-High Point, NC | 6,663 | 2,109 | 869 | 13 | 41 |
| Bakersfield, CA | 8,398 | 3,367 | 866 | 10 | 26 |
| Stockton-Lodi, CA | 6,824 | 2,548 | 859 | 13 | 34 |
| Albany-Schenectady-Troy, NY | 8,505 | 2,629 | 858 | 10 | 33 |
| Gary, IN | 7,670 | 2,524 | 836 | 11 | 33 |
| Wichita, KS | 7,791 | 2,535 | 828 | 11 | 33 |
| Ocala, FL | 3,589 | 1,530 | 819 | 23 | 54 |
| Winston-Salem, NC | 6,153 | 1,910 | 819 | 13 | 43 |
| Oxnard-Thousand Oaks-Ventura, CA | 7,004 | 1,897 | 817 | 12 | 43 |
| Naples-Immokalee-Marco Island, FL | 4,580 | 1,427 | 787 | 17 | 55 |

| MSA | Total applicants | Total weak applicants | Total denied | % denied | % weak denied |
|---|---|---|---|---|---|
| Chattanooga, TN-GA | 6,007 | 2,030 | 777 | 13 | 38 |
| Augusta-Richmond County, GA-SC | 6,383 | 2,540 | 766 | 12 | 30 |
| Lexington-Fayette, KY | 6,173 | 1,971 | 731 | 12 | 37 |
| Rockingham County-Strafford County, NH | 5,654 | 1,728 | 721 | 13 | 42 |
| Vallejo-Fairfield, CA | 4,936 | 1,881 | 720 | 15 | 38 |
| Wilmington, DE-MD-NJ | 6,754 | 2,386 | 710 | 11 | 30 |
| Madison, WI | 8,599 | 1,904 | 699 | 8 | 37 |
| Pensacola-Ferry Pass-Brent, FL | 5,804 | 2,157 | 695 | 12 | 32 |
| Provo-Orem, UT | 8,386 | 2,578 | 694 | 8 | 27 |
| Lafayette, LA | 5,353 | 1,993 | 691 | 13 | 35 |
| Akron, OH | 7,038 | 1,946 | 667 | 10 | 34 |
| Spokane-Spokane Valley, WA | 6,420 | 1,965 | 661 | 10 | 34 |
| Toledo, OH | 5,634 | 1,797 | 643 | 11 | 36 |
| Corpus Christi, TX | 4,680 | 1,788 | 642 | 14 | 36 |
| Harrisburg-Carlisle, PA | 6,088 | 1,838 | 642 | 11 | 35 |
| Springfield, MA | 5,146 | 1,807 | 617 | 12 | 34 |
| Asheville, NC | 5,157 | 1,292 | 612 | 12 | 47 |
| Killeen-Temple, TX | 5,133 | 2,355 | 612 | 12 | 26 |
| Jackson, MS | 4,531 | 1,812 | 609 | 13 | 34 |
| Greeley, CO | 6,201 | 2,127 | 600 | 10 | 28 |
| Huntsville, AL | 5,726 | 1,980 | 591 | 10 | 30 |
| Crestview-Fort Walton Beach-Destin, FL | 4,082 | 1,597 | 588 | 14 | 37 |
| Durham-Chapel Hill, NC | 6,508 | 1,448 | 586 | 9 | 41 |
| Mcallen-Edinburg-Mission, TX | 3,115 | 1,415 | 579 | 19 | 41 |
