

Redlining Again?
Spatial Differences in Residential Mortgage Accessibility
during Boom and Bust in Ohio

Daisuke Nagase and Rachel Garshick Kleit, PhD
The Ohio State University

This research project is supported by an Education & Research Fund Grant from Ohio Department of Commerce, Division of Real Estate & Professional Licensing. All conclusions and errors are the authors.

Contents

Executive Summary	xi
I. Introduction	1
II. Homeownership and Racial Disparities in Mortgage Lending	5
1. Early Studies of Inequalities in Mortgage Origination	6
2. Racial Disparity in Subprime Lending	8
3. Mortgage Lending in Minority Neighborhoods During and After the Mortgage Crisis	11
4. Research Hypotheses	13
III. Methodology	14
1. Descriptive Analysis	14
Data Sources	14
Time Periods	15
Measuring the Quality and Quantity of Mortgages Originated	15
Descriptive Analysis Methods	18
2. Multivariate Analysis	21
Statistical Modelling	21
Factors Associated with the Neighborhood Racial Composition, the Probability and Cost of Default, Loan Term and Neighborhood Attributes	23
Variables and Data Excluded from Models	30
IV. Changes in Mortgage Lending in Five Ohio MSAs since 2004	31
1. Mortgage Lending at Flood, Ebb, and Rising Tide	31
2. Median Credit Score Increases	33
3. Access to Conventional Mortgage Differs by Neighborhoods Race	34
4. Subprime Share Hit African-American Neighborhoods	35
5. High APR spread for African-American Neighborhoods but Low for White Neighborhoods	35
6. FHA Share Available in African-American Neighborhoods	37
7. Variations in Neighborhood Mortgage Originations across MSAs	38
Period 1: In the Shadow of Mortgage Boom	38
Period 2: Mortgage Bust	44
Period 3: Post Bust Period	50
8. The Geography of Mortgage Origination	56
Period 1: The Geography of Lending in the Shadow of the Mortgage Boom	56
Period 2: Geography of Absence of Mortgage Originations	59
Period 3: Geography of Mortgage Recovery	62
9. Summary	64
V. Multivariate Analysis	67
Period 1 (2004 – 2007): In the Shadow of Mortgage Boom	68
Period 2 (2008 - 2011): Mortgage Bust	73
Period 3 (2012 - 2015): Post Bust Period	79
Summary	86
VI. Conclusion, Policy Implications, and Future Research	89

Work Cited.....	93
Appendix.....	97
Appendix A: Descriptive Analysis of Mortgage Lending across Three Periods in Five Ohio MSAs.....	98
1. Median Rate of Originations by Neighborhood Racial Composition, Income, and Credit Score in Period 1 (2004-2007).....	99
2. Median Rate of Originations by Neighborhood Racial Composition, Income, and Credit Score in Period 2 (2008-2011).....	99
3. Median Rate of Originations by Neighborhood Racial Composition, Income, and Credit Score in Period 3 (2012-2015).....	100
4. Median Subprime Share by Neighborhood Racial Composition, Income, and Credit Score in Period 1 (2004-2007).....	100
5. Median APR Spread by Neighborhood Racial Composition, Income, and Credit Score in Period 2 (2008-2011).....	101
6. Median APR Spread by Neighborhood Racial Composition, Income, and Credit Score in Period 3 (2012-2015).....	101
7. Median FHA Share by Neighborhood Racial Composition, Income, and Credit Score in Period 2 (2008-2011).....	102
8. Median FHA Share by Neighborhood Racial Composition, Income, and Credit Score in Period 3 (2011-2015).....	102
9. Summary Statistics: Zip-Code Level Mean, Median, Standard Deviation for Each Variable by MSA in Period 1 (2004-2007).....	103
10. Summary Statistics: Zip-Code Level Mean, Median, Standard Deviation for Each Variable by MSA in Period 2 (2008-2011).....	104
11. Summary Statistics: Zip-Code Level Mean, Median, Standard Deviation for Each Variable by MSA in Period 3 (2012-2015).....	105
Appendix B: Geography of Mortgages by Racial Compositions and Median Credit Scores, Maps by Metropolitan Statistical Area (MSA).....	106
1. Geography of the Rates of Originations in Neighborhoods in the Cleveland MMSA in Period 1 (2004-2007).....	109
2. Geography of Rate of Originations in Neighborhoods in the Cleveland MSA in Period 2 (2008-2011).....	110
3. Geography of Rate of Originations in Neighborhoods in the Cleveland MSA in Period 3 (2012-2015).....	111
4. Geography of the Share of Subprime Loans in Neighborhoods in the Cleveland MSA in Period 1 (2004-2007).....	112
5. Geography of the Share of FHA-insured Loans in Neighborhoods in the Cleveland MSA in Period 2 (2008-2011).....	113
6. Geography of the Share of FHA-insured Loans in Neighborhoods in the Cleveland MSA in Period 3 (2012-2015).....	114
7. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Cleveland MSA in Period 2 (2008-2011).....	115
8. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Cleveland MSA in Period 3 (2012-2015).....	116
9. Geography of Rate of Originations in Neighborhoods in the Cincinnati MSA in Period 1 (2004-2007).....	117

10. Geography of Rate of Originations in Neighborhoods in the Cincinnati MSA in Period 2 (2008-2011)	118
11. Geography of Rate of Originations in Neighborhoods in the Cincinnati MSA in Period 3 (2012-2015)	119
12. Geography of the Share of Subprime Loans in Neighborhoods in the Cincinnati MSA in Period 1 (2004-2007)	120
13. Geography of the Share of FHA-insured Loans in Neighborhoods in the Cincinnati MSA in Period 2 (2008-2011)	121
14. Geography of the Share of FHA-insured Loans in Neighborhoods in the Cincinnati MSA in Period 3 (2012-2015)	122
15. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Cincinnati MSA in Period 2 (2008-2011)	123
16. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Cincinnati MSA in Period 3 (2012-2015)	124
17. Geography of Rate of Originations in Neighborhoods in the Columbus MSA in Period 1 (2004-2007)	125
18. Geography of Rate of Originations in Neighborhoods in the Columbus MSA in Period 2 (2008-2011)	126
19. Geography of Rate of Originations in Neighborhoods in the Columbus MSA in Period 3 (2012-2015)	127
20. Geography of the Share of Subprime Loans in Neighborhoods in the Columbus MSA in Period 1 (2004-2007)	128
21. Geography of the Share of FHA-insured Loans in Neighborhoods in the Columbus MSA in Period 2 (2008-2011)	129
22. Geography of the Share of FHA-insured Loans in Neighborhoods in the Columbus MSA in Period 3 (2012-2015)	130
23. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Columbus MSA in Period 2 (2008-2011)	131
24. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Columbus MSA in Period 3 (2012-2015)	132
25. Geography of Rate of Originations in Neighborhoods in the Dayton MSA in Period 1 (2004-2007)	133
26. Geography of Rate of Originations in Neighborhoods in the Dayton MSA in Period 2 (2008-2011)	134
27. Geography of Rate of Originations in Neighborhoods in the Dayton MSA in Period 3 (2012-2015)	135
28. Geography of the Share of Subprime Loans in Neighborhoods in the Dayton MSA in Period 1 (2004-2007)	136
29. Geography of the Share of FHA-insured Loans in Neighborhoods in the Dayton MSA in Period 2 (2008-2011)	137
30. Geography of the Share of FHA-insured Loans in Neighborhoods in the Dayton MSA in Period 3 (2012-2015)	138
31. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Dayton MSA in Period 2 (2008-2011)	139
32. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Dayton MSA in Period 3 (2012-2015)	140
33. Geography of Rate of Originations in Neighborhoods in the Toledo MSA in Period 1 (2004-2007)	141
34. Geography of Rate of Originations in Neighborhoods in the Toledo MSA in Period 2 (2008-2011)	142
35. Geography of Rate of Originations in Neighborhoods in the Toledo MSA in Period 3 (2012-2015)	143
36. Geography of Shares of Subprime Loans in the Toledo MSA in Period 1 (2004-2007)	144

37. Geography of Shares of FHA-insured Loans in the Toledo MSA in Period 2 (2008-2011).....	145
38. Geography of Shares of FHA-insured Loans in the Toledo MSA in Period 3 (2012-2015).....	146
39. Geography of Costlier Mortgages (APR Spread) in the Toledo MSA in Period 2 (2008-2011)	147
40. Geography of Costlier Mortgages (APR Spread) in the Toledo MSA in Period 3 (2012-2015)	148
Appendix C: Detailed Modeling Results of Multivariate Analysis of Patterns of Neighborhood Mortgage Lending, 2004-2015	149
1. Modelling Strategy	151
2. Results for Conventional Mortgage Originations in the Cleveland MSA in Period 1 (2004-2007).....	152
3. Results for Conventional Mortgage Originations in the Cincinnati MSA in Period 1 (2004-2007)	153
4. Results for Conventional Mortgage Originations in the <i>Columbus</i> MSA in Period 1 (2004-2007).....	154
5. Results for Conventional Mortgage Originations in the Dayton MSA in Period 1 (2004-2007)	155
6. Results for Conventional Mortgage Originations in the Toledo MSA in Period 1 (2004-2007).....	156
7. Results for Conventional Mortgage Originations in the Cleveland MSA in Period 2 (2008-2011).....	157
8. Results for Conventional Mortgage Originations in the Cincinnati MSA in Period 2 (2008-2011)	158
9. Results for Conventional Mortgage Originations in the Columbus MSA in Period 2 (2008-2011).....	159
10. Results for Conventional Mortgage Originations in the Dayton MSA in Period 2 (2008-2011).....	160
11. Results for Conventional Mortgage Originations in the Toledo MSA in Period 2 (2008-2011)	161
12. Results for Conventional Mortgage Originations in the Cleveland MSA in Period 3 (2012-2015)	162
13. Results for Conventional Mortgage Originations in the Cincinnati MSA in Period 3 (2012-2015)....	163
14. Results for Conventional Mortgage Originations in the Columbus MSA in Period 3 (2012-2015)	164
15. Results for Conventional Mortgage Originations in the Dayton MSA in Period 3 (2012-2015).....	165
16. Results for Conventional Mortgage Originations in the Toledo MSA in Period 3 (2012-2015)	166
17. Results for the Share of Subprime Mortgage in the Cleveland MSA in Period 1 (2004-2007).....	167
18. Results for the Share of Subprime Mortgage in the Cincinnati MSA in Period 1 (2004-2007)	168
19. Results for the Share of Subprime Mortgage in the Columbus MSA in Period 1 (2004-2007).....	169
20. Results for the Share of Subprime Mortgage in the Dayton MSA in Period 1 (2004-2007)	170
21. Results for the Share of Subprime Mortgage in the Toledo MSA in Period 1 (2004-2007).....	171
22. Results for the Share of FHA Mortgage in the Cleveland MSA in Period 2 (2008-2011)	172
23. Results for the Share of FHA Mortgage in the Cincinnati MSA in Period 2 (2008-2011)	173
24. Results for the Share of FHA Mortgage in the Columbus MSA in Period 2 (2008-2011)	174
25. Results for the Share of FHA Mortgage in the Dayton MSA in Period 2 (2008-2011).....	175
26. Results for the Share of FHA Mortgage in the Toledo MSA in Period 2 (2008-2011)	176
27. Results for the Share of FHA Mortgage in the Cleveland MSA in Period 3 (2012-2015)	177
28. Results for the Share of FHA Mortgage in the Cincinnati MSA in Period 3 (2012-2015)	178
29. Results for the Share of FHA Mortgage in the Columbus MSA in Period 3 (2012-2015)	179
30. Results for the Share of FHA Mortgage in the Dayton MSA in Period 3 (2012-2015).....	180
31. Results for the Share of FHA Mortgage in the Toledo MSA in Period 3 (2012-2015)	181
32. Results for the APR Spread for Conventional Mortgages in the Cleveland MSA in Period 2 (2007-2011)	182
33. Results for the APR Spread for Conventional Mortgages in the Cincinnati MSA in Period 2 (2007-2011)	183
34. Results for the APR Spread for Conventional Mortgages in the Columbus MSA in Period 2 (2007-2011)	184
35. Results for the APR Spread for Conventional Mortgages in the Dayton MSA in Period 2 (2007-2011)	185
36. Results for the APR Spread for Conventional Mortgages in the Toledo MSA in Period 2 (2007-2011)	186

37. Results for the APR Spread for Conventional Mortgages in the Cleveland MSA in Period 3 (2012-2015)	187
38. Results for the APR Spread for Conventional Mortgages in the Cincinnati MSA in Period 2 (2007-2011)	188
39. Results for the APR Spread for Conventional Mortgages in the Columbus MSA in Period 2 (2007-2011)	188
40. Results for the APR Spread for Conventional Mortgages in the Dayton MSA in Period 2 (2007-2011)	189
41. Results for the APR Spread for Conventional Mortgages in the Toledo MSA in Period 2 (2007-2011)	189

List of Figures

Figure 1 Annual Changes in the Count of Mortgage Originations, 2004 to 2015, Including Conventional Mortgages, FHA Mortgages, and High Cost Mortgages.....	32
Figure 2 Changes in the Mortgage Origination Count by Period	32
Figure 3 Distribution of Mortgage Origination Types by Period Periods	32
Figure 4 Distribution of Credit Scores for Conventional Mortgage Originations, Periods 1, 2, and 3	33
Figure 5 Distribution of Credit Scores for FHA Mortgage Originations, Periods 1, 2, and 3	33
Figure 6 Race Median Rates of Conventional Mortgage Origination by Neighborhood Racial Composition.....	34
Figure 7 Subprime Share by Neighborhood Race in Period 1	35
Figure 8 APR Spread in Period 2 and 3 by Neighborhood Racial Composition	36
Figure 9 FHA Mortgage Share in Period 1 through 3 by Neighborhood Race	37
Figure 10 Rates of Origination by Proportion White in Neighborhood in Period 1	41
Figure 11 Rates of Origination by Proportion African-Americans in Neighborhood in Period 1	41
Figure 12 Rates of Origination by Neighborhood Income in Period 1	41
Figure 13 Rates of Origination by Neighborhood Credit Score in Period 1	41
Figure 14 Rates of Origination by Neighborhood Income in White Neighborhoods in Period 1	41
Figure 15 Rates of Origination by Neighborhood Income in African-American Neighborhoods in Period 1	41
Figure 16 Rates of Origination by Neighborhood Credit Score in White Neighborhoods in Period 1	41
Figure 17 Rates of Origination by Neighborhood Credit Score in African-American Neighborhoods in Period 1	41
Figure 18 Subprime Share by Proportion White in Neighborhood in Period 1	43
Figure 19 Subprime Share by Proportion African-Americans in Neighborhood in Period 1	43
Figure 20 Subprime Share by Neighborhood Income in Period 1	43
Figure 21 Subprime Share by Neighborhood Credit Score in Period 1	43
Figure 22 Subprime Share by Neighborhood Income in White Neighborhoods in Period 1	43
Figure 23 Subprime Share by Neighborhood Income in African-American Neighborhoods in Period 1	43
Figure 24 Subprime Share by Neighborhood Credit Score in White Neighborhoods in Period 1	43
Figure 25 Subprime Share by Neighborhood Credit Score in African-American Neighborhoods in Period 1	43
Figure 26 Rates of Origination by Proportion White in Period 2	45

Figure 27 Rates of Origination by Proportion African-American in Period 2.....	45
Figure 28 Rates of Origination by Neighborhood Income Level in Period 2.....	45
Figure 29 Rates of Origination by Neighborhood Credit Score in Period 2.....	45
Figure 30 Rates of Origination by Neighborhood Income in White Neighborhoods in Period 2.....	45
Figure 31 Rates of Origination by Neighborhood Income in African-American Neighborhoods in Period 2.....	45
Figure 32 Rates of Origination by Neighborhood Credit Score in White Neighborhoods in Period 2.....	45
Figure 33 Rates of Origination by Neighborhood Credit Score in African-American Neighborhoods in Period 2.....	45
Figure 34 Median APR Spread by Proportion of Whites in Period 2.....	47
Figure 35 Median APR Spread by Proportion of African-Americans in Period 2.....	47
Figure 36 Median APR Spread by Neighborhood Income in Period 2.....	47
Figure 37 Median APR Spread by Neighborhood Credit Score in Period 2.....	47
Figure 38 Median APR Spread by Neighborhood Income in White neighborhoods in Period 2.....	47
Figure 39 Median APR Spread by Neighborhood Income in African-American neighborhoods in Period 2.....	47
Figure 40 Median APR Spread by Neighborhood Credit Score in White Neighborhoods in Period 2.....	47
Figure 41 Median APR Spread by Neighborhood Credit Score in African-American Neighborhoods in Period 2.....	47
Figure 42 FHA Share by Proportion of Whites in Period 2.....	49
Figure 43 FHA Share by Proportion of African-Americans in Period 2.....	49
Figure 44 FHA Share by Neighborhood Income in Period 2.....	49
Figure 45 FHA Share by Neighborhood Credit Score in Period 2.....	49
Figure 46 FHA Share by Neighborhood Income in White Neighborhoods in Period 2.....	49
Figure 47 FHA Share by Neighborhood Income in African-American Neighborhoods in Period 2.....	49
Figure 48 FHA Share by Neighborhood Credit Score in White Neighborhoods in Period 2.....	49
Figure 49 FHA Share by Neighborhood Credit Score in African-American Neighborhoods in Period 2.....	49
Figure 50 Rates of Originations by Proportion of Whites in Period 3.....	51
Figure 51 Rates of Originations by Proportion of African-Americans in Period 3.....	51
Figure 52 Rates of Origination by Neighborhood Income Level in Period 3.....	51
Figure 53 Rates of Origination by Neighborhood Credit Score in Period 3.....	51
Figure 54 Rates of Origination by Neighborhood Income in White Neighborhoods in Period 3.....	51

Figure 55 Rates of Origination by Neighborhood Income in African-American Neighborhoods in Period 3	51
Figure 56 Rates of Origination by Neighborhood Credit Score in White Neighborhoods in Period 3	51
Figure 57 Rates of Origination by Neighborhood Credit Score in African-American Neighborhoods in Period 3	51
Figure 58 APR Spread by Proportion of Whites in Period 3	53
Figure 59 APR Spread by Proportion of African-Americans in Period 3	53
Figure 60 APR Spread by Neighborhood Income in Period 3	53
Figure 61 APR Spread by Neighborhood Credit Score in Period 3	53
Figure 62 APR Spread by Neighborhood Income in White Neighborhoods in Period 3	53
Figure 63 APR Spread by Neighborhood Income in African-American Neighborhoods in Period 3	53
Figure 64 APR Spread by Neighborhood Credit Score in White Neighborhoods in Period 3	53
Figure 65 APR Spread by Neighborhood Credit Score in African-American Neighborhoods in Period 3	53
Figure 66 FHA Share by Proportion of Whites in Period 3	55
Figure 67 FHA Share by Proportion of African-Americans in Period 3	55
Figure 68 FHA Share by Neighborhood Income in Period 3	55
Figure 69 FHA Share by Neighborhood Credit Score in Period 3	55
Figure 70 FHA Share by Neighborhood Income in White Neighborhoods in Period 3	55
Figure 71 FHA Share by Neighborhood Income in African-American Neighborhoods in Period 3	55
Figure 72 FHA Share by Neighborhood Credit Score in White Neighborhoods in Period 3	55
Figure 73 FHA Share by Neighborhood Credit Score in African-American Neighborhoods in Period 3	55
Figure 74 Rates of Originations by Neighborhood Racial Composition and Credit Score in the Cincinnati MSA in Period 1	57
Figure 75 Rates of Originations by Neighborhood Racial Composition and Credit Score in the Cleveland MSA in Period 1	57
Figure 76 Subprime Share by Neighborhood Racial Composition and Credit Score in the Columbus MSA in Period 1	58
Figure 77 Subprime Share by Neighborhood Racial Composition and Credit Score in the Toledo MSA in Period 1	58
Figure 78 Rate of Conventional Mortgage Originations by Neighborhood Racial Composition and Credit Score in the Cleveland MSA in Period 2	59
Figure 79 Rate of Conventional Mortgage Originations by Neighborhood Racial Composition and Credit Score in the Cincinnati MSA in Period 2	59

Figure 80 Median APR spread by Neighborhood Racial Composition and Credit Score in the Cleveland MSA in Period 2	60
Figure 81 Median APR spread by Neighborhood Racial Composition and Credit Score in the Cincinnati MSA in Period 2	60
Figure 82 FHA Loan Share by Neighborhood Racial Composition and Credit Score in Cleveland MSA in Period 2	61
Figure 83 FHA Loan Share by Neighborhood Racial Composition and Credit Score in Columbus MSA in Period 2	61
Figure 84 Rates of Conventional Mortgage Originations by Neighborhood Racial Composition and Credit Score in Dayton MS in Period 3	62
Figure 85 Rates of Conventional Mortgage Originations by Neighborhood Racial Composition and Credit Score in Cleveland MSA in Period 3	62
Figure 86 Median APR spread by Neighborhood Racial Composition and Credit Score in Cleveland MSA in Period 3	63
Figure 87 Median APR spread by Neighborhood Racial Composition and Credit Score in Cincinnati MSA in Period 3	63
Figure 88 FHA Loan Share by Neighborhood Racial Composition and Credit Score in the Cleveland MSA in Period 3	64
Figure 89 FHA Loan Share by Neighborhood Racial Composition and Credit Score in the Columbus MSA In Period 3	64

List of Tables

Table 1 Neighborhood Categorizations Used in this Report	20
Table 2 Multivariate Results for Conventional Mortgage Originations, Period 1 (2004-2007).....	70
Table 3 Multivariate Results for Conventional Mortgage Origination in Neighborhood, Period 1 (2004- 2007).....	71
Table 4 Multivariate Results for Subprime Share in Neighborhood, Period 1 (2004-2007).....	72
Table 5 Multivariate Results for Conventional Mortgage Originations, Period 2 (2008-2011).....	75
Table 6 Multivariate Results for FHA Share in Neighborhood, Period 2 (2008-2011).....	77
Table 7 Multivariate Results for APR Spread, Period 2 (2008-2011).....	79
Table 8 Multivariate Results for Conventional Mortgage Originations, Period 3 (2012-2015).....	82
Table 9 Multivariate Results for Conventional Mortgage Origination, Period 3 (2012-2015)	83
Table 10 Multivariate Results for FHA Share in Neighborhood, Period 3 (2012-2015).....	84
Table 11 Multivariate Results for APR Spread, Period 3 (2012-2015).....	86

Executive Summary

Over time, neighborhoods of color have experienced disadvantages their access to mortgages and receiving relatively high-cost mortgages. Those disadvantages cause not only lower homeownership rates among people of color, but also they can eventually trigger neighborhood declines. Studies have documented the disparate impact of subprime lending during the mortgage boom on neighborhoods and people of color; as mortgage markets recover from the bust, to where has lending returned? Therefore, the main purpose of this study is to investigate the spatial distribution of residential mortgages from 2004 through 2015, mainly concerning the periods of the boom of subprime loan origination (2004-2007), the bust of foreclosure (2008-2011), and the recovery of housing market (2012-2015). To understand how patterns of lending have changed over time, the study examines neighborhood-level changes credit access, including the quantity of mortgages originated, and the quality of that as demonstrated by the cost of the mortgages originated, paying special attention to comparisons by neighborhood racial composition, while taking into consideration other potential causes of observed lending disparities. The study has four main findings:

- **Throughout the three periods studied, conventional mortgage origination tended to be limited in neighborhoods with higher proportions of African-Americans in most MSAs.** In the Cleveland and Dayton MSAs, results indicate that African-American neighborhoods, no matter the neighborhood median credit score, had lower conventional mortgage originations, while accounting for other causes of observed variations in lending. In the Columbus and Toledo MSAs, higher proportions of African-Americans in a neighborhood reduced the origination number in the neighborhood, whereas higher credit scores and income in the neighborhoods increase the number. However, the Cincinnati MSA is distinct in that this negative relationship between the rate of African-American residents and conventional mortgage originations was evident during the mortgage boom (Period 1, 2004-2007).

- **Patterns of FHA mortgage lending needs additional analysis.** In addition to decreases in mortgage lending as the African-American population become more dominant in a neighborhood, our analysis suggests that the higher the median neighborhood income and at higher proportions of African-American residents, the greater FHA loans are as share of all mortgages made in that neighborhood. Our present analysis cannot explain whether this high rate of FHA loans is due to a lack of available conventional lending in the neighborhood or a lack of demand for conventional loans. Given the high rates of FHA lending in neighborhoods with higher proportions of African-American residents, it is likely that demand for mortgages may not to be small but supply may be. However, FHA-insured mortgages can be costly mortgages for those who qualify for conventional mortgages. Therefore, future research should conduct an individual level analysis aimed at understanding whether African-Americans with incomes and credit scores that would qualify for conventional mortgages are more likely to receive FHA-insured loans than their white counterparts.
- **During the mortgage market boom (2004-07) and bust (2008-11), the costs of mortgages increased as rates of African-American residence in neighborhoods increased; after the crisis, such patterns all but disappeared across MSAs, with one notable exception, Cleveland.** The share of subprime loans in a neighborhood is higher in the neighborhoods with higher rates of African-American residents in all five MSAs during the boom. After the boom, higher credit score incorporated with higher African-Americans increases the annual percentage rate (APR) spreads in the Cleveland MSA. In addition, during the recovery period, the proportions of African-Americans had no impact on cost of mortgages in all MSAs but in Cleveland where neighborhoods with higher African-American neighborhoods residence are more likely to receive costlier mortgages, although higher credit scores in the neighborhood can diminish that effect somewhat.

- **Concentrations of older housing are associated with neighborhoods’ experiencing lower levels of mortgage originations.** An explanation is that older housing, when compared with new housing, is more likely to be in physically worse condition, which cause negative spillover effects in neighborhoods (Schill & Wachter, 1993); therefore, lenders regard the age or physical condition of the housing as a risk. Furthermore, neighborhoods with concentration of older housing units are also home to elderly owners. Seniors are more likely to live in older homes and tend to spend less money on their housing (Golant, 2008). These neighborhoods are likely in need of affordable refinancing for home renovations to support housing quality. The need for refinance loans raises another topic for study—what is the spatial distribution of refinance loans as well as refinance lending for elderly residents living in neighborhoods with concentrations of older housing stocks?

I. Introduction

Racial inequality in accesses to mortgage capital has been persistent in the United States (U.S.) housing market. As far back as redlining in the 1930s, discriminatory lending practices manifested as a lack of access to credit for minorities and minority neighborhoods compared to Whites and predominantly White neighborhoods. Even through the enactment of fair lending policies in the late 1960s expanded the range of neighborhoods that were entitled to loans, by the 1990s, African-Americans and other minorities were targeted for subprime loans—that is, high-cost loans that are meant to expanding credit to more risky borrowers and thus increasing parity in homeownership among people of varied income levels and races (Retsinas & Belsky, 2002). However, when used in a predatory manner—as loans to borrowers who do not have the financial capacity to meet the obligations of the mortgage, subprime loans mortgages eventually resulted in high levels of mortgage defaults. By the mid-2000s, subprime mortgages across the US were disproportionately in minority neighborhoods with high concentration of African-Americans or other Hispanics. While one impact was high rates of default among households that used high-cost loans and in neighborhoods with high numbers of minority residents (Immergluck, 2009), a second impact was that housing mortgage discrimination led to a huge gap in homeownership rates between Whites and African-Americans (Quercia, Freeman, & Ratcliffe, 2011). Foreclosures are not only a problem of individual homeowners but for neighborhoods as well. Properties located nearby defaulted properties are usually lose their value in turn (Immergluck & Smith, 2006; Schuetz, Been, & Ellen, 2008), which eventually reduces the local government’s income tax revenues (Mallach, 2012). In addition, higher vacancy rates in a neighborhood are positively associated with the increase in some crimes, including burglary and drug crimes (Raleigh & Galster, 2015). More importantly, however, a lack of credit or continued foreclosures can lead to economic disinvestment in neighborhoods and neighborhood decline (Smith, Caris, & Wyly, 2001).

While disparities in lending during the mortgage boom have been well documented, now that 10 years have passed since its end, little is known about the patterns of lending during the bust and recovery. In the wake of the crisis, major conventional mortgage lenders seriously tightened their underwriting practices, limiting the number of mortgages (Immergluck, 2011). After the peak of mortgage originations for home purchases in 2005, the origination count declined seriously. The lowest number of mortgage originations was 2,430K in 2011, which was about 36% of the origination number in 2005, and the origination number in 2014, 3,235K, was still only half of that in 2005 (Federal Reserve Board of Governors, 2015). In the post mortgage boom world, with its stricter lending criteria, where has that lending happened, who has been receiving loans, and of what quality? Were African-Americans less likely to access mortgage capital after the crisis, during which time the mortgage origination standard became strict and the number of mortgage originations declined?

To date, studies have focused on the dynamics of high-cost lending prior to the crisis and its impact on foreclosure rates thereafter. However, fewer researchers have examined the impact of high-cost lending on residential lending patterns after the crisis. The limited existing evidence suggests that lenders have been tightening their underwriting practices for certain populations. For example, Immergluck (2011) found that neighborhoods with high proportions of minority residents are more likely to originate the Federal Housing Administration (FHA)-insured loans and costly mortgages rather than conventional mortgages. With the use of The Home Mortgage Disclosure Act (HMDA) data, other studies have demonstrated that the denial rate for residential mortgages for minority populations is higher than that for Whites (Stein & Nguyen, 2010) and that most originated residential mortgages go to neighborhoods with predominantly White residents (Richardson, Mitchell, & West, 2016).

Given the current tight mortgage market, especially among minority populations, and the lack of studies on the topic, this study investigates access to residential mortgage capital in the five largest metropolitan statistical areas (MSAs) in Ohio—the Cincinnati, Cleveland, Columbus, Dayton, and Toledo metropolitan statistical areas (MSAs). We examine the assumption that the polarization of mortgage

originations seen elsewhere is also present in Ohio. The impact would be that neighborhoods of color may be less likely to have access to credit than are White neighborhoods. In particular, this study investigates changes in the spatial distribution of residential mortgages since 2004, mainly concerning the periods of the boom of subprime loan origination (2004-2007), the bust of foreclosure (2008-2011), and recovery up to the most recent year available (2012-2015), with two following main objectives.

First, the study describes the varying flow of mortgage capital into neighborhoods in the five MSAs in Ohio before, during, and after the crisis (2004 through 2015), demonstrating how access to credit differs in local communities. Historically, households in neighborhoods with high proportions of minority residents disproportionately experienced a lower likelihood of receiving preferred mortgages, no matter the applicant's creditworthiness (Immergluck, 2009). This happened even though the Fair Housing Act (FaHA) and the Equal Credit Opportunity Act (ECOA) make such inequities illegal at the individual level, and the Community Reinvestment Act (CRA) makes them illegal at the neighborhood level. Therefore, this study compares the distribution of mortgages in minority neighborhoods to that in other neighborhoods before, during, and after the subprime crisis, using variations in the count of conventional mortgage originations as a quantity indicator of differential access to credit. Second, this research describes differences in the quality of mortgages originated based on neighborhood attributes. During the subprime-loan boom, minority neighborhoods were targeted for high-cost loans (Immergluck, 2009). After the boom, are minority neighborhoods still more likely to have higher-cost loans? To investigate this question, this study compares the mortgage interest rates and lending channels within minority neighborhoods to those within non-minority neighborhoods. Furthermore, this study accounts for two additional factors – the annual percentage rate (APR) spread of an originated conventional mortgage and of an originated FHA mortgage as a mortgage quality indicator.

In this study, use descriptive and multivariate statistical analyses as well as GIS mapping to examine the quantity and quality of mortgages originated from 2004 to 2015. The findings demonstrate that mortgage lending patterns at the neighborhood level are not consistent across the five MSAs. The racial composition

of neighborhoods across most MSAs is associated with variations in lending patterns. Additionally, neighborhoods with higher rates of African-American residence are more likely to have higher cost mortgages, particularly during the period when the housing market conditions are not stable (2008-2011). Conventional mortgage origination tended to be limited in neighborhoods with the higher rates of African-American residence in most MSAs before, during, and after the mortgage crisis, even accounting for other factors associated with lending patterns.

II. Homeownership and Racial Disparities in Mortgage Lending

For many years, Americans have recognized the benefits of homeownership: the intangible social or psychological benefits, economic benefits, and neighborhood benefits (Mallach, 2009). Of these benefits, the economic benefits are commonly emphasized, as homeownership enables families to accumulate wealth (Mallach, 2009) by saving through periodic mandatory mortgage payments and by increasing their housing prices. Housing equity is the principal asset particularly for less wealthy households (Quercia et al., 2011). Home equity accumulated can be used for sending children to higher education institutions, for starting a business, or for passing wealth down to children as a bequest. For these reasons, U.S. housing policy has aimed to increase access to housing mortgages since the 1930s (Quercia et al., 2011), emphasizing that a mortgage is a financial vehicle available for a prospective homeowner to purchase a house without paying the entire value of the house in advance (Immergluck, 2009). Although access to mortgages has been improved since then, all Americans have not equally enjoyed the benefits of being homeowners who can accumulate their wealth in housing (Quercia et al., 2011). The 1930's Home Owner's Loan Corporation (HOLC) created redlining in a "residential security map" proposing security in mortgage origination (Reid & Laderman, 2009) based on the assumption that social homogeneity in a neighborhood was necessary for a stable real estate market in the future and for the reduction of any uncertainties causing financial losses that would prevent lender from retrieving his or her investment (Stuart, 2003).

Due to redlining and other inequalities in the housing market, racial and ethnic minorities have suffered from inequities in accessing mortgage financing (Immergluck, 2009). Racial discrepancies in accessing mortgage capital had been tacitly acceptable in the U.S. mortgage market until the middle of the 20th century, when several policies, including 1968 Fair Housing Act (FaHA), the Equal Credit Opportunity Act (ECOA), the Community Reinvestment Act (CRA), and the Home Mortgage Disclosure Act (HMDA), were enacted to address discrimination in the housing mortgage market (Reid & Laderman, 2009). After the enactment of these policies, lending has become the focal point of the housing rights issues in the United States (Apgar & Calder, 2005).

Various studies shedding light on lending inequalities revealed that financial institutions unreasonably deny mortgage originations to certain households or neighborhoods, especially minority and low-income households and communities, thus giving them limited opportunities to become homeowners (Apgar & Calder, 2005; Immergluck, 2009). Furthermore, more in recent memory was the subprime lending that began to expand its market sharply starting in the mid-1990s due to changes in regulations to expand access to credit, the expansion of the secondary mortgage market, and technology that employed automated loan underwriting systems (Chomsisengphet & Pennington-Cross, 2006). Unfortunately, a large volume of studies concluded that low-income and minority households became the prey of such high-cost mortgages (Immergluck, 2009; Quercia et al., 2011). Thus, these households have been less likely to access appropriate housing mortgage loans even after the enactment of fair housing policies (Apgar & Calder, 2005). This unequal access to mortgage lending is due in part to: (1) a huge gap in homeownership rate by race and income – which was by 2010 74% for White families, only 45% for African-American families, 82% for families in the top half of income earners, and 51% for families in the bottom half of the income distribution (Quercia et al., 2011), and (2) the massive foreclosure rate associated with subprime lending, which is 10 to 20 times higher than that associated with prime loans, devastating especially minority households and communities (Immergluck, 2008, 2009).

1. Early Studies of Inequalities in Mortgage Origination

One of the well-cited mortgage lending studies is “The Color of Money” (Dedman, 1988), which disclosed that banks and a savings and loan associations (S&Ls) in metro Atlanta originated home-purchase and home-improvement mortgages for White neighborhoods at rates five times more than for African-American neighborhoods from 1981 to 1986, controlling for income level. Because the early HMDA did not require lenders to report information on the race and ethnicity of a mortgage applicant, this study, like other studies at the time, investigated the neighborhood level rather than the mortgage origination level, assuming that predominantly African-American neighborhoods were less likely to access mortgage capital than were predominantly White neighborhoods. Other studies also use aggregated information at the

neighborhood level, composing mainly of two different dependent variables—aggregate number and aggregate dollar amount of mortgages originated, with differing results. Ahlbrandt (1977), investigating mortgage lending in Pittsburgh, concluding that neighborhood income level and vacancy rate were significantly associated with the aggregate number and dollar amount of mortgages originated, while proportions of African-Americans were not predictors of neighborhood lending. In contrast, Shlay (1988), investigating the lending disparities between African-American and White neighborhoods in the Chicago MSA from 1980 to 1983 and accounting for the aggregate number and dollar amount of conventional and FHA mortgages originated, disclosed that flows of conventional mortgages were uneven based on the neighborhood's racial composition. Shlay (1988) found that census tracts with more African-American and Hispanic populations received less conventional financing than did areas with more White populations, and increases in the African-American population in neighborhoods negatively influenced mortgage origination. Bradbury, Case, and Dunham (1989), accounting for housing transactions as housing demand and supply, concluded that neighborhoods with high concentration of African-Americans were negatively correlated with aggregate number of mortgages originated in Boston from 1982 to 1987.

With the renewed HMDA of 1989, in which lenders were requested to report applicants' characteristics—such as gender and race—as well as the acceptance or rejection of mortgage transactions, most of studies still had the consistent result that African-American mortgage applicants or applicants from a neighborhood where a high proportion of the population was African-American were less likely to receive mortgage origination approval. Canner and Smith (1991), combining the 1989 HMDA data with census data, brought preliminary results with a descriptive analysis: (1) About 40% of low-income applicants (at 80% of area median family income) applied for government-backed home purchase mortgages; (2) among low-income applicants, African-American applicants had higher mortgage denial rates for conventional home purchase loans, 40%, compared to 23% for White applicants; and (3) the larger the minority population, the higher the mortgage denial rates. Munnell, Tootell, Browne, and McEneaney (1996) conducted a study looking at lending discrimination in Boston, integrating the Boston Fed survey and Panel

Study of Income Dynamics (PSID) along with HMDA of 1989. They used binominal logit and OLS regression with independent variables based on the factors affecting lending decisions—the probability of default, costs of default, loan characteristics, and applicant’s characteristics. This financial information was taken into account for the underwriting process because financial factors—credit ratings, for example—influence the default risks (Quercia & Stegman, 1992). Their model yielded a result consistent with those of previous studies that an applicant’s race played a significant role in a lender’s decision to approve or deny the applicant’s application even after controlling for all variables, including financial factors—such as wealth, income, credit history, and LTV. In addition, the rejection rate toward African-American applicants was higher than that toward White applicants, holding other variables constant. Even though studies of patterns of lending to individuals became common after the change in HMDA in 1989, neighborhood-level data were retained as control variables, continuing to demonstrate that minority neighborhoods were still less likely to have access to mortgages than White neighborhoods (Munnell et al., 1996).

2. Racial Disparity in Subprime Lending

Amid growing concern about subprime mortgage originations, studies have shifted their focus to the racial discrepancy in subprime lending and to the cost of credit from access to mortgage capital for African-American borrowers and neighborhoods (Reid & Laderman, 2009). The emergence and surge of risk-based subprime mortgages stemmed from the adoption of three acts. The first is the Depository Institutions Deregulation and Monetary Control Act (DIDMCA) in 1980, which removed the ceiling of mortgage interest rates payable on deposit. The second act is the Alternative Mortgage Transaction Parity Act (AMTPA) in 1982, which allowed lenders to provide not only fixed-rate mortgages but also additional mortgage transactions, such as the adjustable-rate loan, balloon payment loan, or interest-only loan. Thanks to technological improvements, future risks were automatically calculated, taken into account underwriting with the use of credit scores, and mortgage securitization for investors in the secondary market. The third act is the Tax Reform Act of 1986 (TRA), which prohibited interest deductions on consumer loans but still

allowed deductions on home purchase mortgages (Chomsisengphet & Pennington-Cross, 2006; Green & Malpezzi, 2003; Quercia et al., 2011).

Due to banking deregulation as well as technological advancement, risk-based mortgages made it possible to create a tailored mortgage based on borrower's credit risks, which was deemed to open a new door for those who were not qualified for prime mortgages (Bocian, Li, Reid, & Quercia, 2011). Even former Federal Reserve Board (FRB) Chairman Alan Greenspan mentioned at the Federal Reserve System's Fourth Annual Community Affairs Research Conference in Washington, D.C. (April 8, 2005), "Where once marginal applicants would have simply been denied credit, lenders are now able to quite efficiently judge the risk posed by individuals and price that risk appropriately (Federal Reserve Board, 2005¹)." The risk of default associated with lending to riskier borrowers for mortgage origination was offset by charging higher interest rates or by modifying mortgage transactions so that they included high-cost upfront fees, prepayment penalties, balloon payments, or adjustable-rate loan. However, the surge of the subprime market, fueled by mortgage securitization in the 1990s, brought new concerns that minority borrowers were disproportionately targeted for subprime or higher-cost loans. Research has shown that many subprime borrowers (as many as half) could have qualified for less costly prime mortgages (Barwick, 2010), and high-cost mortgages were originated in neighborhoods with high concentrations of minority residents (Bocian et al., 2011).

An early study on subprime lending addressed the association between neighborhood characteristics and subprime refinancing from 1993 to 1998 in Chicago by looking at the subprime lending institutions using HMDA data. This study found that African-American neighborhoods were more likely to receive refinance lending originated by subprime institutions than were White neighborhoods (Immergluck & Wiles, 1999). Also, they found that most of the mortgage lenders who originated refinance loans in White and higher-income neighborhoods were prime lenders, and they underserved African-American and lower-

¹ <https://www.federalreserve.gov/BoardDocs/speeches/2005/20050408/>

income neighborhoods during the period (Immergluck & Wiles, 1999). Calem, Hershaff, and Wachter (2004), employing various neighborhood characteristics as well as borrowers' characteristics in seven cities, including Atlanta, Baltimore, Chicago, Dallas, Los Angeles, New York, and Philadelphia, in 1997 and 2002, investigated the allocation of subprime mortgage origination. The result showed that census tracts with higher proportions of households headed by African-Americans were consistently and positively associated with the likelihood of subprime origination rather than prime origination when compared to neighborhoods with households headed by Whites. This was true even after controlling for various economic factors, including the capitalization rate, the percent of residents with high-risk credit scores, and the percentage with no credit ratings.

Studying prevalence of subprime lending was difficult until the later revision of HMDA in 2004. Prior to that, the list of lending institutions that the U.S. Department of Housing and Urban Development (HUD) developed was the only resource for figuring out the likelihood of prime or subprime origination (Avery, Canner, & Cook, 2005). Most studies identified subprime loans by referencing the HUD's list of HMDA lenders. The downside of using that list was that institutions with less than \$30 million in assets and branches in MSAs were not listed. Therefore, a model based on the list might have potential measurement errors because subprime lending has traditionally been most common among small mortgage companies (Wyly, Atia, & Hammel, 2004).

HMDA in 2004, however, revised its report and began to request that all lenders, including small lending institutions, report the rate spread between the APR at the time of the loan origination and the market APR that HMDA estimated based on survey results. From the revision, studies, instead of looking at lending institutions that HUD listed, began to use the rate spread to identify subprime mortgages. With the new criteria, Lei, Ratcliffe, Stegman, and Quercia (2008) addressed the association between the lending pattern for high-cost mortgages, neighborhood attributes including racial composition and income level, and housing market in Atlanta. The study used the revised HMDA of 2004, with which the authors could define high-price lending if the APR spread for the first originated lien mortgages was three percentage

points above the market rate with a comparable maturity. Based on the high-cost loan defined by the threshold above, they found that the proportion of high-cost loan origination in African-American neighborhoods was 12% higher for purchase loans and 14% higher for refinancing loans compared to White neighborhoods. Bocian, Ernst, and Li (2008), using HMDA data with their proprietary data, including credit scores, addressed the issue regarding lending disparities in the likelihood of receiving a higher-rate loan by race. They found a consistent result with those of other studies, that African-American people are more likely to receive high-cost home purchase and refinancing mortgages than are White borrowers in similar financial conditions (Bocian et al., 2008).

3. Mortgage Lending in Minority Neighborhoods During and After the Mortgage Crisis

The mortgage market peaked around 2006, then went into decline along with massive housing foreclosures. In the wake of the mortgage crisis, major conventional mortgage lenders have seriously tightened their underwriting practices, thus limiting the number of mortgages they underwrite (Immergluck, 2011, Federal Reserve Board of Governors, 2009, 2015). However, the tighter underwriting practices seriously hit particular populations: African-Americans and Hispanics are less likely to access mortgage capital when compared to Whites, being disproportionately affected by the tight mortgage market (Goodman, Zhu, & George, 2014; Immergluck, 2011; Richardson et al., 2016).

These disparities are evident in other research. Goodman et al. (2014) studied declines in the mortgage market from 2000 to 2013 by investigating the association among declines in the number of mortgages originated, credit scores, and the LTV by using data sets from HMDA and CoreLogic. They concluded that the origination number dropped by 54%, from 6.03 million in 2005 to 2.74 million in 2012 (Goodman et al., 2014). This decline seriously struck African-Americans and Hispanics. Although the share of purchase loans originated for White and Asian borrowers increased, the share for African-American and Hispanic borrowers declined (Goodman et al., 2014). In addition, regarding credit scores, the number of borrowers of home purchase loans with FICO scores of 660 or less dropped by 70% from 2000 to 2013, which indicates that those who had lower credit scores were less likely to access mortgage capital (Goodman et al., 2014).

A study by Richardson et al. (2016) looked at the mortgage origination number in three MSAs—St. Louis, Milwaukee, and Minneapolis—to investigate inequalities in access to mortgages by neighborhood racial composition. Although the study confirmed that neighborhoods with high proportions of the African-American population in all three MSAs were less likely to have access to mortgage capital than were White neighborhoods, serious disparities were observed in the Milwaukee MSA: The White population, making up 70% of the total population in the MSA, received 81% of the total number of loans in the MSA, whereas the African-American population, making up only 16% of the total population, received less than 4% of all loans. Furthermore, the mortgage application denial rate differed by the borrower's race—29% for White applicants and 53% for African-American applicants (Richardson et al., 2016). To support their findings from their descriptive analysis, the researchers also included a regression analysis at the neighborhood level with a dependent variable, including the mortgage origination per capita, and with limited independent variables, including racial composition, median income, homeowner occupancy, and poverty level. Unfortunately, they omitted credit score and other factors associated with lending making it difficult to support their conclusion that race negatively influenced mortgage origination.

Looking at FHA mortgages and conventional mortgages, Immergluck (2011) studied lending channels during the crisis period by neighborhood racial composition. In particular, his study examined geographical differences in the home purchase mortgage distribution between FHA and government-sponsored enterprises (GSEs), both of which became the main lenders after the mortgage market collapse in 2006. The study also is concerned that FHA mortgages are more costly mortgages than conventional mortgages so that lending disparities in access to FHA over conventional loans may raise a fair lending issue (Immergluck, 2011). Including loan risks, property types, MSA-level variables, and neighborhood characteristics including the median age of housing units, home value, poverty rate, and racial composition, the study finds: the lower the credit score of a mortgage applicant, the more an FHA loan is likely to be originated, and the ZIP code racial and ethnic composition are statistically significant and positively associated with the odds of FHA-insured loan origination. However, this study did not address if FHA mortgage lending

was disproportionately concentrated in African-American neighborhoods controlling for income and high credit scores. This study does not explain whether African-American neighborhoods receiving higher rates of FHA lending also have lower credit scores that would preclude qualifying for a conventional mortgage.

4. Research Hypotheses

Based on results of these previous studies, we know that neighborhoods with higher proportions of the African-Americans have been less likely to have access to mortgages in terms of quality and quantity as far back as the start of institutionalized redlining in the 1930s. Furthermore, after the loan crisis, the mortgage market shrank and only a limited number of people could originate mortgages. Therefore, we hypothesize that neighborhoods with more African Americans will have less access to conventional mortgages neighborhoods and the access they have will be to costlier loans both during and after the mortgage crisis

III. Methodology

This report we undertake three types of analyses. Two of them are essentially descriptive of patterns of mortgage lending – charts and maps – while the third method uses multivariate regression techniques to examine patterns of mortgage lending controlling for multiple causes.

1. Descriptive Analysis

The study begins with a description of the quantity and quality of residential mortgages originated in three periods, including the boom (from 2004 to 2007, Period 1), bust (from 2008 to 2011, Period 2), and recovery (from 2012 to 2015, Period 3) of the mortgage market in the five MSAs in Ohio including the Cleveland, Cincinnati, Columbus, Dayton, and Toledo MSA. First, the study looks at the overall transition of mortgage origination by neighborhood attributes in five MSAs in Ohio, addressing the diverse facets of mortgage lending patterns to include (1) the number of mortgage originations per 100 owner-occupied housing units as the quantity indicator, (2) the median subprime share as a quality indicator, (3) the median APR spread as a quality indicator, and (4) the FHA share as quantity indicator. Second, this study uses the geographic information system (GIS) to investigate where mortgage originations have occurred in each MSA, overlaying them on neighborhood attributes.

Data Sources

HMDA, the US Census, the American Community Survey (ACS), and data from CoreLogic© provide the cumulative data set for this descriptive analysis. HMDA offers loan data at the mortgage application level, including mortgage types, collateral types, applicants' attributes, and geographic information at the census tract level. Census and ACS data contain neighborhood attributes. However, the publicly obtainable HMDA data sets omit credit scores. Credit score is an important consideration in lending, and its omission from the analysis creates omitted variable bias, thus inhibiting the accurate capture of lending patterns. Therefore, this study additionally uses mortgage origination data from CoreLogic©, including loan-level FICO credit score information at origination. Because mortgage origination data from CoreLogic© offer

geographical information only at the ZIP code level, all information was geographically aggregated to the ZIP code level and the ZIP code is used as the geographic boundary for this analysis.

However, while the Census and ACS five-year Estimates after 2011 offer ZIP code–level neighborhood information, HMDA does not. To transfer from census tract-level HMDA data to ZIP code–level data, this study uses crosswalk files from the Missouri Census Data Center (MABLE)², which correspond to the 2000 Census boundaries, and from HUD³, which offers both the 2000 and 2010 Census boundaries.

Time Periods

Next, to track the flow of mortgage lending before, during, and after the mortgage crisis, we divide our study periods into three periods – (1) the mortgage boom period from 2004 to 2007, (2) the mortgage crisis period from 2008 to 2011, and (3) the mortgage recovery period from 2012 to 2015. These divisions mitigate the impact of temporal changes in the housing market, such as housing market saturation or new housing construction that directly influence the mortgage origination count. The sources of demographic information by ZIP code vary by period: Period 1 uses the 2000 Census, Period 2 uses the 2011 ACS five-year estimate (2007-2011), and Period 3 uses the 2015 ACS five-year estimate (2011-2015).

Measuring the Quality and Quantity of Mortgages Originated

From the HMDA data, we extract the mortgages for first lien, home purchase, and owner-occupied purposes to examine the quantity and quality of mortgages originated. Mortgage quantity is based on the count of mortgages originated in the ZIP Code, describing how many mortgages a neighborhood received. For the quality of mortgages, the study includes three types of mortgages: the rate of conventional (prime) mortgage originations, subprime loans as share of all lows, and FHA-insured mortgages as a share of all

² <http://mcdc.missouri.edu/>

³ https://www.huduser.gov/portal/datasets/usps_crosswalk.html

loans in the neighborhood. In addition, to investigate the quality of mortgages we use the APR spread. This variable allows us to understand where expensive mortgages were originated.

The Rate of Conventional Mortgage Originations

To make the first variable, rate of conventional mortgage origination, we first determine if a mortgage is conventional (prime) or subprime. We employ the well-used threshold to determine this: If a mortgage has its interest rate with a risk premium/ APR spread of 3% or above the market rate, then it is subprime, and otherwise, it is prime. After distinguishing loan types, we make the annualized conventional mortgage origination count for each tract and transferred this to the ZIP code-level by using crosswalk files from MABLE and HUD. Furthermore, the annualized ZIP code-level mortgage origination counts are aggregated for each of our three study periods. Finally, the conventional mortgage origination count at the ZIP code level for each period is transformed to a normalized number, considering the different housing units of each ZIP code boundary. To transform the count to a normalized number, we divide the mortgage origination count by the number of owner-occupied housing units in a neighborhood. In addition, considering that this is the neighborhood study, by multiplying 100 (owner-occupied units), the variable becomes the conventional mortgage origination count per 100 owner-occupied units or the rate of conventional mortgage originations (hereafter, the rate of originations).

$$P_{ij} = \frac{p_{ij}}{h_{ij}} \times 100$$

P_{ij} : Rates of conventional mortgage origination in ZIP j in Period i

p_{ij} : Conventional mortgage origination count in ZIP j in Period i

h_{ij} : Owner-occupied housing in ZIP j in Period i

Subprime share

The subprime share is made by dividing the subprime mortgage origination count in ZIP j in Period i by the total mortgage origination count in ZIP j in Period i , including the conventional mortgage origination count, subprime mortgage origination count, and FHA mortgage origination count.

$$S_{ij} = \frac{s_{ij}}{p_{ij} + s_{ij} + f_{ij}} \times 100$$

S_{ij} : Subprime share in ZIP j in Period i

s_{ij} : Subprime mortgage origination count in ZIP j in Period i

p_{ij} : Conventional mortgage origination count in ZIP j in Period i

f_{ij} : FHA mortgage origination count in ZIP j in Period i

FHA mortgage share

The FHA mortgage share is made by dividing the FHA-insured mortgage origination count in ZIP j in Period i by the total mortgage origination count (including the sum of count of conventional mortgages, subprime mortgages, and FHA mortgages).

$$F_{ij} = \frac{f_{ij}}{p_{ij} + s_{ij} + f_{ij}} \times 100$$

F_{ij} : FHA mortgage share in ZIP j in Period i

p_{ij} : Conventional mortgage origination count in ZIP j in Period i

s_{ij} : Subprime mortgage origination count in ZIP j in Period i

f_{ij} : FHA mortgage origination count in ZIP j in Period i

APR spread

We use two resources to make an annual percentage rate (APR) spread variable: data on initial interest rates at origination from CoreLogic© and Average Prime Offer Rates Tables⁴ from the Federal Financial Institutions Examination Council (FFIEC). CoreLogic© has information on the initial interest rate at origination, whereas FFIEC offers the estimated market rate based on a survey by HMDA. Because FFIEC renews the estimated market rate five times a month and CoreLogic© offers only an origination month and year (but not the date), we use the mean estimated market rate each month for making the spread at the origination level. Finally, we convert an APR spread at the loan origination level to information at the ZIP code level. To do this, we use the median APR spread, excluding outliers.

⁴ <https://www.ffiec.gov/ratespread/aportables.htm>

Neighborhood Attributes

This study extracts neighborhood economic and demographic information at the ZIP code level mainly from the 2000 Census, 2011 ACS, 2015 ACS, and CoreLogic©, using the 2000 Census for Period 1, 2011 ACS for Period 2, and 2015 ACS for Period 3. The proportion of African-American population or White population in a ZIP code comprise the neighborhood racial characteristics. For neighborhood economic status, we use two variables – the median family income and the median credit score in a neighborhood. We expect that a higher median family income may work positively for mortgage lending. The median family income is extracted from Census and ACS. Additionally, we use the median credit score at the ZIP code level from CoreLogic©. Corelogic© data set includes loan-level FICO credit score information at the origination as well as geographical information of housing purchased. We constructed the median credit score for a neighborhood by accumulating all credit score at the ZIP code level. As Chomsisengphet and Pennington-Cross (2006), Immergluck (2011), and Calem, Gillen, & Wachter (2004) indicated, we expect that credit score is an important factor for mortgage origination and for an APR spread. Thus, the higher the credit score, the higher the conventional mortgage origination and the higher the APR spread. In addition, FHA mortgages are designed for those who have lower credit scores; thus, we expect that the higher the credit score, the lower the FHA share.

Descriptive Analysis Methods

We first create descriptive charts to show the overall changes in mortgage lending by neighborhood racial composition in the five MSAs in Ohio. For this descriptive analysis, the study looks at six factors – the flow of mortgage originations from 2004 to 2015 (Period 1 to 3), changes in median credit scores associated with mortgage originations from Period 1 to 3, changes in access to conventional mortgage, subprime share, APR spread, and FHA Share by neighborhood race from Period 1 to 3. We expect to understand (1) how the mortgage market changed over time during this study period and (2) the differences in access to mortgages in predominantly White and African-American neighborhoods in each period.

Second, the study investigates the differences in access to mortgages and cost of mortgages by neighborhood attributes including income, credit scores, and racial composition (see Table 1). Furthermore, this study looks at the simultaneous influence of two factors, either credit score and race or income and race on each of the four dependent variables in each MSA in each period. We know that financial credibility is significant for the mortgage lending. Therefore, we investigate the association between mortgage lending and neighborhood racial composition by controlling the neighborhood financial credibility.

Lastly, we create maps to describe the spatial patterns of the quantity and quality of residential mortgages originated, using Geographic Information System (GIS). By overlaying four descriptive factors – rates of originations, subprime share, APR spread, FHA mortgage share – on neighborhood credit scores and racial composition, we area describe the geography of access to credits and cost of credit in each MSA. In particular, we expect that access to mortgages and the cost of mortgages by neighborhood attributes varies by MSA. For instance, the extent to which African-American neighborhoods with lower-credit scores have access to mortgage capital is not uniform among five MSAs. GIS Maps made allow us to visually compare the geography of capital within each MSA and to compare across them. In addition, maps also allow us to visually investigate the mortgage originations over time by neighborhood attributes in each MSA.

Table 1 Neighborhood Categorizations Used in this Report

Neighborhood Income		
High-Income Neighborhoods		Neighborhoods where median family income is over 120 percent of MSA area median income (AMI)
Medium-Income Neighborhoods		Neighborhoods where median family income is between 80.1 and 120 percent of MSA-AMI
Low-Income Neighborhoods		Neighborhoods where median family income is 80 or less of MSA-AMI
Neighborhood Credit Score (associated with conventional mortgage originations)		
High-Credit Score Neighborhoods	Period 1	Neighborhoods where the median FICO credit score is over 700
	Period 2 and 3	Neighborhoods where the median FICO credit score is over 740
Middle-Credit Score Neighborhoods	Period 1	Neighborhoods where the median FICO credit score is between 660.1 and 700
	Period 2 and 3	Neighborhoods where the median FICO credit score is between 700.1 and 740
Lower-Credit Score neighborhoods	Period 1	Neighborhoods where the median FICO credit score is 660 or lower
	Period 2 and 3	Neighborhoods where the median FICO credit score is 700 or lower
Neighborhood Racial Composition (African-American neighborhoods)		
Predominantly African-American Neighborhoods or Mostly-African-American Neighborhoods		Neighborhoods where proportion of African-Americans is over 30 percent of the total population*
African-American-Mixed Neighborhoods		Neighborhoods where proportion of African-American is between 15.1 and 30 percent of the total population*
Partly-African-American Neighborhoods		Neighborhoods where proportion of African-Americans is 15 percent or fewer of the total population
African-American Neighborhoods		Neighborhoods where proportion of African-Americans is over 15 percent of the total population**
Neighborhood Racial Composition (White neighborhoods)		
Predominantly White neighborhoods or Mostly-White Neighborhoods		Neighborhoods where proportion of Whites is over 85 percent of the total population
White-Mixed Neighborhood		Neighborhoods where proportion of Whites is between 70.1 and 85 percent of the total population
Partly-White Neighborhoods		Neighborhoods where proportion of Whites is 70 percent or fewer of the total population
Neighborhood Racial Composition × Neighborhood Income		
White (African-American) Neighborhoods with Higher-Incomes		Neighborhoods where proportion of Whites (African-American) is over 85 (15) percent of the total population and median family income is over 120 percent of MSA area median income (AMI)
White (African-American) Neighborhoods with Middle-Incomes		Neighborhoods where proportion of Whites (African-American) is over 85 (15) percent of the total population and median family income is between 80.1 and 120 percent of MSA-AMI
White (African-American) Neighborhoods with Lower-Incomes		Neighborhoods where proportion of Whites (African-American) is over 85 (15) percent of the total population and median family income is 80 or lower of MSA-AMI
Neighborhood Racial Composition × Neighborhood Credit Score		
White (African-American) Neighborhoods with Higher-Credit Score	Period 1	Neighborhoods where proportion of Whites (African-American) is over 85 (15) percent of the total population and the median FICO credit score is over 700
	Period 2 and 3	Neighborhoods where proportion of Whites (African-American) is over 85 (15) percent of the total population and the median FICO credit score is over 740
White (African-American) Neighborhoods with Middle-Credit Score	Period 1	Neighborhoods where proportion of Whites (African-American) is over 85 (15) percent of the total population and the median FICO credit score is between 660.1 and 700
	Period 2 and 3	Neighborhoods where proportion of Whites (African-American) is over 85 (15) percent of the total population and the median FICO credit score is between 700.1 and 740
White (African-American) Neighborhoods with Lower-Credit Score	Period 1	Neighborhoods where proportion of Whites (African-American) is over 85 (15) percent of the total population and the median FICO credit score is 660 or lower
	Period 2 and 3	Neighborhoods where proportion of Whites (African-American) is over 85 (15) percent of the total population and the median FICO credit score is 700 or lower

* The Federal Housing Enterprises Financial Safety and Soundness Act of 1992 designates underserved minority neighborhoods as neighborhoods where 30% of total population is Minority residents.

**Due to limited number of predominantly African-American neighborhoods with higher financial credibility, we create African-American neighborhoods by combining African-American-Mixed neighborhoods and Mostly-African-American neighborhoods in the descriptive analysis.

2. Multivariate Analysis

We use multivariate regression analysis to investigate lending patterns in African-American neighborhoods, while accounting for the simultaneous consideration of other factors influencing mortgage lending. The lending patterns investigated, as in the descriptive analysis, include conventional mortgage origination number in a neighborhood during Period 1 (2004-2007), Period 2 (2008-2011), and Period 3 (2012-2015), the share of subprime loans of all loans originated in a neighborhood (subprime share) in Period 1, the share of FHA loans of all loans originated in a neighborhood (FHA share) in Period 2 and 3, and the APR spread within the neighborhood as dependent variables in Period 2 and 3. For the share of subprime loans, share of FHA loans, and the APR spread, we use ordinary least squares (OLS) regressions to control for other potential causes of neighborhood level differences in lending. To investigate the quantity of mortgages in neighborhoods we use the count of conventional mortgage originations in a neighborhood as a dependent variable, while controlling for the number of owner-occupied homes in the neighborhood. To analyze the count of mortgages originated, we use negative binomial regression models, as they are a better fit for modeling non-negative count data.⁵

Statistical Modelling

The main hypothesis is that lending patterns in predominantly African-American neighborhoods are different from those in predominantly White neighborhoods, in terms of quality and quantity. To rule out other potential causes of observed differences, we identify other factors that may influence mortgage origination and mortgage pricing. Perhaps the most important consideration in lending is the perception of risk on the part of lender. Because mortgages, unlike other investments, are long-term monetary investments and lenders are pursuing profit maximization (Calem, Gillen, & Wachter, 2004; Munnell et al., 1996), lenders regard the risks of return or on the net present value (NPV) of loans as important, accounting for

⁵ Because mortgage origination is a non-negative count and is over-dispersed—that is the variance of the variable is significantly higher than the mean—a negative binomial regression model is more appropriate than an ordinary least-squares (OLS) linear regression model.

future risks (Lei et al., 2008; Yinger, 1995). Based on Yinger's (1995) model accounting for the rate of return, we frame a conceptual lending model for identifying lending patterns in neighborhoods. The investment decision from the lender's perspective is written as follows:

$$I = f(r, M)$$

I: Decision for Mortgage Origination

r: Rate of Return

M: African-American Neighborhoods

The rate of return depends on three functions: the probability of default, the cost of default, and loan terms (Yinger, 1995). Based on the discussion, the rate of return is written as follows:

$$r = g(D, C, T)$$

D: Probability of Default

C: Cost of Default

T: Loan Terms

g: Function

The probability of default is based on the neighborhood characteristics and loan terms. The default probability depends on the characteristics of neighborhood P and the terms of loan T. For instance, the higher median credit score of the neighborhood is associated with a lower default rate in the neighborhood. Specifically, one default in the neighborhood is expected to causes further defaults nearby (Immergluck & Smith, 2006); thus, the neighborhood's economic status is an important factor in the default risk in the neighborhood as well as in the underwriting practices supporting the mortgage origination decision. Calem, Gillen, et al. (2004) also discussed that economic conditions and subprime mortgage lending, and they mentioned that the better the neighborhood, the lower the number of subprime originations. In other words, neighborhoods with strong economic condition is more likely to receive conventional mortgages.

$$D = h(P_F, T)$$

D: Probability of Default

P_F: Neighborhood Characteristics associated with the probability of Foreclosure

T: Loan Terms

h: Function Term

Next, the cost of default depends on the differences between the expected value of the property and the amount of the loan amortized. The housing market condition in a neighborhood becomes the key factor. For instance, if the housing value is over the loan amount amortized, then the cost of default will be minimized. However, if the housing value is lower than the loan amount amortized, then lender may need to incur some debts left. Thus, the cost of default is described as follows:

$$C = k(P_C, T)$$

P_C: Neighborhood Characteristics Associated with Costs of Foreclosure

T: Loan Terms

k: Function Term

$$r = g(f(P_F, T), k(P_C, T), T) = \tilde{g}(P_F, P_C, T)$$

$$I = f(\tilde{g}(P_F, P_C, T), M)$$

$$I = \tilde{f}(P_F, P_C, T, M)$$

Based on the conceptual framework above, we create the lending model to investigate four different mortgage lending patterns.

$$LP_{Z,T} = \beta_1 * RACE_{Z,T} + \beta_2 * NBHD.porbDef_{Z,T} + \beta_3 * NBHD.costDef_{Z,T} + \beta_4 * LT_{Z,T} + \beta_5 * NBHD.other_{Z,T} + \varepsilon_{Z,T} \quad (Z=1,2,3 \dots, n : T=1,2, \text{ or } 3,) \quad (1)$$

LP_{Z,T}: Mortgage Lending Pattern in Neighborhood Z in Period T

RACE_{Z,T}: Neighborhood Racial Composition

NBHD.porbDef_{Z,T}: Neighborhood Characteristics Associated with the probability of Foreclosure in Neighborhood Z in Period T

NBHD.costDef_{Z,T}: Neighborhood Characteristics Associated with Costs of Foreclosure in Neighborhood Z in Period T

LT_{Z,T}: Loan Term in Neighborhood Z in Period T

NBHD.other_{Z,T}: Other Neighborhoods Attributes in Neighborhood Z in Period T

Factors Associated with the Neighborhood Racial Composition, the Probability and Cost of Default, Loan Term and Neighborhood Attributes

We control for a number of factors associated with patterns of neighborhood lending to rule out other possible causes of neighborhood lending patterns. A discussion of how we measure those factors follows.

Neighborhood Racial Composition

A key question for this study is how do lending patterns differ by neighborhood racial composition? As described in the descriptive analysis methodology, we use the proportion of African-Americans in a neighborhood (**Proportion AA**). We calculated them with Census 2000 for Period 1, ACS 2011 for Period 2, and ACS 2015 for Period 3

Factors Associated with the Probability of Default

As in the descriptive analysis, we examine the relationship of the neighborhood's median credit score and median family income with lending patterns. In addition, we take into account self-employment in the neighborhood as a measure of risk and the level of education in the neighborhood as a measure of knowledge of the system of lending.

- Median credit score

As Chomsisengphet and Pennington-Cross (2006) and other studies indicated, we expect the credit score to be the most important factor in mortgage lending. The higher the median credit score in a neighborhood, the less the default risk in the neighborhood. Given that, we expect that lenders are more likely to originate conventional mortgages and less costly mortgages for neighborhoods with higher median credit scores. In this analysis, we use the median credit score associated with all mortgage originated in a neighborhood (**Credit Score**) from the CoreLogic© as a measure of risk in the neighborhood.

- Median family income

A higher median family income is associated with a lower probability of default. Lower-income families are expected to be more likely to experience default due to the limited financial leeway for absorbing unexpected expenditure. Therefore, the foreclosure rate is higher in neighborhoods with higher proportions of lower income families. Given this expectation, we predict that lenders are more likely to (1) disinvest, (2) give neighborhoods subprime mortgages, and (3) require higher interest rates for neighborhoods with lower median family incomes. In this statistical analysis, we use the log of the median

family income in a neighborhood (**Log Income**) from Census 2000 for Period 1, ACS 2011 for period 2, and ACS 2015 for Period 3 as a measure of risk within the neighborhood.

- Self-employment rate

The self-employment rate (**Selfemployment**) indicates the stability of the neighborhood economy. Lenders tend to investigate those who are self-employed in depth regarding their qualifications for mortgage originations, particularly concerning their length of employment and their personal and business incomes to identify the stability of their income. Therefore, the higher the self-employment rate in a neighborhood, the lower the expected income stability, and the higher the risk. We thus expect that lenders are more likely to originate (1) fewer prime mortgages and (2) costlier mortgages for neighborhoods with higher proportions of self-employment. We use data from Census 2000 for Period 1, ACS 2011 for period 2, and ACS 2015 for Period 3.

- Proportions of individual 25 years of age or older with a college degree

Higher education attainment is associated with financial savvy and contributes to the better economic conditions in a neighborhood (Calem, Hershaff, et al., 2004). Thus, foreclosure rates are lower in neighborhoods with better economic conditions. We expect that for neighborhoods with higher proportion of people having higher education attainment, lenders will be more likely to (1) invest their funding, (2) originate conventional mortgages, and (3) require lower APR spreads. We use data from Census 2000 for Period 1, ACS 2011 for period 2, and ACS 2015 for Period 3.

Factors Associated with the Cost of Default

In addition to factors associated with lending risk, we also control for the cost of default to the lender, including the changes in housing prices, the turnover rate of houses sold, the fraction of the neighborhood dwellings that are rental housing, neighborhood the vacancy rate, the capitalization rate, and the median age of housing units in the neighborhood.

- House price percentage changes

The house price percentage change describes percentage change in the housing price between two selected periods (**House Price Change**). Positive and larger housing price changes indicate the better condition of housing market in a neighborhood, which reduce the expected cost of default, and reduced lender’s risk. We expect that even if a borrower defaults, a lender is more likely to be able to retrieve debts unpaid within a better housing market. Thus, lenders are more likely (1) to invest in prime mortgages and (2) to originate less costly mortgages for neighborhoods with higher housing price changes. To calculate this variable, we use data Census 2000, ACS 2011 and 2015, and GeoLytics©. GeoLytics© provides geographic information that is geographically normalized to other survey years because geographical boundaries are continuously changing.

$$\text{Housing Price Change} = \frac{(\text{Current Housing Price} - \text{Past Housing Price})}{\text{Past Housing Price}} \times 100 (\%)$$

- Turnover rate

We include the turnover rate defined as the number of housing units sold divided by the total number of housing units for sale (**Turnover**), expecting that the higher the turnover rate, the healthier the housing market (Calem, Hershaff, et al., 2004; Lei et al., 2008; Ling & Wachter, 1998). We calculate this variable by dividing the total mortgage origination number, including prime, FHA, and subprime loans during each period, which are from HMDA, by the number of owner-occupied units in a neighborhood from Census 2000 for Period 1, ACS 2011 for Period 2, and ACS 2015 for Period 3. We predict that neighborhoods with higher turnover rates are associated with (1) higher prime origination number, (2) fewer subprime loan originations, and (3) less APR spread.

$$\text{Turnover Rate} = \frac{\text{Total mortgage Origination Counts}}{\text{Owner Occupied Units}} \times 100 (\%)$$

- Proportion of rental housing

The proportion of rental housing within the neighborhood tells us the economic condition of a neighborhood. We expect that the wealth of the neighborhood can be negatively associated with the proportion of rental units in the neighborhood. Thus, lenders will be less likely (1) to invest in prime

mortgages and (2) to originate less costly mortgages for neighborhoods with higher proportions of rental units. We calculate the rate of rental housing units by dividing the number of rental units by the total number of housing units in a neighborhood with Census 2000 for Period 1, ACS 2011 for period 2, and ACS 2015 for Period 3.

- Vacancy rates

Originating mortgages in neighborhoods with high vacancy rates will be risky for lenders. Lenders attempt to retrieve their investments by selling the housing in which they invested to mitigate the unpaid debt. If the vacancy rate is high in a neighborhood, the housing will most likely be unable to be sold shortly after the foreclosure, which leads higher holding costs as well as a reduction of the housing price. We use the mean of vacancy rate in a neighborhood from Census 2000 and ACS 2011 and 2015.

- Capitalization rate

The capitalization rate indicates risks of investment; a higher capitalization rate is associated with lower expectations of housing price increases, or future housing prices are uncertain (Calem, Hershaff, et al., 2004; Wachter, Russo, & Hershaff, 2005). Empirical studies showed that the appreciation of owner-occupied housing units is generally faster in a neighborhood with a lower capitalization rate (Lei et al., 2008). Thus, we expect that lenders are more likely (1) to make fewer mortgage originations and (2) to originate costly mortgages for neighborhoods with higher capitalization rate. We calculate a capitalization rate by dividing the neighborhood-level annualized median rent by the neighborhood-level median housing value from Census 2000 for Period 1, ACS 2011 for Period 2, and ACS 2015 for Period 3.

- Median age of housing units

The higher the median age of housing units, the lower the number of conventional mortgage originations and the higher the cost of mortgages. As Schill and Wachter (1993) explained, older homes, that are worse physical condition than the newer homes, imposes negative externalities on surrounding neighborhoods. Thus, lenders may not prefer to invest their money into neighborhoods with higher

concentration of aged housing. Considering these conditions, we expect that neighborhoods with older housing units negatively influence conventional mortgage originations (**House Age**).

Factors Associated with the Risk of Loans

The mortgage crisis demonstrated how loan term can be related to the risk of default. Therefore, we include in our modeling the median loan to value ratio in the neighborhood and the median debt to income ratio as a measure of default risk in the neighborhood.

- Median Loan to Value

A higher LTV is associated with a higher likelihood of foreclosures. Specifically, the likelihood of foreclosure is higher when LTV is higher due to the limited leeway to absorb the difference between the price of housing and the debt amount, the underwater situation. Hence, we expect that a higher LTV ratio within a neighborhood is associated with (1) fewer conventional mortgage originations and (2) a higher probability of mortgages being subprime and high cost. For this multivariate regression analysis, we employ two types of LTV ratios: median LTV accounting for all types of mortgages originated in a neighborhood (**LTV-all**) and LTV accounting only for conventional mortgages originated in a neighborhood (**LTV-conv**). The loan term linked to the risks of particular types of mortgage originated. Therefore, on the one hand, we use median LTV accounting for all mortgages originated with the aim of evaluating subprime shares and FHA shares which embraces all mortgage types; on the other hand, we use median LTV for conventional mortgages in order to evaluate conventional mortgage origination numbers and APR spreads for conventional mortgages. Both numbers are calculated using CoreLogic© data.

- Debt to income ratios (DTI)

Higher DTIs are generally more likely to induce higher likelihoods of default. Therefore, we expect that a higher median DTI in a neighborhood will be associated with (1) fewer prime mortgage originations and (2) a higher likelihood of mortgages' being subprime and high cost. As with LTV, we also prepare two types of DTIs—a median DTI in a neighborhood accounting for all mortgages originated (**DTI-all**) and a median DTI in a neighborhood accounting for conventional mortgages originated (**DTI-conv**). While using

DTIs for all mortgages originated for evaluating subprime share and FHA share which accounts for all mortgage types, and we use the DTI for conventional mortgages to evaluate conventional mortgage origination number and APR spreads for conventional mortgages. Both numbers are calculated with CoreLogic© data.

Other Neighborhood Characteristics

Other factors may influence either the willingness to lend on the part of banks or the availability of credit on the part of loan seekers. Therefore, we include the number banks of banks in the neighborhood normalized by the number of housing units. In the model of the count of conventional mortgages using negative binomial regression we include the number of housing units as a measure of size of the neighborhood. This is not necessary to include in the OLS regressions, as the dependent variable in those models is a ratio of the number of mortgages of a certain type as a proportion of all housing units in the neighborhood.

- Number of bank branch

We include ratio of the number of bank branch over the number of housing units in a neighborhood (**Bank Ratio**) to represent the access of neighborhoods to bank lending. Since 2000, mortgages have more frequently originated through the Independent Mortgage Banks (IMB) rather than local banks, although local banks have more knowledge about the neighborhoods in which they are located. In addition, if a bank is located near a property purchased, then the homeowner in that neighborhood will have more opportunity to discuss mortgages with that lender. In addition, due to CRA, a neighborhood where a bank branch is located can be expected to be more likely to receive mortgages. To calculate this variable, we use a bank location data set from the Federal Deposit Insurance Corporation (FDIC).

- Owner-occupied units

This is a control variable for the negative binomial models whose dependent variable is conventional mortgage origination. Because the sizes of neighborhoods and the sizes of potential inventories particularly

influence the mortgage origination number, we use this variable to control for the sizes of neighborhoods and inventories (**Owner-Occupied**).

Variables and Data Excluded from Models

We prepared a wide variety of variables for modeling; however, some variables are highly correlated with each other, which reduce the ability of the model to distinguish statistically significant results. In particular, some variables are highly and negatively correlated with the median income, including the proportion of rental housing, the vacancy rate, and the capitalization rate. The LTV for all mortgages is highly and negatively correlated with neighborhood credit scores. The proportion of individuals 25 years of age or older with a college degree is highly and positively correlated both with the median credit score and income. To facilitate the clarity of our results, we did not use these highly-correlated variables in the analysis. We also excluded two zip-codes from the study, one due to a lack of sufficient data for the neighborhood credit score, LTV and DTI, and another because an airport comprises more than half of the neighborhood. Furthermore, in this study, we excluded four counties who became part of one of our MSAs during the period under study: Morrow County, Union County, Preble County, and Ottawa County. Because they were not part of one of the MSA at the start of the study, we excluded them entirely.

We tested a number of models of neighborhood mortgage lending, but present only 2 for each MSA in the main body of this report. One model is a constrained model of lending (Model A) while a second model (Model B) includes an interaction terms between the median credit score and the proportion of African-Americans in a neighborhood ($CS \times AA$), between the median income and the proportion of African-Americans in a neighborhood ($INC \times AA$), or both. The inclusion of the interaction terms allows for us to model variations by racial composition given variations in credit scores and income in neighborhoods. Full modelling results are available in the Appendix.

IV. Changes in Mortgage Lending in Five Ohio MSAs since 2004

This section describes the overall changes in patterns of lending for three different mortgage types – conventional, subprime, and FHA – in five MSAs in Ohio between 2004 and 2015, dividing study years into three discrete periods: Period 1 is 2004-2007; Period 2 is 2008-2011; and Period 3 is 2011-2015. We also examine mortgage originations by neighborhood racial composition, particularly comparing White neighborhoods and African-American neighborhoods. We include four measures of mortgage access; the mortgage origination count as the quantity indicator of mortgages, and subprime share, APR spread, and FHA mortgage share as the quality indicator of mortgages.

1. Mortgage Lending at Flood, Ebb, and Rising Tide

The mortgage market experienced a tidal wave, having a flood in 2004, the ebb in 2010, and a rising tide after 2012. The overall mortgage origination count peaks around 2004 and 2005 and subprime mortgages surge in 2005 and 2006 before the decline begins. The bottom of the mortgage origination count is in 2010 and 2011, and it begins to recover after 2012 (Figure 1).

The total number of mortgages originated the five MSAs was over 100K in each of 2004 and 2005 (Figure 1 Annual Changes in the Count of Mortgage Originations, 2004 to 2015, Including Conventional Mortgages, FHA Mortgages, and Subprime Mortgages Figure 1), and totaled nearly 400K during all of Period 1 (Figure 2). In Period 1, conventional mortgages and high-cost subprime mortgages each were 74.8% and 14.3% of the mortgage market respectively, while the FHA mortgage share, 10.9% of the market, was the lowest share among them (Figure 3). During the mortgage crisis (Period 2), the total number of mortgage origination declined to below 50K in each of 2010 and 2011 (Figure 1), with a total of 200K throughout Period 2 (Figure 2), which half of the Period 1 total. In addition, unlike Period 1 where conventional mortgages dominate the market, conventional mortgage originations are only about half of all loans in Period 2; the total for Period 2, 108K, is one third the number it was in Period 1 (Figure 2). In addition, high-cost mortgages, which triggered the mortgage crisis, almost disappear from the mortgage market after 2009. By Periods 2 and 3, high-cost subprime mortgages comprise only 1.8% and 0.6% of the mortgage market in each period respectively (Figure 3). In the meantime, FHA

mortgages increase their share and act as a substitute for conventional mortgage capital during the crisis in Period 2: The share of FHA mortgage originations in the market increases from 10.9% in Period 1 to 44.9% in Period 2. After 2011 (Figure 3), the mortgage origination count seems to bounce back, and the level of access to mortgage capital nearly equals 2007 mortgage originations (Figure 1 and Figure 2). Conventional mortgages begin to increase their originations starting in 2012, and their origination count in Period 3 is about 1.5 times higher than Period 2 (Figure 2). Also, FHA originations maintain a higher number although their origination count declines from 91K to 74K, and their proportion in the market declines to 30.2% in Period 3 (Figure 2 and Figure 3).

Figure 1 Annual Changes in the Count of Mortgage Originations, 2004 to 2015, Including Conventional Mortgages, FHA Mortgages, and Subprime Mortgages

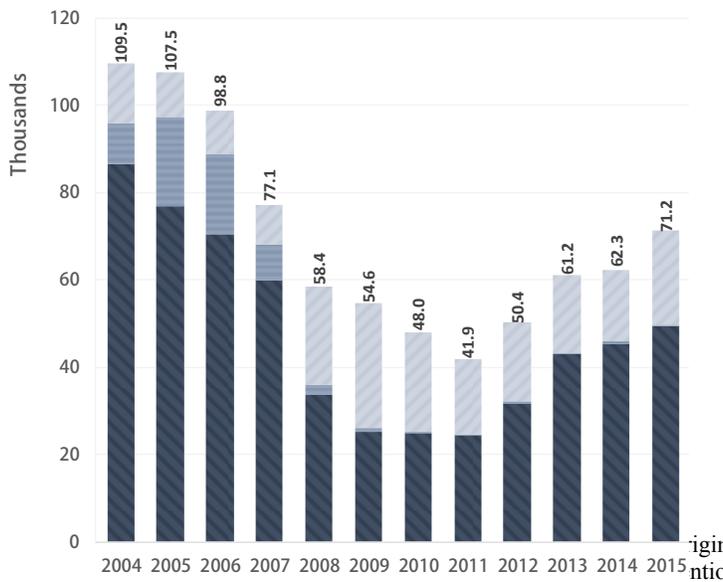
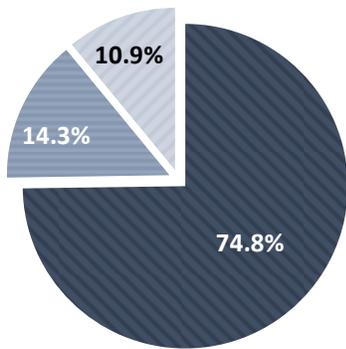
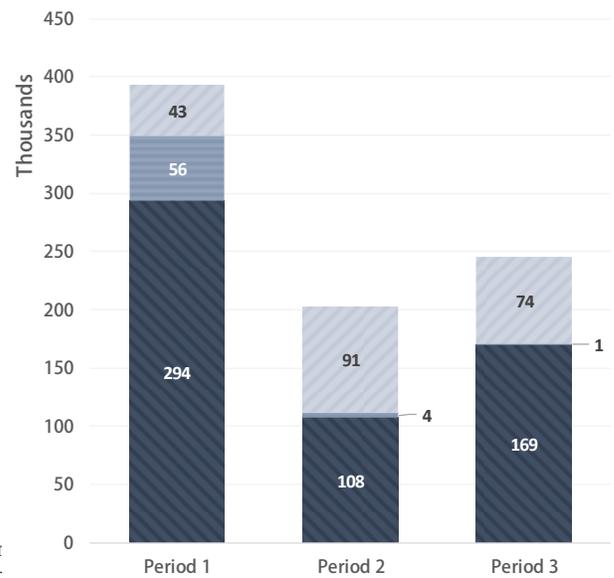
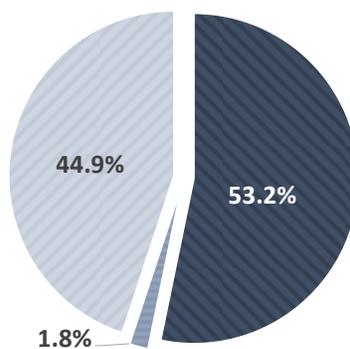


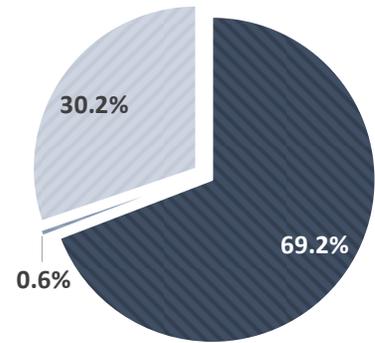
Figure 2 Changes in the Mortgage Origination Count by Period
Period 1: 2004-07 / Period 2: 2008-11 / Period 3: 2012-15



Period1
(N= 392,861)



Period2
(N= 202,851)



Period3
(N= 245,048)

■ Conventional ■ High-Cost Conventional ■ FHA

2. Median Credit Score Increases

While the mortgage market follows a tidal flow, the qualifying FICO credit score for conventional mortgage origination increases period to period. The proportion of neighborhoods with higher median FICO credit scores associated with conventional mortgage originations substantially increased over time. The proportion of neighborhoods with a median credit score for the mortgages originated of 700 or over increases from 54% in Period 1 to 90% in Period 2, and to 97% in Period 3 (Figure 4). However, neighborhoods with a median credit score of less than 660-- 14.4% of all mortgages in Period 1--do not exist in Period 3. Since the crisis, underwriting practices for conventional mortgage origination have become increasingly strict, causing a tight mortgage market where only borrowers with higher financial credibility have access to mortgage capital. The result is that we observe conventional mortgage originations only in neighborhoods maintaining higher median credit scores, at least 700 (Figure 4). Interestingly, the credit score for FHA mortgage originations also has increased since the crisis (Figure 5). In Period 1, 82% of neighborhoods in All MSAs have a median credit score for FHA mortgage origination of less than 660. During Periods 2 and 3, however, most neighborhoods have a median FHA credit score from 660 to 699, even though FHA is technically available to those with a score less than 600.