| Syracuse, NY | 5,881 | 1,847 | 577 | 10 | 31 |
| Shreveport-Bossier City, La | 3,838 | 1,554 | 558 | 15 | 36 |
| Scranton--Wilkes-Barre--Hazleton, PA | 3,899 | 1,339 | 545 | 14 | 41 |
| Mobile, AL | 3,242 | 1,378 | 545 | 17 | 40 |
| Lansing-East Lansing, MI | 4,906 | 1,609 | 534 | 11 | 33 |
| Flint, MI | 3,992 | 1,525 | 531 | 13 | 35 |
| Manchester-Nashua, NH | 4,577 | 1,421 | 527 | 12 | 37 |
| Savannah, GA | 4,706 | 1,808 | 525 | 11 | 29 |
| Modesto, CA | 4,896 | 1,826 | 525 | 11 | 29 |
| York-Hanover, PA | 4,747 | 1,689 | 516 | 11 | 31 |
| Youngstown-Warren-Boardman, OH-PA | 4,176 | 1,398 | 515 | 12 | 37 |
| Springfield, MO | 5,231 | 1,643 | 510 | 10 | 31 |
| Salem, OR | 4,151 | 1,469 | 508 | 12 | 35 |
| Reno, NV | 5,724 | 1,745 | 501 | 9 | 29 |
| Fort Wayne, IN | 5,701 | 1,819 | 501 | 9 | 28 |
| Salisbury, MD-DE | 3,653 | 1,460 | 490 | 13 | 34 |
| Davenport-Moline-Rock Island, IA-IL | 4,622 | 1,364 | 483 | 11 | 35 |
| Anchorage, AK | 6,502 | 2,205 | 482 | 7 | 22 |
| Reading, PA | 3,759 | 1,323 | 475 | 13 | 36 |
| Gainesville, FL | 2,465 | 845 | 473 | 19 | 56 |
| Montgomery, AL | 3,299 | 1,260 | 469 | 14 | 37 |
| Spartanburg, SC | 3,326 | 1,455 | 468 | 14 | 32 |
| Gulfport-Biloxi-Pascagoula, MS | 3,004 | 1,271 | 465 | 16 | 37 |
| Ann Arbor, MI | 3,949 | 1,028 | 459 | 12 | 45 |
| Fort Collins, CO | 5,826 | 1,360 | 456 | 8 | 34 |
| Evansville, IN-KY | 3,437 | 1,072 | 452 | 13 | 42 |
| Huntington-Ashland, WV-KY-OH | 2,936 | 1,026 | 438 | 15 | 43 |
| Tallahassee, FL | 3,051 | 980 | 431 | 14 | 44 |
| Clarksville, TN-KY | 4,151 | 1,922 | 425 | 10 | 22 |
| Canton-Massillon, OH | 3,656 | 1,135 | 422 | 12 | 37 |
| Lancaster, PA | 4,733 | 1,477 | 420 | 9 | 28 |
| Fayetteville, NC | 3,698 | 1,758 | 408 | 11 | 23 |
| Duluth, MN-WI | 3,063 | 913 | 407 | 13 | 45 |
| Hagerstown-Martinsburg, MD-WV | 3,105 | 1,346 | 405 | 13 | 30 |
| Trenton, NJ | 2,904 | 801 | 398 | 14 | 50 |
| Kingsport-Bristol-Bristol, TN-VA | 2,561 | 874 | 397 | 16 | 45 |