Figure 4 Distribution of Credit Scores for Conventional Mortgage Originations, Periods 1, 2, and 3

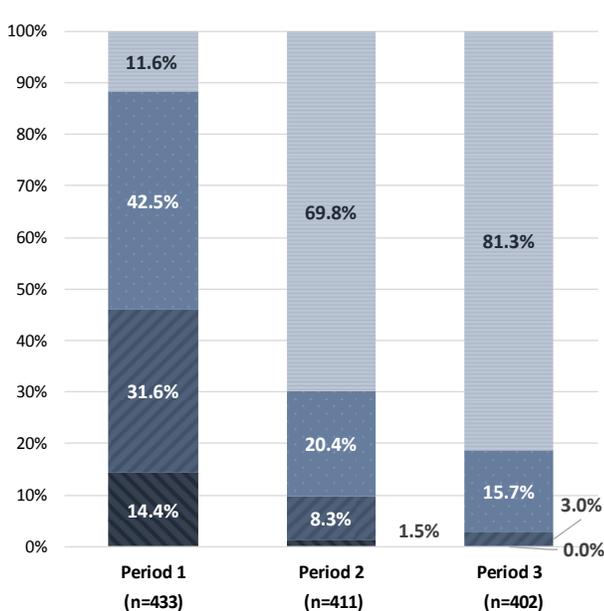
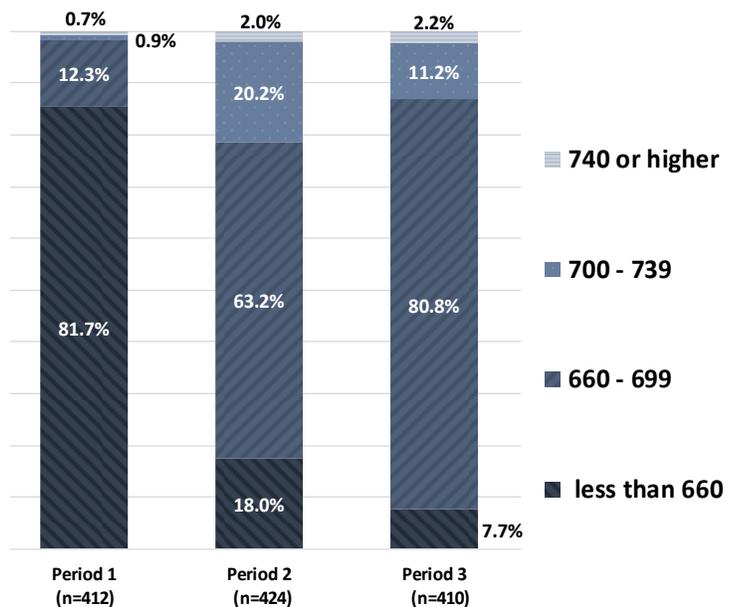


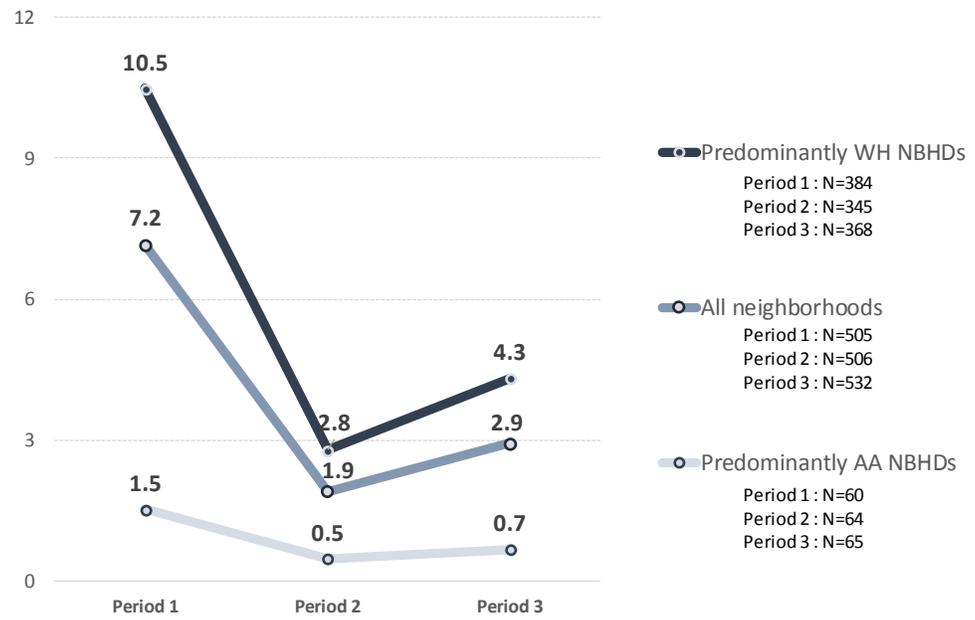
Figure 5 Distribution of Credit Scores for FHA Mortgage Originations, Periods 1, 2, and 3



3. Access to Conventional Mortgage Differs by Neighborhoods Race

Mortgage originations rose and fell and then began to rise again over the study period (Figure 1 and Figure 3). Rates of conventional mortgage originations at the neighborhood level follows this pattern, regardless of racial composition (Figure 6). The gap, however, between the rate of origination among predominantly White neighborhoods and African-American neighborhoods is large. For all MSAs in each period, the rate of originations in predominantly White neighborhoods is higher than that in predominantly African-American neighborhoods. In addition, rates of originations among predominantly African-American neighborhoods are always low, less than one conventional mortgage origination per 100 owner-occupied units in the neighborhood in Periods 2 and 3. This number indicates that predominantly African-American neighborhoods are much less likely to have access to mortgage capital than predominantly White neighborhoods, regardless of mortgage market.

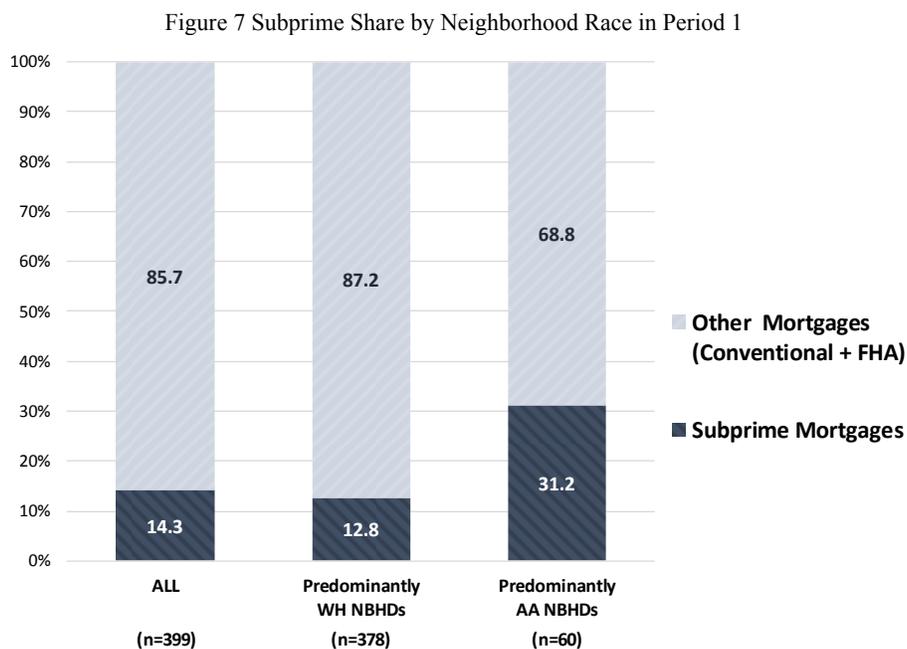
Figure 6 Race Median Rates of Conventional Mortgage Origination by Neighborhood Racial Composition



NOTE: Predominantly WH NBHDs: Neighborhoods where the proportion of Whites is over 85 percent of the total population
 Predominantly AA NBHDs: Neighborhoods where the proportion of African-Americans is over 30 percent of the total population

4. Subprime Share Hit African-American Neighborhoods

Across all MSAs during the surge of subprime mortgage lending in Period 1, predominantly African-American neighborhoods had higher proportions of subprime mortgages, when compared to predominantly White neighborhoods. Half of all neighborhoods had a rate of subprime lending of 14% or less among all neighborhoods in five MSAs (Figure 7). For predominantly African-American neighborhoods, half had a rate of subprime lending at 31%, more than twice that of the median predominantly White neighborhoods at nearly 13%. These results agree with findings from existing studies elsewhere.



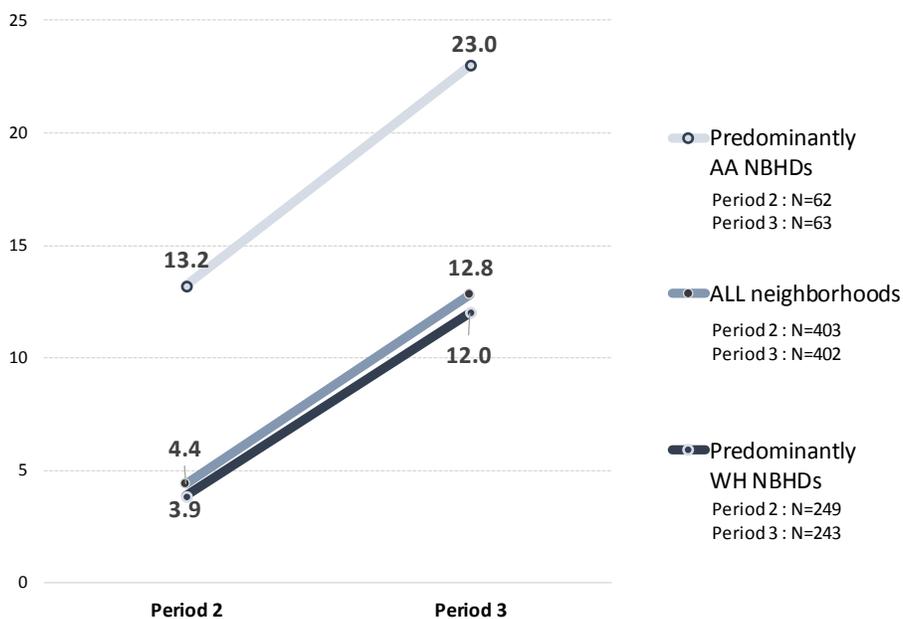
NOTE: Predominantly WH NBHDs: Neighborhoods where the proportion of Whites is over 85 percent of the total population
Predominantly AA NBHDs: Neighborhoods where the proportion of African-Americans is over 30 percent of the total population

5. High APR spread for African-American Neighborhoods but Low for White Neighborhoods

We examine the median neighborhood APR spread in Period 2 and 3 utilizing the interest rate data from CoreLogic© and the market rate data from HMDA to investigate the cost of mortgages. The results show that predominantly African-American neighborhoods, which had higher proportion subprime mortgages in Period 1, still receive conventional mortgages with higher APR spread in Period 2 and 3. Overall changes in APR spread between Period 2 and 3 show that the median APR spreads in predominantly White and African-American neighborhoods increase from Period 2 to Period 3. The median APR spread

among all neighborhoods is 4.4 basis points (bps)⁶ in Period 2 and 12.8 bps in Period 3. By neighborhood racial composition, the median APR spread among predominantly African-American neighborhoods is higher than that among predominantly White neighborhoods. The median spread among predominantly White neighborhoods is 3.9 bps in Period 2 and 12.0 bps in Period 3, which are about 10 bps lower than the median spread for predominantly African-American neighborhoods of 13.2 bps in Period 2 and 23.0 bps in Period 3. In addition, the gap between the two neighborhood types does not shrink in the market recovery period in Period 3. The gaps in median APR spreads are 9.3 bps in Period 2 and 11.0 bps in Period 3. This indicates that predominantly African-American neighborhoods appear to suffer from two constraints in Period 3: they have little access to mortgages and when they have access, the mortgages are expensive (Figure 6 and Figure 8). These results suggest that predominantly African-American neighborhoods may disproportionately receive higher interest rates both during the crisis and the recovery period.

Figure 8 APR Spread in Period 2 and 3 by Neighborhood Racial Composition



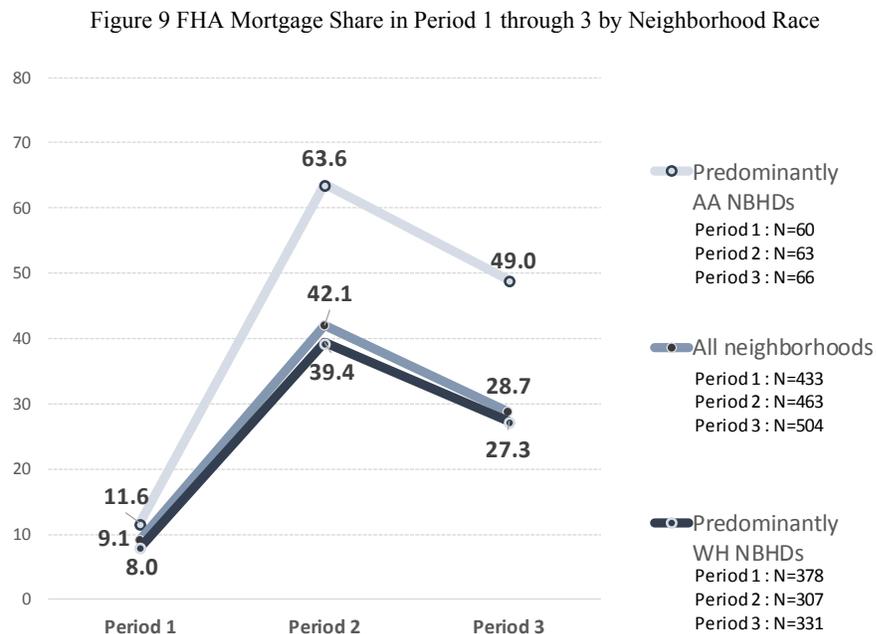
NOTE: Predominantly WH NBHDs: Neighborhoods where the proportion of Whites is over 85 percent of the total population
 Predominantly AA NBHDs: Neighborhoods where the proportion of African-Americans is over 30 percent of the total population

⁶ One basis point is equivalent to 0.01%

6. FHA Share Available in African-American Neighborhoods

Regarding cost of loans and access to mortgages, this study looks at the proportion of FHA mortgages in a neighborhood: FHA mortgages work for those with a lower credit score or less down payment, while FHA mortgages are sometimes costlier than conventional mortgages for those qualified to use conventional mortgages (Immergluck, 2011).

The result (Figure 9) shows that during the mortgage boom the rate of FHA-insured loans did not vary by the racial composition of the neighborhood, but post boom it did. In Period 1, the median FHA shares is nearly the same across neighborhoods of varied racial composition. The gap in the median FHA share among predominantly White neighborhoods and among predominantly African-American neighborhoods is very close to the median FHA share among all neighborhoods at 9%. After the boom, in Period 2, the gap between the two types of neighborhoods expands with half of predominantly African-American neighborhoods having median shares of FHA-insured loans of 64% or less, which is 25 percentage points higher than rate of FHA lending in half of predominantly White neighborhoods at 39% or less. Although the mortgage market begins to recover from Period 3, the gap between the rate of FHA lending for predominantly African-American and for predominantly White neighborhoods does not decrease. Still, half



NOTE: Predominantly WH NBHDs: Neighborhoods where the proportion of Whites is over 85 percent of the total population
 Predominantly AA NBHDs: Neighborhoods where the proportion of African-Americans is over 30 percent of the total population

of predominantly African-American neighborhoods have rates of FHA lending 49% or less, while the median share FHA loans for predominantly White neighborhoods is 27%.

7. Variations in Neighborhood Mortgage Originations across MSAs

We have shown that access to mortgages and cost of mortgages varies by neighborhood racial composition. Predominantly African-American neighborhoods seem to be at a disadvantage in all respects. However, we know that lenders consider the borrower's financial credibility for mortgage origination during the underwriting process to mitigate any risks causing deficits on their business. Income and credit score are important factors to measure financial credibility. Neighborhoods with higher incomes and credit scores have: (1) more conventional mortgage originations, (2) lower APR spreads, and (3) lower subprime shares and FHA shares. This section compares those three dimensions of each neighborhood, in each period across five MSAs, using neighborhood racial composition and financial credibility (median family income and credit score).

Period 1: In the Shadow of Mortgage Boom

Access to Mortgages in Period 1

Looking at the conventional mortgage origination count per 100 owner-occupied units (hereafter, rates of originations) by different neighborhood demographic patterns during Period 1 (Figure 10 through Figure 17), African-American neighborhoods did not experience the mortgage boom.

Rates of originations vary by the proportion of Whites and African-Americans in a neighborhood across the five MSAs (Figure 10 and Figure 11). Rates of originations increase as the proportion of Whites increases in a neighborhood, while rates of origination decrease as the proportion of African-Americans in a neighborhood increases. For example, in the Cleveland MSA, rates of originations among Partly-White Neighborhoods is 0.9 per 100 owner-occupied units (hereafter, per 100 units). This number is lower than the rate of originations for Mostly- (or predominantly) White Neighborhoods, 4.7 per 100 units. Meanwhile, the mortgage origination count among Mostly-African-American Neighborhoods in the Cleveland MSA is

0.9 per 100 units, which is lower than the origination count among Partly-African-American Neighborhoods, at 4.4 per 100 units.

Logically, originations should be higher in neighborhoods with higher levels of financial credibility versus lower financial credibility. The Cleveland, Dayton, and Toledo MSAs clearly exhibit this pattern (Figure 12 and Figure 13). In the Columbus MSA, however, the rate of originations among neighborhoods with lower financial credibility is larger than the rate of originations among neighborhoods with higher financial credibility. The rate of originations among Lower-Income Neighborhoods is 14.0 per 100 units, which is larger than the rate of originations among Higher-Income Neighborhoods of 9.0 per 100 units. Additionally, the rate of originations among Lower-Credit Score Neighborhoods is 26.7 per 100 units, which is larger than the rate of originations among Higher-Credit Score Neighborhoods of 8.5 per 100 units. One possible explanation is that due to GSE Act that requires government sponsored enterprises (GSEs), Fannie Mae and Freddie Mac, to expand their business for underserved areas, such as lower income neighborhoods.

For further investigation in rates of originations by race, this study looks both neighborhood racial composition – predominantly (or Mostly-) White neighborhoods and African-American Neighborhoods⁷– and financial credibility – income and FICO credit score level simultaneously (Figure 14 through Figure 17). In Period 1, income and credit scores appear to be irrelevant for predominantly White Neighborhoods. Lower-Income White Neighborhoods receive larger rates of origination than Higher-Income White Neighborhoods in the Cincinnati, Columbus, and Toledo MSAs. For instance, in the Cincinnati MSA, rates of originations among Lower-Income and Lower-Credit Score White Neighborhoods are 24.7 and 28.1, whereas rates of originations among Higher-Income and Higher-Credit Score White Neighborhoods are 6.4 and 6.9 respectively (Figure 14 and Figure 16). Yet, unlike predominantly White neighborhoods, African-American Neighborhoods across all MSAs seem to have a consistent pattern: Higher-Income and Higher-

⁷ Due to limited number of predominantly (Mostly-) African-American neighborhoods with higher financial credibility, we combined African-American-Mixed neighborhoods and Mostly-African-American neighborhoods in the descriptive analysis as African-American neighborhoods (see Table 1 for definition).

Credit Score African-American Neighborhoods receive larger rates of originations than Lower-Income and Lower-Credit Score African-American Neighborhoods. In the Cincinnati MSA, for instance, rates of originations among Higher-Income and Higher-Credit Score African-American Neighborhoods are 8.0 and 9.4 per 100 units, respectively, while the rates of originations for Lower-Income and Lower-Credit Score African-American Neighborhoods drop to 2.5 and 1.9 per 100 units, respectively (Figure 15 and Figure 17). Thus, it may be that financial credibility is regarded as an important factor for African-American Neighborhoods, but not for predominantly White neighborhoods. In addition, no matter the financial credibility, African-American Neighborhoods receive substantially lower rates of originations than do predominantly White neighborhoods. For example, in the Columbus MSA, rates of originations in Lower-Income and Lower-Credit Score White neighborhoods are 190.5 and 132.1, while rates of originations among African-American Neighborhoods with the same financial credibility is 1.5 (Figure 14 through Figure 17). These trends suggest racial disparities in access to conventional mortgage.

Rates of Mortgage Origination by Neighborhood Racial Composition, Credit Score, and Income: Period 1 (2004-2007)
 (See Table 1 for category definitions)

Figure 10 Rates of Origination by Proportion White in Neighborhood in Period 1

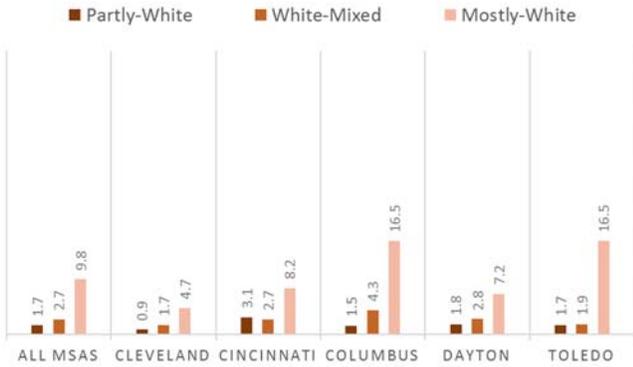


Figure 11 Rates of Origination by Proportion African-American in Neighborhood in Period 1

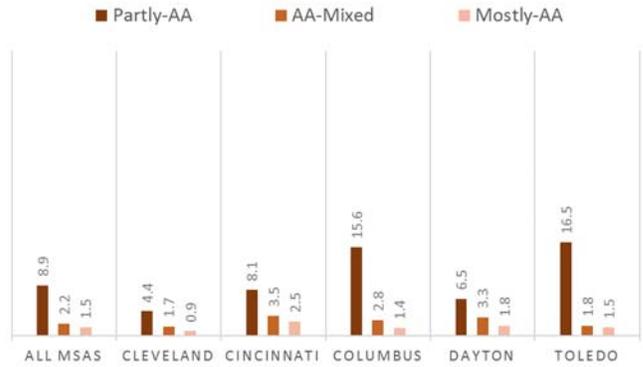


Figure 12 Rates of Origination by Neighborhood Income in Period 1

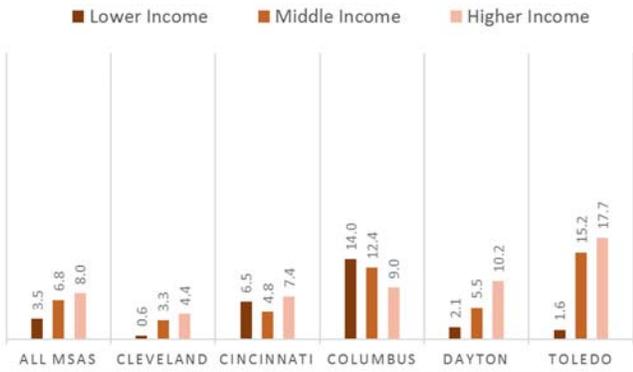


Figure 13 Rates of Origination by Neighborhood Credit Score in Period 1

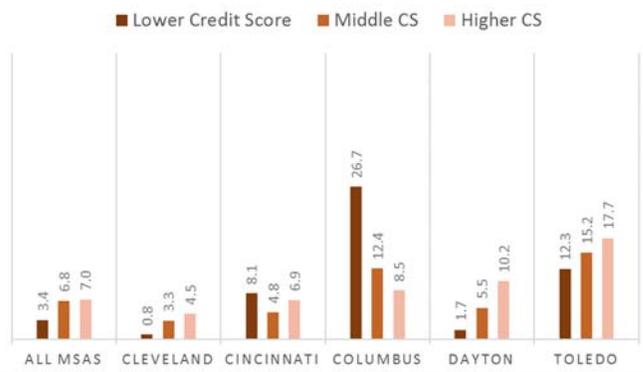


Figure 14 Rates of Origination by Neighborhood Income in Mostly-White Neighborhoods in Period 1

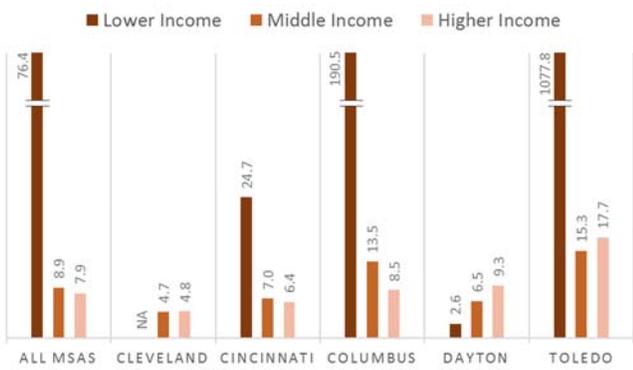


Figure 15 Rates of Origination by Neighborhood Income in African-American Neighborhoods in Period 1

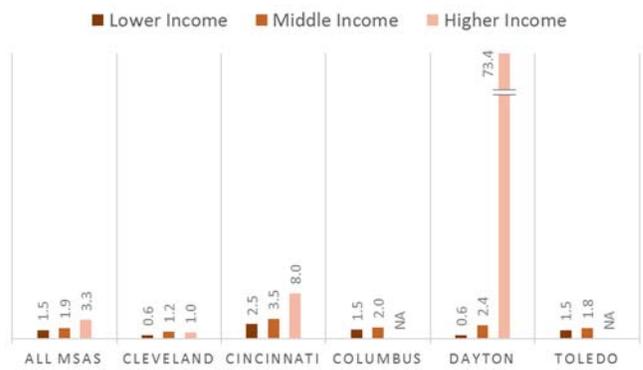
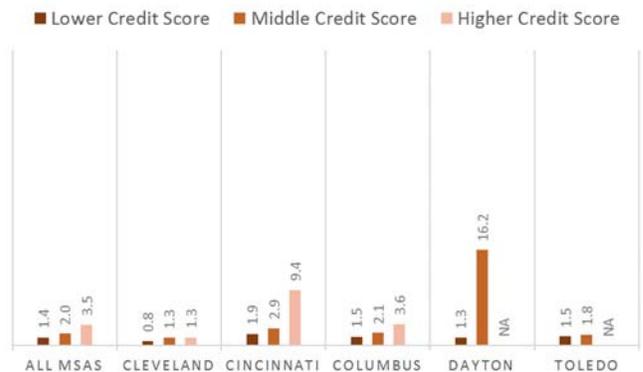


Figure 16 Rates of Origination by Neighborhood Credit Score in Mostly-White Neighborhoods in Period 1



Figure 17 Rates of Origination by Neighborhood Credit Score in African-American Neighborhoods in Period 1



Cost of Mortgages: Subprime Mortgage Origination in Period 1

In Period 1, the overall trend for median subprime shares seems relatively consistent across the five MSAs. Mostly-White Neighborhoods have lower subprime share, while Mostly-African-American Neighborhoods have higher subprime share (Figure 18 and Figure 19). For example, in the Cleveland MSA, the median subprime share among Partly-White Neighborhoods is 33.1%, while the subprime share among Mostly-White Neighborhoods is 11.0%. However, the subprime share is higher among Mostly-African-American Neighborhoods, 34.5%, than the share among Partly-African-American Neighborhoods, 11.4%.

Plus, the subprime share seems to be highly related to financial credibility as well: Lower-Income and Lower-Credit Score Neighborhoods have high subprime shares (Figure 20 and Figure 21). In Cleveland, for example, the median subprime share among Lower-Income and Lower-Credit Score Neighborhoods is 33.2% and 33.5%, respectively, while the numbers among Higher-Income and Higher-Credit Score Neighborhoods is 7.6% and 8.2%, respectively.

When looking at race and financial credibility together, we observe the same tendency with financial credibility alone. Neighborhoods with higher financial credibility, no matter the racial composition, have a lower share of subprime loans. Notably, African-American Neighborhoods have higher rates of subprime lending when compared to predominantly White neighborhoods, when look at the same income and credit score brackets. For instance, in the Dayton MSA, the half of all Lower-, Middle-, and Higher-Income White Neighborhoods had subprime loans comprise 22.0%, 12.3%, and 6.8% or fewer of their loans respectively (Figure 24), while among the comparable African-American Neighborhoods the rates are 47.3%, 33.7%, and 19.7% (Figure 25). Thus, inequality is not limited to access to conventional mortgages only, so that African-American Neighborhoods appear to pay more for limited access to mortgages in Period 1.

Subprime Share by Neighborhood Racial Composition, Credit Score, and Income: Period 1 (2004-2007)

(See Table 1 for category definitions)

Figure 18 Subprime Share by Proportion White in Neighborhood in Period 1

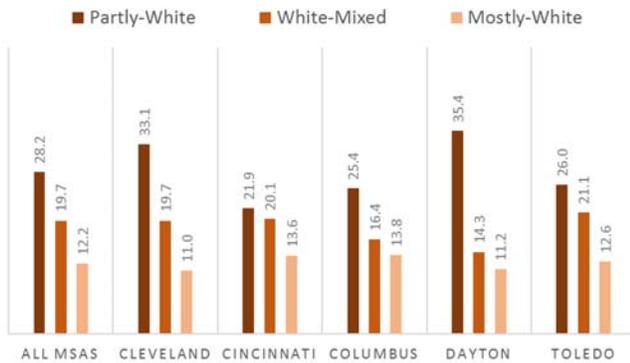


Figure 19 Subprime Share by Proportion African-Americans in Neighborhood in Period 1

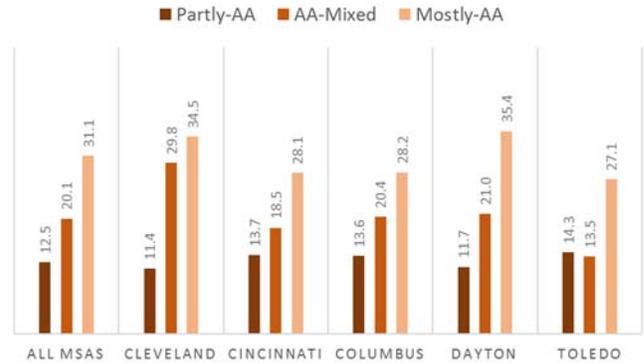


Figure 20 Subprime Share by Neighborhood Income in Period 1

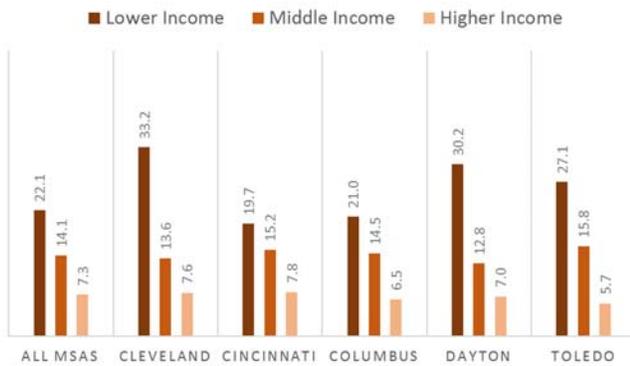


Figure 21 Subprime Share by Neighborhood Credit Score in Period 1

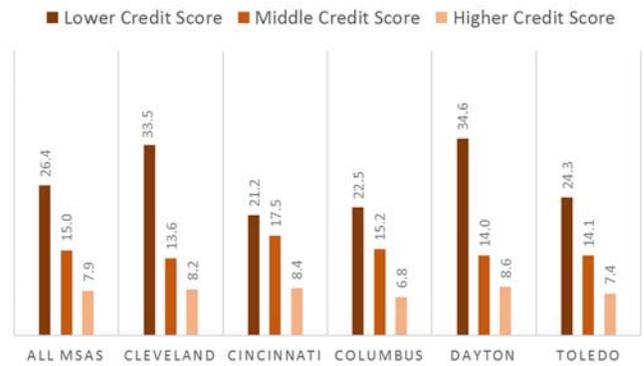


Figure 22 Subprime Share by Neighborhood Income in Mostly-White Neighborhoods in Period 1

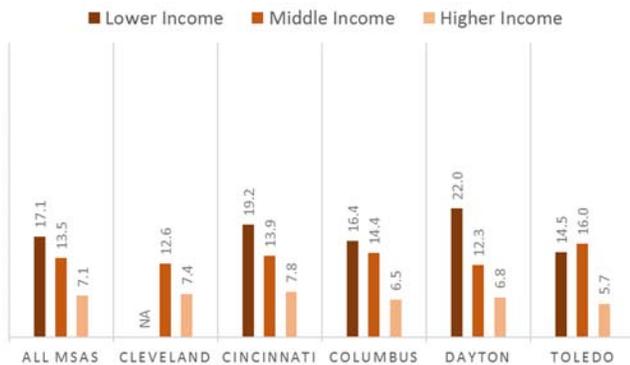


Figure 23 Subprime Share by Neighborhood Income in African-American Neighborhoods in Period 1

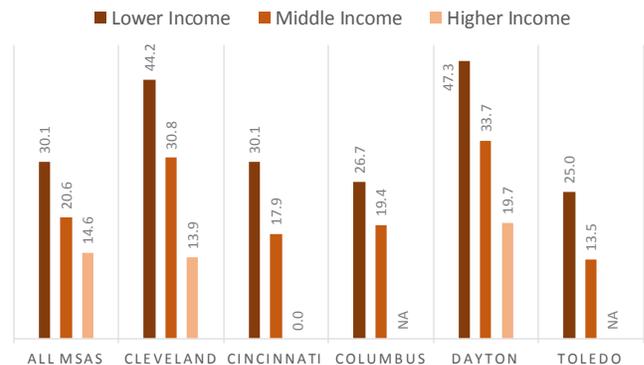


Figure 24 Subprime Share by Neighborhood Credit Score in Mostly-White Neighborhoods in Period 1

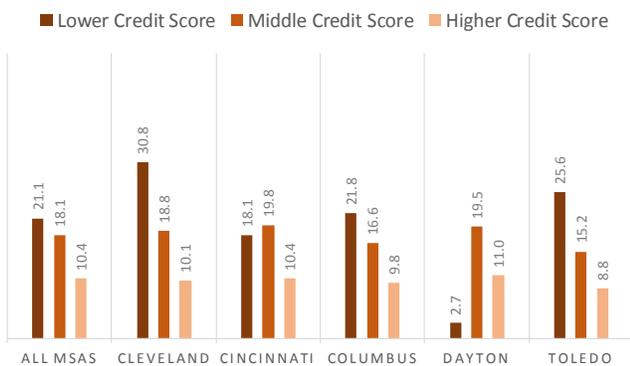
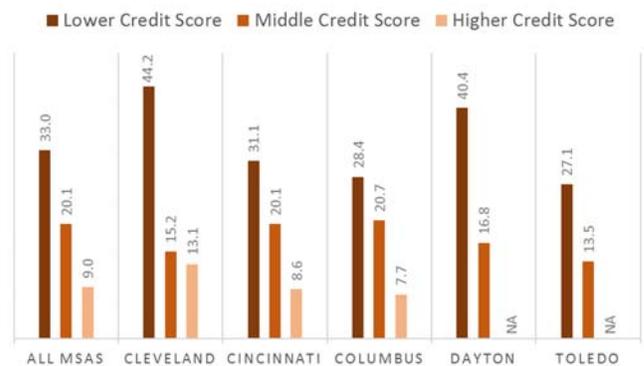


Figure 25 Subprime Share by Neighborhood Credit Score in African-American Neighborhoods in Period 1



Period 2: Mortgage Bust

Access to Mortgages in Period 2

In Period 2, the rate of originations seriously declined due to the tight mortgage market, and, in the previous section, we have already observed that market tightness varies by neighborhood racial composition (Figure 6). The rate of originations also varies by the racial composition of the neighborhood. As in Period 1, the rate of originations increases as the proportion of Whites in a neighborhood increases (Figure 26), while the rate declines as the proportion of African-Americans increases (Figure 27). There seems to be a large gap in rate of originations between Partly- and Mostly-African-American Neighborhoods. In the Toledo MSA, for instance, the rate of originations among Partly-African-American Neighborhoods, 3.6 per 100 units, is nine times higher than the rate of originations among neighborhoods Mostly-African-American Neighborhoods, 0.4 per 100 units (Figure 27).

Financial credibility seems to be stricter during Period 2 than Period 1: the higher the financial credibility, the higher the rate of originations (Figure 28 and Figure 29). In most predominantly White neighborhoods across MSAs, the higher the financial credibility the higher the rate of originations (Figure 30 and Figure 32). The exceptions are in Lower-Income White Neighborhoods in Columbus (Figure 30) and Lower-Credit Score White Neighborhoods in Toledo (Figure 31), which have slightly higher rates of originations than do other White neighborhoods. Most importantly, (1) the median mortgage origination rates among African-American Neighborhoods are less than one per 100 units no matter the median income and credit score of the neighborhood (Figure 31 and Figure 33), and (2) the rate of origination for predominantly White neighborhoods is higher than that for African-American Neighborhoods in all financial brackets across five MSAs.

Rates of Mortgage Origination by Neighborhood Racial Composition, Credit Score, and Income: Period 2 (2008-2011)
 (See Table 1 for category definitions)

Figure 26 Rates of Origination by Proportion White in Period 2

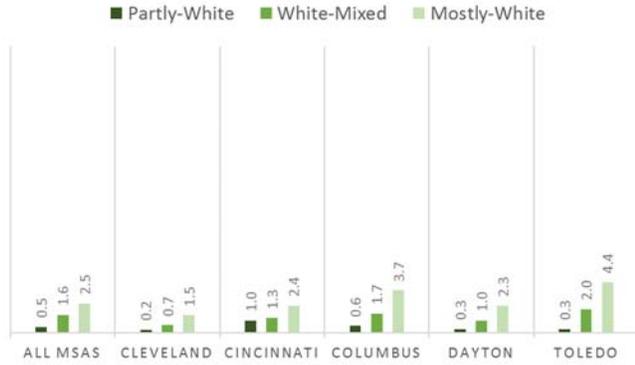


Figure 27 Rates of Origination by Proportion African-American in Period 2

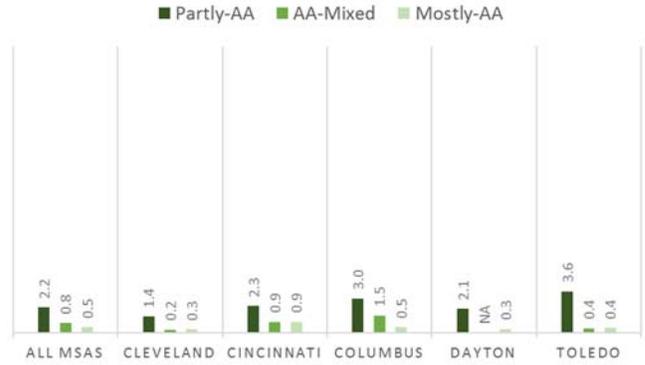


Figure 28 Rates of Origination by Neighborhood Income Level in Period 2

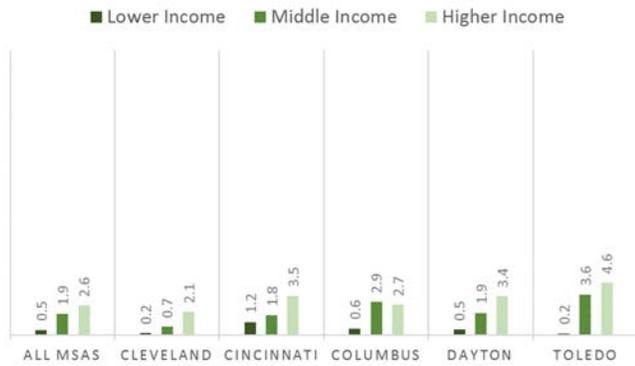


Figure 29 Rates of Origination by Neighborhood Credit Score in Period 2

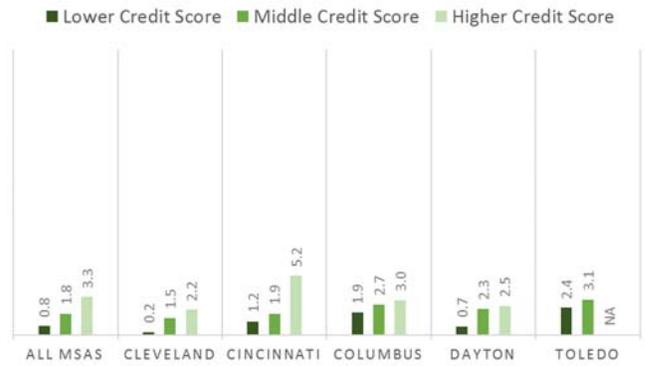


Figure 30 Rates of Origination by Neighborhood Income in Mostly-White Neighborhoods in Period 2

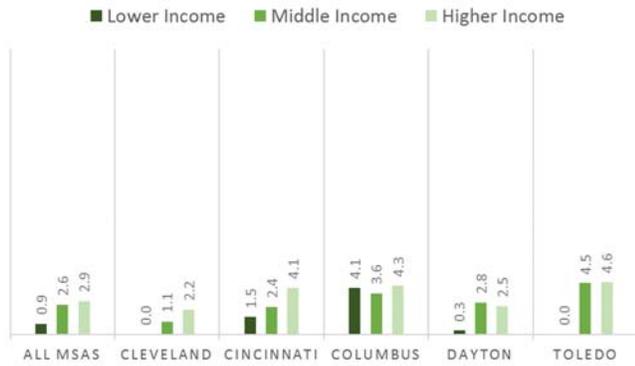


Figure 31 Rates of Origination by Neighborhood Income in African-American Neighborhoods in Period 2

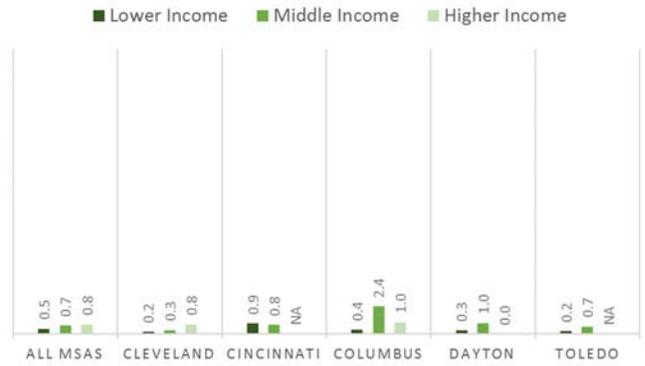


Figure 32 Rates of Origination by Neighborhood Credit Score in Mostly-White Neighborhoods in Period 2

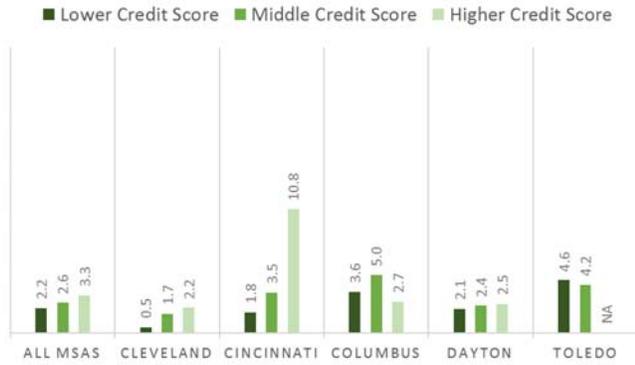
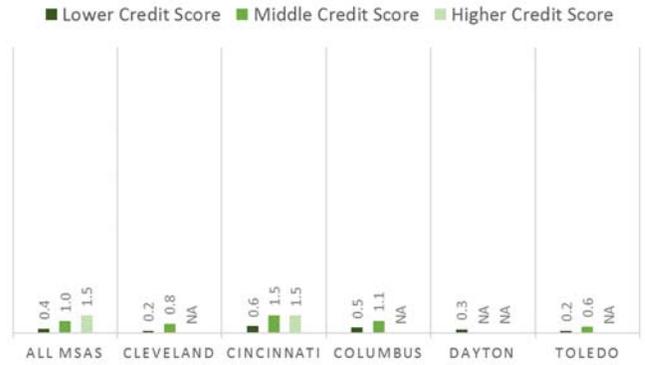


Figure 33 Rates of Origination by Neighborhood Credit Score in African-American Neighborhoods in Period 2



Cost of Mortgages: High Cost Loans Measured as APR Spread in Period 2

Among Partly-White Neighborhoods, the median APR spread is larger than Mostly-White Neighborhoods, while the trend in the African-American neighborhood bracket follows in the reverse order (Figure 34 and Figure 35). In the Columbus MSA, for example, the median APR spread is low, -1.0bps, for Partly-African-American Neighborhoods, while the median spread is high, 14.9bps, for Mostly-African-American Neighborhoods (Figure 35).