| MSA | Total applicants | Total weak applicants | Total denied | % denied | % weak denied |
|---|---|---|---|---|---|
| Santa Rosa, CA | 3,965 | 961 | 392 | 10 | 41 |
| Peoria, IL | 4,581 | 1,364 | 392 | 9 | 29 |
| Rockford, IL | 3,118 | 1,013 | 382 | 12 | 38 |
| Kalamazoo-Portage, MI | 3,745 | 1,193 | 381 | 10 | 32 |
| Punta Gorda, FL | 1,906 | 681 | 361 | 19 | 53 |
| Beaumont-Port Arthur, TX | 3,143 | 1,141 | 356 | 11 | 31 |
| Rochester, MN | 3,255 | 968 | 355 | 11 | 37 |
| Atlantic City-Hammonton, NJ | 1,932 | 793 | 352 | 18 | 44 |
| Boulder, CO | 4,512 | 866 | 350 | 8 | 40 |
| Wilmington, NC | 3,568 | 979 | 348 | 10 | 36 |
| Eugene, OR | 3,328 | 1,006 | 347 | 10 | 35 |
| Olympia-Tumwater, WA | 3,502 | 1,238 | 345 | 10 | 28 |
| Green Bay, WI | 3,707 | 1,026 | 344 | 9 | 34 |
| Hickory-Lenoir-Morganton, NC | 2,759 | 1,053 | 344 | 13 | 33 |
| Panama City, FL | 2,228 | 831 | 340 | 15 | 41 |
| Salinas, CA | 2,351 | 802 | 335 | 14 | 42 |
| Fort Smith, AR-OK | 2,322 | 957 | 334 | 14 | 35 |
| Merced, CA | 2,049 | 899 | 320 | 16 | 36 |
| Lincoln, NE | 4,142 | 1,069 | 320 | 8 | 30 |
| Cedar Rapids, IA | 3,932 | 946 | 319 | 8 | 34 |
| Elizabethtown-Fort Knox, KY | 1,618 | 798 | 317 | 20 | 40 |
| Waco, TX | 2,213 | 805 | 315 | 14 | 39 |
| South Bend-Mishawaka, IN-MI | 2,967 | 941 | 311 | 11 | 33 |
| Laredo, TX | 1,832 | 879 | 309 | 17 | 35 |
| Charleston, WV | 1,640 | 630 | 303 | 19 | 48 |
| San Luis Obispo-Paso Robles-Arroyo Grande, CA | 2,632 | 688 | 300 | 11 | 44 |
| Bend-Redmond, OR | 3,061 | 866 | 300 | 10 | 35 |
| Kennewick-Richland, WA | 3,622 | 1,035 | 299 | 8 | 29 |
| Joplin, MO | 2,107 | 730 | 294 | 14 | 40 |
| Norwich-New London, CT | 2,352 | 855 | 290 | 12 | 34 |
| Brownsville-Harlingen, TX | 1,661 | 763 | 289 | 17 | 38 |
| Prescott, AZ | 2,590 | 844 | 288 | 11 | 34 |
| Bellingham, WA | 2,522 | 688 | 286 | 11 | 42 |
| Lake Charles, LA | 2,093 | 784 | 284 | 14 | 36 |
| Sebastian-Vero Beach, FL | 1,796 | 570 | 283 | 16 | 50 |
| Sioux Falls, SD | 4,288 | 1,053 | 283 | 7 | 27 |
| Visalia-Porterville, CA | 3,222 | 1,195 | 282 | 9 | 24 |
| Macon, GA | 1,342 | 555 | 280 | 21 | 51 |
| Longview, TX | 1,938 | 743 | 277 | 14 | 37 |
| Topeka, KS | 2,406 | 813 | 276 | 12 | 34 |
| Bremerton-Silverdale, WA | 3,359 | 1,131 | 275 | 8 | 24 |
| Sioux City, IA-NE-SD | 1,989 | 635 | 274 | 14 | 43 |
| Yakima, WA | 1,798 | 689 | 269 | 15 | 39 |
| Coeur d'Alene, ID | 2,564 | 782 | 269 | 11 | 34 |
| Utica-Rome, NY | 2,081 | 783 | 266 | 13 | 34 |
| Tyler, TX | 2,370 | 741 | 263 | 11 | 36 |
| Appleton, WI | 3,079 | 775 | 255 | 8 | 33 |
| Lake Havasu City-Kingman, AZ | 1,815 | 701 | 253 | 14 | 36 |
| Houma-Thibodaux, LA | 1,892 | 721 | 252 | 13 | 35 |
| Gainesville, GA | 2,090 | 690 | 248 | 12 | 36 |
| Roanoke, VA | 2,748 | 876 | 248 | 9 | 28 |
| Tuscaloosa, AL | 2,030 | 776 | 247 | 12 | 32 |
| Terre Haute, IN | 1,492 | 544 | 241 | 16 | 44 |
| Charlottesville, VA | 2,390 | 597 | 241 | 10 | 40 |
| Barnstable Town, MA | 2,215 | 601 | 241 | 11 | 40 |
| Columbus, GA-AL | 2,299 | 982 | 238 | 10 | 24 |
| Springfield, IL | 2,878 | 956 | 236 | 8 | 25 |
| Erie, PA | 2,192 | 641 | 233 | 11 | 36 |
| Florence, SC | 1,331 | 479 | 227 | 17 | 47 |
| Hattiesburg, MS | 1,258 | 521 | 227 | 18 | 44 |