As one might expect, APR spreads are associated with financial risk (or financial credibility), that is income levels and credit scores. Results show that Higher-Income and Credit Score Neighborhoods have lower median APR spreads, and Lower-Income and Credit Score Neighborhoods have higher median APR spreads: The gap in median APR spread between Lower-Income and Credit Score Neighborhoods and Higher- Income and Credit Score Neighborhoods is about 20 bps (Figure 36 and Figure 37). Figure 38 through 41 take neighborhood racial composition into account, and indicate a similar tendency: neighborhoods with higher credit scores have lower median APR spreads among both predominantly White and African-American Neighborhoods, except in the Cleveland MSA. From this result, we expect that while there might be a small gap between predominantly White neighborhoods and African-American Neighborhoods, financial credibility including income and credit score seems to be tightly related to APR spreads.

Median APR Spread by Neighborhood Racial Composition, Credit Score, and Income: Period 2 (2008-2011)

(See Table 1 for category definitions)

Figure 34 Median APR Spread by Proportion of Whites in Period 2

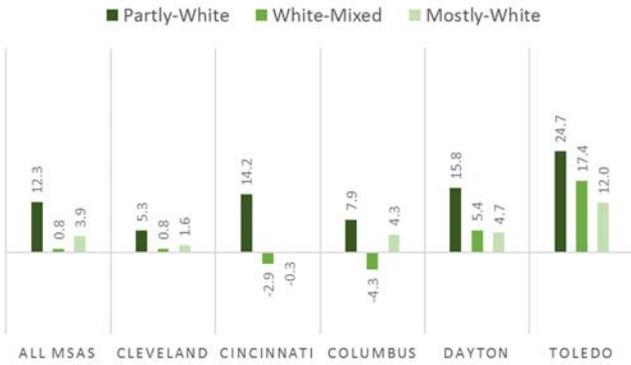


Figure 35 Median APR Spread by Proportion of African-Americans in Period 2

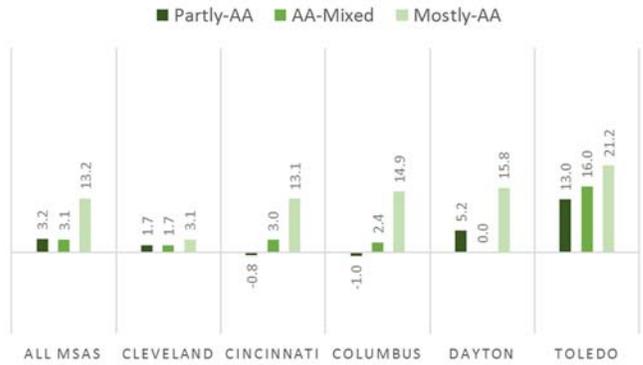


Figure 36 Median APR Spread by Neighborhood Income in Period 2

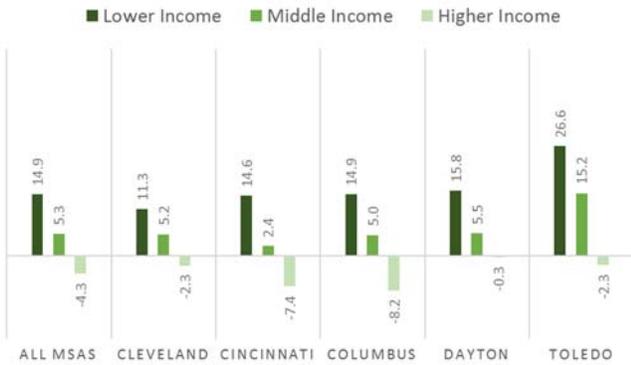


Figure 37 Median APR Spread by Neighborhood Credit Score in Period 2

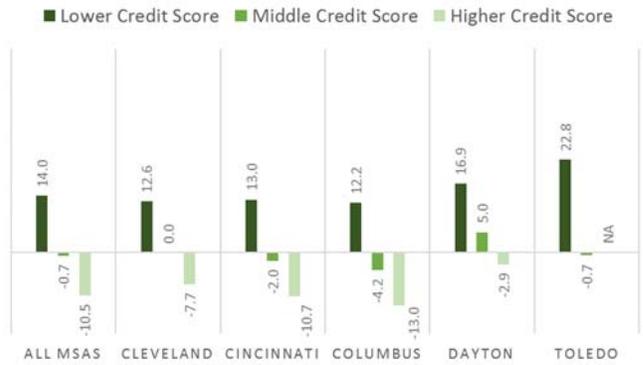


Figure 38 Median APR Spread by Neighborhood Income in Mostly-White neighborhoods in Period 2

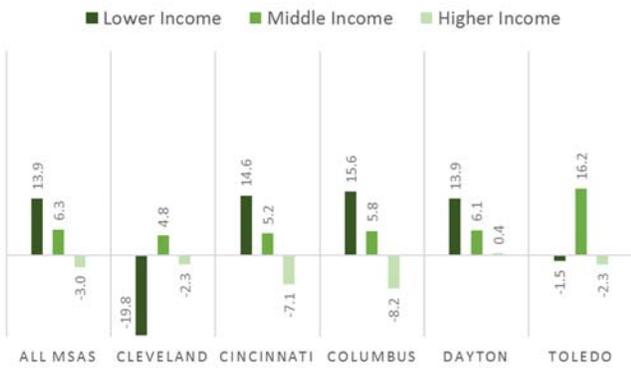


Figure 39 Median APR Spread by Neighborhood Income in African-American neighborhoods in Period 2

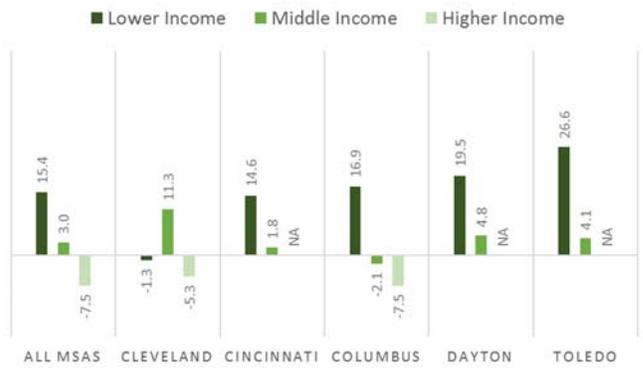


Figure 40 Median APR Spread by Neighborhood Credit Score in Mostly-White Neighborhoods in Period 2

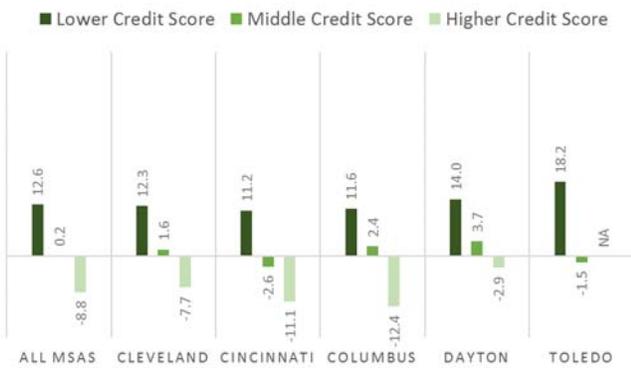
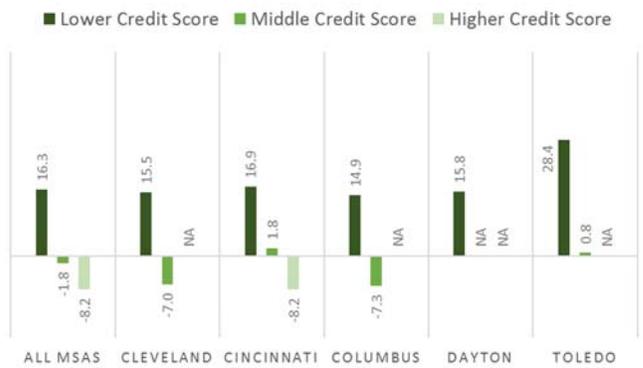


Figure 41 Median APR Spread by Neighborhood Credit Score in African-American Neighborhoods in Period 2



Access to Mortgage: FHA Mortgage Origination in Period 2

After the subprime boom in Period 1, FHA began to increase its share of originations, supporting the collapsed mortgage market; FHA became about 45% of the mortgage market, up from 11% in Period 1 (Figure 3). In addition, predominantly African-American neighborhoods have higher median FHA Share (Figure 9), while Mostly-White neighborhoods were more likely to have higher rates of origination compared to Mostly-African-American Neighborhoods (Figure 10 and Figure 11). We can confirm these general trends occur across MSAs as well in Period 2; the higher the proportion of African-Americans the higher the median FHA share, and the higher the Whites the lower the median FHA share (Figure 42 and Figure 43). Taking into account the credit score, median FHA share, not surprisingly, decreases as financial credibility increases – the median FHA share is lower in Higher-Income and Higher-Credit Score Neighborhoods (Figure 44 and Figure 45). In the Cleveland MSA, for instance, the median FHA share among Lower-Credit Score Neighborhoods is 67.9%, about 50 percentage points higher than median FHA share of 17.4% for Higher Credit Score Neighborhoods (Figure 45). This is reasonable since borrowers with better credit scores will be more likely to apply for conventional mortgages instead of FHA mortgages, so neighborhoods having higher credit scores will receive lower of FHA mortgages.

Once both race and financial credibility for the neighborhood median FHA share are accounted for, we still observe (and not surprisingly) that FHA loans comprise fewer of the mortgages originated among Higher-Income and High-Credit Score Neighborhoods (Figure 46 through Figure 49). Yet, the median FHA share for African-American Neighborhoods with lower- and middle- financial credibility is always higher than the share for predominantly White neighborhoods with comparable financial credibility.

Median FHA Share by Neighborhood Racial Composition, Credit Score, and Income: Period 2 (2008-2011)

(See Table 1 for category definitions)

Figure 42 FHA Share by Proportion of Whites in Period 2

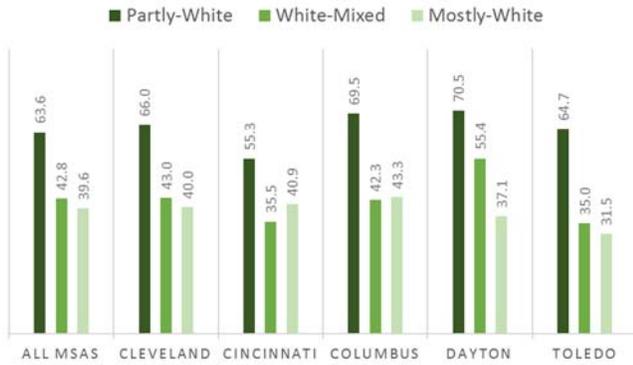


Figure 43 FHA Share by Proportion of African-Americans in Period 2

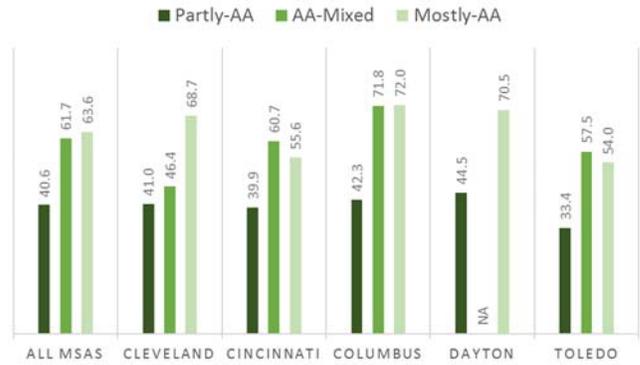


Figure 44 FHA Share by Neighborhood Income in Period 2

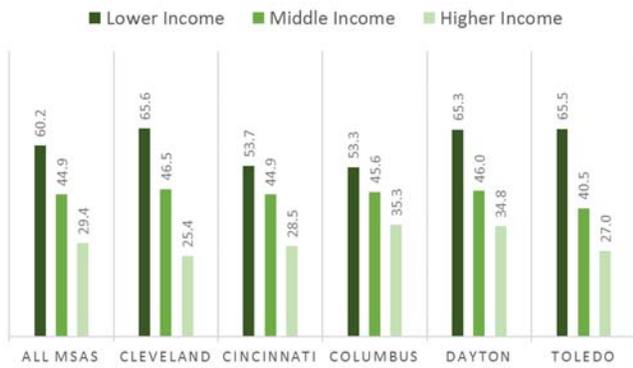


Figure 45 FHA Share by Neighborhood Credit Score in Period 2

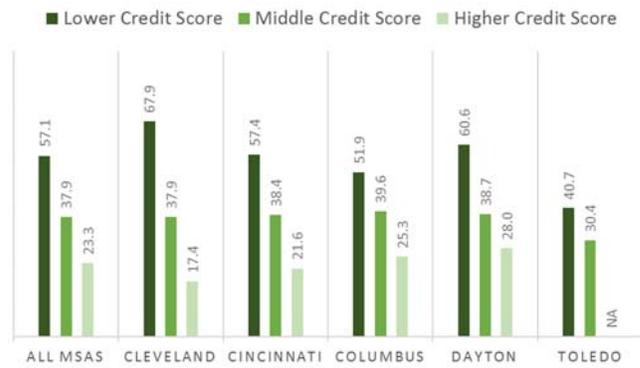


Figure 46 FHA Share by Neighborhood Income in Mostly-White Neighborhoods in Period 2

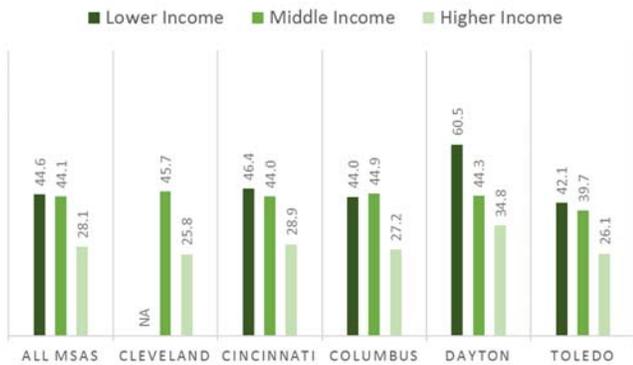


Figure 47 FHA Share by Neighborhood Income in African-American Neighborhoods in Period 2

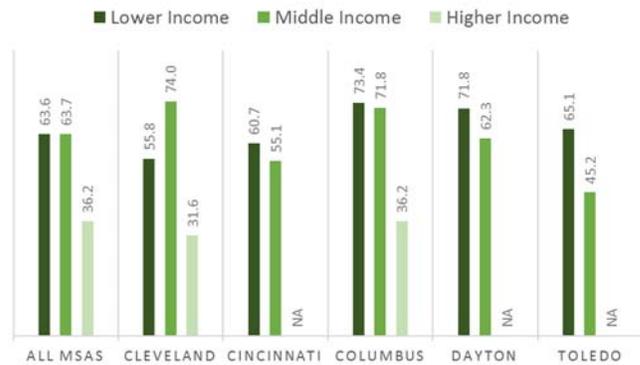


Figure 48 FHA Share by Neighborhood Credit Score in Mostly-White Neighborhoods in Period 2

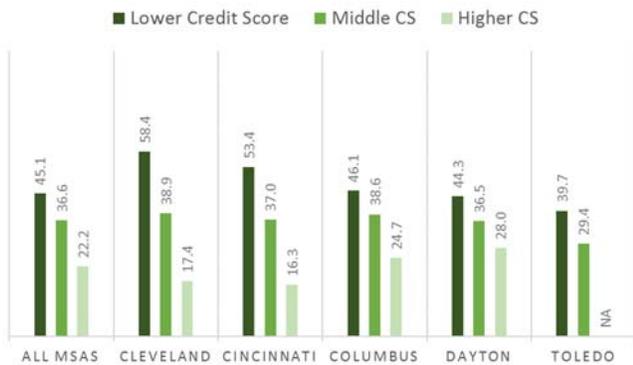
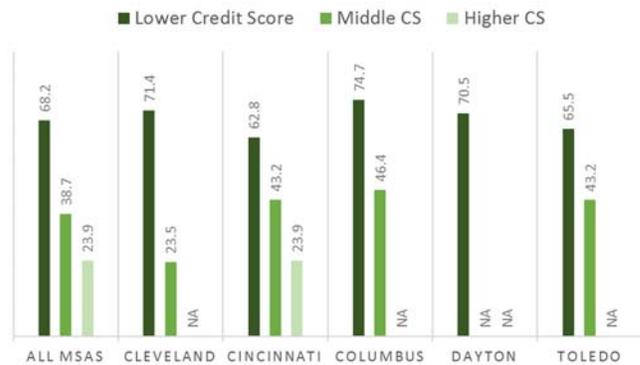


Figure 49 FHA Share by Neighborhood Credit Score in African-American Neighborhoods in Period 2



Period 3: Post Bust Period

Access to Mortgages in Period 3

During the market recovery period, the trend in the rate of originations by neighborhood racial composition was consistent across the five MSAs as in the boom and crisis period: neighborhoods with higher proportions of Whites had higher rates of origination, while neighborhoods with higher proportions of African-Americans had lower rates of origination (Figure 50 and Figure 51).

The rate of originations among Higher-Income and Credit Score Neighborhoods is higher than Lower-Income Neighborhoods (Figure 52). In the Dayton MSA, the rate of originations among Higher-Income Neighborhoods is about nine times higher than the rate among Lower-Income Neighborhoods. In contrast, the rate of origination has an inconsistent relationship with neighborhood credit score in the Columbus MSA: Lower-Credit Score Neighborhoods receive higher rates of origination (Figure 53).

In Period 3, the rate of origination recovered when compared to Period 2, but increases in rates of originations were most frequently higher in predominantly White neighborhoods. A comparison between predominantly White neighborhoods and African-American Neighborhoods with the same median credit scores demonstrates the higher rates of originations in predominantly White neighborhoods across all levels of credit scores (Figure 56 and Figure 57). In addition, even Lower-Credit Score White Neighborhoods have higher rates of origination than African-American Neighborhoods regardless of their credit scores. In African-American Neighborhoods, the overall rate of originations was low, and Lower- and Middle-Credit Score Neighborhoods had lower rates of originations. Unexpectedly, predominantly White neighborhoods with lower credit scores had higher rates of originations, compared to African-American Neighborhoods (Figure 56 and Figure 57). This result can solve the unexpected finding concerning the credit score level in the Columbus MSA (Figure 53), namely, that Lower-Credit Score Neighborhoods have a chance for a higher rate of originations. Predominantly White neighborhoods, no matter what the credit score and income level is, only had opportunities to have high rates of originations, but African-American Neighborhoods do not.

Rates of Mortgage Originations by Neighborhood Racial Composition, Credit Score, and Income: Period 3(2011-2015)
 (See Table 1 for category definitions)

Figure 50 Rates of Originations by Proportion of Whites in Period 3

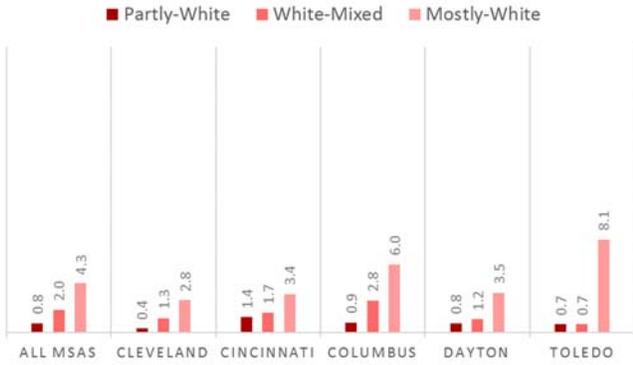


Figure 51 Rates of Originations by Proportion of African-Americans in Period 3

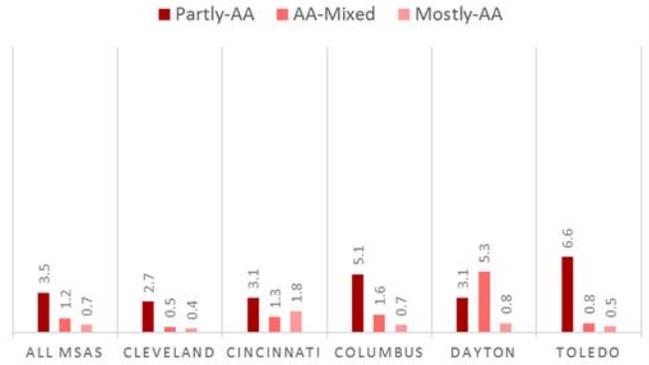


Figure 52 Rates of Origination by Neighborhood Income Level in Period 3

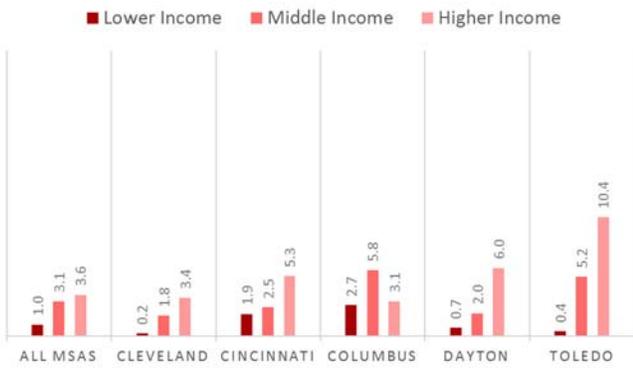


Figure 53 Rates of Origination by Neighborhood Credit Score in Period 3

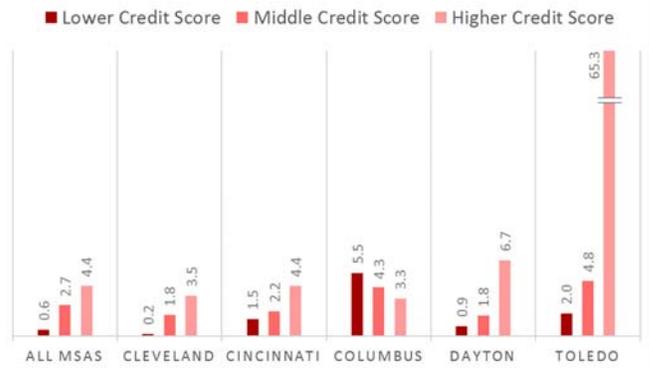


Figure 54 Rates of Origination by Neighborhood Income in Mostly-White Neighborhoods in Period 3

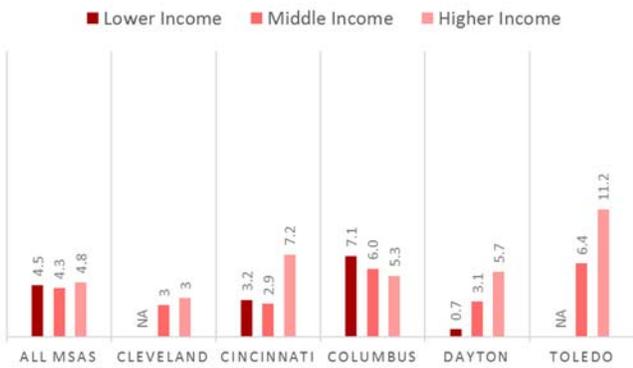


Figure 55 Rates of Origination by Neighborhood Income in African-American Neighborhoods in Period 3

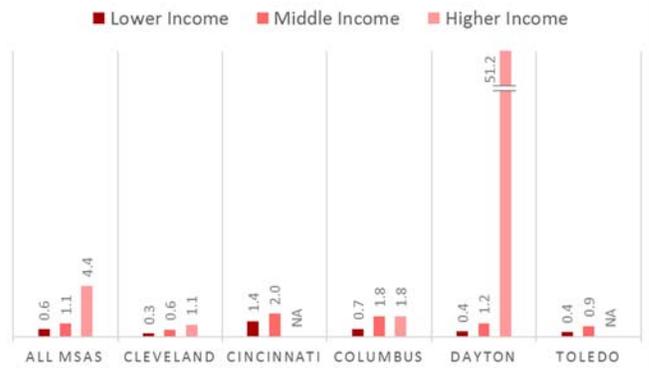


Figure 56 Rates of Origination by Neighborhood Credit Score in Mostly-White Neighborhoods in Period 3

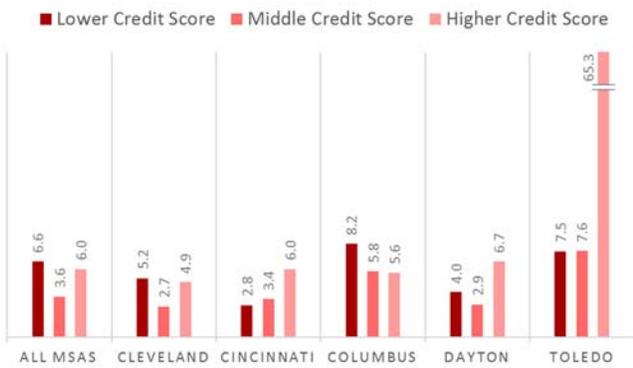
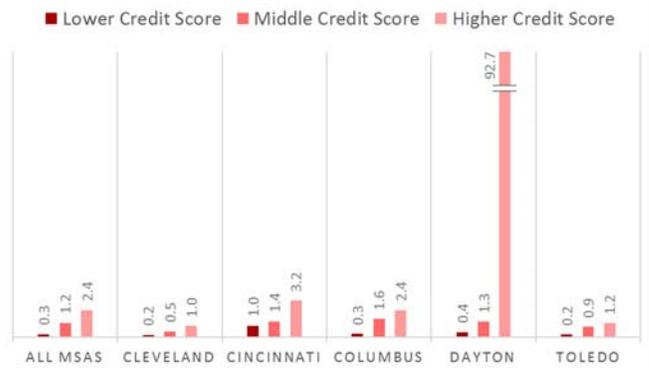


Figure 57 Rates of Origination by Neighborhood Credit Score in African-American Neighborhoods in Period 3



Cost of Mortgages: High Cost Loans Measured by APR Spread in Period 3

The trend in the median APR spread seems to be consistent across the five MSAs. In Partly-White Neighborhoods, the median APR spread is relatively high, compared to Mostly-White Neighborhoods, across all MSAs (Figure 58). This is exactly the opposite for the African-American neighborhood bracket, where those higher shares of African-Americans have a higher median APR spread (Figure 59). In the Columbus MSA, for example, the median APR spread for Partly-African-American Neighborhoods, 13.4 bps, is one half the number for Mostly-African-American Neighborhoods at 27.7bps (Figure 59).

As expected, the higher the financial credibility that neighborhoods have, the lower the median APR spread. For example in the Cincinnati MSA, the gap between lower and higher credibility is a median spread of about 19.6bps between the lowest and the highest income neighborhoods (Figure 60), and a median spread of about 28.8bps between the lowest and highest neighborhood credit scores (Figure 61). MSAs follow the pattern of higher credibility being associated with lower median APR spread, even taking into account race and neighborhood income level together (Figure 62 and Figure 63). Little gap in median APR spreads exist between African-American Neighborhoods and predominantly White neighborhoods with the comparable financial credibility, except for neighborhoods with lower credit scores (Figure 64 and Figure 65). African-American Neighborhoods with lower credit score tend to have higher median APR spread than do predominantly White neighborhoods with the comparable credit score in all MSAs but not in Cincinnati. In the Cincinnati MSA, predominantly White neighborhoods with lower credit score have higher APR spread than do African-American Neighborhoods with the comparable credit score.

Median APR Spread by Neighborhood Racial Composition, Credit Score, and Income in Period 3 (2011-2015)

(See Table 1 for category definitions)

Figure 58 APR Spread by Proportion of Whites in Period 3

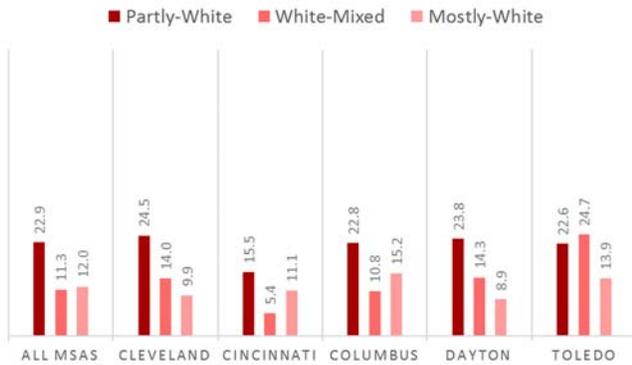


Figure 59 APR Spread by Proportion of African-Americans in Period 3

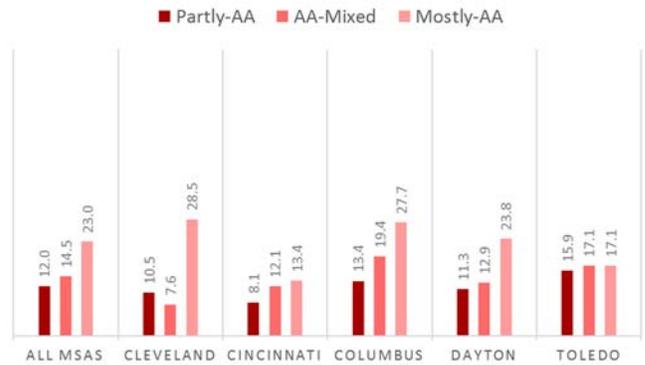


Figure 60 APR Spread by Neighborhood Income in Period 3

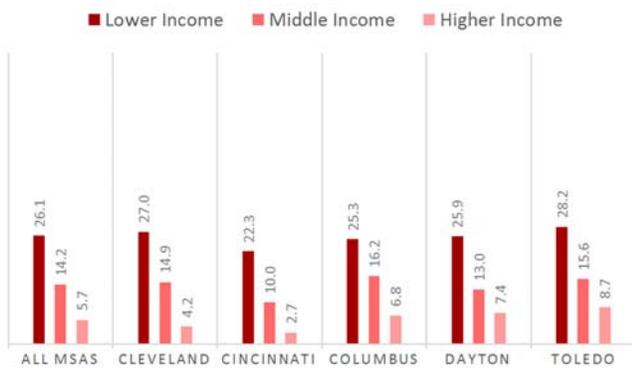


Figure 61 APR Spread by Neighborhood Credit Score in Period 3

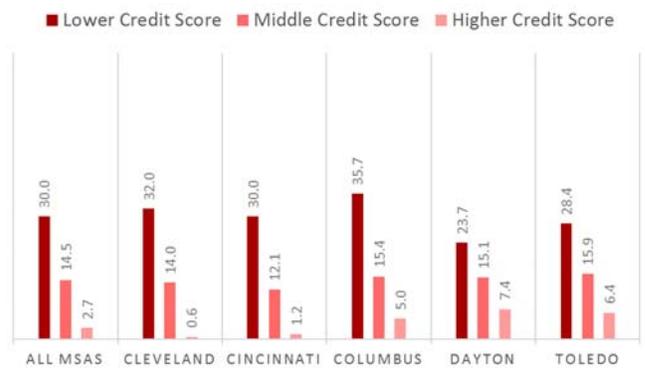


Figure 62 APR Spread by Neighborhood Income in Mostly-White Neighborhoods in Period 3

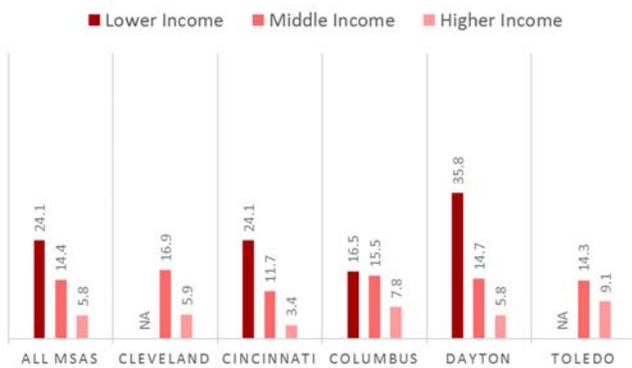


Figure 63 APR Spread by Neighborhood Income in African-American Neighborhoods in Period 3

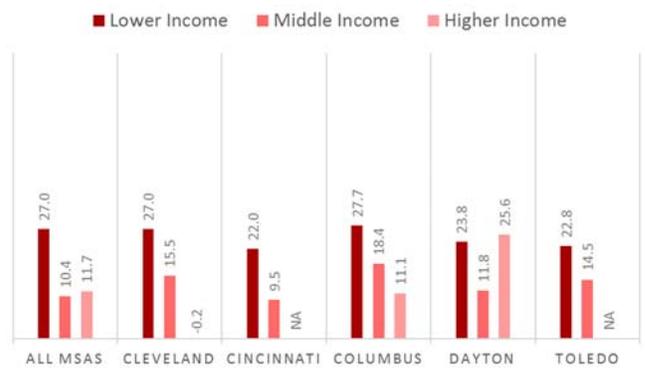


Figure 64 APR Spread by Neighborhood Credit Score in Mostly-White Neighborhoods in Period 3

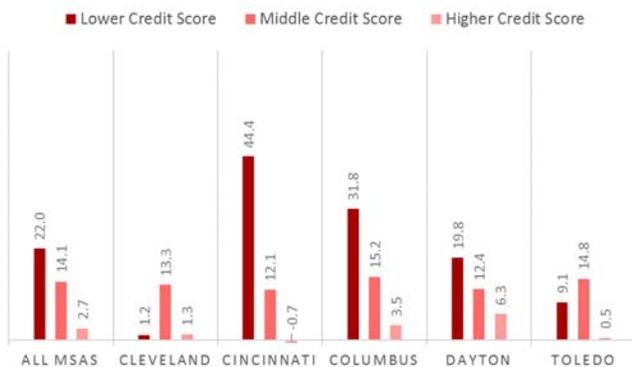
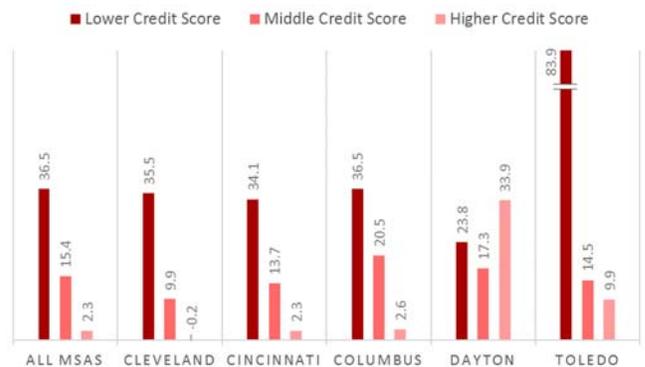


Figure 65 APR Spread by Neighborhood Credit Score in African-American Neighborhoods in Period 3



Access to Mortgage: FHA Mortgage Origination in Period 3

During Period 3, FHA came to be 30 percent of all mortgage originations, down from its supportive 45 percent in Period 2, but still higher than its 11% share prior to the mortgage crisis in Period 1 (Figure 3). At the neighborhood level, Period 3 looks much like Period 2: Median neighborhood FHA share is still higher as the proportion of White population decreases or as the proportion of African-American population increases (Figure 66 and Figure 67). For example, in the Cleveland MSA, the median FHA share for Mostly-African-American Neighborhoods is 60.0% (Figure 67), double the median FHA share for all neighborhoods in five MSA of 27.6% (Figure 11). In terms of neighborhood income level, the five MSAs tend towards consistency: The higher the income, the lower median FHA share (Figure 68), similar to the trend in Period 2. Higher Credit Score Neighborhoods have the lower median FHA share (Figure 69). Again, this trend makes sense since neighborhoods with higher financial credibility are more likely to go to conventional mortgages rather than FHA mortgages.

In terms of both race and financial credibility, the trend of higher financial credibility being associated with lower median FHA share is fairly consistent across most neighborhoods (Figure 70 through Figure 73). The significant finding is that the median FHA share among African-American Neighborhoods in every financial credit level is much higher than the median FHA share among predominantly White neighborhoods in comparable financial credibility level. For example, in the Columbus MSA, median FHA shares for predominantly White neighborhoods with lower-, middle-, higher- credit scores are 30.3%, 27.6%, and 12.2% respectively, which are 38.6, 18.6, and 4.9% percentage points lower than those for African-American Neighborhoods with the comparable credit scores.

Median FHA Share by Neighborhood Racial Composition, Credit Score, and Income in Period 3 (2011-2015)

(See Table 1 for category definitions)

Figure 66 FHA Share by Proportion of Whites in Period 3

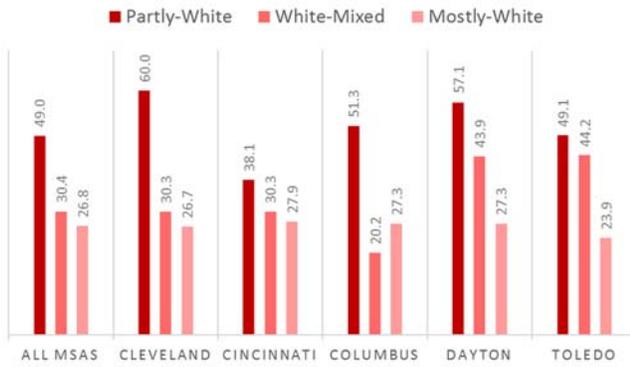


Figure 67 FHA Share by Proportion of African-Americans in Period 3

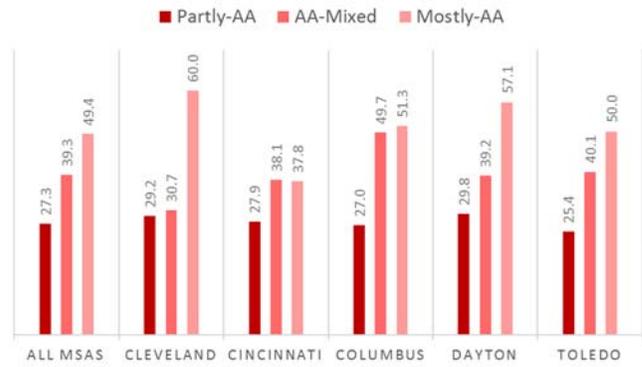


Figure 68 FHA Share by Neighborhood Income in Period 3

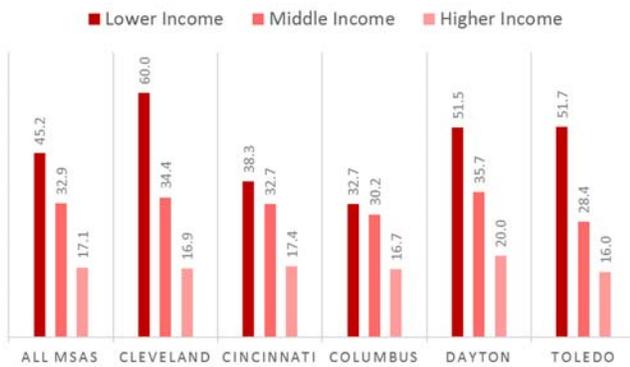


Figure 69 FHA Share by Neighborhood Credit Score in Period 3

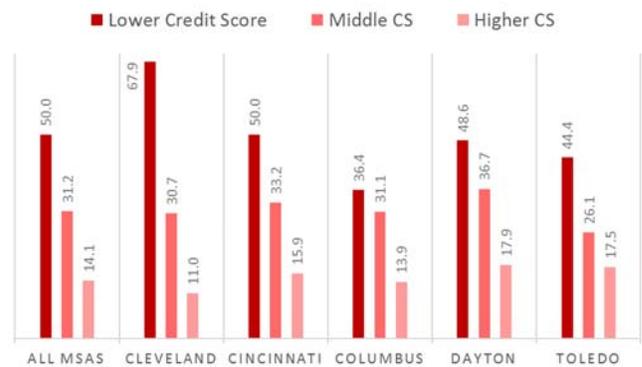


Figure 70 FHA Share by Neighborhood Income in Mostly-White Neighborhoods in Period 3

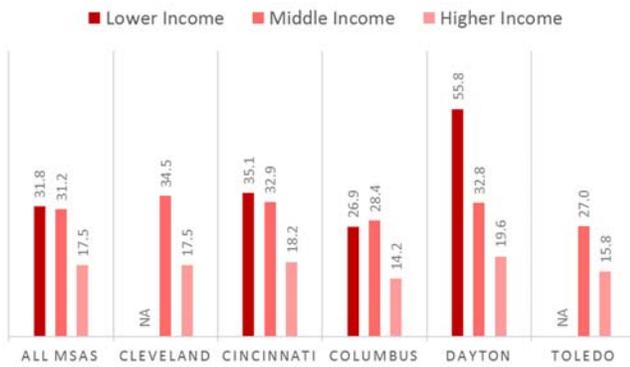


Figure 71 FHA Share by Neighborhood Income in African-American Neighborhoods in Period 3

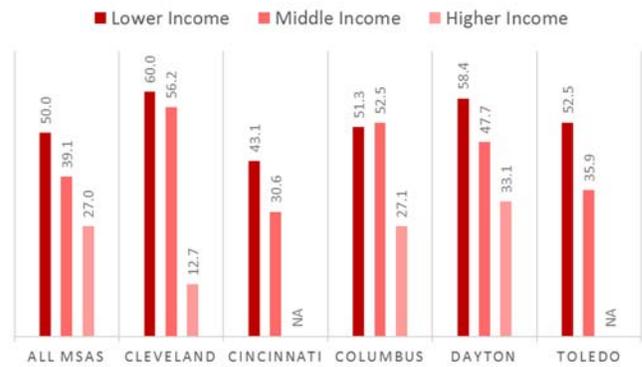


Figure 72 FHA Share by Neighborhood Credit Score in Mostly-White Neighborhoods in Period 3

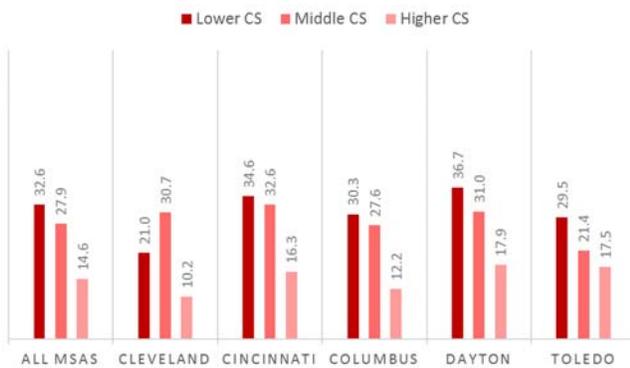
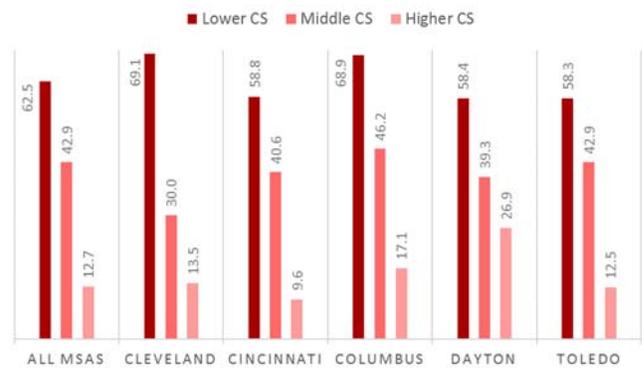


Figure 73 FHA Share by Neighborhood Credit Score in African-American Neighborhoods in Period 3



8. The Geography of Mortgage Origination

In this section, we analyze the geographic distribution of mortgages in the three periods. We map the distribution of four different mortgage origination measures — (1) the rate of mortgage originations, (2) the share of subprime loans, (3) the share of FHA-insured loans, and (4) the APR spread within the neighborhood. We overlay these measures on maps of neighborhood racial composition (proportions of African-Americans) and the median credit score in the neighborhood. We use ZIP code boundaries as the boundary for each neighborhood. Within each of the five MSAs, Mostly-African-American Neighborhoods (proportion of African-Americans in a neighborhood is over 30 percent of the total population) and African-American-Mixed Neighborhoods (proportion of African-Americans in a neighborhood is 15.1-30%) are concentrated in the downtown areas, while Partly-African-American Neighborhoods (proportion of African-Americans in a neighborhood is 15 percent or less of the total population) are just outside of and adjacent to Mostly-African-American Neighborhoods. On the other hand, there is no consistent geographic pattern in credit scores. In the body of the report, we present maps of only two MSAs for each measure and time period as illustration of general trends or key differentiations among MSAs. A complete set of maps for each MSA is available in the Appendix.

Period 1: The Geography of Lending in the Shadow of the Mortgage Boom

Access to Credit in Period 1

Across all five MSAs during the mortgage boom (Period 1), conventional mortgages were accessible in Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods, when compared to Periods 2 and 3. However, Mostly-African-American Neighborhoods have less access to mortgages no matter the credit score, when compared to Partly-African-American Neighborhoods. Plus, some Mostly-African-American Neighborhoods with Lower-Credit score (credit score of lower than 700) had rates of less than one per 100 owner-occupied units despite the mortgage boom. This pattern can be seen across MSAs except in the Cincinnati MSA.

Thus, access to capital is problematic in most MSAs, but the magnitude of gaps between those neighborhoods is not necessarily similar across all neighborhoods. In the Cleveland MSA (Figure 75), the rate of originations is higher in suburban neighborhoods no matter the credit scores. The rates increase as neighborhoods are closer to the fringe; the rate of originations in Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods, located downtown and to the south of downtown, is lower. Rates of originations among neighborhoods adjacent to Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods are small as well. In contrast, the Cincinnati MSA has the slightly different pattern. In Cincinnati, Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods are concentrated from downtown to its north side; we can observe that there are mortgage originations in those neighborhoods, unlike the Cleveland MSA. The rates of originations in Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods seems to be slightly lower than Partly-African-American Neighborhoods with comparable credit scores (Figure 74). However, the gap between rates of origination in Mostly-African-American and Partly-African-American Neighborhoods are to be smaller in the Cincinnati MSA than in the Cleveland MSA.

Figure 75 Rates of Originations by Neighborhood Racial Composition and Credit Score in the Cleveland MSA in Period 1

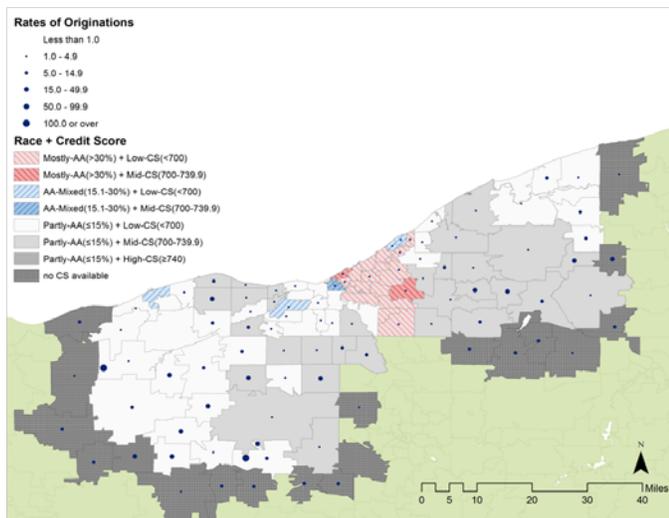
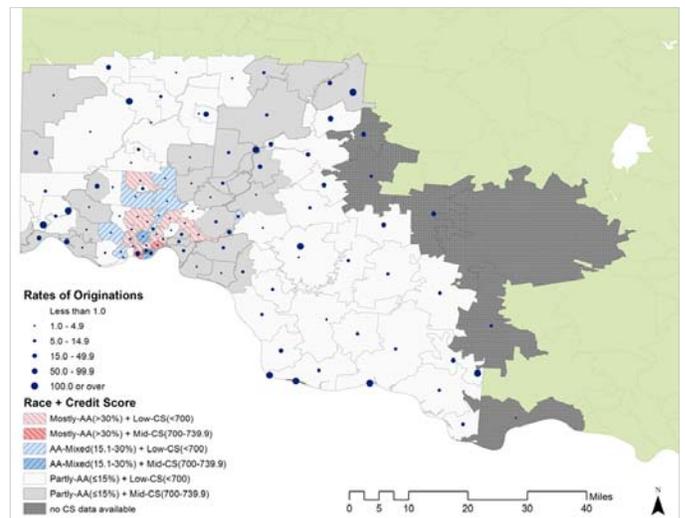


Figure 74 Rates of Originations by Neighborhood Racial Composition and Credit Score in the Cincinnati MSA in Period 1



Geographic Concentration of Subprime Loans in Period 1

Given the country’s recent lending history, it is not surprising that a large share of subprime mortgage were originated in Mostly-African-American Neighborhoods across all five MSAs during Period 1 (Figure 76 and Figure 77). Even in the Cincinnati MSA where we observed relatively higher rates of conventional mortgage originations in those African-American neighborhoods, the subprime share is high and concentrated in those African-American neighborhoods in the downtown area (Appendix B-12). Additionally, some fringe Partly-African-American Neighborhoods across five MSAs also have high subprime shares. In the Columbus and Toledo MSAs, for example, while subprime share is still high in Mostly-African-American Neighborhoods, there are other fringe neighborhoods in the south showing higher subprime share (Figure 76 and Figure 77). Those Partly-African-American Neighborhoods have lower credit scores. Thus, while lower credit scores seem to be related to higher subprime share, we can still see that subprime loans comprise a larger proportion of all loans in Mostly-African-American Neighborhoods and as compared to Partly-African-American Neighborhoods across all five MSAs regardless of credit score.

Figure 76 Subprime Share by Neighborhood Racial Composition and Credit Score in the Columbus MSA in Period 1

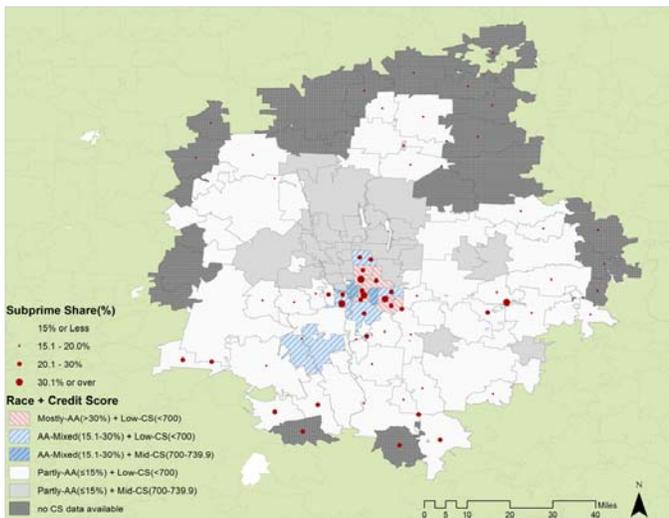
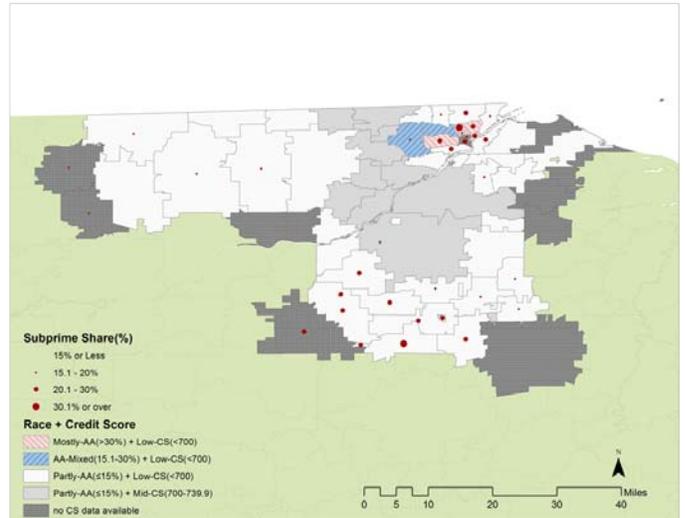


Figure 77 Subprime Share by Neighborhood Racial Composition and Credit Score in the Toledo MSA in Period 1



Period 2: Geography of Absence of Mortgage Originations

Lack of Access to Mortgage in Period 2

After the mortgage crisis, the mortgage market shrank in Period 2, and Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods suffer more from the lack of access to conventional mortgages than Partly-African-American Neighborhoods, regardless of credit score. The maps demonstrate an overall shrinkage in rates of conventional mortgage originations. Further, conventional mortgages are absent from most African-American neighborhoods no matter the credit score. In the Cleveland MSA in particular, only three Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods have a mortgage origination rate more than one per 100 units, while Partly-African-American Neighborhoods had higher rates of originations (Figure 78). Accounting for credit scores, the three Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods with a rate of origination of 1 or higher have middle credit scores (credit score ranging from 700 to 739.9), while Partly-African-American Neighborhoods with the comparable credit scores have higher rates of originations. In the Cincinnati MSA, on the other hand, there are some Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods had some mortgage originations although the rate was lower compared to Partly-African-American Neighborhoods with comparable credit score levels

Figure 78 Rate of Conventional Mortgage Originations by Neighborhood Racial Composition and Credit Score in the Cleveland MSA in Period 2

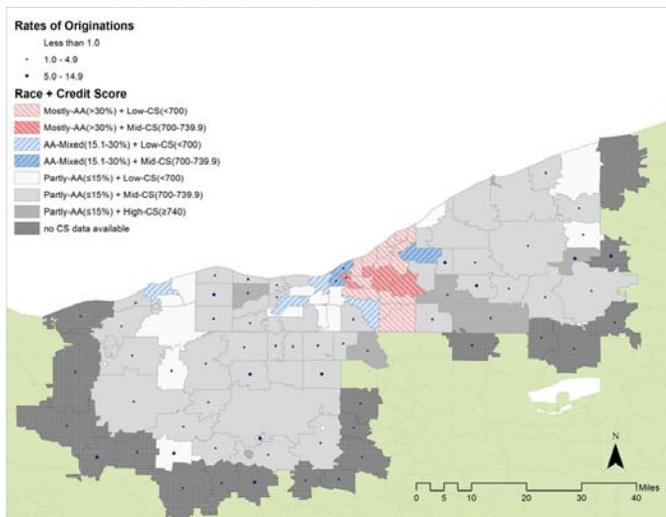
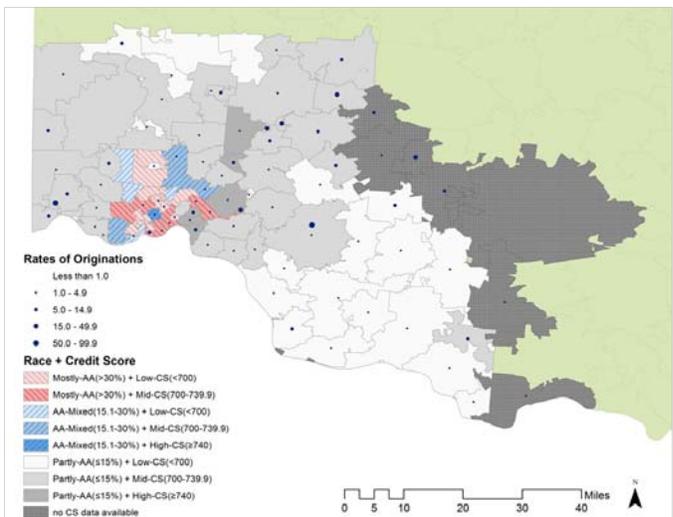


Figure 79 Rate of Conventional Mortgage Originations by Neighborhood Racial Composition and Credit Score in the Cincinnati MSA in Period 2



(Figure 79). This pattern in the Cincinnati MSA may be unique, given that rates of originations in other MSAs for most Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods are less than one per 100 units.

Negative APR Spread in Partly-African-American Neighborhoods in Period 2

While having limited access to mortgage originations in Period 2, Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods in some MSAs concurrently had high mortgage APR spread, when compared to Partly-African-American Neighborhoods having similar credit scores. In the Cincinnati MSA, some Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods had access to mortgages when compared to those African-American neighborhoods in other MSA; however, those African-American neighborhoods in the Cincinnati MSA had higher APR spread when compared to Partly-African-American Neighborhoods with comparable credit scores (Figure 81). In contrast, the Cleveland MSA demonstrates a different pattern: Mostly-African-American Neighborhoods did not necessarily have higher APR spread, and some Mostly-African-American Neighborhoods actually had negative APR spread (Figure 80). Thus, Most-African-American Neighborhoods and African-American-Mixed Neighborhoods in the Cleveland MSA were more likely to suffer from a lack of access to credit than the high cost of credit. In other MSAs, Columbus, Dayton, and Toledo, neighborhoods with lower credit score experienced higher APR spreads.

Figure 81 Median APR spread by Neighborhood Racial Composition and Credit Score in the Cincinnati MSA in Period 2

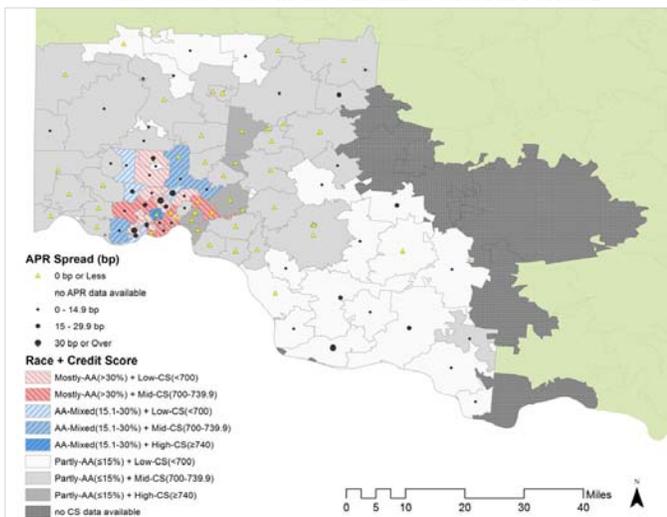
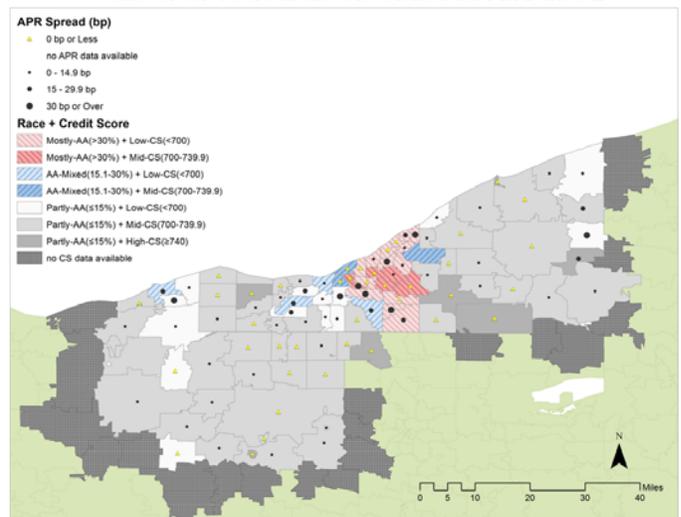


Figure 80 Median APR spread by Neighborhood Racial Composition and Credit Score in the Cleveland MSA in Period 2



High Concentration of FHA Loans in Downtown

The geographic pattern of the share of FHA loans in Period 2 is similar to the pattern of the share of subprime loans in Period 1: in most MSAs, the proportion of FHA loans was higher in the downtown area, which are mainly Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods. In addition, neighborhoods with higher FHA share tended to have lower credit scores (credit score of lower than 700). The Cincinnati MSA was different, however; the share of FHA loans is high even in Fewer African-American located outside of downtown (Appendix B-13). The Cleveland MSA is closer to the dominant pattern, where the share of FHA loans was concentrated in Lower Credit Score African-American Neighborhoods with (Figure 82). Most of Mostly-African-American Neighborhoods in the Cleveland MSA had a median FHA share of 70 percent or more, although Partly-African-American Neighborhoods with the comparable credit scores had lower FHA shares. The Dayton MSA’s higher rates of FHA lending were in the downtown area, but not necessarily within Mostly-African-American neighborhoods (Appendix B-29). In Toledo, higher FHA share was concentrated around the downtown area (Appendix B-37). The Columbus MSA is also distinct, when compared to other MSAs. Overall FHA share in the Columbus MSA was higher than in other MSAs, and those neighborhoods with higher FHA shares are neighborhoods with lower credit score located near downtown or in fringe areas; the median share of FHA loans is still higher in Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods (Figure 83).

Figure 82 FHA Loan Share by Neighborhood Racial Composition and Credit Score in Cleveland MSA in Period 2

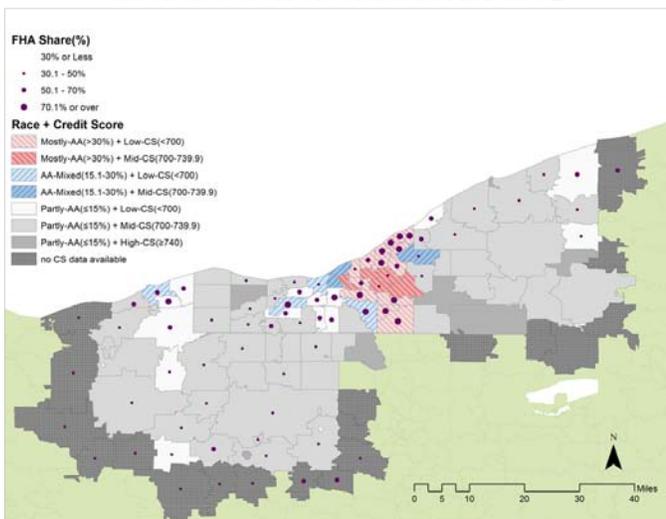
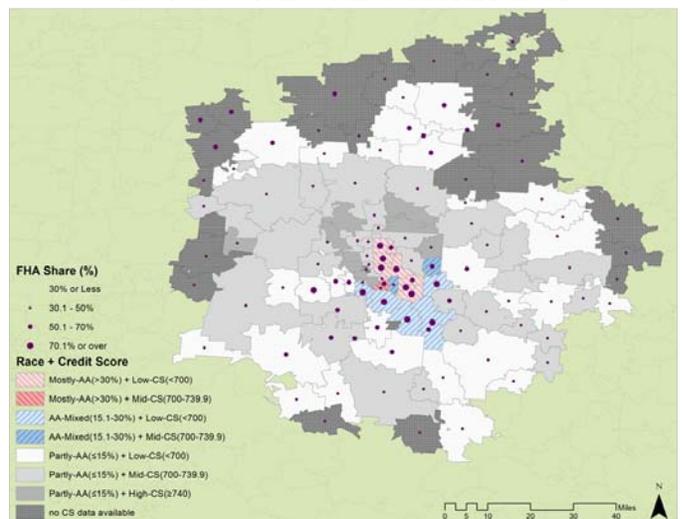


Figure 83 FHA Loan Share by Neighborhood Racial Composition and Credit Score in Columbus MSA in Period 2



Period 3: Geography of Mortgage Recovery

Recovery of Access to Mortgage

Period 3 is the recovery period for access to mortgage capital. However, the maps show that the recovery occurred primarily in Partly-African-American Neighborhoods, and Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods were less likely to experience recovery of rates of originations. Therefore, we expect that mortgage recovery did not occur equally across neighborhoods. In the Cleveland and Dayton MSAs, Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods, which previously had less access to conventional mortgages, continued to have little access. The rate of originations in the majority of Mostly-American-American neighborhoods was still less than one per 100 units (Figure 84 and Figure 85). In the Cincinnati MSA, although Mostly-African-American Neighborhoods at each credit score level had less access to conventional mortgages than Partly-African-American Neighborhoods, the gap in access to mortgages between those neighborhoods is not large (Appendix B-11).

Figure 84 Rates of Conventional Mortgage Originations by Neighborhood Racial Composition and Credit Score in Cleveland MSA in Period 3

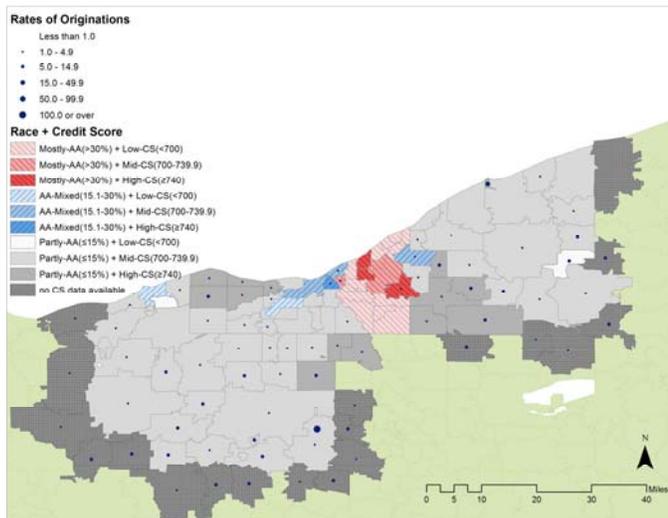
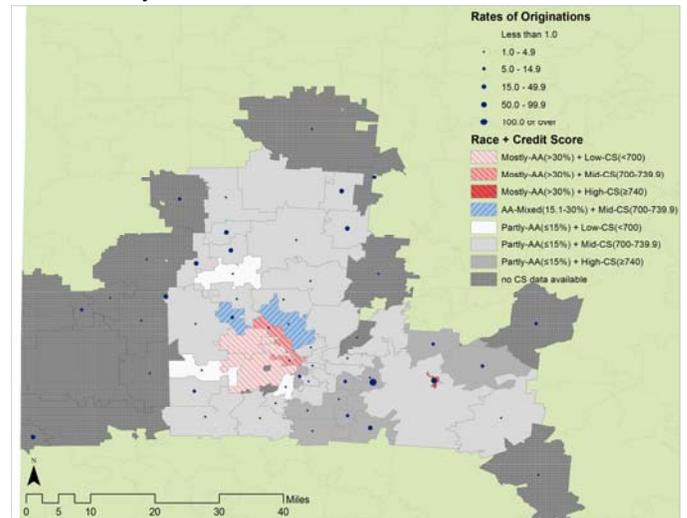


Figure 85 Rates of Conventional Mortgage Originations by Neighborhood Racial Composition and Credit Score in Dayton MS in Period 3

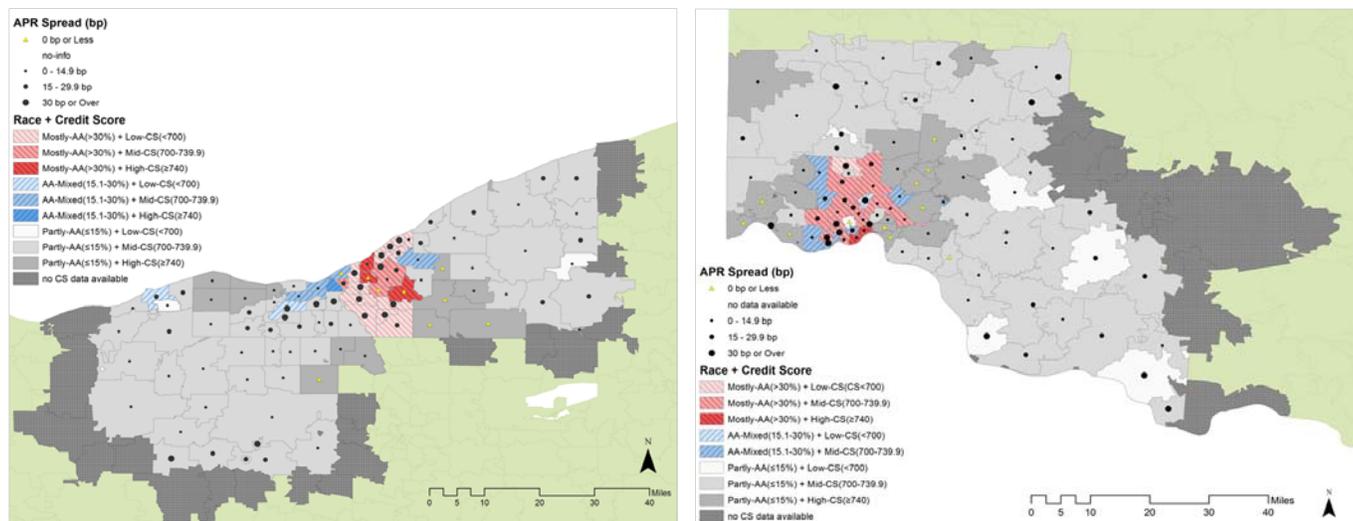


Moderate APR Spread

In the previous descriptive analysis, we observed very few differences in the APR spread between African-American Neighborhoods and predominantly White neighborhoods, except at lower credit score

levels. The spatial analysis also demonstrates this pattern. In the Cleveland MSA (Figure 86), among Mostly-African-American Neighborhoods, neighborhoods with lower credit-score have higher APR spread, while neighborhoods with higher credit-score have lower APR spread. We can see the similar trend among Partly-African-American Neighborhoods: the higher the credit score the lower the APR spread, although neighborhoods with lower credit score have lower APR spread than do some neighborhoods with middle credit score. Comparing credit score level, Mostly-African-American Neighborhoods with lower credit score may have higher APR spread than do Partly-African-American Neighborhoods with comparable credit score. In the other MSAs, the pattern is not as clear. Using the Cincinnati MSA (Figure 87) as an example, neighborhoods with similar median credit scores have similar median APR spreads. However, in the fringe areas, the Partly-African-American Neighborhoods had a relatively higher APR spread. Thus, racial composition might not be a decisive factor on APR spread in all the MSAs except Cleveland.

Figure 86 Median APR spread by Neighborhood Racial Composition and Credit Score in Cleveland MSA in Period 3 Figure 87 Median APR spread by Neighborhood Racial Composition and Credit Score in Cincinnati MSA in Period 3



High Concentration of FHA Loans in African-American Neighborhoods

The overall median FHA share declined across neighborhoods in the five MSAs in Period 3. Partly-African-American Neighborhoods in all MSAs were less likely to have a higher FHA share, while some Mostly-African-American Neighborhoods had a lower credit score, relying more on FHA mortgages than other mortgage channels. The size of the neighborhood FHA share is mainly associated with the credit score,

although neighborhood racial composition may still have an impact as well. For example, Mostly-African-American Neighborhoods with lower median credit scores in the Cleveland MSA had a median FHA share of 70% or higher (Figure 88). In Columbus, in contrast, even African-American neighborhoods with middle credit scores had relatively higher FHA share, when compared to Partly-African-American Neighborhoods with comparable credit scores (Figure 89).

Figure 88 FHA Loan Share by Neighborhood Racial Composition and Credit Score in the Cleveland MSA in Period 3

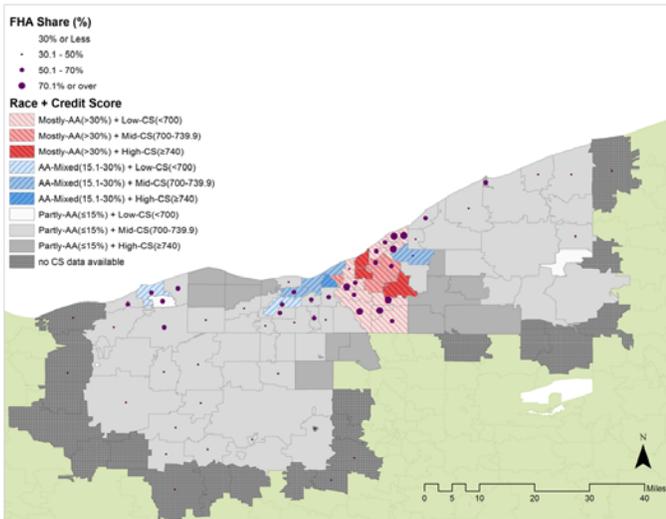
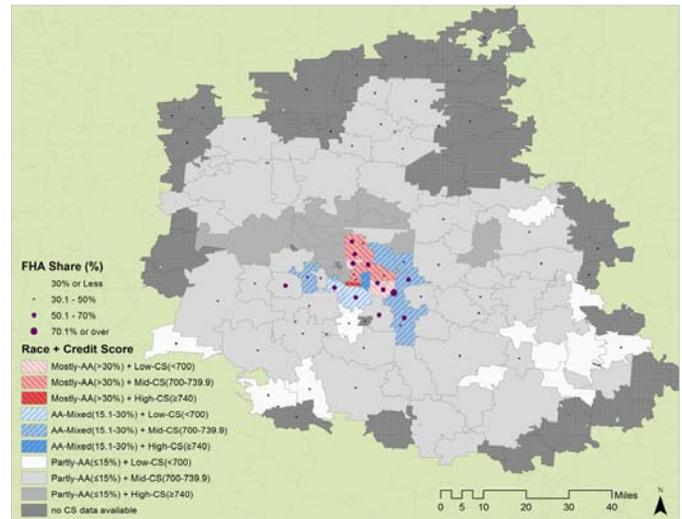


Figure 89 FHA Loan Share by Neighborhood Racial Composition and Credit Score in the Columbus MSA In Period 3



9. Summary

Thus far, we have investigated multiple aspects of mortgage lending in the five MSAs in three periods, accounting for neighborhood racial composition and neighborhood financial credibility. Our focus is on access to capital and cost of capital in African-American and White neighborhoods during the mortgage boom, bust, and recovery periods, while controlling for financial credibility. In addition, we investigated the geographical distribution of different types of mortgages using GIS maps. Overall, results show a consistent trend: African-American Neighborhoods (neighborhoods where the rate of African-American residence is over 15%) seem to be at a disadvantage in mortgage lending in every aspect examined in every period.

In terms of mortgage originations, results from descriptive analyses indicated that no matter the financial credibility, African-American Neighborhoods overall received substantially lower rates of conventional mortgage originations than did predominantly White neighborhoods where the rate of Whites in a neighborhood is over 85% in a neighborhood in every period. During the mortgage boom period, predominantly White neighborhoods with lower incomes and credit scores received much higher rates of originations than did African-American neighborhoods with higher income and credit scores. During the crisis period, although even predominantly White neighborhoods were suffering from a dearth of mortgages, they still had higher accessibility of conventional mortgage capital than did African-American Neighborhoods. After the crisis, predominantly White neighborhoods experienced the recovery of access to mortgage capital, but rates of origination in African-American Neighborhoods were nearly equal to the rates in the bust period in all MSAs. These patterns are shown in GIS maps and indicate the lower distribution of conventional mortgage originations in Mostly-African-American Neighborhoods. From these results, we see that African-American Neighborhoods, when compared with predominantly White neighborhoods, had lower conventional mortgage originations, no matter the financial credibility and the mortgage market conditions, while the significance in gaps could vary by MSAs and period.

In terms of quality of mortgages, while subprime share was always high in African-American Neighborhoods, there was only consistent tendency in APR spread by neighborhood racial composition only concerning financial credibility. The largest shares of subprime loans were concentrated in African-American Neighborhoods, which corresponding with existing studies. Particularly, Lower Income and Credit Score African-American Neighborhoods had higher shares of subprime loans. Geographically, GIS maps demonstrate that higher subprime shares were concentrated in Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods located around downtown of each MSA. However, results for APR spreads, another quality indicator of mortgage originated, revealed no difference in APR spread between African-American Neighborhoods and predominantly White neighborhoods. Nonetheless, an obvious pattern is that in neighborhoods with higher credit score and incomes, the APR

spreads are lower. It may be that APR spread could be mostly explained by financial credibility. In Period 2, however, a small gap might exist between predominantly White neighborhoods and African-American Neighborhoods, particularly among lower income and credit score neighborhoods. In Period 3, only in the Cleveland MSA were gaps in lending demonstrated between predominantly White and African-American Neighborhoods; African-American Neighborhoods with lower credit-score had higher APR spreads than did predominantly White neighborhoods with comparable credit scores.

Lastly, the share of FHA-insured loans was always higher in African-American Neighborhoods across all periods. While the general pattern for neighborhoods of any racial composition was that as credit score and income increased, the share of FHA loans was lower, the median FHA share among African-American Neighborhoods with lower- and mid-financial credit levels were higher than the median FHA share among predominantly White neighborhoods with comparable financial credibility. The geographical distribution of higher FHA shares in Period 2 and 3 looked similar to the distribution of subprime shares in Period 1. These results imply that African-American Neighborhoods had higher FHA share than did predominantly White neighborhoods. Furthermore, the higher FHA-share was geographically concentrated in the downtown area of each MSA.

Thus far, we have investigated multiple aspects of mortgage lending in the five MSAs in three periods, accounting for neighborhood racial composition and neighborhood financial credibility. In addition, we investigated the geographical distribution of different types of mortgages using GIS maps. Overall, results show a consistent trend: African-American Neighborhoods seem to be at a disadvantage in mortgage lending in every aspect examined in every period. In addition, we understand lending patterns can be varied by MSAs. However, these results do not take into account other possible causes of the patterns of lending observed. Therefore, we conduct multivariate regression analysis allowing for the simultaneous consideration of a variety of causes of differential neighborhood mortgage originations.

V. Multivariate Analysis

While the descriptive results suggest that African-American Neighborhoods including both Mostly-African-American Neighborhoods and African-American-Mixed Neighborhoods had lower rates of lending than did predominantly White neighborhoods, we do not know if this pattern holds up when other causal factors taken into consideration. Thus, we use multivariate regression analysis to investigate lending patterns, while accounting for the simultaneous consideration of other factors influencing mortgage lending. The lending patterns investigated, as in the descriptive analysis, include conventional mortgage origination number in a neighborhood during Period 1 (2004-2007), Period 2 (2008-2011), and Period 3 (2012-2015), the share of subprime loans of all loans originated in a neighborhood (subprime share) in Period 1, the share of FHA loans of all loans originated in a neighborhood (FHA share) in Period 2 and 3, and the APR spread within the neighborhood as dependent variables in Period 2 and 3. For the share of subprime loans, share of FHA loans, and the APR spread, we use ordinary least squares (OLS) regressions to control for other potential causes of neighborhood level differences in lending. To investigate the quantity of mortgages in neighborhoods we use the count of conventional mortgage originations in a neighborhood as a dependent variable, while controlling for the number of owner-occupied homes in the neighborhood. To analyze the count of mortgages originated, we use negative binomial regression models, as they are a better fit for modeling non-negative count data.⁸ For each analysis, we present two models, although considered many. Full model results can be found in the Appendix.

The following analysis is organized by period, and discusses overall lending patterns by each period under study. Throughout, we compare lending patterns across MSAs. For MSA specific results, please see the Appendix.

⁸ Because mortgage origination is a non-negative count and is over-dispersed—that is the variance of the variable is significantly higher than the mean—a negative binomial regression model is more appropriate than an ordinary least-squares (OLS) linear regression model.

Period 1 (2004 – 2007): In the Shadow of Mortgage Boom

Access to Conventional Mortgages

The results across all five MSAs show that three main factors – proportion of African-Americans, median credit score, and median income – commonly predict conventional mortgage originations in neighborhoods (Table 2, Models A and B). Importantly, while controlling for other factors, the proportion of African-Americans in a neighborhood is negatively and significantly associated with conventional mortgage originations. In other words, the higher the proportion of African-Americans in a neighborhood, the fewer conventional mortgage originations. For example, in the Cincinnati MSA, a one-percentage-point increase in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 1.4 percentage points (Table 2, Model A). Thus, given that the mean conventional neighborhood mortgage origination in the Cincinnati MSA was 181 during Period 1 (see Appendix A-9), a ten-percentage-point increase in the proportion of African-Americans in a neighborhood with a median origination count of 181 is expected to decrease its origination count in the neighborhood by 25 mortgages.

Both median credit score and median income are positively associated with conventional mortgage originations: The higher the median credit score and income in a neighborhood, the higher number of conventional mortgage originations. For example, in the Cleveland MSA (Table 2, Model A), for every additional point of credit score, the expected conventional mortgage origination increases by 0.9 percentage point in this period. In terms of income, a one-percentage point increase in the median income in the neighborhood is expected to result in 168.3 percentage point more conventional mortgage originated in a neighborhood in this mortgage boom period. In the Dayton and Toledo MSAs, credit scores do not have a constant relationship to lending (Table 3). Thus, we vary our modeling technique and use piecewise regression. The implication is that up to some point credit score has one relationship to lending, and above that it has another. For the Dayton MSA, the relationship between credit scores and lending is different for neighborhood median credit scores at or under 660 and over 660. Holding the proportion of African-

Americans in a neighborhood at zero, if the median credit score is less than 660, the credit score is negatively associated with conventional mortgage originations; meanwhile, if the median credit score is 660 or higher, the credit score is positively associated with originations, which is to be expected. Holding credit score constant, the higher the proportion of African-Americans in the neighborhood, the few mortgage originations. When both are taken into account (an interaction term, Table 3, Model D), there is little or no meaningful impact. The interaction term between the median credit score of 660 or less and the proportions of African-Americans (**CS(Low)×AA**) tells us that there is only a negligible positive impact when low-credit scores and the proportion of African-American in a neighborhood are taken into account together (Table 3, Model D). In addition, for neighborhoods with a median credit score of over 660, the combination of median neighborhood credit score and the proportion of African-Americans (**CS(High)×AA**) has negative impact on mortgage originations. In the Toledo MSA, being a neighborhood with a median credit score of 670 or less has no impact on originations. In contrast, neighborhoods with a median credit score of 670 or higher have more conventional mortgage originations. In the Toledo MSA, Model C shows that a one-percentage-point increase in the proportion of African-Americans in a neighborhood is expected to decrease conventional mortgage originations by 0.8 percentage points.

Additionally, across all MSAs, the age of housing units in the neighborhood is associated with originations. The older the median age of the housing units in the neighborhood, the fewer conventional mortgages.

Table 2 Multivariate Results for Conventional Mortgage Originations, Period 1 (2004-2007)

	Cleveland				Cincinnati				Columbus			
	Model A		Model B		Model A		Model B		Model A		Model B	
	Exponentiated Coefficient											
Credit Score	0.009	1.009 ***	0.011	1.011 ***	0.008	1.008 ***	0.008	1.008 ***	0.005	1.005 ***	0.004	1.004 *
Proportion AA	-0.007	0.993 ***	0.065	1.067 *	-0.014	0.986 ***	-0.018	0.982	-0.006	0.994 *	-0.155	0.856 *
Log Income	0.987	2.683 ***	0.905	2.471 ***	0.665	1.945 ***	0.672	1.959 ***	1.017	2.764 ***	1.043	2.837 ***
DTI-conv (Low)	0.113	1.120 ***	0.167	1.181 ***	0.149	1.160 ***	0.149	1.161 ***	-0.069	0.934 **	-0.069	0.933 ***
DTI-conv (High)	-0.075	0.928 **	-0.129	0.879 ***	-0.115	0.892 ***	-0.115	0.891 ***	0.050	1.051	0.051	1.052
DTI-conv (intersect)	-0.483	0.617 ***	-0.596	0.551 ***	0.238	1.269	0.236	1.266	0.261	1.298 **	0.284	1.328 **
House Age	-0.016	0.984 ***	-0.015	0.985 **	-0.009	0.991 ***	-0.009	0.991 ***	-0.015	0.985 ***	-0.015	0.985 ***
Selfemployment	-0.029	0.972 *	-0.032	0.969 **	-0.013	0.987	-0.013	0.987	0.001	1.001	4E-04	1.000
CS×AA			-1E-04	1.000 **			7E-06	1.000			2E-04	1.000 *
Owner-Occupied	2E-05	1.000	2E-05	1.000	1E-05	1.000	1E-05	1.000	-5E-05	1.000 ***	-5E-05	1.000 ***
Constant	-14.387	6E-07 ***	-16.957	4E-08 ***	-12.131	5E-06 ***	-12.141	5E-06 ***	-5.991	0.003 **	-5.467	0.004 **
n		94		94		97		97		111		111
Log pseudolikelihood		-496.69		-495.10		-562.70		-551.75		-659.59		-659.59
BIC		1043.36		1044.73		1153.82		1158.39		1375.69		1375.69

	Dayton				Toledo			
	Model A		Model B		Model A		Model B	
	Exponentiated Coefficient							
Credit Score	5E-05	1.000	-0.001	0.999	0.005	1.005	0.005	1.006 *
Proportion AA	-0.016	0.984 ***	-0.046	0.955	-0.005	0.995	0.067	1.069
Log Income	1.621	5.058 ***	1.638	5.145 ***	1.456	4.288 **	1.375	3.954 **
DTI-conv (Low)	0.033	1.033	0.027	1.027	0.303	1.354 ***	0.295	1.343 ***
DTI-conv (High)	0.006	1.006	0.012	1.012	-0.292	0.747 ***	-0.281	0.755 ***
DTI-conv (intersect)	0.062	1.064	0.056	1.058	-1.250	0.287 ***	-1.248	0.287 ***
Hous Age	-0.012	0.988 **	-0.013	0.987 **	-0.008	0.992	-0.008	0.992
Selfemployment	-0.027	0.974 **	-0.026	0.974 **	-0.012	0.988	-0.009	0.991
CS×AA			5E-05	1.000			-1E-04	1.000
Owner-Occupied	2E-05	1.000 **	2E-05	1.000	2E-05	1.000	2E-05	1.000
Constant	-12.935	2E-06	-12.543	4E-06 ***	-22.583	2E-10 ***	-21.980	3E-10 ***
n		55		55		55		55
Log pseudolikelihood		-289.68		-289.13		-298.71		-293.10
BIC		617.41		620.74		641.49		642.29

Note 1. Model: Piecewise Negative Binomial Regression
 2. DTI (Low/High) : 34% for Cleveland, Cincinnati, Toledo and 36.2% for Columbus, Dayton
 3. *** (**)(*) :Significant at the 99% (95%) (90%) level

Table 3 Multivariate Results for Conventional Mortgage Origination in Neighborhood, Period 1 (2004-2007)

	Dayton				Toledo			
	Model C		Model D		Model C		Model D	
	Coefficient	Exponentiated Coefficient						
Credit Score (LOW)	3E-04	1.000	-0.024	0.977 **	-0.001	0.999	-0.001	0.999
Credit Score (HIGH)	-0.001	0.999	0.026	1.026 **	0.010	1.010 **	0.010	1.010 *
CS (Intersect)	0.069	1.072	0.167	1.182	0.051	1.052	0.066	1.068
Proprtion AA	-0.015	0.985 ***	-0.152	0.859 *	-0.008	0.992 **	-0.019	0.981
Log Income	1.607	4.990 ***	1.632	5.114 ***	1.173	3.230	1.246	3.475 *
DTI-conv (Low)	0.032	1.032	0.031	1.032	0.240	1.271 ***	0.240	1.271 **
DTI-conv (High)	0.007	1.007	0.022	1.022	-0.223	0.800 **	-0.224	0.799 **
DTI-conv (intersect)	0.059	1.060	0.054	1.055	-1.008	0.365 ***	-1.014	0.363 ***
House Age	-0.013	0.987 **	-0.014	0.986 ***	-0.010	0.990	-0.010	0.990
Selfemployment	-0.027	0.974 **	-0.028	0.973 **	-0.010	0.990	-0.010	0.991
CS(LOW)×AA			2E-04	1.000 *			2E-05	1.000
CS(HIGH)×AA			-0.001	0.999 **			-3E-04	1.000
CS(Ints.)×AA			2E-02	1.020			-0.004	0.996
Owner-Occupied	2E-05	1.000	2E-05	1.000	2E-05	1.000	2E-05	1.000
Constant	-12.982	2E-06 *	2.351	10.495	-14.094	8E-07 *	-14.867	3E-07 *
n		55		55		55		55
Log pseudolikelihood		-286.40		-284.66		-295.81		-295.59
BIC		624.90		633.44		643.72		655.31

Note 1. Model: Piecewise Negative Binomial Regression
2. Credit Score (Low/High) : 660 for Dayton at 670 for Toledo
3. DTI (Low/High) : 36.2% for Dayton, and 34% for Toledo
4. *** (**)(*) :Significant at the 99% (95%) (90%) level

The Share of Subprime Loans in the Neighborhood

Our models (Table 4) show that the proportion of African-Americans is significantly and positively associated with the shares of subprime loans across the five MSAs, while controlling for credit scores and income, both of which are negatively associated with the share of subprime loans. That is, the higher the proportion of African-Americans in a neighborhood, the higher the share of subprime loans. This result concurs with the results of other studies showing that subprime mortgages are concentrated in African-American neighborhoods (Calem, Gillen, et al., 2004; Immergluck & Wiles, 1999). In the Columbus MSA, for instance, a one-percentage-point increase in the proportion of African-Americans in a neighborhood is expected to increase the subprime share by 0.16 percentage points, holding other variables constant (Table 4, Model A). In all MSAs but Columbus, when the median neighborhood credit score is taken into account simultaneously with the proportion of African-Americans (the interaction term between the median credit score and proportion of African-Americans ($CS \times AA$) in Table 2, Model B), neighborhoods with higher proportions of African-Americans with lower median credit scores are expected to have higher shares of subprime loans.