| MSA | Total applicants | Total weak applicants | Total denied | % denied | % weak denied |
|---|---|---|---|---|---|
| Eau Claire, WI | 1,905 | 569 | 227 | 12 | 40 |
| St. George, UT | 2,440 | 766 | 226 | 9 | 30 |
| Midland, TX | 2,988 | 914 | 223 | 8 | 24 |
| Lynchburg, VA | 1,995 | 647 | 222 | 11 | 34 |
| Burlington, NC | 1,685 | 555 | 221 | 13 | 40 |
| Burlington-South Burlington, VT | 2,592 | 641 | 221 | 9 | 35 |
| Billings, MT | 2,522 | 670 | 220 | 9 | 33 |
| Niles-Benton Harbor, MI | 1,534 | 503 | 219 | 14 | 44 |
| Racine, WI | 1,834 | 600 | 218 | 12 | 36 |
| Warner Robins, GA | 1,984 | 795 | 218 | 11 | 27 |
| Medford, OR | 2,310 | 648 | 217 | 9 | 34 |
| Janesville-Beloit, WI | 1,698 | 561 | 214 | 13 | 38 |
| Dover, DE | 1,873 | 790 | 213 | 11 | 27 |
| Yuba City, CA | 1,630 | 693 | 210 | 13 | 30 |
| Johnson City, TN | 1,794 | 541 | 209 | 12 | 39 |
| College Station-Bryan, TX | 2,241 | 602 | 208 | 9 | 35 |
| Muskegon, MI | 1,763 | 674 | 208 | 12 | 31 |
| Oshkosh-Neenah, WI | 1,832 | 510 | 206 | 11 | 40 |
| Monroe, LA | 1,472 | 614 | 204 | 14 | 33 |
| Champaign-Urbana, IL | 2,517 | 653 | 204 | 8 | 31 |
| Jacksonville, NC | 2,545 | 1,208 | 201 | 8 | 17 |
| Pueblo, CO | 1,854 | 693 | 200 | 11 | 29 |
| Fargo, ND-MN | 3,724 | 821 | 200 | 5 | 24 |
| Monroe, MI | 1,626 | 552 | 199 | 12 | 36 |
| Idaho Falls, ID | 1,806 | 574 | 199 | 11 | 35 |
| Rapid City, SD | 1,993 | 680 | 199 | 10 | 29 |
| Odessa, TX | 1,707 | 737 | 199 | 12 | 27 |
| Jackson, MI | 1,411 | 584 | 197 | 14 | 34 |
| Saginaw, MI | 1,477 | 507 | 196 | 13 | 39 |
| Elkhart-Goshen, IN | 1,943 | 712 | 196 | 10 | 28 |
| Redding, CA | 1,569 | 598 | 194 | 12 | 32 |
| Decatur, AL | 1,267 | 492 | 193 | 15 | 39 |
| St. Cloud, MN | 2,232 | 658 | 192 | 9 | 29 |
| Santa Cruz-Watsonville, CA | 1,868 | 410 | 190 | 10 | 46 |
| Cleveland, TN | 1,186 | 451 | 189 | 16 | 42 |
| Texarkana, TX-AR | 1,067 | 452 | 189 | 18 | 42 |
| Grand Junction, CO | 2,124 | 717 | 188 | 9 | 26 |
| Albany, GA | 857 | 424 | 187 | 22 | 44 |
| Lubbock, TX | 3,414 | 1,033 | 187 | 6 | 18 |
| Sherman-Denison, TX | 1,228 | 497 | 186 | 15 | 37 |
| Bloomington, IN | 1,502 | 403 | 185 | 12 | 46 |
| Morristown, TN | 1,032 | 456 | 185 | 18 | 41 |
| Mount Vernon-Anacortes, WA | 1,526 | 493 | 185 | 12 | 38 |
| Battle Creek, MI | 1,290 | 510 | 185 | 14 | 36 |
| Waterloo-Cedar Falls, IA | 2,107 | 437 | 182 | 9 | 42 |
| Wausau, WI | 1,435 | 576 | 182 | 13 | 32 |
| Bowling Green, KY | 1,531 | 533 | 179 | 12 | 34 |
| Winchester, VA-WV | 1,582 | 525 | 178 | 11 | 34 |
| Morgantown, WV | 1,357 | 356 | 177 | 13 | 50 |
| Jonesboro, AR | 1,241 | 463 | 176 | 14 | 38 |
| Binghamton, NY | 1,545 | 574 | 175 | 11 | 31 |
| Auburn-Opelika, AL | 1,699 | 565 | 173 | 10 | 31 |
| Springfield, OH | 1,202 | 456 | 170 | 14 | 37 |
| Valdosta, GA | 1,058 | 536 | 168 | 16 | 31 |
| Jefferson City, MO | 1,566 | 648 | 168 | 11 | 26 |
| Dothan, AL | 1,160 | 445 | 167 | 14 | 38 |
| Alexandria, LA | 1,276 | 524 | 166 | 13 | 32 |
| Glens Falls, NY | 992 | 424 | 164 | 17 | 39 |
| Madera, CA | 1,156 | 499 | 164 | 14 | 33 |
| Florence-Muscle Shoals, AL | 1,387 | 416 | 163 | 12 | 39 |