The income of the neighborhood also is associated with the share of subprime loans. In all MSAs but in the Cleveland MSA, the lower the neighborhood income, the higher the share of subprime loans; in the Cleveland MSA, neighborhood income had no impact on subprime lending. In the Cincinnati MSA, higher proportions of African-Americans with higher incomes were associated with an additional increase in the share of loans in the neighborhood that were subprime. That is to say, income magnified the relationship between race and the proportion of loans in a neighborhood that were subprime. The Cleveland MSA was distinctive in this period because of the positive relationship between bank branches in the neighborhood and the proportion of loans that were subprime. The higher the ratio of bank branches to housing units, the higher the share of subprime loans.

Table 4 Multivariate Results for Subprime Share in Neighborhood, Period 1 (2004-2007)

	Cleveland		Cincinnati		Columbus	
	Model A	Model B	Model A	Model B	Model A	Model B
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Credit Score	-0.332 ***	-0.295 ***	-0.124 ***	-0.070 **	-0.110 ***	-0.078 ***
Proportion AA	0.149 ***	2.095 ***	0.090 ***	1.345 **	0.161 ***	3.685 ***
Log Income	-1.017	-1.831	-6.322 **	-11.513 ***	-6.474 **	-7.474 ***
House Price Change	0.000	0.006	-0.015 ***	-0.001	0.004	0.005
DTI-all	-0.099	-0.060	0.784 ***	0.601 ***	0.374 *	0.327 *
Turnover	4.309 ***	4.812 ***	-2.063 **	-1.737 **	-0.076	-0.076
HPC×Turnover	-0.109 **	-0.151 ***				
Bank Ratio	0.110 **	0.184 ***				
Log Inc×AA				0.124 ***		
CS×AA		-0.003 ***		-0.004 ***		-0.005 ***
Constant	257.4 ***	239.1 ***	139.795 ***	165.287 ***	144.314 ***	135.978 ***
n	94	94	98	98	112	112
adjusted R ²	0.906	0.925	0.756	0.802	0.641	0.720
BIC	571.8	554.7	568.7	555.4	687.1	666.3

	Dayton		Toledo	
	Model A	Model B	Model A	Model B
	Coefficient	Coefficient	Coefficient	Coefficient
Credit Score	-0.115 ***	-0.172 ***	-0.105 **	-0.084 **
Proportion AA	0.231 ***	2.768 ***	-0.048	1.910 **
Log Income	-15.987 ***	-7.986 **	-15.532 ***	-17.647 ***
House Price Change	-0.056 ***	-0.046 ***	0.002	-0.003
DTI-all	0.385 *	-0.026	0.255	0.244
Turnover	-1.657 ***	-1.416 ***	-0.261	-0.453
Log Inc×AA		-0.246 ***		
CS×AA		3E-05		-0.003 **
Constant	255.748 ***	223.168 ***	244.719 ***	254.898 ***
n	55	55	58	58
adjusted R ²	0.907	0.928	0.629	0.649
BIC	312.1	303.6	362.9	362.7

Note 1. Model: OLS Regression

Period 2 (2008 - 2011): Mortgage Bust

Access to Conventional Mortgages

During the mortgage bust period, the racial composition of the neighborhood in four MSAs is associated with lower rates of conventional mortgage origination, while one has a distinct positive relationship. Holding all else equal, including the median neighborhood credit score, income, and the riskiness of loans in the neighborhood, all MSAs but Cincinnati demonstrate a pattern where the higher the proportion of African-Americans in a neighborhood, the fewer conventional mortgages are originated (Table 5). For example, in the Dayton MSA, a one-percentage-point increase in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 2.2 percentage points (Table 2, Model A). Thus, given that the mean conventional neighborhood mortgage origination in the Dayton MSA was 66 during Period 2 (see Appendix A-10), a ten-percentage-point increase in the proportion of African-Americans in a neighborhood with a median origination count of 66 is expected to decrease its origination count in the neighborhood by 15 mortgages. The Cincinnati MSA is distinct, however: for higher rates of African-American residence *more* conventional loans were originated during the bust (Table 5, Model B).

Credit score matters in this story, however, in the Columbus and Toledo MSAs. In those MSAs, neighborhood racial composition only matters for lending when credit scores are considered in tandem with racial composition (Table 5, Model B for each MSA). In the Columbus MSA, for example, accounting for an interaction term between the proportions of African-Americans and median credit scores, generally as credit scores increase with increasing proportions of African-Americans, the neighborhood had slightly improved conventional mortgage origination counts.

The median income is, not surprisingly, positively associated with conventional mortgage originations in all MSAs. The higher the median income in a neighborhood, the more mortgage originations. For example, in the Cleveland MSA, a one-percent increase in the median income in neighborhood is expected to result in 179.2 percentage point more conventional mortgages originated in a neighborhood in this period

(Table 5, Model A). Furthermore, another financial factor, the median neighborhood credit score, is positively associated with conventional mortgage originations in three of the five MSAs (Cleveland, Cincinnati, and Columbus, Tables 5). In the Cleveland, Cincinnati, and Columbus MSAs, the higher the median credit scores within a neighborhood, the more conventional mortgage originations there. For example, in the Cincinnati MSA, for every additional point of credit score, the expected conventional mortgage origination increases by 1.8 percentage points in this period (Table 5, Model A).

Another variable commonly seen across five MSAs as a significant factor in the median conventional mortgage origination is the median age of housing units. The median age of housing units is negatively associated with mortgage originations, meaning that the higher proportions of older housing units in a neighborhood, the fewer conventional mortgage originations.

In this housing market bust period, the debt-to-income ratio explains variations in lending patterns. In all MSAs, an average DTI exists at which mortgages are fewer in number or after which the DTI has no impact on the number of mortgages. For example, in the Cincinnati MSA, at or below a DTI of 38 percent mortgage originations in neighborhoods tend to increase; at DTIs above 38 percent, the number of mortgage originations in a neighborhood decrease. The presence of some difference in lending above and below levels of DTI may reflect Fannie Mae and Freddie Mac lending guidelines, which allow the higher DTI, up to 45%, depending on the borrowers' financial credibility or LTVs.⁹

⁹ Fannie MAE: https://www.fanniemae.com/content/eligibility_information/eligibility-matrix.pdf
Freddie MAC: http://www.freddiemac.com/singlefamily/news/2014/0102_lp_new_feedback_messages.html

Table 5 Multivariate Results for Conventional Mortgage Originations, Period 2 (2008-2011)

	Cleveland				Cincinnati				Columbus			
	Model A		Model B		Model A		Model B		Model A		Model B	
	Coefficient	Exponentiated Coefficient										
Credit Score	0.014	1.014 ***	0.012	1.012 **	0.018	1.018 ***	0.021	1.021 ***	0.016	1.016 ***	0.013	1.014 **
Proportion AA	-0.006	0.994 **	-0.061	0.941	-0.007	0.993 *	0.136	1.146 *	-0.002	0.998	-0.305	0.737 **
Log Income	1.027	2.792 ***	1.086	2.963 ***	0.623	1.865 ***	0.526	1.693 **	1.071	2.919 ***	1.045	2.844 ***
DTI-conv (Low)	-0.001	0.999	-2E-04	1.000	0.109	1.115 **	0.122	1.130 **	-0.035	0.965	-0.040	0.961
DTI-conv (High)	-0.104	0.901 **	-0.105	0.900 **	-0.180	0.835 ***	-0.190	0.827 ***	-0.192	0.825 **	-0.169	0.844 **
DTI-conv (intersect)	0.271	1.311	0.289	1.334	-0.057	0.945	-0.065	0.937	0.563	1.756 **	0.549	1.731 **
House Age	-0.021	0.979 ***	-0.022	0.978 ***	-0.021	0.980 ***	-0.020	0.980 ***	-0.021	0.980 ***	-0.021	0.979 ***
CS×AA			8E-05	1.000			-2E-04	1.000 *			4E-04	1.000 **
Owner-Occupied	3E-05	1.000 ***	3E-05	1.000 ***	3E-07	1.000	-6E-07	1.000	-1E-05	1.000	-1E-05	1.000
Constant	-16.700	6E-08 ***	-15.942	1E-07 ***	-17.591	2E-08 ***	-19.210	5E-09 ***	-16.485	7E-08 ***	-14.404	6E-07 ***
n		94		94		91		91		99		99
Log pseudolikelihood		-403.81		-403.45		-453.99		-453.00		-511.43		-509.60
BIC		853.06		856.88		953.08		955.63		1068.82		1069.60

	Dayton				Toledo			
	Model A		Model B		Model A		Model B	
	Coefficient	Exponentiated Coefficient						
Credit Score	0.003	1.003	0.001	1.001	0.003	1.003	-0.001	0.999
Proportion AA	-0.022	0.978 ***	-0.186	0.831	-0.004	0.996	-0.216	0.806 **
Log Income	0.756	2.131 *	0.818	2.266 *	2.262	9.598 ***	2.375	10.755 ***
DTI-conv (Low)	0.135	1.144 **	0.134	1.144 **	0.123	1.130 ***	0.131	1.139 ***
DTI-conv (High)	-0.196	0.822 **	-0.189	0.828 **	-0.103	0.902 **	-0.110	0.896 **
DTI-conv (intersect)	-0.311	0.733	-0.371	0.690 *	-0.332	0.717 *	-0.370	0.691 **
House Age	-0.018	0.982 ***	-0.019	0.981 ***	-0.014	0.987 **	-0.015	0.985 **
CS×AA			2E-04	1.000			3E-04	1.000 **
Owner-Occupied	-4E-06	1.000	-1E-05	1.000	-7E-06	1.000	-6E-06	1.000
Constant	-9.225	1E-04 **	-8.244	3E-04 **	-25.975	5E-12 ***	-24.628	2E-11 ***
n		53		53		49		49
Log pseudolikelihood		-240.66		-240.06		-209.69		-207.67
BIC		521.02		523.80		458.29		458.93

Note 1. Model: Piecewise Negative Binomial Regression
 2. DTI (Low/High) : 34% for Dayton and Toledo, 37% for Columbus, 38% for Cleveland and Cincinnati
 3. *** (**) (*) :Significant at the 99% (95%) (90%) level

Share of FHA Loans

During the bust, racial composition is associated with FHA lending patterns, all else constant; however, whether the impact is positive or negative varies across MSAs (Table 6). In the Cincinnati and Toledo MSAs (Table 6, Model A), the higher the proportion of African-Americans in the neighborhood, the higher the share of FHA loans. For instance, in the Toledo MSA, a one-percentage point increase in the rate of African-American resident increases the share of loans being a FHA-insured by 0.34% (Table 6, Model A)

In contrast, once one takes the combined relationship between racial composition and the neighborhood-level income into account (**Inc×AA**), the higher the proportion of African-Americans in the neighborhood, the lower the share of FHA loans, holding credit score, income and market factors constant, in the Cleveland, Columbus, and Dayton MSAs (Table 7, Model A).

The neighborhood income itself plays no role unless race and income are considered together, except in the Dayton MSA, where the higher the median neighborhood income, the lower the share of FHA loans, the expected result. However, in the Cleveland, Columbus and Dayton MSAs, an additional impact exists once taking the racial composition of the neighborhood and income into account: the higher the proportion of African-Americans combined with higher median incomes are expected to have higher FHA shares. This is a point that requires further investigation because FHA mortgages are designed more for less-wealthy members of the population who do not have large down-payments (and high credit scores). An additional, individual-level analysis would reveal whether African-Americans who qualified for conventional loans instead got FHA loans, which might counter-intuitively be costlier to them in the long run.

More generally, credit scores play an important role in the share of FHA loans of all loans in neighborhoods in across all five MSAs during this period of bust: neighborhood median credit scores are significantly and negatively associated with the proportion of FHA loans within the neighborhood. This means that the higher the median credit score, the lower the share of FHA loans in a neighborhood. For

instance, in the Cincinnati MSA, a one-point increase in the median neighborhood credit score is associated with a decrease in the share of FHA loans of 0.43 percentage points (Table 6, Model A).

An unexpected result is the role that the self-employment rate plays; the higher the rate of self-employment, the lower the share of FHA loans, holding all else constant. One possible explanation for this is that FHA-insured mortgages can be more stringent than conventional mortgages (Immergluck, 2011). Individual self-employed borrowers, regardless of whether they apply for conventional or FHA mortgages, are required to submit substantial documentation to demonstrate the stability of their income. However, an existing study showed that the condition of low or no documentation for mortgage originations actually reduces the likelihood of mortgage originated being FHA mortgages when compared with Government-sponsored enterprise (GSE) mortgages (Immergluck, 2011). These decisions about individual borrowers and loans could aggregate to this neighborhood level result we observe.

Table 6 Multivariate Results for FHA Share in Neighborhood, Period 2 (2008-2011)

	Cleveland		Cincinnati		Columbus	
	Model A	Model B	Model A	Model B	Model A	Model B
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Credit Score	-0.854 ***	-0.929 ***	-0.430 ***	-0.376 ***	-0.413 ***	-0.349 ***
Proportion AA	-3.514 ***	-4.165 ***	0.194 ***	2.821	-7.144 ***	-2.122
Log Income	4.140	8.068	3.472	1.813	-3.669	-4.961
Selfemployment	-0.902 ***	-0.888 ***	-0.490	-0.504	-0.913 ***	-0.826 ***
Turnover	-0.531 **	-0.517 **	0.004	-0.008	0.017	0.010
Inc×AA	0.311 ***	0.243 *			0.708 ***	0.782 ***
CS×AA		0.002		-0.004		-0.008 **
Constant	614.006 ***	623.079 ***	311.544 ***	291.874 ***	383.268 ***	351.913 ***
n	93	93	92	92	97	97
adjusted R ²	0.8258	0.8260	0.5744	0.5812	0.6780	0.6968
BIC	683.05	686.39	699.93	701.89	725.06	722.72

	Dayton		Toledo	
	Model A	Model B	Model A	Model B
	Coefficient	Coefficient	Coefficient	Coefficient
Credit Score	-0.280 **	-0.237 **	-0.249 ***	-0.128
Proportion AA	-10.521 ***	-6.436 *	0.338 ***	3.794 **
Log Income	-19.481 **	-20.325 **	16.117 *	9.050
Selfemployment	-0.945 **	-1.071 ***	-3.349 ***	-3.214 ***
Turnover	-0.286 ***	-0.292 ***	-0.533 ***	-0.512 ***
Inc×AA	0.998 ***	0.914 ***		
CS×AA		-0.005		-0.005 **
Constant	467.549 ***	447.981 ***	61.862	54.779
n	51	51	51	51
adjusted R ²	0.7239	0.7275	0.5918	0.6103
BIC	381.11	383.20	401.14	401.56

Note 1. Model: OLS Regression
2. *** (**) (*) :Significant at the 99% (95%) (90%) level

APR Spread

APR spread is a measure of cost, and the higher the spread, the costlier the loan. The relationship between neighborhood racial composition and median APR spread is not consistent. In the Columbus and Toledo MSAs, the higher the proportion of African-Americans in the neighborhood during this bust period, the higher the spread, and the more expensive the loans, holding all else constant (Table 7, Model B). In those MSAs, when credit score is taken into account in combination with neighborhood racial composition, the impact is a slight decrease. In the Cincinnati and Dayton MSAs, neighborhood racial composition has little relationship to the APR spread, while in the Cleveland MSA the higher the proportion of African-Americans, the lower the spread. However, in the case of Cleveland, when the median neighborhood credit score is considered in concert with neighborhood racial composition, the median APR spread is slightly larger, indicating that there may be some inflation of the spread in neighborhoods with higher proportions of African-Americans and with higher credit scores (Table 7, Model B).

Across all five MSAs, higher median neighborhood credit scores are consistently associated with lower median APR spreads, a result which is expected. For example, in the Dayton MSA, one-point increase in the median credit score is expected to decrease the median APR spread in a neighborhood by 0.35 basis points (Table 7, Model A). However, whether there is an additional impact of the combination of credit score and the proportion African-American varies by MSA. In the Columbus and Toledo MSAs, the greater the proportion African-American in a neighborhood, the higher the APR spread. However, once credit score is taken account, the increase in APR spread is slightly lower.

Table 7 Multivariate Results for APR Spread, Period 2 (2008-2011)

	Cleveland		Cincinnati		Columbus	
	Model A	Model B	Model A	Model B	Model A	Model B
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Credit Score	-0.363	-0.662 ***	-0.320 ***	-0.326 ***	-0.401 ***	-0.293 ***
Proportion of AA	-0.372 **	-12.341 **	-0.156 *	-0.355	-0.007	9.982 ***
Log Income	13.502	14.144	-5.469	-5.284	-5.969	-6.721
Turnover	-1.407 **	-0.733	-0.025	-0.024	-0.148 ***	-0.153 ***
House Age	0.315	0.195	0.342 ***	0.342 ***	0.145	0.172 *
DTI-conv	0.239	0.455	1.402 *	1.393 *	0.695 *	0.781 **
Bank Ratio	-1.581 ***	-0.289	0.157	0.158	-0.226	-0.182
Bank×AA		-0.098 **				
CS×AA		0.018 **		3E-04		-0.014 ***
cons	109.293	299.012 **	231.01 ***	233.11 ***	327.99 ***	257.08 ***
n	94	94	91	91	99	99
adjusted R ²	0.1898	0.3070	0.5497	0.5443	0.5823	0.6399
BIC	896.23	888.42	728.78	733.28	776.01	764.82

	Dayton		Toledo	
	Model A	Model B	Model A	Model B
	Coefficient	Coefficient	Coefficient	Coefficient
Credit Score	-0.351 ***	-0.385 ***	-0.566 ***	-0.360 ***
Proportion of AA	-0.063	-3.656	0.104	5.363 ***
Log Income	-12.373	-10.524	0.480	-4.877
Turnover	0.109	0.111	-0.405	-0.380
House Age	-0.059	-0.046	-0.172	-0.057
DTI-conv	-0.178	-0.164	0.072	-0.037
Bank Ratio	0.209	0.129	-0.844	-0.912
CS×AA		0.005		-0.008 ***
cons	400.774 ***	402.682 ***	417.697 ***	331.712 ***
n	53	53	49	49
adjusted R ²	0.4545	0.4595	0.5045	0.5334
BIC	427.01	429.30	425.59	425.32

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

Period 3 (2012 - 2015): Post Bust Period

Access to Conventional Mortgages

The proportion African-American in a neighborhood is generally associated with fewer mortgage originations, except in the Cincinnati MSA (Table 8). In the Cleveland MSA, for example, a one-percentage-point increase in the proportion of African-Americans reduces the conventional mortgage originations in a neighborhood by 1.2%, holding other variables constant (Table 8, Model A). Given that the median conventional neighborhood mortgage origination in the Cleveland MSA was 75 during Period 3 (see Appendix A-11), a ten-percentage-point increase in the proportion of African-Americans in a neighborhood with a median origination count of 75 is expected to decrease its origination count in the

neighborhood by 9 mortgages. In the Cincinnati MSA, racial composition is unrelated to conventional mortgage originations.

Median neighborhood income is also a predictor of mortgage originations across all MSAs; generally, as median neighborhood income increases, so do originations (Table 8). However, median neighborhood credit score does not have a similar consistent positive relationship with lending. In four MSAs (Cleveland, Cincinnati, Columbus, and Toledo), as neighborhood median credit score increases, so do originations in this most recent period (Table 8). In Dayton, however, credit score has a somewhat different relationship with mortgage lending (Table 9). At or below a neighborhood median credit score of 700, the higher the credit score, the more mortgages originated in the neighborhood (Table 9, Model D). If the median neighborhood credit score is higher than 700, then there are fewer conventional mortgage originations. Furthermore, when the interaction of the median credit score and the proportion African-American held constant, the relationship of race to mortgage origination changes (this is the difference between Table 9, Model C and Model D). That is, although credit scores at or below 700 are associated with more lending, as the proportion of African Americans increase, this positive result reduces in size. Similarly, when credit scores are above 700, the number of mortgages originated falls; but, as the proportion of African American increases, this negative impact is moderated. Additionally, once other aspects of loans are held constant, the higher the proportion African-American in a neighborhood, the more mortgage originations.

Mortgage originations in this post bust period are associated with two additional factors: the age of the housing units in the neighborhood and the neighborhood housing market (Table 8). The higher the median age of the homes in the neighborhood, the less lending. The positive increases in neighborhood housing prices between 2011 and 2015 are associated with more mortgage originations in the Cleveland and Cincinnati MSAs—but this local market effect is not present in the Columbus, Dayton, and Toledo MSAs.

In this post bust period, it is perhaps not surprising that the debt-to-income ratio explains variations in lending patterns. All MSAs but Columbus, an average DTI exists after which mortgages in the

neighborhood as fewer or when DTI has no impact. For example, in Cleveland, at or below a DTI of 32 percent, mortgage originations in neighborhoods tend to increase; at DTIs above 32 percent, the number of mortgage originations in a neighborhood decrease. In the Cincinnati MSA, at or below a neighborhood average DTI of 36 percent more mortgage originations occur; above a neighborhood median DTI of above 36 percent, DTI is not associated with the number of mortgages. The presence of some difference in lending above and below levels of DTI may reflect Fannie Mae and Freddie Mac lending guidelines, which allow the higher DTI, up to 45%, depending on the borrowers' financial credibility or LTVs.¹⁰

¹⁰ Fannie MAE: https://www.fanniemae.com/content/eligibility_information/eligibility-matrix.pdf
Freddie MAC: http://www.freddie.mac.com/singlefamily/news/2014/0102_lp_new_feedback_messages.html

Table 8 Multivariate Results for Conventional Mortgage Originations, Period 3 (2012-2015)

	Cleveland				Cincinnati				Columbus			
	Model A		Model B		Model A		Model B		Model A		Model B	
	Coefficient	Exponentiated Coefficient										
Credit Score	0.018	1.018 ***	0.017	1.017 ***	0.009	1.009 **	0.007	1.007	0.010	1.010 **	0.005	1.005
Proportion AA	-0.012	0.988 ***	-0.035	0.966	0.008	1.008	-0.076	0.926	-0.013	0.987 ***	-0.473	0.623 ***
Log Income	0.662	1.938 ***	0.674	1.961 ***	1.360	3.897 ***	1.411	4.099 ***	0.927	2.528 ***	0.926	2.524 ***
DTI-conv									0.012	1.012	0.011	1.011
DTI-conv (Low)	0.086	1.089 ***	0.087	1.091 ***	0.058	1.060 **	0.059	1.061 **				
DTI-conv (High)	-0.127	0.881 ***	-0.129	0.879 ***	-0.059	0.943	-0.061	0.940				
DTI-conv (intersect)	-0.113	0.893	-0.110	0.896	-0.292	0.747	-0.306	0.736				
House Age	-0.021	0.979 ***	-0.021	0.979 ***	-0.018	0.982 ***	-0.018	0.982 ***	-0.011	0.989 **	-0.014	0.986 ***
House Price Change	0.010	1.010 ***	0.010	1.010 ***	0.018	1.018 **	0.017	1.017 **	-0.010	0.990 *	-0.008	0.992
CS×AA			3E-05	1.000			1E-04	1.000			0.001	1.001 ***
Owner-Occupied	2E-05	1.000 **	1E-05	1.000 **	3E-06	1.000	3E-06	1.000	1E-05	1.000	1E-05	1.000
Constant	-17.166	4E-08 ***	-16.826	5E-08 ***	-17.808	2E-08 ***	-17.153	4E-08 ***	-13.003	2E-06 ***	-8.564	2E-04 ***
n		92		92		92		92		98		98
Log pseudolikelihood		-398.93		-398.84		-479.19		-478.98		-526.66		-518.58
BIC		847.60		851.94		1008.11		1012.22		1094.59		1083.01

	Dayton				Toledo			
	Model A		Model B		Model A		Model B	
	Coefficient	Exponentiated Coefficient						
Credit Score	0.008	1.009 *	0.004	1.004	0.013	1.013 ***	0.012	1.012 ***
Proportion AA	-0.012	0.988 ***	-0.186	0.830	-0.010	0.990 ***	-0.131	0.877 **
Log Income	0.739	2.093 **	0.956	2.601 ***	1.745	5.723 ***	1.788	5.979 ***
DTI-conv (Low)	0.094	1.099 *	0.086	1.090	0.064	1.066 ***	0.063	1.065 ***
DTI-conv (High)	-0.117	0.890 *	-0.102	0.903	-0.029	0.971	-0.029	0.972
DTI-conv (intersect)	-0.088	0.916	-0.099	0.906	-0.399	0.671 **	-0.411	0.663 ***
House Age	-0.013	0.987 **	-0.013	0.987 **	-0.017	0.984 ***	-0.016	0.984 ***
House Price Change	0.006	1.006	0.004	1.004	-0.010	0.990 *	-0.010	0.990
CS×AA			2E-04	1.000			2E-04	1.000 **
Owner-Occupied	-9E-06	1.000	8E-06	1.000	-1E-05	1.000	-1E-05	1.000
Constant	-12.130	5E-06 ***	-12.342	4E-06 ***	-25.331	1E-11 ***	-25.033	1E-11 ***
n		50		50		49		49
Log pseudolikelihood		-236.19		-234.98		-219.28		-218.84
BIC		515.41		516.90		481.37		484.39

Note

1. Model: Piecewise Negative Binomial Regression for Cleveland, Cincinnati, Dayton, and Toledo / Negative Binomial Regression for Columbus
2. DTI (Low/High) : 32% for Cleveland, Dayton and Toledo, 36% for Cincinnati
3. *** (**) (*) :Significant at the 99% (95%) (90%) level

Table 9 Multivariate Results for Conventional Mortgage Origination, Period 3 (2012-2015)

	Dayton			
	Model C		Model D	
	Exponentiated		Exponentiated	
	Coefficient	Coefficient	Coefficient	Coefficient
Credit Score (LOW)	-0.018	0.982	0.299	1.349 ***
Credit Score (HIGH)	0.029	1.029	-0.297	0.743 ***
CS (Intersect)	-0.052	0.950	-1.029	0.358 ***
Proportion AA	-0.015	0.985 **	3.701	40.487 ***
Log Income	0.632	1.881	0.941	2.564 **
DTI-conv (Low)	0.104	1.109 *	0.120	1.127 **
DTI-conv (High)	-0.130	0.878 **	-0.133	0.875 **
DTI-conv (intersect)	-0.114	0.892	-0.246	0.782
House Age	-0.012	0.988	-0.013	0.987 **
House Price Change	0.007	1.007	0.001	1.001
CS(Low)×AA			-0.005	0.995 ***
CS(High)×AA			0.006	1.006 ***
CS(Ints.)×AA			0.013	1.013
Owner-Occupied	-8E-06	1.007	-8E-06	1.000
Constant	7.367	1.007	-217.13	5E-95 ***
n		50		50
Log pseudolikelihood		-235.61		-226.53
BIC		522.08		515.65

Note

1. Model: Piecewise Negative Binomial Regression
2. Credit Score (Low/High) : 700
3. DTI (Low/High) : 32%
4. *** (**) (*) :Significant at the 99% (95%) (90%) level

Share of FHA Loans

In the mortgage market recovery period, the proportion of African-Americans is associated with the share of loans in the neighborhood that are FHA-insured, although the relationship is not constant across MSAs (Table 10). In the Cincinnati MSA (Table 10, Model B) the higher the proportion African-Americans in the neighborhood, the larger the share of FHA loans of all mortgages in the neighborhood. These effects are apparent after holding constant interactions of racial composition with the neighborhood median credit score. Neighborhood median credit score reduce this positive relationship slightly.

Credit scores have an important role in the share of FHA loans of all loans in neighborhood across all five MSAs during this mortgage recovery period: Neighborhood median credit scores are significantly and negatively associated with the share of FHA loans in the neighborhood. This indicates that the higher the median credit score, the lower the share of FHA loans in a neighborhood. In the Columbus MSA, for

example, a one-point increase in the median neighborhood credit score is associated with a decrease in the share of FHA loans of by 0.3 percentage point (Table 10, Model B).

The neighborhood income is also important factor on the share of FHA loans in the Cleveland, Dayton and Toledo MSAs: the higher the median neighborhood income, the lower the share of FHA loans. In other MSAs, neighborhood income itself shows no significance on the share of FHA loans; however, in all MSAs but in the Cincinnati MSAs, there is an impact on the share when taking the racial composition of the neighborhood and median income into account together. The higher the proportion of African-Americans combined with higher median incomes are expected to have higher FHA loans (Table 10, Model A and B).

Table 10 Multivariate Results for FHA Share in Neighborhood, Period 3 (2012-2015)

	Cleveland		Cincinnati		Columbus	
	Model A	Model B	Model A	Model B	Model A	Model B
	coeff	coeff	coeff	coeff	coeff	coeff
Credit Score	-0.412 **	-0.152	-0.514 ***	-0.452 ***	-0.329 ***	-0.256 ***
Proportion AA	-4.820 ***	-2.012	0.086	3.290 **	-3.767 **	3.960 *
Log Income	-12.368 *	-23.581 **	-0.201	-1.790	-2.450	-4.696
Selfemployment	-1.235 ***	-1.250 ***	-0.322	-0.345	-0.226	-0.099
House Price Change	-0.296 *	-0.319 **	-0.286 **	-0.257 **	-0.216 *	-0.261 ***
DTI-all	1.164 **	1.190 **	0.897 **	0.843 **	0.913 **	0.472
Log Inc×AA	0.456 ***	0.653 ***			0.386 ***	0.495 ***
CS×AA		-0.007 *		-0.004 **		-0.013 ***
Constant	434.286 ***	371.318 ***	376.43 ***	351.07 ***	260.03 ***	247.78 ***
n	93	93	91	91	101	101
adjusted R ²	0.7796	0.8118	0.7547	0.7622	0.6515	0.7032
BIC	711.6	700.3	644.1	644.7	752.3	739.6

	Dayton		Toledo	
	Model A	Model B	Model A	Model B
	coeff	coeff	coeff	coeff
Credit Score	-0.385 ***	-0.364 ***	-0.175 **	-0.034
Proportion AA	-6.969 ***	-6.594 ***	-10.436 ***	2.918
Log Income	-15.572 ***	-16.437 ***	-23.905 ***	-25.418 ***
Selfemployment	-1.118 ***	-1.111 ***	-1.238 **	-1.230 **
House Price Change	-0.185	-0.183	-0.022	-0.114
DTI-all	-0.391	-0.338	0.586	0.619
Log Inc×AA	0.659 ***	0.665 ***	1.016 ***	0.644 ***
CS×AA		-0.001		-0.013 ***
Constant	506.12 ***	499.08 ***	403.589 ***	319.009 ***
n	50	50	52	52
adjusted R ²	0.7513	0.7456	0.6308	0.7187
BIC	365.1	368.9	407.6	396.2

- Note
1. Model: OLS Regression
 2. *** (**) (*): Significant at the 99% (95%) (90%) level
 3. Cincinnati: CS×AA was not significant

The same trend was seen in Period 2. Due to FHA mortgage insurance premium (MIP), FHA-insured mortgages are more expensive, depending on DTI and LTV, when compared with conventional mortgages (An & Bostic, 2008). This requires additional, individual-level analysis to understand if African-Americans who qualified for conventional loans instead got FHA loans, which might counter-intuitively be costlier to them in the long run.

APR Spread

In the post-bust period, neighborhood racial composition is unrelated to the cost of loans as indicated by the APR spread in four of the five MSAs; only in the Cleveland MSA, higher rates of African-Americans in a neighborhood are associated with a higher spread. The interaction of the median credit score and the proportion African-American does ameliorate this impact slightly. Nonetheless, in total, the higher the proportions of African-Americans in a neighborhood in the Cleveland MSA, the higher the APR spread, even holding constant credit score and the median neighborhood income. Across all MSAs, median neighborhood credit score is associated with lower APR spread. This result is what one would expect given the tight lending climate generally, and continues the pattern from the period of the mortgage bust (Period 2). For the APR spread in Period 2, the median credit score is significantly and negatively associated with the median APR spread. This means that the higher the median credit score in a neighborhood, the lower the median APR spread. For instance, in the Columbus MSA, a one-point increase in the median credit score in a neighborhood is expected to lower the median APR spread in the neighborhood by 0.30 bps (Table 11, Model A). In the Cleveland and Cincinnati MSAs, higher median incomes are also expected to lower the APR spreads. For example, in the Cincinnati MSA, a one-percentage-point increase in the median income is expected to decrease the median APR spread by 18.5 bps (Table 11, Model A).

Table 11 Multivariate Results for APR Spread, Period 3 (2012-2015)

	Cleveland		Cincinnati		Columbus	
	Model A	Model B	Model A	Model B	Model A	Model B
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Credit Score	-0.458 ***	-0.262 **	-0.248 ***	-0.253 **	-0.300 **	-0.249
Proportion of AA	0.042	4.104 ***	-0.102	-0.276	-0.038	4.012
Log Income	-4.706	-9.187 **	-18.523 ***	-18.415 ***	-10.165	-11.020 *
CS×AA		-0.006 ***		2E-04		-0.006
Constant	396.769 ***	305.652 ***	336.918 ***	329.570 ***	346.955 ***	320.021 ***
n	92	92	92	92	98	98
adjusted R ²	0.5716	0.6189	0.5416	0.5363	0.3295	0.3344
BIC	697.44	690.16	687.07	691.58	783.63	786.44

	Dayton		Toledo	
	Model A	Model B	Model A	Model B
	Coefficient	Coefficient	Coefficient	Coefficient
Credit Score	-0.214 ***	-0.246 ***	-0.299 **	-0.134
Proportion of AA	0.142	-1.076	0.069	11.387 *
Log Income	-2.967	-1.675	-8.147	-14.827 *
CS×AA		0.002		-0.016 *
Constant	198.629 ***	207.357 ***	321.944 ***	278.342 ***
n	50	50	49	49
adjusted R ²	0.2845	0.2718	0.2012	0.3250
BIC	383.07	386.77	409.24	403.79

Note 1. Model: OLS Regression

2. *** (**) (*): Significant at the 99% (95%) (90%) level

Summary

While the descriptive results suggested that African-American neighborhoods had disadvantage in mortgage lending – lower rates of conventional mortgage originations in all three periods, higher shares of subprime loans in Period 1, higher APR spreads in Period 2, and the higher shares of FHA-insured loans in Period 2 and 3 when compared with predominantly White neighborhoods – we did not know whether these results would stand when taking other causal factors into account. Multiple regression analysis allowed for the simultaneous consideration of a variety of causes for differential neighborhood mortgage originations, and we found both expected and unexpected results.

First, while controlling for other financial factors, we confirmed that conventional mortgage origination was limited in neighborhoods with higher proportions of African-American residence in most MSAs in all three periods, which confirms the results of the descriptive analysis. The multivariate analysis

revealed that the disadvantages for neighborhoods with higher proportions of African-Americans varies by MSAs and periods. In Period 1, neighborhoods with higher proportions of African-Americans, no matter the financial credibility, receive lower conventional mortgage count in all five MSAs. In addition, in the Cleveland MSA, in the same period, particularly lower credit scores as the proportion of African-Americans increased in neighborhoods reduced the origination counts. During Period 2 and 3, in the Columbus and Toledo MSAs, lower credit scores as the proportion of African-Americans increased in neighborhoods reduced the origination counts, while neighborhoods with higher proportions of African-Americans, no matter the financial credibility, had lower originations in the Cleveland and Dayton MSAs. Furthermore, the Cincinnati MSA was unique that lower mortgage origination in neighborhoods with higher proportions of African Americans was confirmed only in Period 1, the mortgage boom period.

Second, in Period 1 the share of subprime loans was higher in neighborhoods with higher proportions of African-Americans in all five MSAs, which is not a surprising result as GIS maps clearly indicated the concentration of high subprime shares in Mostly-African-American neighborhoods and African-American-Mixed Neighborhoods. Multivariate regression and interaction terms demonstrated, in most MSAs, that higher credit scores as the proportion of African-Americans increased in neighborhoods reduced the higher neighborhood subprime shares. However, in the Cincinnati MSAs, the higher the income and proportion of African-Americans in neighborhoods, the higher the share of subprime loans.

Third, while the descriptive analysis suggested that APR spreads were higher in African-American neighborhoods, multivariate regression results indicated that this pattern was seen only in the Columbus and Toledo MSAs in Period 2. Meanwhile, credit score, in general, explains much of the variation in APR spread in Period 2 and 3. Unexpectedly, in the Cleveland MSA, as the proportion African-American increased, APR spread decreases. In Period 2, as the proportion African-American increased along with higher credit scores, neighborhoods tended to have higher APR spreads. Furthermore, in Period 3, only in the Cleveland MSA did neighborhoods with increasing rates of African-American residence have higher APR spreads; however, higher credit scores mitigate high the APR spread.

Lastly, the most unexpected result is that the higher the income in neighborhoods with increasing proportions of African-Americans, the higher the share of FHA-insured loans in neighborhoods in all MSAs except the Cincinnati MSA. The descriptive results indicated that African-American neighborhoods with lower- or middle-credit scores had larger shares of FHA-insured loans; additionally, FHA loans are in general designed for populations with lower credit scores and lower down-payments. However, results from the multivariate analysis indicates that in most MSAs, as income and the proportion African-American increase in a neighborhood, the higher the share of FHA-insured loans.

VI. Conclusion, Policy Implications, and Future Research

In this study, we investigated neighborhood patterns of mortgage lending across five MSAs in Ohio: Cincinnati, Cleveland, Columbus, Dayton, and Toledo, using descriptive and multivariate statistical analyses as well as GIS mapping to examine the quantity and quality of mortgages originated from 2004 to 2015. Mortgage lending patterns at the neighborhood level are not consistent across the five MSAs. Our results indicate that the racial composition of neighborhoods across most MSAs is associated with variations in lending patterns. Additionally, neighborhoods with higher rates of African-American residence are more likely to have higher cost mortgages, particularly during the period when the housing market conditions are not stable (2008-2011). Specifically, four findings from the study stand out.

First, conventional mortgage origination tended to be limited in neighborhoods with the higher rates of African-American residence in most MSAs before, during, and after the mortgage crisis. The higher the proportions of African-Americans in a neighborhood, the lower the number of conventional mortgage originations, while simultaneously taking credit scores, income, and the size of the neighborhood into account. Particularly in the Cleveland and Dayton MSAs, the results indicate that African-American neighborhoods, no matter the neighborhood median credit scores, have lower numbers of conventional mortgage originations. While conventional mortgage originations decrease with higher rates of African-American residence in the Columbus and Toledo MSAs as well, in those MSAs the number of originations increases as credit scores and incomes improve. The Cincinnati MSA is distinct from all the others; this negative relationship between the rate of African-American residence and mortgage originations was only apparent prior to the mortgage bust (2004-2007). During the crisis, the number of conventional mortgages increases with increases in the rate of African-American residence, while after there is no relationship between neighborhood racial composition and lending patterns. This difference in Cincinnati may be the result of efforts in the Over-the-Rhine neighborhood and other community development efforts.

From a neighborhood standpoint, the lack of mortgage lending is associated with neighborhood (Smith et al., 2001), and neighborhood decline will cause further disinvestment (Raleigh & Galster, 2015). Our

analysis demonstrates that pattern of reduction in conventional mortgage originations for neighborhoods as the proportion of African-Americans increases continues throughout the entire period studies, during which time we experienced a mortgage boom, bust, and recovery in most MSAs. That is, no matter the mortgage market conditions, racial composition of the neighborhoods influences access to conventional mortgage capital. Furthermore, by looking at the results of the descriptive, spatial, and multivariate statistical analyses together, in all MSAs neighborhoods with higher proportions of African-American residents are concentrated in downtown or surrounding areas, and a lack of mortgage capital tends to be geographically concentrated in certain neighborhoods. This continuous deficit in conventional mortgage capital in neighborhoods with more African-Americans has lasted at least twelve years in four of the five MSAs, which can eventually be a serious trigger of neighborhood decline.

Second, these results describe a pattern; we do not know whether the lack of conventional mortgages in African-American neighborhoods occurs because lenders are less likely to originate mortgages there or because homeowners in those neighborhoods seek conventional mortgages less frequently. The patterns of FHA lending in some MSA suggests that supply for conventional mortgages may be lacking: African-American neighborhoods with higher median incomes are have higher rates of FHA-insured loans. In all MSAs but Cincinnati, neighborhoods with higher rates of African-American residence and with higher incomes are more likely to have higher shares of FHA-insured loans in Period 2 or 3, or both. We speculate, therefore, it may not be that demand for conventional mortgage is lacking but that supply is. FHA mortgages work well to provide access to mortgages for those who do not have the credit scores or down payments to qualify for conventional loans. However, an FHA mortgage can actually be costlier than a conventional mortgage for those who qualify for a conventional mortgage (An & Bostic, 2008; Immergluck, 2011). The extent to which this mortgage mismatch is a problem is a matter for a future investigation into individual lending patterns: are African-Americans with incomes and credit scores that qualify for conventional loans more likely to get FHA loans than their white counterparts?

Third, during times of mortgage market turbulence, costs of mortgages increased as rates of African-American residence in neighborhoods increases, while after the crisis (2012-2015), such patterns all but disappeared across MSAs, with one notable exception, Cleveland. During the mortgage boom (2005-2007), as the rate African-American residence increased in a neighborhood, so did the share of subprime loans in a neighborhood, across all five MSAs. During the mortgage bust period (2008-2011), the pattern of more expensive loans (higher APR spreads) in neighborhoods with higher proportions of African-Americans persists in the Columbus and Toledo MSAs, although better credit scores in the neighborhood did decrease the costs slightly. In the Cleveland MSA, the opposite occurs. After the crisis, in four of the five MSAs (Cincinnati, Columbus, Dayton, and Toledo MSAs), differences in the cost of mortgages by neighborhood racial composition all but disappear, with credit scores and income being more strongly associated with the cost of credit. Thus, we may need additional protection for African-American neighborhoods from costly mortgagees during the mortgage market turbulence. The outstanding question is why the pattern in the Cleveland MSA is so distinct: neighborhoods with Mostly-African-American Neighborhoods residence are more likely to receive costlier mortgages, although higher credit scores in the neighborhood can diminish that effect somewhat.

Fourth, the age of the housing in the neighborhood is a significant predictor of mortgage originations, even holding racial composition constant. Higher concentrations of older housing in a neighborhood is associated with fewer conventional mortgage originations. One possible explanation for this result is that older homes' physical conditions are mostly worse than newer homes, which impose negative externalities on surrounding neighborhoods (Schill & Wachter, 1993). Thus, lenders will regard those neighborhoods as a risk factor. Connecting neighborhoods with older housing stocks with repair and upgrade programs is one way to address this dynamic, while taking steps to avoid the residential displacement that upgrading can cause. The availability of refinance loans is another option to give current residents opportunities to improve their housing, and eventually their neighborhood, without moving out. Understanding patterns of refinance loans is fundamental to understanding the ability of neighborhoods to upgrade without displacement.

Additionally, neighborhoods with concentration of older housing stocks are usually also home to elderly owners. Seniors are most likely to live in older homes, and they tend to spend less money on their housing (Golant, 2008). Neighborhoods are likely to be filtered down or decline if a lot of housing are physically rundown or depreciating due to disinvestment (Quercia & Rohe, 1992). Thus, not only are patterns of home purchase loans important to understand for the trajectory of neighborhoods, but also patterns of mortgage refinance, especially among elderly residents in neighborhoods with concentrations of older housing.

Work Cited

- Ahlbrandt, R. S. (1977). Exploratory Research on the Redlining Phenomenon. *Real Estate Economics*, 5(4), 473-481.
- An, X., & Bostic, R. (2008). GSE Activity, FHA Feedback, and Implications for the Efficacy of the Affordable Housing Goals. *The Journal of Real Estate Finance and Economics*, 36(2), 207-231.
- Apgar, W. C., & Calder, A. (2005). The Dual Mortgage Market The Persistence of Discrimination in Mortgage Lending. In X. S. Briggs (Ed.), *The geography of opportunity: Race and housing choice in metropolitan America*. Washington D.C.: Brookings Institution Press.
- Avery, R. B., Canner, G. B., & Cook, R. E. (2005). New information reported under HMDA and its application in fair lending enforcement. *Federal Reserve Bulletin*, 91(3), 344-394.
- Barwick, C. (2010). Patterns of Discrimination against Blacks and Hispanics in the US Mortgage Market. *Journal of Housing and the Built Environment*, 25(1), 117-124.
- Bocian, D. G., Ernst, K. S., & Li, W. (2008). Race, Ethnicity and Subprime Home Loan Pricing. *Journal of Economics and Business*, 60(1-2), 110-124.
- Bocian, D. G., Li, W., Reid, C., & Quercia, R. G. (2011). *Lost Ground, 2011 Disparities in Mortgage Lending and Foreclosures*. Retrieved from <http://www.responsiblelending.org/mortgage-lending/research-analysis/lost-ground-2011.html>
- Bradbury, K. L., Case, K. E., & Dunham, C. R. (1989). Geographic Patterns of Mortgage Lending in Boston, 1982-1987. *New England economic review*. 3-30
- Calem, P. S., Gillen, K., & Wachter, S. (2004). The Neighborhood Distribution of Subprime Mortgage Lending. *The Journal of Real Estate Finance and Economics*, 29(4), 393-410.
- Calem, P. S., Hershaff, J. E., & Wachter, S. (2004). Neighborhood Patterns of Subprime Lending: Evidence from Disparate Cities. *Housing Policy Debate*, 15(3), 603-622.
- Canner, G. B., & Smith, D. S. (1991). Home Mortgage Disclosure Act: Expanded data on residential lending. *Federal Reserve Bulletin*, 77(11).
- Chomsisengphet, S., & Pennington-Cross, A. (2006). The Evolution of the Subprime Mortgage Market. *Federal Reserve Bank of St. Louis Review*, 31-56.
- Dedman, B. (1988). *The color of money : home mortgage lending practices discriminate against blacks*. Atlanta, Ga.: Atlanta Journal and Atlanta Constitution.
- Ding, L., Quercia, R. G., & Ratcliffe, J. (2010). Neighborhood subprime lending and the performance of community reinvestment mortgages. *Journal of Real Estate Research*, 32, 3, 341-376.

- Federal Reserve Bank of Kansas, C. (2008). *Housing, housing finance, and monetary policy : a symposium sponsored by the Federal Reserve Bank of Kansas City, Jackson Hole, Wyoming, August 30-September 1, 2007*. Kansas City, Mo.: Federal Reserve Bank of Kansas City.
- Federal Reserve Board of Governors. (2009). Senior Loan Officer Opinion Survey on Bank Lending Practices. *The Federal Reserve Board*. Retrieved October 1, 2015 from <http://www.federalreserve.gov/boarddocs/snloansurvey/>
- Federal Reserve Board of governors. (2015). Senior Loan Officer Opinion Survey on Bank Lending Practices. *The Federal Reserve Board*. Retrieved October 1, 2015 from <http://www.federalreserve.gov/boarddocs/snloansurvey/>
- Golant, S. M. (2008). Low-Income Elderly Homeowners in Very Old Dwellings: The Need for Public Policy Debate. *Journal of Aging & Social Policy*, 20(1), 1-28.
- Goodman, L., Zhu, J., & George, T. (2014). Where Have All the Loans Gone? The Impact of Credit Availability on Mortgage Volume. *Journal of Structured Finance*, 20(2), 45-53.
- Green, R. K., & Malpezzi, S. (2003). *A primer on U.S. housing markets and housing policy*. Washington: Urban Institute Press.
- Immergluck, D. (2008). From the Subprime to the Exotic: Excessive Mortgage Market Risk and Foreclosures. *Journal of the American Planning Association*, 74(1), 59-76.
- Immergluck, D. (2009). *Foreclosed : high-risk lending, deregulation, and the undermining of America's mortgage market*. Ithaca: Cornell University Press.
- Immergluck, D. (2011). From Minor to Major Player: The Geography of FHA Lending During the U.S. Mortgage Crisis. *Journal of Urban Affairs*, 33(1), 1-20.
- Immergluck, D., & Smith, G. (2006). The external costs of foreclosure: The impact of singlefamily mortgage foreclosures on property values. *Housing Policy Debate*, 17(1), 57-79.
- Immergluck, D., & Wiles, M. (1999). *Two steps back : the dual mortgage market, predatory lending, and the undoing of community development*. Chicago, IL: Woodstock Institute.
- Lei, D., Ratcliffe, J., Stegman, M. A., & Quercia, R. G. (2008). Neighborhood Patterns of High-Cost Lending: The Case of Atlanta. *Journal of Affordable Housing & Community Development Law*, 17(3).
- Ling, D. C., & Wachter, S. M. (1998). Information Externalities and Home Mortgage Underwriting. *Journal of Urban Economics Journal of Urban Economics*, 44(3), 317-332.
- Mallach, A. (2009). *A decent home : planning, building, and preserving affordable housing*. Chicago IL: American Planning Association Planners Press.

- Mallach, A. (2012). Laying the groundwork for change: Demolition, urban strategy and policy reform. Retrieved from <https://www.brookings.edu/research/laying-the-groundwork-for-change-demolition-urban-strategy-and-policy-reform/>
- Munnell, A. H., Tootell, G. M. B., Browne, L. E., & McEneaney, J. (1996). Mortgage Lending in Boston: Interpreting HMDA Data. *American Economic Review*, 86(1), 25-53.
- Quercia, R. G., Freeman, A., & Ratcliffe, J. (2011). *Regaining the dream how to renew the promise of homeownership for America's working families*. Washington, D.C.: Brookings Institution Press.
- Quercia, R. G., & Rohe, W. M. (1992). Housing Adjustments among Older Home Owners. *Urban Affairs Review*, 28(1), 104-125.
- Quercia, R. G., & Stegman, M. A. (1992). Residential Mortgage Default: A Review of the Literature. *Journal of Housing Research*, 3(2), 341-379.
- Raleigh, E., & Galster, G. (2015). Neighborhood Disinvestment, Abandonment, And Crime Dynamics. *Journal of Urban Affairs*, 37(4), 367-396.
- Reid, C., & Laderman, E. (2009). The Untold Costs of Subprime Lending Examining the Links among Higher - Priced Lending, Foreclosures and Race in California. *Federal Reserve Bank of San Francisco*.
- Retsinas, N. P., & Belsky, E. S. (2002). *Low-income Homeownership : Examining the Unexamined Goal*. Washington, D.C.: The Brookings Institute.
- Richardson, J., Mitchell, B., & West, N. (2016). *Home Mortgage Lending in St.Louis, Milwaukee, Minneapolis and Surrounding Areas*. Retrieved from <http://www.ncrc.org/media-center/press-releases/item/1160-new-report-on-lending-in-st-louis-milwaukee-and-minneapolis-shows-clear-racial-disparities>
- Schill, M. H., & Wachter, S. M. (1993). A Tale of Two Cities: Racial and Ethnic Geographic Disparities in Home Mortgage Lending in Boston and Philadelphia. *Journal of Housing Research*, 4(2), 245-275.
- Schuetz, J., Been, V., & Ellen, I. G. (2008). Neighborhood Effects of Concentrated Mortgage Foreclosures. *Journal of Housing Economics*, 17(4), 306-319.
- Shlay, A. B. (1988). Not in that Neighborhood: The Effects of Population and Housing on the Distribution of Mortgage Finance within the Chicago SMSA. *Social Science Research*, 17(2), 137-163.
- Smith, N., Caris, P., & Wyly, E. (2001). The "Camden Syndrome" and the menace of suburban decline: Residential disinvestment and its discontents in Camden County, New Jersey. *Journal of Planning Literature*, 16(1), 80-163.

- Stein, K., & Nguyen, T. (2010). *From Foreclosure to Re-Redlining: How America's Largest Financial Institutions Devastated California Communities*. Retrieved from San Francisco, CA: <http://www.calreinvest.org/publications/california-reinvestment-coalition-research>
- Stuart, G. (2003). *Discriminating risk : the U.S. mortgage lending industry in the twentieth century*. Ithaca, NY: Cornell University Press.
- Wachter, S. M., Russo, K., & Hershaff, J. E. (2005). Subprime Lending Neighborhood Patterns Over Time. *University of Pennsylvania, Institute for Law and Economics, Research Paper*.
- Wyly, E. K., Atia, M., & Hammel, D. J. (2004). Has mortgage capital found an innercity spatial fix? *Housing Policy Debate Housing Policy Debate*, 15(3), 623-685.
- Yinger, J. (1995). *Closed doors, opportunities lost : the continuing costs of housing discrimination*. New York: Russell Sage Foundation.

Appendix

Appendix A: Descriptive Analysis of Mortgage Lending across Three Periods in Five Ohio MSAs

1. Median Rate of Originations by Neighborhood Racial Composition, Income, and Credit Score in Period 1 (2004-2007)	99
2. Median Rate of Originations by Neighborhood Racial Composition, Income, and Credit Score in Period 2 (2008-2011)	99
3. Median Rate of Originations by Neighborhood Racial Composition, Income, and Credit Score in Period 3 (2012-2015)	100
4. Median Subprime Share by Neighborhood Racial Composition, Income, and Credit Score in Period 1 (2004-2007)	100
5. Median APR Spread by Neighborhood Racial Composition, Income, and Credit Score in Period 2 (2008-2011).....	101
6. Median APR Spread by Neighborhood Racial Composition, Income, and Credit Score in Period 3 (2012-2015).....	101
7. Median FHA Share by Neighborhood Racial Composition, Income, and Credit Score in Period 2 (2008-2011).....	102
8. Median FHA Share by Neighborhood Racial Composition, Income, and Credit Score in Period 3 (2011-2015).....	102
9. Summary Statistics: Zip-Code Level Mean, Median, Standard Deviation for Each Variable by MSA in Period 1 (2004-2007)	103
10.Summary Statistics: Zip-Code Level Mean, Median, Standard Deviation for Each Variable by MSA in Period 2 (2008-2011)	104
11.Summary Statistics: Zip-Code Level Mean, Median, Standard Deviation for Each Variable by MSA in Period 3 (2012-2015)	105

1. Median Rate of Originations by Neighborhood Racial Composition, Income, and Credit Score in Period 1 (2004-2007)

Zip Code Characteristics			Rate of Originations % (n=Zip-code count)					
			ALL MSAs	Cleveland	Cincinnati	Columbus	Dayton	Toledo
ALL			6.5 (422)	2.6 (95)	5.8 (100)	12.1 (114)	5.8 (55)	12.3 (58)
Access to Mortgage Capital by Race								
Zip White Population (%)	Fewer Whites	≤ 70%	1.7 (68)	0.9 (23)	3.1 (19)	1.5 (13)	1.8 (7)	1.7 (6)
	Middle Whites	70.1% - 85%	2.7 (44)	1.7 (9)	2.7 (9)	4.3 (14)	2.8 (5)	1.9 (7)
	Higher Whites	> 85.1%	9.8 (310)	4.7 (63)	8.2 (72)	16.5 (87)	7.2 (43)	16.5 (45)
Zip African American (%)	Fewer African-Americans	≤ 15%	8.9 (341)	4.4 (71)	8.1 (76)	15.6 (96)	6.5 (47)	16.5 (51)
	Middle AA	15.1% - 30%	2.2 (28)	1.7 (5)	3.5 (10)	2.8 (10)	3.3 (1)	1.8 (2)
	Higher AA	> 30.1%	1.5 (53)	0.9 (19)	2.5 (14)	1.4 (8)	1.8 (7)	1.5 (5)
Access to Mortgage Capital by Income								
Zip Median Family Income (ZIPINC)	Lower Income	≤ 80% AMI	3.5 (100)	0.6 (18)	6.5 (31)	14.0 (34)	2.1 (8)	1.6 (9)
	Middle Income	80.1% - 120% AMI	6.8 (231)	3.3 (50)	4.8 (49)	12.4 (61)	5.5 (32)	15.2 (39)
	Higher Income	> 120.1% AMI	8.0 (91)	4.4 (27)	7.4 (20)	9.0 (19)	10.2 (15)	17.7 (10)
Access to Mortgage Capital by Income								
Median Zip Credit Score (ZIPCS)	Lower Credit Score	≤ 660	3.4 (97)	0.8 (22)	8.1 (22)	26.7 (27)	1.7 (8)	12.3 (18)
	Middle Credit Score	660 - 700	6.5 (195)	3.4 (39)	4.7 (47)	10.7 (57)	5.8 (24)	11.1 (28)
	Higher Credit Score	> 700	7.0 (130)	4.5 (34)	6.9 (31)	8.5 (30)	10.2 (23)	17.7 (12)
Access to Credit by Race and Income								
Zip White (>85%) × ZIPINC	Lower Income	≤ 80% AMI	76.4 (40)	NA (0)	24.7 (18)	190.5 (18)	2.6 (3)	1077.8 (1)
	Middle Income	80.1% - 120% AMI	8.9 (190)	4.7 (39)	7.0 (36)	13.5 (53)	6.5 (28)	15.3 (34)
	Higher Income	> 120.1% AMI	7.9 (80)	4.8 (24)	6.4 (18)	8.5 (16)	9.3 (12)	17.7 (10)
Zip AA (>15%) × ZIPINC	Lower Income	≤ 80% AMI	1.5 (49)	0.6 (15)	2.5 (12)	1.5 (13)	0.6 (4)	1.5 (5)
	Middle Income	80.1% - 120% AMI	1.9 (27)	1.2 (7)	3.5 (11)	2.0 (5)	2.4 (2)	1.8 (2)
	Higher Income	> 120.1% AMI	3.3 (5)	1.0 (2)	8.0 (1)	NA (0)	73.4 (2)	NA (0)
Access to Credit by Race and Credit Score								
Zip White (>85%) × ZIPCS	Lower Credit Score	≤ 660	35.4 (42)	214.1 (2)	28.1 (14)	132.1 (16)	1.5 (1)	22.7 (9)
	Middle Credit Score	660 - 700	68.0 (152)	4.6 (30)	7.3 (31)	13.2 (47)	6.5 (20)	12.3 (24)
	Higher Credit Score	> 700	7.9 (116)	4.7 (31)	6.9 (27)	10.5 (24)	9.3 (22)	17.7 (12)
Zip AA (>15%) × ZIPCS	Lower Credit Score	≤ 660	1.4 (44)	0.8 (17)	1.9 (7)	1.5 (9)	1.3 (6)	1.5 (5)
	Middle Credit Score	660 - 700	2.0 (27)	1.3 (4)	2.9 (13)	2.1 (6)	16.2 (2)	1.8 (2)
	Higher Credit Score	> 700	3.5 (10)	1.3 (3)	9.4 (4)	3.6 (3)	NA (0)	NA (0)

2. Median Rate of Originations by Neighborhood Racial Composition, Income, and Credit Score in Period 2 (2008-2011)

Zip Code Characteristics			Rate of Originations % (n=Zip-code count)					
			ALL MSAs	Cleveland	Cincinnati	Columbus	Dayton	Toledo
Total			1.7 (422)	0.9 (98)	1.8 (101)	2.2 (111)	1.6 (55)	2.8 (57)
Origination Number by Race								
Zip Proportion of White Population (Zip White)	Fewer Whites	≤ 70%	0.5 (92)	0.2 (31)	1.0 (26)	0.6 (18)	0.3 (8)	0.3 (9)
	Middle Whites	70.1% - 85%	1.6 (63)	0.7 (7)	1.3 (13)	1.7 (21)	1.0 (14)	2.0 (8)
	Higher Whites	> 85.1%	2.5 (267)	1.5 (60)	2.4 (62)	3.7 (72)	2.3 (33)	4.4 (40)
Zip Proportion of African American (Zip AA)	Fewer African-Americans	≤ 15%	2.2 (332)	1.4 (71)	2.3 (73)	3.0 (92)	2.1 (47)	3.6 (49)
	Middle AA	15.1% - 30%	0.8 (26)	0.2 (7)	0.9 (9)	1.5 (8)	- (0)	0.4 (2)
	Higher AA	> 30.1%	0.5 (64)	0.3 (20)	0.9 (19)	0.5 (11)	0.3 (8)	0.4 (6)
Origination Number by Income								
Zip Median Family Income (ZIPINC)	Lower Income	≤ 80% AMI	0.5 (118)	0.2 (24)	1.2 (30)	0.6 (36)	0.5 (16)	0.2 (12)
	Middle Income	80.1% - 120% AMI	1.9 (194)	0.7 (44)	1.8 (47)	2.9 (47)	1.9 (24)	3.6 (32)
	Higher Income	> 120.1% AMI	2.6 (110)	2.1 (30)	3.5 (24)	2.7 (28)	3.4 (15)	4.6 (13)
Origination Number by Credit Score								
Zip Median Credit Score (ZIPCS)	Lower Credit Score	≤ 700	0.8 (199)	0.2 (35)	1.2 (46)	1.9 (58)	0.7 (24)	2.4 (36)
	Middle Credit Score	700 - 740	1.8 (191)	1.5 (56)	1.9 (46)	2.7 (41)	2.3 (27)	3.1 (21)
	Higher Credit Score	> 740	3.3 (32)	2.2 (7)	5.2 (9)	3.0 (12)	2.5 (4)	NA (0)
Origination Number by Race and Income								
Zip White (>85%) × ZIPINC	Lower Income	≤ 80% AMI	0.9 (40)	0.0 (2)	1.5 (11)	4.1 (18)	0.3 (6)	0.0 (3)
	Middle Income	80.1% - 120% AMI	2.6 (145)	1.1 (31)	2.4 (32)	3.6 (39)	2.8 (17)	4.5 (26)
	Higher Income	> 120.1% AMI	2.9 (82)	2.2 (27)	4.1 (19)	4.3 (15)	2.5 (10)	4.6 (11)
Zip AA (>15%) × ZIPINC	Lower Income	≤ 80% AMI	0.5 (61)	0.2 (18)	0.9 (17)	0.4 (14)	0.3 (6)	0.2 (6)
	Middle Income	80.1% - 120% AMI	0.7 (25)	0.3 (7)	0.8 (11)	2.4 (4)	1.0 (1)	0.7 (2)
	Higher Income	> 120.1% AMI	0.8 (4)	0.8 (2)	NA (0)	1.0 (1)	0.0 (1)	NA (0)
Origination Number by Race and Credit Score								
Zip White (>85%) × ZIPCS	Lower Credit Score	≤ 700	2.2 (117)	0.5 (12)	1.8 (29)	3.6 (40)	2.1 (11)	4.6 (25)
	Middle Credit Score	700 - 740	2.6 (127)	1.7 (41)	3.5 (28)	5.0 (25)	2.4 (18)	4.2 (15)
	Higher Credit Score	> 740	3.3 (23)	2.2 (7)	10.8 (5)	2.7 (7)	2.5 (4)	NA (0)
Zip AA (>15%) × ZIPCS	Lower Credit Score	≤ 700	0.4 (62)	0.2 (18)	0.6 (16)	0.5 (15)	0.3 (8)	0.2 (5)
	Middle Credit Score	700 - 740	1.0 (27)	0.8 (9)	1.5 (11)	1.1 (4)	NA (0)	0.6 (3)
	Higher Credit Score	> 740	1.5 (1)	NA (0)	1.5 (1)	NA (0)	NA (0)	NA (0)

3. Median Rate of Originations by Neighborhood Racial Composition, Income, and Credit Score in Period 3 (2012-2015)

Zip Code Characteristics			Rate of Originations % (n=Zip-code count)					
			ALL MSAs	Cleveland	Cincinnati	Columbus	Dayton	Toledo
Total			2.8 (420)	1.5 (97)	2.7 (97)	4.2 (117)	2.4 (54)	4.7 (55)
Origination Number by Race								
Zip Proportion of White Population (Zip White)	Fewer Whites	≤ 70%	0.8 (93)	0.4 (30)	1.4 (26)	0.9 (19)	0.8 (8)	0.7 (10)
	Middle Whites	70.1% - 85%	2.0 (69)	1.3 (12)	1.7 (16)	2.8 (22)	1.2 (12)	0.7 (7)
	Higher Whites	> 85.1%	4.3 (258)	2.8 (55)	3.4 (55)	6.0 (76)	3.5 (34)	8.1 (38)
Zip Proportion of African American (Zip AA)	Fewer African-Americans	≤ 15%	3.5 (324)	2.7 (69)	3.1 (68)	5.1 (97)	3.1 (44)	6.6 (46)
	Middle AA	15.1% - 30%	1.2 (31)	0.5 (7)	1.3 (9)	1.6 (9)	5.3 (2)	0.8 (4)
	Higher AA	> 30.1%	0.7 (65)	0.4 (21)	1.8 (20)	0.7 (11)	0.8 (8)	0.5 (5)
Origination Number by Income								
Zip Median Family Income (ZIPINC)	Lower Income	≤ 80% AMI	1.0 (120)	0.2 (26)	1.9 (32)	2.7 (41)	0.7 (11)	0.4 (10)
	Middle Income	80.1% - 120% AMI	3.1 (185)	1.8 (42)	2.5 (40)	5.8 (47)	2.0 (27)	5.2 (29)
	Higher Income	> 120.1% AMI	3.6 (115)	3.4 (29)	5.3 (25)	3.1 (29)	6.0 (16)	10.4 (16)
Origination Number by Credit Score								
Median Zip Credit Score (ZIPCS)	Lower Credit Score	≤ 700	0.6 (72)	0.2 (18)	1.5 (9)	5.5 (26)	0.9 (7)	2.0 (12)
	Middle Credit Score	700 - 740	2.7 (267)	1.8 (60)	2.2 (65)	4.3 (69)	1.8 (35)	4.8 (38)
	Higher Credit Score	> 740	4.4 (81)	3.5 (19)	4.4 (23)	3.3 (22)	6.7 (12)	65.3 (5)
Origination Number by Race and Income								
Zip White (>85%) × ZIPINC	Lower Income	≤ 80% AMI	4.5 (37)	NA (0)	3.2 (12)	7.1 (24)	0.7 (1)	NA (0)
	Middle Income	80.1% - 120% AMI	4.3 (135)	3 (29)	2.9 (25)	6.0 (38)	3.1 (20)	6.4 (23)
	Higher Income	> 120.1% AMI	4.8 (86)	3 (26)	7.2 (18)	5.3 (14)	5.7 (13)	11.2 (15)
Zip AA (>15%) × ZIPINC	Lower Income	≤ 80% AMI	0.6 (67)	0.3 (22)	1.4 (18)	0.7 (15)	0.4 (6)	0.4 (6)
	Middle Income	80.1% - 120% AMI	1.1 (23)	0.6 (5)	2.0 (11)	1.8 (2)	1.2 (2)	0.9 (3)
	Higher Income	> 120.1% AMI	4.4 (6)	1.1 (1)	NA (0)	1.8 (3)	51.2 (2)	NA (0)
Origination Number by Race and Credit Score								
Zip White (>85%) × ZIPCS	Lower Credit Score	≤ 700	6.6 (37)	5.2 (2)	2.8 (5)	8.2 (21)	4.0 (2)	7.5 (7)
	Middle Credit Score	700 - 740	3.6 (173)	2.7 (40)	3.4 (36)	5.8 (47)	2.9 (22)	7.6 (28)
	Higher Credit Score	> 740	6.0 (48)	4.9 (13)	6.0 (14)	5.6 (8)	6.7 (10)	65.3 (3)
Zip AA (>15%) × ZIPCS	Lower Credit Score	≤ 700	0.3 (29)	0.2 (15)	1.0 (2)	0.3 (5)	0.4 (4)	0.2 (3)
	Middle Credit Score	700 - 740	1.2 (56)	0.5 (9)	1.4 (24)	1.6 (13)	1.3 (5)	0.9 (5)
	Higher Credit Score	> 740	2.4 (11)	1.0 (4)	3.2 (3)	2.4 (2)	92.7 (1)	1.2 (1)

4. Median Subprime Share by Neighborhood Racial Composition, Income, and Credit Score in Period 1 (2004-2007)

Zip Code Characteristics			Subprime Share % (n=Zip-code count)					
			ALL MSAs	Cleveland	Cincinnati	Columbus	Dayton	Toledo
ALL			13.8 (422)	13.0 (95)	15.3 (100)	14.5 (114)	12.3 (55)	14.9 (58)
Access to Mortgage Capital by Race								
Zip White Population (%)	Fewer Whites	≤ 70%	28.2 (68)	33.1 (23)	21.9 (19)	25.4 (13)	35.4 (7)	26.0 (6)
	Middle Whites	70.1% - 85%	19.7 (44)	19.7 (9)	20.1 (9)	16.4 (14)	14.3 (5)	21.1 (7)
	Higher Whites	> 85.1%	12.2 (310)	11.0 (63)	13.6 (72)	13.8 (87)	11.2 (43)	12.6 (45)
Zip African American (%)	Fewer African-Americans	≤ 15%	12.5 (341)	11.4 (71)	13.7 (76)	13.6 (96)	11.7 (47)	14.3 (51)
	Middle AA	15.1% - 30%	20.1 (28)	29.8 (5)	18.5 (10)	20.4 (10)	21.0 (1)	13.5 (2)
	Higher AA	> 30.1%	31.1 (53)	34.5 (19)	28.1 (14)	28.2 (8)	35.4 (7)	27.1 (5)
Access to Mortgage Capital by Income								
Zip Median Family Income (ZIPINC)	Lower Income	≤ 80% AMI	22.1 (100)	33.2 (18)	19.7 (31)	21.0 (34)	30.2 (8)	27.1 (9)
	Middle Income	80.1% - 120% AMI	14.1 (231)	13.6 (50)	15.2 (49)	14.5 (61)	12.8 (32)	15.8 (39)
	Higher Income	> 120.1% AMI	7.3 (91)	7.6 (27)	7.8 (20)	6.5 (19)	7.0 (15)	5.7 (10)
Access to Mortgage Capital by Credit Score								
Median Zip Credit Score (ZIPCS)	Lower Credit Score	≤ 660	26.4 (97)	33.5 (22)	21.2 (22)	22.5 (27)	34.6 (8)	24.3 (18)
	Middle Credit Score	660 - 700	15.0 (195)	13.6 (39)	17.5 (47)	15.2 (57)	14.0 (24)	14.1 (28)
	Higher Credit Score	> 700	7.9 (130)	8.2 (34)	8.4 (31)	6.8 (30)	8.6 (23)	7.4 (12)
Access to Credit by Race and Income								
Zip White (>85%) × ZIPINC	Lower Income	≤ 80% AMI	17.1 (40)	NA (0)	19.2 (18)	16.4 (18)	22.0 (3)	14.5 (1)
	Middle Income	80.1% - 120% AMI	13.5 (190)	12.6 (39)	13.9 (36)	14.4 (53)	12.3 (28)	16.0 (34)
	Higher Income	> 120.1% AMI	7.1 (80)	7.4 (24)	7.8 (18)	6.5 (16)	6.8 (12)	5.7 (10)
Zip AA (>15%) × ZIPINC	Lower Income	≤ 80% AMI	30.1 (49)	44.2 (15)	30.6 (12)	26.7 (13)	46.4 (4)	27.1 (5)
	Middle Income	80.1% - 120% AMI	20.6 (27)	30.8 (7)	17.9 (11)	20.2 (5)	34.6 (2)	13.5 (2)
	Higher Income	> 120.1% AMI	14.6 (5)	13.9 (2)	0.0 (1)	NA (0)	19.7 (2)	NA (0)
Access to Credit by Race and Credit Score								
Zip White (>85%) × ZIPCS	Lower Credit Score	≤ 660	19.3 (42)	20.9 (2)	19.4 (14)	17.9 (16)	30.0 (1)	17.6 (9)
	Middle Credit Score	660 - 700	14.3 (152)	13.1 (30)	15.9 (31)	15.0 (47)	13.8 (20)	13.4 (24)
	Higher Credit Score	> 700	7.9 (116)	7.9 (31)	8.4 (27)	6.8 (24)	8.9 (22)	7.4 (12)
Zip AA (>15%) × ZIPCS	Lower Credit Score	≤ 660	33.0 (44)	44.2 (17)	31.1 (7)	28.4 (9)	40.4 (6)	27.1 (5)
	Middle Credit Score	660 - 700	20.1 (27)	15.2 (4)	20.1 (13)	20.7 (6)	16.8 (2)	13.5 (2)
	Higher Credit Score	> 700	9.0 (10)	13.1 (3)	8.6 (4)	7.7 (3)	NA (0)	NA (0)

5. Median APR Spread by Neighborhood Racial Composition, Income, and Credit Score in Period 2 (2008-2011)

APR Spread bps (n=Zip-code count)

Zip Code Characteristics		ALL MSAs	Cleveland	Cincinnati	Columbus	Dayton	Toledo	
Total		4.4 (403)	1.7 (96)	3.0 (95)	2.8 (104)	5.3 (53)	13.5 (55)	
APR Spread by Race								
Zip Proportion of White Population (Zip White)	Fewer Whites	≤ 70%	12.3 (90)	5.3 (31)	14.2 (25)	7.9 (18)	15.8 (7)	24.7 (9)
	Middle Whites	70.1% - 85%	0.8 (63)	0.8 (7)	-2.9 (13)	-4.3 (21)	5.4 (14)	17.4 (8)
	Higher Whites	> 85.1%	3.9 (250)	1.6 (58)	-0.3 (57)	4.3 (65)	4.7 (32)	12.0 (38)
Zip Proportion of African American (Zip AA)	Fewer African-Americans	≤ 15%	3.2 (315)	1.7 (69)	-0.8 (68)	-1.0 (85)	5.2 (46)	13.0 (47)
	Middle AA	15.1% - 30%	3.1 (26)	1.7 (7)	3.0 (9)	2.4 (8)	NA (0)	16.0 (2)
	Higher AA	> 30.1%	13.2 (62)	3.1 (20)	13.1 (18)	14.9 (11)	15.8 (7)	21.2 (6)
APR Spread by Income								
Zip Median Family Income (ZIPINC)	Lower Income	≤ 80% AMI	14.9 (108)	11.3 (23)	14.6 (27)	14.9 (33)	15.8 (15)	26.6 (10)
	Middle Income	80.1% - 120% AMI	5.3 (189)	5.2 (43)	2.4 (46)	5.0 (44)	5.5 (24)	15.2 (32)
	Higher Income	> 120.1% AMI	-4.3 (106)	-2.3 (30)	-7.4 (22)	-8.2 (27)	-0.3 (14)	-2.3 (13)
APR Spread by Credit Score								
Zip Median Credit Score (ZIPCS)	Lower Credit Score	≤ 700	14.0 (182)	12.6 (33)	13.0 (40)	12.2 (52)	16.9 (22)	22.8 (35)
	Middle Credit Score	700 - 740	-0.7 (190)	0.0 (56)	-2.0 (46)	-4.2 (41)	5.0 (27)	-0.7 (20)
	Higher Credit Score	> 740	-10.5 (31)	-7.7 (7)	-10.7 (9)	-13.0 (11)	-2.9 (4)	NA (0)
APR Spread by Race and Income								
Zip White (>85%) × ZIPINC	Lower Income	≤ 80% AMI	13.9 (31)	-19.8 (0)	14.6 (9)	15.6 (15)	13.9 (5)	-1.5 (3)
	Middle Income	80.1% - 120% AMI	6.3 (140)	4.8 (0)	5.2 (31)	5.8 (36)	6.1 (17)	16.2 (30)
	Higher Income	> 120.1% AMI	-3.0 (79)	-2.3 (0)	-7.1 (17)	-8.2 (14)	0.4 (10)	-2.3 (13)
Zip AA (>15%) × ZIPINC	Lower Income	≤ 80% AMI	15.4 (60)	-1.3 (18)	14.6 (16)	16.9 (14)	19.5 (6)	26.6 (6)
	Middle Income	80.1% - 120% AMI	3.0 (25)	11.3 (7)	1.8 (11)	-2.1 (4)	4.8 (1)	4.1 (2)
	Higher Income	> 120.1% AMI	-7.5 (3)	-5.3 (2)	NA (0)	-7.5 (1)	NA (0)	NA (0)
APR Spread by Race and Credit Score								
Zip White (>85%) × ZIPCS	Lower Credit Score	≤ 700	12.6 (102)	12.3 (10)	11.2 (24)	11.6 (34)	14.0 (10)	18.2 (24)
	Middle Credit Score	700 - 740	0.2 (126)	1.6 (41)	-2.6 (28)	2.4 (25)	3.7 (18)	-1.5 (14)
	Higher Credit Score	> 740	-8.8 (22)	-7.7 (7)	-11.1 (5)	-12.4 (6)	-2.9 (4)	- (0)
Zip AA (>15%) × ZIPCS	Lower Credit Score	≤ 700	16.3 (60)	15.5 (18)	16.9 (15)	14.9 (15)	15.8 (7)	28.4 (5)
	Middle Credit Score	700 - 740	-1.8 (27)	-7.0 (9)	1.8 (11)	-7.3 (4)	NA (0)	0.8 (3)
	Higher Credit Score	> 740	-8.2 (1)	NA (0)	-8.2 (1)	NA (0)	NA (0)	NA (0)

6. Median APR Spread by Neighborhood Racial Composition, Income, and Credit Score in Period 3 (2012-2015)

APR Spread bps (n=Zip-code count)

Zip Code Characteristics		ALL MSAs	Cleveland	Cincinnati	Columbus	Dayton	Toledo	
Total		12.8 (402)	12.4 (94)	10.8 (95)	14.5 (107)	13.0 (53)	16.6 (53)	
APR Spread by Race								
Zip Proportion of White Population (Zip White)	Fewer Whites	≤ 70%	22.9 (90)	24.5 (29)	15.5 (25)	22.8 (19)	23.8 (7)	22.6 (10)
	Middle Whites	70.1% - 85%	11.3 (69)	14.0 (12)	5.4 (16)	10.8 (22)	14.3 (12)	24.7 (7)
	Higher Whites	> 85.1%	12.0 (243)	9.9 (53)	11.1 (54)	15.2 (66)	8.9 (34)	13.9 (36)
Zip Proportion of African American (Zip AA)	Fewer African-Americans	≤ 15%	12.0 (308)	10.5 (67)	8.1 (66)	13.4 (87)	11.3 (44)	15.9 (44)
	Middle AA	15.1% - 30%	14.5 (31)	7.6 (7)	12.1 (9)	19.4 (9)	12.9 (2)	17.1 (4)
	Higher AA	> 30.1%	23.0 (63)	28.5 (20)	13.4 (20)	27.7 (11)	23.8 (7)	17.1 (5)
APR Spread by Income								
Zip Median Family Income (ZIPINC)	Lower Income	≤ 80% AMI	26.1 (110)	27.0 (25)	22.3 (31)	25.3 (34)	25.9 (10)	28.2 (10)
	Middle Income	80.1% - 120% AMI	14.2 (181)	14.9 (40)	10.0 (40)	16.2 (46)	13.0 (27)	15.6 (28)
	Higher Income	> 120.1% AMI	5.7 (111)	4.2 (29)	2.7 (24)	6.8 (27)	7.4 (16)	8.7 (15)
APR Spread by Credit Score								
Median Zip Credit Score (ZIPCS)	Lower Credit Score	≤ 700	30.0 (58)	32.0 (16)	30.0 (7)	35.7 (18)	23.7 (6)	28.4 (11)
	Middle Credit Score	700 - 740	14.5 (265)	14.0 (60)	12.1 (65)	15.4 (67)	15.1 (35)	15.9 (38)
	Higher Credit Score	> 740	2.7 (79)	0.6 (18)	1.2 (23)	5.0 (22)	7.4 (12)	6.4 (4)
APR Spread by Race and Income								
Zip White (>85%) × ZIPINC	Lower Income	≤ 80% AMI	24.1 (29)	- (0)	24.1 (11)	16.5 (17)	35.8 (1)	- (0)
	Middle Income	80.1% - 120% AMI	14.4 (131)	16.9 (27)	11.7 (25)	15.5 (37)	14.7 (20)	14.3 (22)
	Higher Income	> 120.1% AMI	5.8 (83)	5.9 (26)	3.4 (18)	7.8 (12)	5.8 (13)	9.1 (14)
Zip AA (>15%) × ZIPINC	Lower Income	≤ 80% AMI	27.0 (65)	27.0 (21)	22.0 (18)	27.7 (15)	23.8 (5)	22.8 (6)
	Middle Income	80.1% - 120% AMI	10.4 (23)	15.5 (5)	9.5 (11)	18.4 (2)	11.8 (2)	14.5 (3)
	Higher Income	> 120.1% AMI	11.7 (6)	-0.4 (1)	NA (0)	11.1 (3)	25.6 (2)	NA (0)
APR Spread by Race and Credit Score								
Zip White (>85%) × ZIPCS	Lower Credit Score	≤ 700	22.0 (26)	1.2 (1)	44.4 (4)	31.8 (13)	19.8 (2)	9.1 (6)
	Middle Credit Score	700 - 740	14.1 (171)	13.3 (40)	12.1 (36)	15.2 (45)	12.4 (22)	14.8 (28)
	Higher Credit Score	> 740	2.7 (46)	1.3 (12)	-0.7 (14)	3.5 (8)	6.3 (10)	0.5 (2)
Zip AA (>15%) × ZIPCS	Lower Credit Score	≤ 700	36.5 (27)	35.5 (14)	34.1 (2)	36.5 (5)	23.8 (3)	83.9 (3)
	Middle Credit Score	700 - 740	15.4 (56)	9.9 (9)	13.7 (24)	20.5 (13)	17.3 (5)	14.5 (5)
	Higher Credit Score	> 740	2.3 (11)	-0.2 (4)	2.3 (3)	2.6 (2)	33.9 (1)	9.9 (1)