| MSA | Total applicants | Total weak applicants | Total denied | % denied | % weak denied |
|---|---|---|---|---|---|
| Abilene, TX | 1,879 | 650 | 163 | 9 | 25 |
| Wheeling, WV-OH | 1,141 | 321 | 162 | 14 | 51 |
| Greenville, NC | 1,406 | 454 | 162 | 12 | 36 |
| Columbia, MO | 2,169 | 693 | 162 | 8 | 23 |
| Kingston, NY | 969 | 359 | 160 | 17 | 45 |
| Athens-Clarke County, GA | 1,622 | 419 | 160 | 10 | 38 |
| Rocky Mount, NC | 868 | 367 | 157 | 18 | 43 |
| Bangor, ME | 1,225 | 503 | 155 | 13 | 31 |
| Amarillo, TX | 2,858 | 812 | 155 | 5 | 19 |
| Las Cruces, NM | 1,529 | 513 | 154 | 10 | 30 |
| Kankakee, IL | 991 | 373 | 153 | 15 | 41 |
| El Centro, CA | 1,154 | 555 | 152 | 13 | 27 |
| Owensboro, KY | 1,306 | 418 | 150 | 12 | 36 |
| Cape Girardeau, MO-IL | 955 | 301 | 149 | 16 | 49 |
| Blacksburg-Christiansburg-Radford, VA | 1,283 | 425 | 146 | 11 | 34 |
| Logan, UT-ID | 1,581 | 518 | 146 | 9 | 28 |
| Hot Springs, AR | 925 | 376 | 144 | 16 | 38 |
| Santa Fe, NM | 1,116 | 289 | 143 | 13 | 49 |
| Jackson, TN | 1,113 | 440 | 143 | 13 | 33 |
| Lewiston-Auburn, ME | 958 | 422 | 142 | 15 | 34 |
| Johnstown, PA | 946 | 361 | 141 | 15 | 39 |
| Dalton, GA | 837 | 364 | 140 | 17 | 38 |
| Vineland-Bridgeton, NJ | 819 | 376 | 138 | 17 | 37 |
| Michigan City-La Porte, IN | 973 | 385 | 137 | 14 | 36 |
| Anniston-Oxford-Jacksonville, AL | 729 | 318 | 136 | 19 | 43 |
| Lebanon, PA | 1,262 | 429 | 136 | 11 | 32 |
| Chico, CA | 1,699 | 467 | 136 | 8 | 29 |
| Gadsden, AL | 720 | 328 | 135 | 19 | 41 |
| Yuma, AZ | 1,643 | 651 | 135 | 8 | 21 |
| Napa, CA | 1,012 | 250 | 132 | 13 | 53 |
| Brunswick, GA | 909 | 316 | 130 | 14 | 41 |
| State College, PA | 1,276 | 326 | 130 | 10 | 40 |
| Flagstaff, AZ | 1,082 | 362 | 130 | 12 | 36 |
| Pittsfield, MA | 1,050 | 381 | 130 | 12 | 34 |
| San Angelo, TX | 1,444 | 536 | 130 | 9 | 24 |
| St. Joseph, MO-KS | 1,031 | 344 | 129 | 13 | 38 |
| La Crosse-Onalaska, WI-MN | 1,377 | 374 | 129 | 9 | 35 |
| Sheboygan, WI | 1,117 | 306 | 128 | 12 | 42 |
| Wenatchee, WA | 1,203 | 341 | 127 | 11 | 37 |
| Ocean City, NJ | 750 | 253 | 125 | 17 | 49 |
| Columbus, IN | 1,167 | 330 | 124 | 11 | 38 |
| Rome, GA | 677 | 268 | 121 | 18 | 45 |
| Muncie, IN | 780 | 266 | 120 | 15 | 45 |
| Harrisonburg, VA | 1,027 | 281 | 120 | 12 | 43 |
| Bay City, MI | 945 | 322 | 116 | 12 | 36 |
| Cheyenne, WY | 1,789 | 490 | 116 | 7 | 24 |
| Longview, WA | 1,142 | 372 | 115 | 10 | 31 |
| Parkersburg-Vienna, WV | 815 | 244 | 114 | 14 | 47 |
| Sumter, SC | 765 | 332 | 113 | 15 | 34 |
| Iowa City, IA | 2,474 | 537 | 113 | 5 | 21 |
| Casper, WY | 1,598 | 511 | 112 | 7 | 22 |
| Altoona, PA | 1,013 | 344 | 111 | 11 | 32 |
| Wichita Falls, TX | 1,232 | 408 | 111 | 9 | 27 |
| Bismarck, ND | 2,190 | 448 | 111 | 5 | 25 |
| Fond du Lac, WI | 994 | 343 | 107 | 11 | 31 |
| Great Falls, MT | 1,098 | 342 | 105 | 10 | 31 |
| Pine Bluff, AR | 433 | 221 | 104 | 24 | 47 |
| Ames, IA | 1,075 | 283 | 104 | 10 | 37 |
| Mansfield, OH | 1,020 | 351 | 101 | 10 | 29 |
| Lima, OH | 987 | 322 | 100 | 10 | 31 |

| MSA | Total applicants | Total weak applicants | Total denied | % denied | % weak denied |
|---|---|---|---|---|---|
| Danville, IL | 507 | 174 | 99 | 20 | 57 |
| Victoria, TX | 970 | 336 | 99 | 10 | 30 |
| Kokomo, IN | 830 | 279 | 98 | 12 | 35 |
| Fairbanks, AK | 1,130 | 429 | 97 | 9 | 23 |
| Decatur, IL | 1,078 | 293 | 95 | 9 | 32 |
| Hinesville, GA | 805 | 431 | 95 | 12 | 22 |
| Lawrence, KS | 1,207 | 269 | 93 | 8 | 35 |
| Williamsport, PA | 960 | 282 | 93 | 10 | 33 |
| Mankato-North Mankato, MN | 1,152 | 491 | 90 | 8 | 18 |
| Pocatello, ID | 1,026 | 265 | 88 | 9 | 33 |
| Manhattan, KS | 1,005 | 278 | 83 | 8 | 30 |
| Farmington, NM | 790 | 291 | 82 | 10 | 28 |
| Lawton, OK | 1,076 | 445 | 82 | 8 | 18 |
| Dubuque, IA | 1,229 | 281 | 81 | 7 | 29 |
| Hanford-Corcoran, CA | 1,029 | 432 | 79 | 8 | 18 |
| Missoula, MT | 1,198 | 252 | 78 | 7 | 31 |
| Cumberland, MD-WV | 650 | 298 | 77 | 12 | 26 |
| Goldsboro, NC | 819 | 329 | 75 | 9 | 23 |
| Corvallis, OR | 852 | 176 | 73 | 9 | 41 |
| Elmira, NY | 709 | 256 | 71 | 10 | 28 |
| Grand Forks, ND-MN | 1,074 | 258 | 68 | 6 | 26 |
| Lewiston, ID-WA | 687 | 247 | 64 | 9 | 26 |
| Carson City, NV | 443 | 139 | 41 | 9 | 29 |
| Ithaca, NY | 692 | 131 | 34 | 5 | 26 |

# Notes

1. This does not include many clients who received NeighborWorks homeownership education and counseling but did not originate a mortgage to purchase a home in 2014.
2. Propensity score matching is a statistical matching technique to develop a comparison group that is similar to the treatment group by projecting a large number of variables to a scalar propensity score. Mayer and Temkin (2013) used this technique based on Experian data as one of the ways to control for selection bias when examining the effect of pre-purchase counseling.
3. Urban Institute's Housing Credit Availability Index is available at http://www.urban.org/policy-centers/housing-finance-policy-center/projects/housing-credit-availability-index.
4. Borrowers who took out loans in 2011-Q2 2015 period are performing better than past borrowers with the same risk profiles. More details can be found at http://www.urban.org/urban-wire/squeaky-clean-loans-lead-near-zero-borrower-defaults-and-not-good-thing.

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# About the Authors

**Wei Li** is a senior research associate in the Housing Finance Policy Center (HFPC) at the Urban Institute, where his research focuses on the social and political aspects of the housing finance market and their implications for urban policy. His research led to the creation of the HFPC Credit Availability Index and the real denial rate. He received the Urban Institute President's Award for Outstanding Research in 2015.

Li's work has been published widely in various academic journals and has been covered in the *Wall Street Journal*, the *Washington Post*, and the *New York Times*, as well as in other print and broadcast media. Li is also a quantitative research methodologist with a deep understanding of cost-benefit analysis, program evaluation, and causal inference in social and political science.

Before joining Urban, Li was a principal researcher with the Center for Responsible Lending, where he wrote numerous publications on the housing finance market and created and managed the nonprofit organization's comprehensive residential mortgage database. Li received his MA in statistics and his PhD in environmental science, policy, and management from the University of California, Berkeley.

**Bing Bai** is a research associate with the Housing Finance Policy Center at the Urban Institute, where he helps build, manage, and explore data to analyze housing finance trends and related policy issues. Formerly an economic modeling senior at Freddie Mac, Bai conducted research on housing and mortgage markets and developed models to evaluate foreclosure alternatives for nonperforming mortgage loans. He holds a PhD in economics from Clemson University.

**Laurie Goodman** is the director of the Housing Finance Policy Center at the Urban Institute. The center is dedicated to providing policymakers with data-driven analysis of housing finance policy issues that they can depend on for relevance, accuracy, and independence. Before joining Urban in 2013, Goodman spent 30 years as an analyst and research department manager at a number of Wall Street firms. From 2008 to 2013, she was a senior managing director at Amherst Securities Group, LP, where her strategy effort became known for its analysis of housing policy issues. From 1993 to 2008, Goodman was head of global fixed income research and manager of US securitized products research at UBS and predecessor firms, which were ranked number one by *Institutional Investor* for 11 straight years. Before that, she was a senior fixed income analyst, a mortgage portfolio manager, and a senior economist at the Federal Reserve Bank of New York. Goodman was inducted into the Fixed Income Analysts Hall of Fame in 2009.

Goodman is on the board of directors of MFA Financial, is an advisor to Amherst Capital Management, and is a member of the Bipartisan Policy Center's Housing Commission, the Federal Reserve Bank of New York's Financial Advisory Roundtable, and Fannie Mae's Affordable Housing Advisory Council. She has published more than 200 journal articles and has coauthored and coedited five books.

Goodman has a BA in mathematics from the University of Pennsylvania and an MA and PhD in economics from Stanford University.

**Jun Zhu** is a senior research associate in the Housing Finance Policy Center at the Urban Institute. She designs and conducts quantitative studies of housing finance trends, challenges, and policy issues.

Before joining Urban, Zhu worked as a senior economist in the Office of the Chief Economist at Freddie Mac, where she conducted research on the mortgage and housing markets, including default and prepayment modeling. She was also a consultant to the Treasury Department on housing and mortgage modification issues.

Zhu received her PhD in real estate from the University of Wisconsin–Madison in 2011.

## Statement of Independence

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2100 M Street NW
Washington, DC 20037

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