7. Median FHA Share by Neighborhood Racial Composition, Income, and Credit Score in Period 2 (2008-2011)

Zip Code Characteristics		ALL MSAs	Cleveland	Cincinnati	Columbus	Dayton	Toledo	
Total		42.6 (387)	42.2 (93)	43.2 (93)	43.9 (98)	45.9 (51)	35.2 (52)	
FHA Share by Race								
Zip Proportion of White Population (Zip White)	Fewer Whites	≤ 70%	63.6 (91)	66.0 (31)	55.3 (26)	69.5 (18)	70.5 (7)	64.7 (9)
	Middle Whites	70.1% - 85%	42.8 (62)	43.0 (7)	35.5 (13)	42.3 (21)	55.4 (14)	35.0 (7)
	Higher Whites	> 85.1%	39.6 (234)	40.0 (55)	40.9 (54)	43.3 (59)	37.1 (30)	31.5 (36)
Zip Proportion of African American (Zip AA)	Fewer African-Americans	≤ 15%	40.6 (298)	41.0 (66)	39.9 (65)	42.3 (79)	44.5 (44)	33.4 (44)
	Middle AA	15.1% - 30%	61.7 (26)	46.4 (7)	60.7 (9)	71.8 (8)	NA (0)	57.5 (2)
	Higher AA	> 30.1%	63.6 (63)	68.7 (20)	55.6 (19)	72.0 (11)	70.5 (7)	54.0 (6)
FHA Share by Income								
Zip Median Family Income (ZIPINC)	Lower Income	≤ 80% AMI	60.2 (98)	65.6 (22)	53.7 (26)	53.3 (28)	65.3 (13)	65.5 (9)
	Middle Income	80.1% - 120% AMI	44.9 (185)	46.5 (42)	44.9 (45)	45.6 (44)	46.0 (24)	40.5 (30)
	Higher Income	> 120.1% AMI	29.4 (104)	25.4 (29)	28.5 (22)	35.3 (26)	34.8 (14)	27.0 (13)
FHA Share by Credit Score								
Zip Median Credit Score (ZIPCS)	Lower Credit Score	≤ 700	57.1 (172)	67.9 (32)	57.4 (38)	51.9 (48)	60.6 (21)	40.7 (33)
	Middle Credit Score	700 - 740	37.9 (187)	37.9 (56)	38.4 (46)	39.6 (39)	38.7 (27)	30.4 (19)
	Higher Credit Score	> 740	23.3 (28)	17.4 (5)	21.6 (9)	25.3 (11)	28.0 (3)	- (0)
FHA Share by Race and Income								
Zip White (>85%) × ZIPINC	Lower Income	≤ 80% AMI	44.6 (21)	NA (0)	46.4 (7)	44.0 (10)	60.5 (3)	42.1 (1)
	Middle Income	80.1% - 120% AMI	44.1 (136)	45.7 (29)	44.0 (30)	44.9 (36)	44.3 (17)	39.7 (24)
	Higher Income	> 120.1% AMI	28.1 (77)	25.8 (26)	28.9 (17)	27.2 (13)	34.8 (10)	26.1 (11)
Zip AA (>15%) × ZIPINC	Lower Income	≤ 80% AMI	63.6 (61)	55.8 (18)	60.7 (17)	73.4 (14)	71.8 (6)	65.1 (6)
	Middle Income	80.1% - 120% AMI	63.7 (25)	74.0 (7)	55.1 (11)	71.8 (4)	62.3 (1)	45.2 (2)
	Higher Income	> 120.1% AMI	36.2 (3)	31.6 (2)	NA (0)	36.2 (1)	NA (0)	NA (0)
FHA Share by Race and Credit Score								
Zip White (>85%) × ZIPCS	Lower Credit Score	≤ 700	45.1 (91)	58.4 (9)	53.4 (21)	46.1 (30)	44.3 (9)	39.7 (22)
	Middle CS	700 - 740	36.6 (124)	38.9 (41)	37.0 (28)	38.6 (23)	36.5 (18)	29.4 (14)
	Higher CS	> 740	22.2 (19)	17.4 (5)	16.3 (5)	24.7 (6)	28.0 (3)	NA (0)
Zip AA (>15%) × ZIPCS	Lower Credit Score	≤ 700	68.2 (61)	71.4 (18)	62.8 (16)	74.7 (15)	70.5 (7)	65.5 (5)
	Middle CS	700 - 740	38.7 (27)	23.5 (9)	43.2 (11)	46.4 (4)	NA (0)	43.2 (3)
	Higher CS	> 740	23.9 (1)	NA (0)	23.9 (1)	NA (0)	NA (0)	NA (0)

8. Median FHA Share by Neighborhood Racial Composition, Income, and Credit Score in Period 3 (2011-2015)

Zip Code Characteristics		ALL MSAs	Cleveland	Cincinnati	Columbus	Dayton	Toledo	
Total		29.6 (403)	30.6 (94)	30.5 (92)	27.7 (111)	34.0 (52)	26.6 (54)	
FHA Share by Race								
Zip Proportion of White Population (Zip White)	Fewer Whites	≤ 70%	49.0 (92)	60.0 (30)	38.1 (25)	51.3 (19)	57.1 (8)	49.1 (10)
	Middle Whites	70.1% - 85%	30.4 (69)	30.3 (12)	30.3 (16)	20.2 (22)	43.9 (12)	44.2 (7)
	Higher Whites	> 85.1%	26.8 (242)	26.7 (52)	27.9 (51)	27.3 (70)	27.3 (32)	23.9 (37)
Zip Proportion of African American (Zip AA)	Fewer African-Americans	≤ 15%	27.3 (307)	29.2 (66)	27.9 (63)	27.0 (91)	29.8 (42)	25.4 (45)
	Middle AA	15.1% - 30%	39.3 (31)	30.7 (7)	38.1 (9)	49.7 (9)	39.2 (2)	40.1 (4)
	Higher AA	> 30.1%	49.4 (65)	60.0 (21)	37.8 (20)	51.3 (11)	57.1 (8)	50.0 (5)
FHA Share by Income								
Zip Median Family Income (ZIPINC)	Lower Income	≤ 80% AMI	45.2 (115)	60.0 (26)	38.3 (30)	32.7 (38)	51.5 (11)	51.7 (10)
	Middle Income	80.1% - 120% AMI	32.9 (180)	34.4 (41)	32.7 (38)	30.2 (47)	35.7 (25)	28.4 (29)
	Higher Income	> 120.1% AMI	17.1 (108)	16.9 (27)	17.4 (24)	16.7 (26)	20.0 (16)	16.0 (15)
FHA Share by Credit Score								
Median Zip Credit Score (ZIPCS)	Lower Credit Score	≤ 700	50.0 (63)	67.9 (17)	50.0 (7)	36.4 (21)	48.6 (7)	44.4 (11)
	Middle Credit Score	700 - 740	31.2 (260)	30.7 (59)	33.2 (62)	31.1 (68)	36.7 (33)	26.1 (8)
	Higher Credit Score	> 740	14.1 (80)	11.0 (18)	15.9 (23)	13.9 (22)	17.9 (12)	17.5 (5)
FHA Share by Race and Income								
Zip White (>85%) × ZIPINC	Lower Income	≤ 80% AMI	31.8 (32)	- (0)	35.1 (10)	26.9 (21)	55.8 (1)	- (0)
	Middle Income	80.1% - 120% AMI	31.2 (130)	34.5 (28)	32.9 (23)	28.4 (38)	32.8 (18)	27.0 (23)
	Higher Income	> 120.1% AMI	17.5 (80)	17.5 (24)	18.2 (18)	14.2 (11)	19.6 (13)	15.8 (14)
Zip AA (>15%) × ZIPINC	Lower Income	≤ 80% AMI	50.0 (67)	60.0 (22)	43.1 (18)	51.3 (15)	58.4 (6)	52.5 (6)
	Middle Income	80.1% - 120% AMI	39.1 (23)	56.2 (5)	30.6 (11)	52.5 (2)	47.7 (2)	35.9 (3)
	Higher Income	> 120.1% AMI	27.0 (6)	12.7 (1)	- (0)	27.1 (3)	33.1 (2)	- (0)
FHA Share by Race and Credit Score								
Zip White (>85%) × ZIPCS	Lower CS	≤ 700	32.6 (29)	21.0 (1)	34.6 (4)	30.3 (16)	36.7 (2)	29.5 (6)
	Middle CS	700 - 740	27.9 (166)	30.7 (39)	32.6 (33)	27.6 (46)	31.0 (20)	21.4 (28)
	Higher CS	> 740	14.6 (47)	10.2 (12)	16.3 (14)	12.2 (8)	17.9 (10)	17.5 (3)
Zip AA (>15%) × ZIPCS	Lower CS	≤ 700	62.5 (29)	69.1 (15)	58.8 (2)	68.9 (5)	58.4 (4)	58.3 (3)
	Middle CS	700 - 740	42.9 (56)	30.0 (9)	40.6 (24)	46.2 (13)	39.3 (5)	42.9 (5)
	Higher CS	> 740	12.7 (11)	13.5 (4)	9.6 (3)	17.1 (2)	26.9 (1)	12.5 (1)

9. Summary Statistics: Zip-Code Level Mean, Median, Standard Deviation for Each Variable by MSA in Period 1 (2004-2007)

	Cleveland		Cincinnati		Columbus		Dayton		Toledo	
	Mean	Median SD								
n	94		97		111		55		55	
Conv. Mortgage Origination (count)	171.7 137.5	144.0	235.9 180.6	200.0	289.4 280.4	217.0	199.7 147.3	162.0	192.5 164.6	156.0
Subprime Share (%)	18.1 14.0	13.0	16.0 7.9	15.2	15.0 7.7	14.5	15.3 11.2	12.3	15.6 7.6	14.4
Credit Score (point)	684.5 31.5	692.1	684.1 28.5	684.4	681.5 29.0	678.6	688.7 32.1	690.3	673.8 30.0	675.6
Proportion of AA (%)	15.2 25.7	1.7	13.4 22.3	2.0	7.7 16.6	1.0	11.2 22.4	2.3	7.8 18.4	0.3
Log Income (%)	10.9 0.4	10.9	10.8 0.4	10.9	10.8 0.3	10.8	10.9 0.3	10.9	10.8 0.3	10.8
Selfemployment (%)	8.8 4.4	8.0	8.2 3.0	7.9	8.8 5.2	8.7	8.2 4.1	8.0	7.8 2.7	7.4
House Price Change (%)	101.2 321.0	62.3	75.4 148.6	53.7	66.4 35.2	67.3	59.2 44.4	51.6	64.3 29.2	63.6
Turnover (%)	0.2 0.9	0.0	0.3 0.6	0.1	1.7 5.3	0.2	0.4 1.5	0.1	0.4 0.9	0.1
House Age (year)	39.0 12.3	37.0	36.6 15.6	31.0	35.2 16.5	34.0	40.8 12.0	39.0	43.7 13.1	46.0
Bank Ratio (%)	8.5 9.4	7.2	9.7 12.1	7.6	7.1 13.8	5.2	8.4 12.5	5.9	9.3 12.2	8.2
LTV-conv (%)	82.2 4.3	80.0	81.9 4.4	80.0	82.4 5.3	80.0	82.9 5.2	80.0	84.3 5.3	80.6
LTV-all (%)	84.3 5.6	80.0	85.9 6.5	83.8	87.4 6.8	89.3	87.9 7.1	90.0	88.1 6.2	89.5
DTI-conv (%)	38.0 38.0	38.2	37.9 37.9	38.0	37.1 37.1	36.8	36.6 36.6	36.5	38.7 38.7	38.7
DTI-all (%)	38.3 2.3	38.6	38.4 1.9	38.7	37.4 3.1	37.8	36.9 2.8	37.0	38.5 2.7	38.7
Owner-Occupied Units (count)	6143.9 4414.0	5685.5	4128.3 3694.3	2903.0	3621.2 3955.8	2040.0	3740.8 3109.7	2949.0	2955.6 3132.9	1365.0

10. Summary Statistics: Zip-Code Level Mean, Median, Standard Deviation for Each Variable by MSA in Period 2 (2008-2011)

	Cleveland		Cincinnati		Columbus		Dayton		Toledo	
	n		n		n		n		Mean	Median
	94	94	91	91	99	99	53	53	SD	SD
Conv. Mortgage Origination (count)	65.4	46.0 67.1	103.9	63.0 100.6	117.9	86.0 148.2	73.0	66.0 67.5	71.6	51.0 80.5
FHA Share (%)	43.5	42.2 20.0	43.6	42.9 14.8	46.7	43.9 15.9	46.3	45.9 15.9	39.3	34.6 16.8
APR Spread (bp)	2.6	1.7 27.2	5.0	1.8 17.0	4.6	2.6 16.3	9.0	5.3 14.8	14.7	14.1 21.0
Credit Score (point)	706.5	710.1 24.4	709.1	709.8 23.6	705.9	701.1 22.5	707.2	709.0 24.9	696.8	697.1 23.8
Proportion of AA (%)	17.6	2.2 27.1	14.8	3.1 22.2	9.9	2.0 18.0	12.7	4.0 22.7	10.3	1.1 20.4
Log Income (%)	11.0	11.1 0.4	11.0	11.1 0.4	11.1	11.1 0.4	11.0	11.0 0.3	11.0	11.0 0.4
Selfemployment (%)	8.7	7.6 4.2	8.7	8.4 3.6	9.2	8.9 4.1	8.5	7.4 4.0	7.6	7.9 2.9
House Price Change (%)	10.9	12.1 14.1	19.0	20.6 20.7	21.0	20.8 16.5	7.6	7.4 13.1	16.6	17.1 18.4
Turnover (%)	0.0	0.0 0.0	0.1	0.0 0.2	0.2	0.1 0.3	0.1	0.0 0.2	0.1	0.0 0.1
House Age (year)	48.0	48.0 14.3	44.3	40.0 17.8	39.2	38.0 17.1	48.7	46.0 12.8	48.5	47.0 15.4
Bank Ratio (%)	7.5	6.9 6.2	7.7	6.9 7.4	6.9	6.4 9.1	5.7	5.6 4.3	6.5	6.3 5.7
LTV-conv (%)	80.9	80.0 3.1	82.6	80.0 6.4	82.7	80.0 5.7	82.1	80.0 5.2	85.0	80.0 8.4
LTV-all (%)	94.5	97.0 94.5	95.1	97.5 95.1	95.9	97.5 95.9	96.3	97.5 96.3	96.8	97.5 96.8
DTI-conv (%)	35.0	34.8 4.0	34.1	33.6 3.9	34.3	34.0 4.0	33.9	33.6 4.7	33.9	34.0 5.2
DTI-all (%)	38.2	38.7 2.6	36.6	36.7 3.4	37.3	37.1 2.5	36.5	36.8 3.2	37.1	37.6 4.7
Owner-Occupied Units (count)	6025.3	5721.5 4287.4	4606.0	3305.0 4048.1	4529.1	3047.0 4361.6	4040.5	3323.0 3274.8	3276.8	1942.0 3071.1

11. Summary Statistics: Zip-Code Level Mean, Median, Standard Deviation for Each Variable by MSA in Period 3 (2012-2015)

	Cleveland		Cincinnati		Columbus		Dayton		Toledo	
	n		n		n		n		Mean	Median
	92	92	98	50	49	SD				
Conv. Mortgage Origination (count)	101.9 74.5 96.9	139.4 86.0 144.4	156.0 122.0 123.0	92.7 83.0 62.9	113.0 82.0 132.1					
FHA Share (%)	34.7 30.4 20.4	31.2 30.6 14.8	31.3 28.7 14.9	34.8 34.4 14.6	29.7 26.3 14.7					
APR Spread (bp)	15.9 12.4 15.2	12.7 10.5 13.9	17.4 14.9 15.0	13.4 12.4 11.8	19.0 16.8 15.7					
Credit Score (point)	719.7 722.2 20.7	726.5 727.9 18.4	720.9 716.5 21.4	722.3 722.4 18.2	714.6 712.3 20.2					
Proportion of AA (%)	18.1 3.3 27.2	15.8 3.8 22.6	10.2 2.4 17.3	12.3 3.6 21.5	9.0 1.0 17.8					
Log Income (%)	11.1 11.2 0.4	11.1 11.1 0.5	11.1 11.1 0.4	11.0 11.1 0.4	11.0 11.1 0.4					
Selfemployment (%)	8.3 7.0 4.2	7.9 7.1 3.3	8.4 8.2 3.0	8.5 7.2 4.3	7.2 6.7 3.0					
House Price Change (%)	-8.0 -7.7 11.2	-3.6 -3.8 8.5	-3.3 -2.4 8.5	-3.8 -3.7 9.7	-7.1 -8.5 11.0					
Turnover (%)	0.0 0.0 0.0	0.1 0.0 0.2	0.2 0.1 0.3	0.1 0.0 0.1	0.2 0.1 0.5					
House Age (year)	51.2 51.0 14.5	46.6 42.0 18.3	40.7 39.5 16.0	51.9 51.0 12.4	51.1 50.0 15.0					
Bank Ratio (%)	7.2 6.7 5.7	6.7 6.1 5.1	5.6 5.5 4.9	5.4 5.3 3.7	6.1 5.9 5.4					
LTV-conv (%)	84.2 83.7 4.8	83.5 80.0 5.1	86.4 87.3 5.5	85.6 85.0 6.3	86.8 85.7 6.4					
LTV-all (%)	93.7 95.0 93.7	93.3 95.0 93.3	95.0 97.5 95.0	96.9 97.5 96.9	96.3 97.5 96.3					
DTI-conv (%)	32.6 32.7 3.5	31.8 32.0 3.7	32.7 33.0 3.5	31.2 31.3 4.8	33.0 33.0 5.2					
DTI-all (%)	35.9 36.6 3.6	34.5 35.0 3.0	36.0 36.0 2.4	34.7 35.1 3.3	35.8 36.0 3.1					
Owner-Occupied Units (count)	5957.1 5676.0 4145.8	4480.2 3266.0 3975.1	4548.5 3143.0 4349.6	4116.0 3289.0 3172.5	3057.8 1810.0 2952.0					

Appendix B: Geography of Mortgages by Racial Compositions and Median Credit Scores, Maps by Metropolitan Statistical Area (MSA)

Geography of Mortgages in the Cleveland MSA

1. Geography of Rate of Originations in Neighborhoods in the Cleveland MSA in Period 1 (2004-2007)	109
2. Geography of Rate of Originations in Neighborhoods in the Cleveland MSA in Period 2 (2008-2011)	110
3. Geography of Rate of Originations in Neighborhoods in the Cleveland MSA in Period 3 (2012-2015)	111
4. Geography of the Share of Subprime Loans in Neighborhoods in the Cleveland MSA in Period 1 (2004-2007).....	112
5. Geography of the Share of FHA-insured Loans in Neighborhoods in the Cleveland MSA in Period 2 (2008-2011).....	113
6. Geography of the Share of FHA-insured Loans in Neighborhoods in the Cleveland MSA in Period 3 (2012-2015).....	114
7. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Cleveland MSA in Period 2 (2008-2011)	115
8. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Cleveland MSA in Period 3 (2012-2015)	116

< Geography of Mortgage in the Cincinnati MSA >

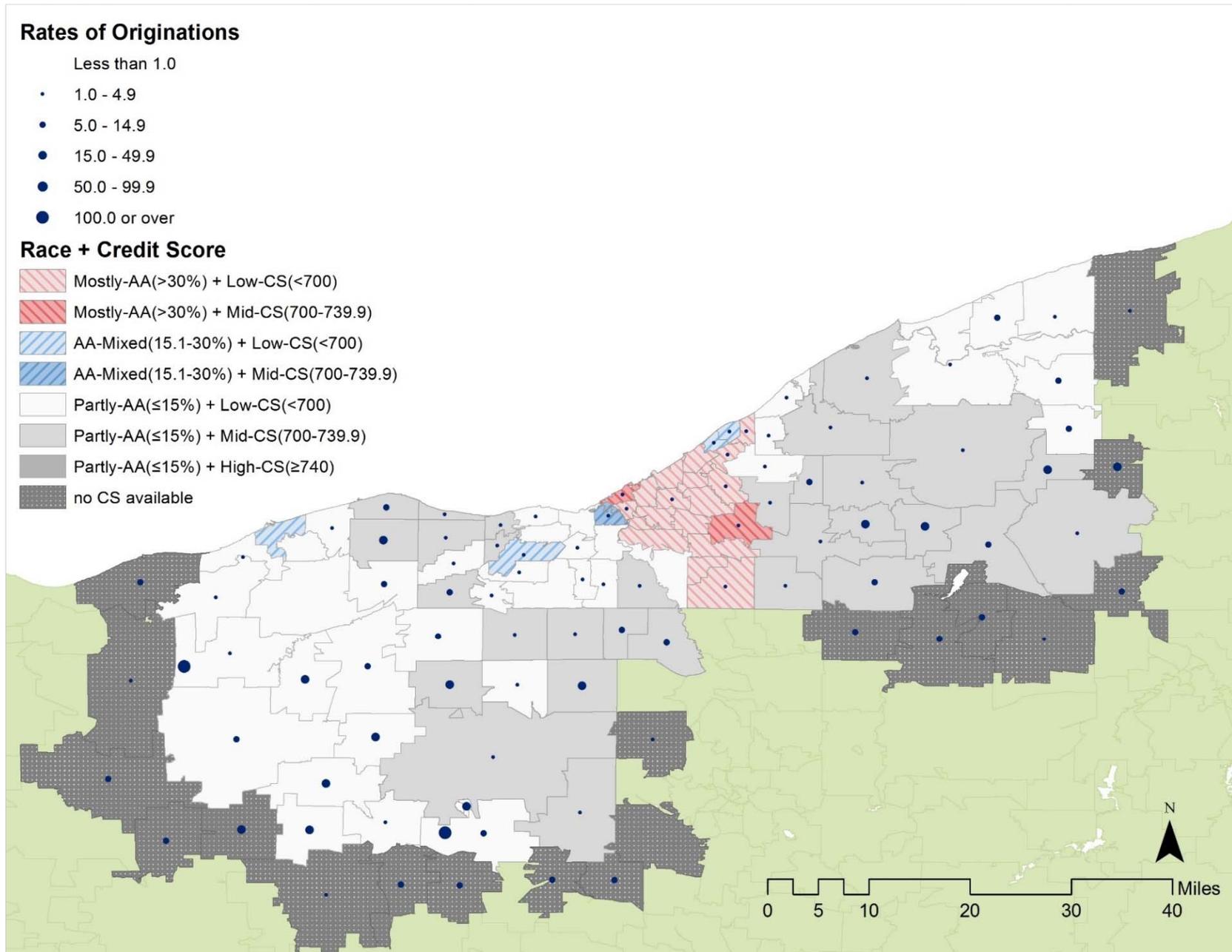
9. Geography of Rate of Originations in Neighborhoods in the Cincinnati MSA in Period 1 (2004-2007)	117
10. Geography of Rate of Originations in Neighborhoods in the Cincinnati MSA in Period 2 (2008-2011)	118
11. Geography of Rate of Originations in Neighborhoods in the Cincinnati MSA in Period 3 (2012-2015)	119
12. Geography of the Share of Subprime Loans in Neighborhoods in the Cincinnati MSA in Period 1 (2004-2007).....	120
13. Geography of the Share of FHA-insured Loans in Neighborhoods in the Cincinnati MSA in Period 2 (2008-2011)	121
14. Geography of the Share of FHA-insured Loans in Neighborhoods in the Cincinnati MSA in Period 3 (2012-2015)	122
15. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Cincinnati MSA in Period 2 (2008-2011)	123
16. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Cincinnati MSA in Period 3 (2012-2015)	124

< Geography of Mortgage in the Columbus MSA >

17. ... Geography of Rate of Originations in Neighborhoods in the Columbus MSA in Period 1 (2004-2007)	125
18. ... Geography of Rate of Originations in Neighborhoods in the Columbus MSA in Period 2 (2008-2011)	126
19. ... Geography of Rate of Originations in Neighborhoods in the Columbus MSA in Period 3 (2012-2015)	127
20. .Geography of the Share of Subprime Loans in Neighborhoods in the Columbus MSA in Period 1 (2004-2007).....	128
21. Geography of the Share of FHA-insured Loans in Neighborhoods in the Columbus MSA in Period 2 (2008-2011).....	129
22. Geography of the Share of FHA-insured Loans in Neighborhoods in the Columbus MSA in Period 3 (2012-2015).....	130
23. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Columbus MSA in Period 2 (2008-2011)	131
24. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Columbus MSA in Period 3 (2012-2015)	132
< Geography of Mortgage in the Dayton MSA >	
25. Geography of Rate of Originations in Neighborhoods in the Dayton MSA in Period 1 (2004-2007)	133
26. Geography of Rate of Originations in Neighborhoods in the Dayton MSA in Period 2 (2008-2011)	134
27. Geography of Rate of Originations in Neighborhoods in the Dayton MSA in Period 3 (2012-2015)	135
28. Geography of the Share of Subprime Loans in Neighborhoods in the Dayton MSA in Period 1 (2004-2007).....	136
29. Geography of the Share of FHA-insured Loans in Neighborhoods in the Dayton MSA in Period 2 (2008-2011).....	137
30. Geography of the Share of FHA-insured Loans in Neighborhoods in the Dayton MSA in Period 3 (2012-2015).....	138
31. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Dayton MSA in Period 2 (2008-2011)	139
32. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Dayton MSA in Period 3 (2012-2015)	140
< Geography of Mortgage in the Toledo MSA >	
33. Geography of Rate of Originations in Neighborhoods in the Toledo MSA in Period 1 (2004-2007)	141
34. Geography of Rate of Originations in Neighborhoods in the Toledo MSA in Period 2 (2008-2011)	142
35. Geography of Rate of Originations in Neighborhoods in the Toledo MSA in Period 3 (2012-2015)	143
36. Geography of Shares of Subprime Loans in the Toledo MSA in Period 1 (2004-2007)	144

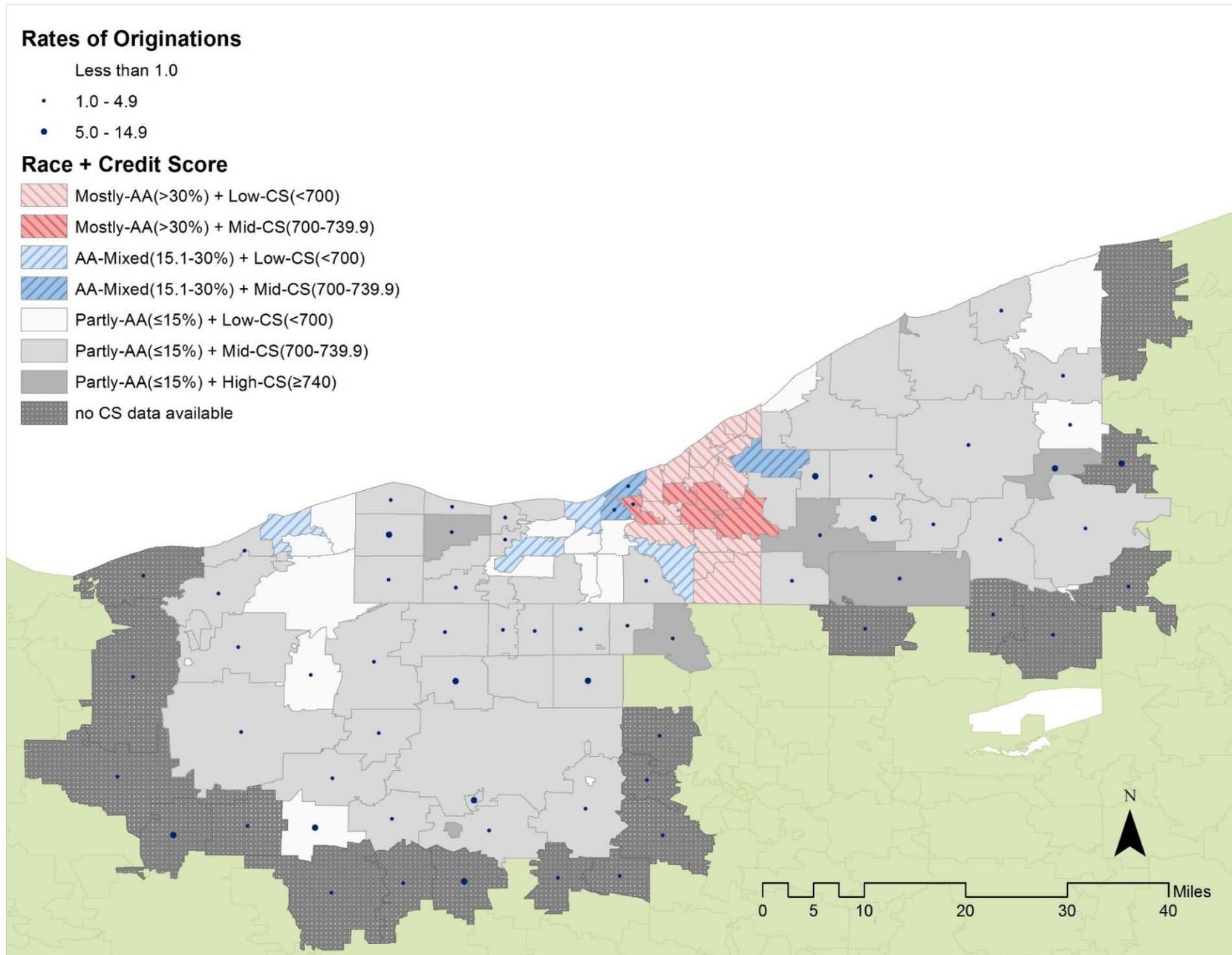
37. Geography of Shares of FHA-insured Loans in the Toledo MSA in Period 2 (2008-2011).....	145
38. Geography of Shares of FHA-insured Loans in the Toledo MSA in Period 3 (2012-2015).....	146
39. Geography of Costlier Mortgages (APR Spread) in the Toledo MSA in Period 2 (2008-2011) .	147
40. Geography of Costlier Mortgages (APR Spread) in the Toledo MSA in Period 3 (2012-2015) .	148

1. Geography of the Rates of Originations in Neighborhoods in the Cleveland MMSA in Period 1 (2004-2007)



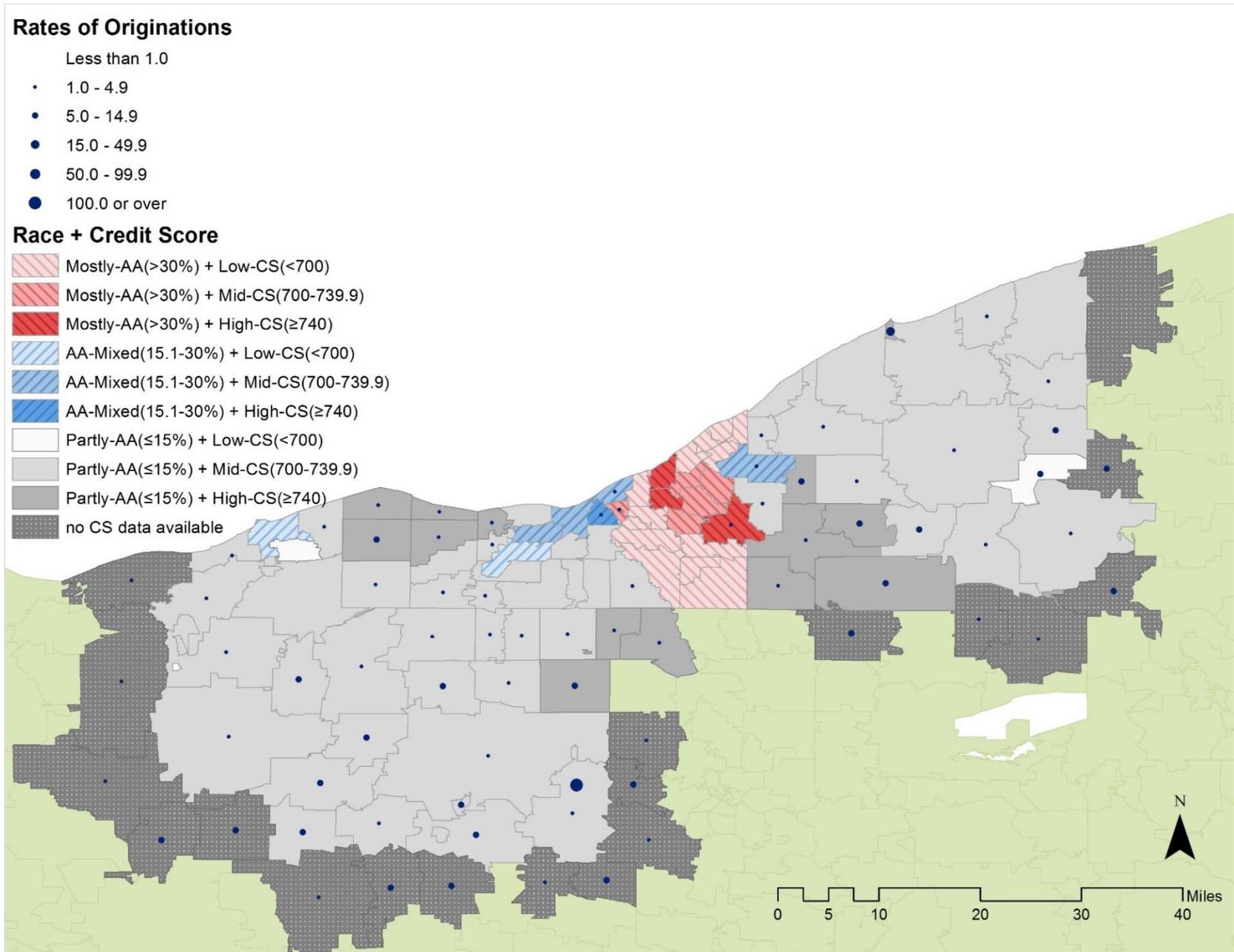
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

2. **Geography of Rate of Originations in Neighborhoods in the Cleveland MSA in Period 2 (2008-2011)**



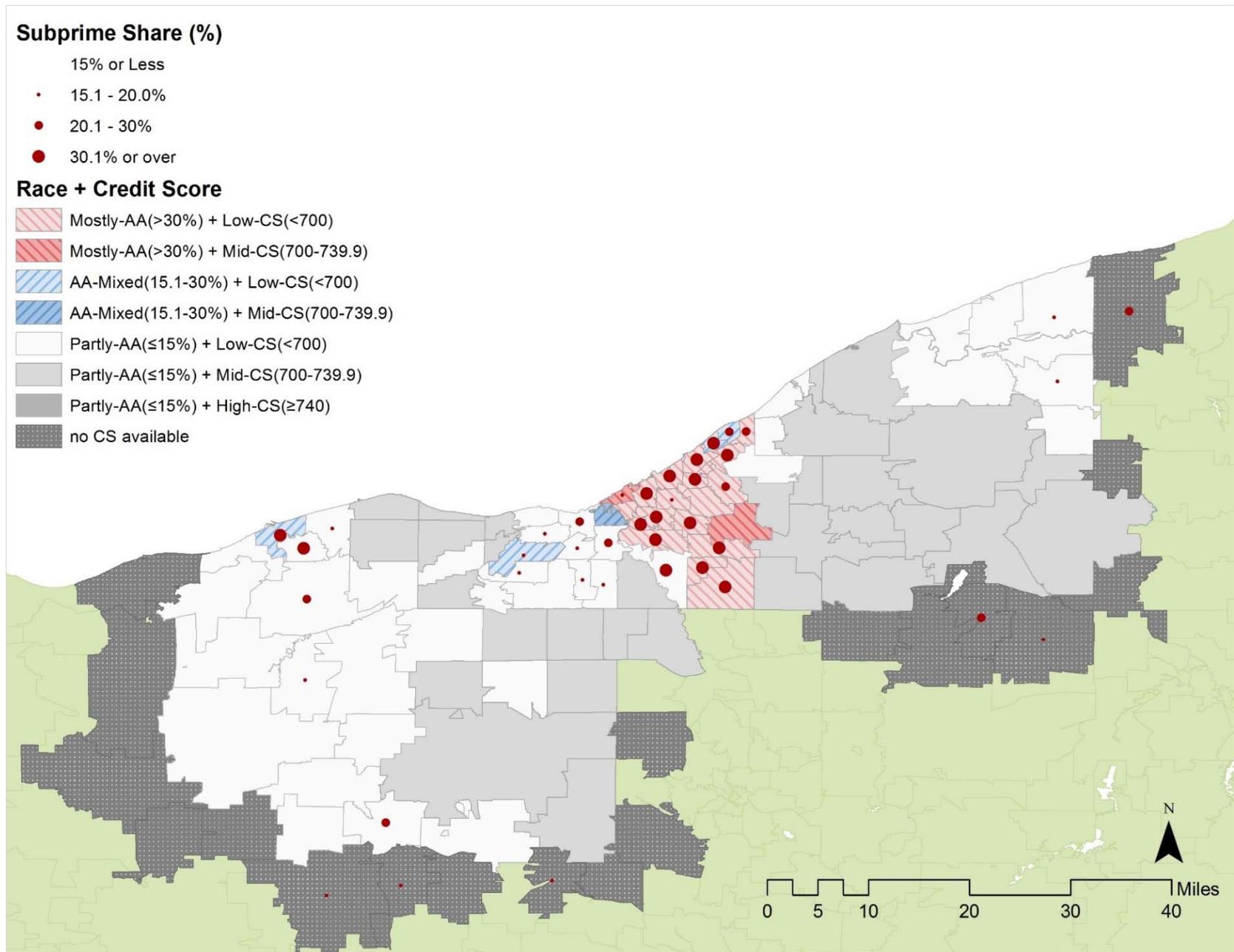
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

3. Geography of Rate of Originations in Neighborhoods in the Cleveland MSA in Period 3 (2012-2015)



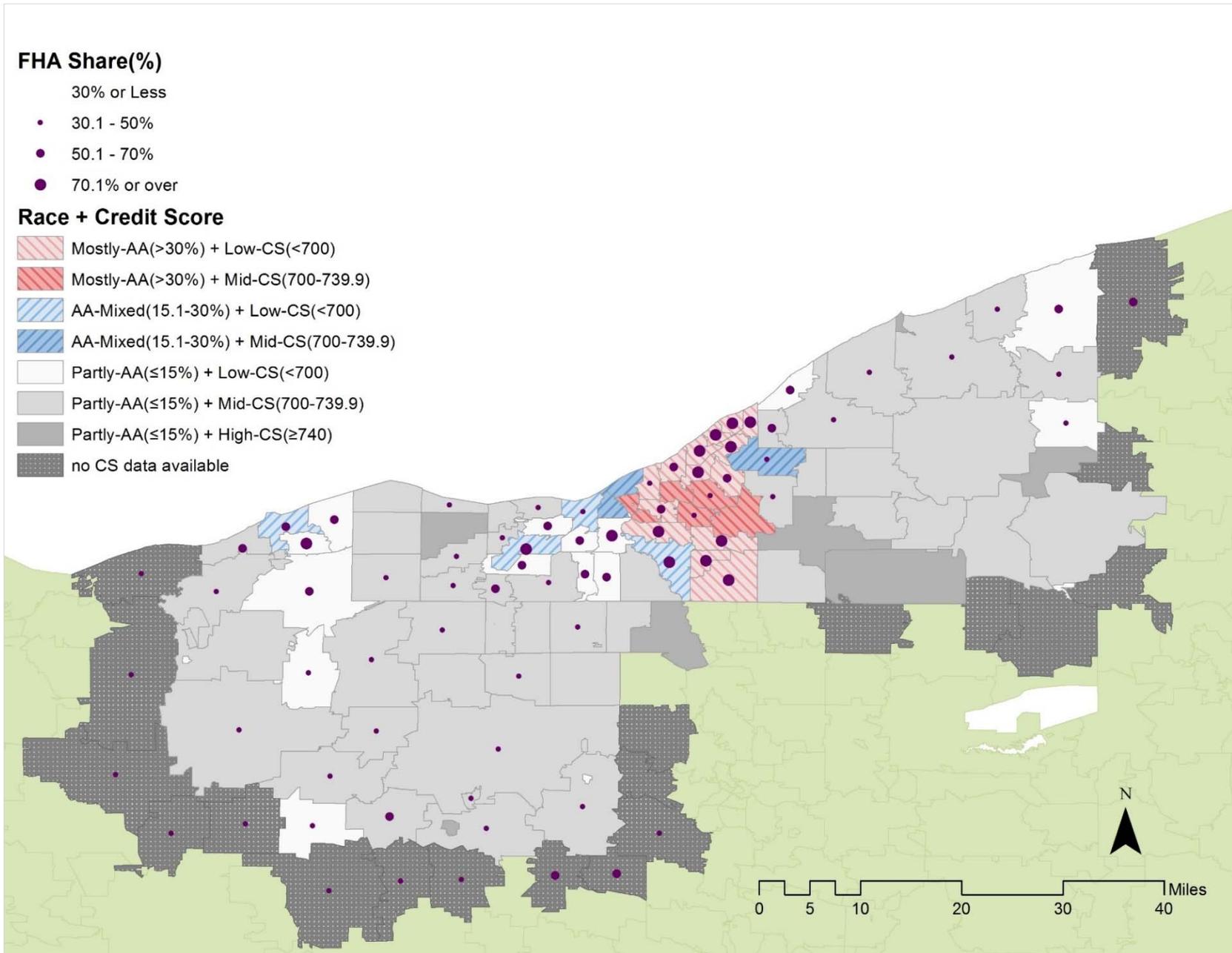
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

4. Geography of the Share of Subprime Loans in Neighborhoods in the Cleveland MSA in Period 1 (2004-2007)



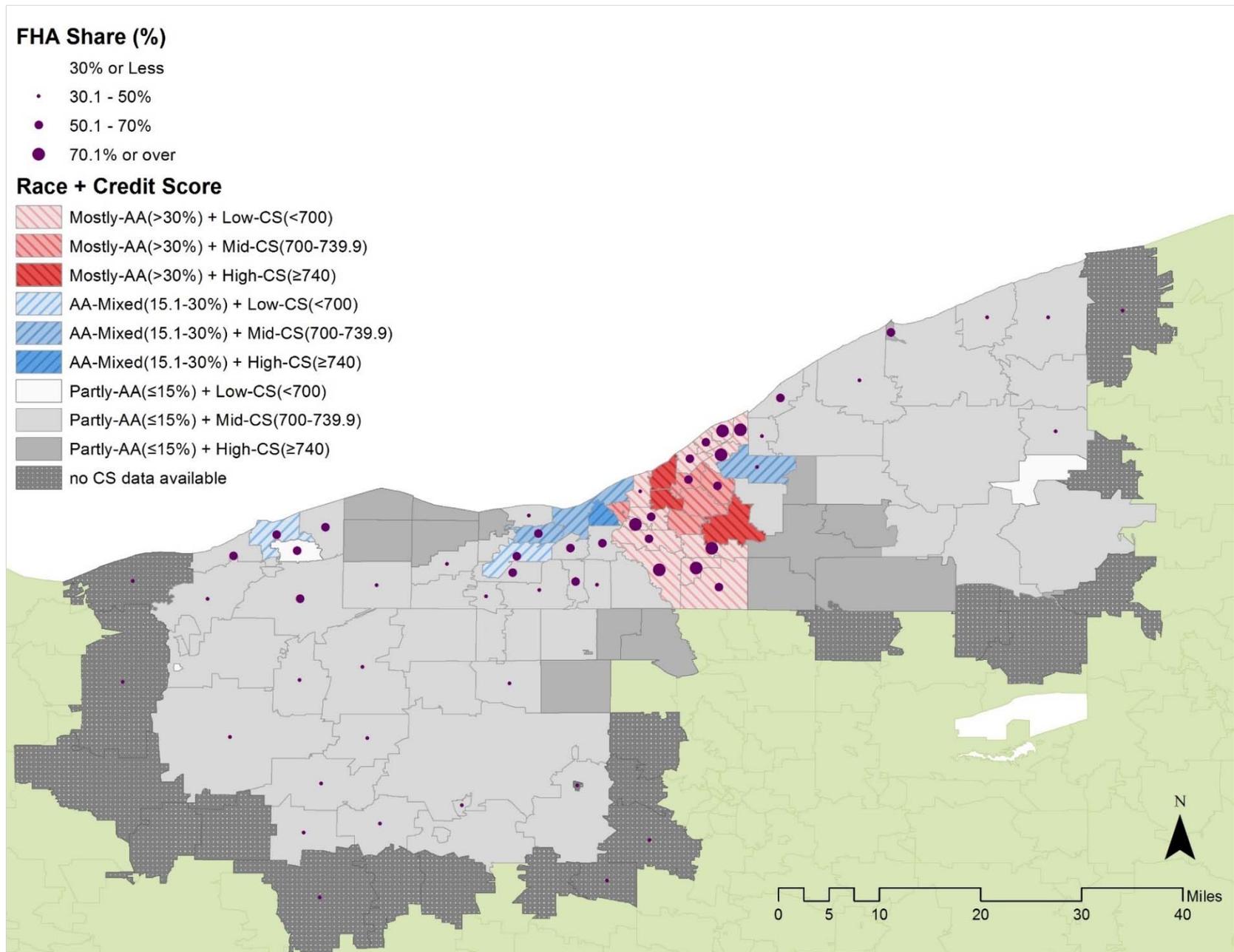
Subprime Share: a proportion of the subprime mortgage origination count to the total mortgage origination count in a neighborhood

5. Geography of the Share of FHA-insured Loans in Neighborhoods in the Cleveland MSA in Period 2 (2008-2011)



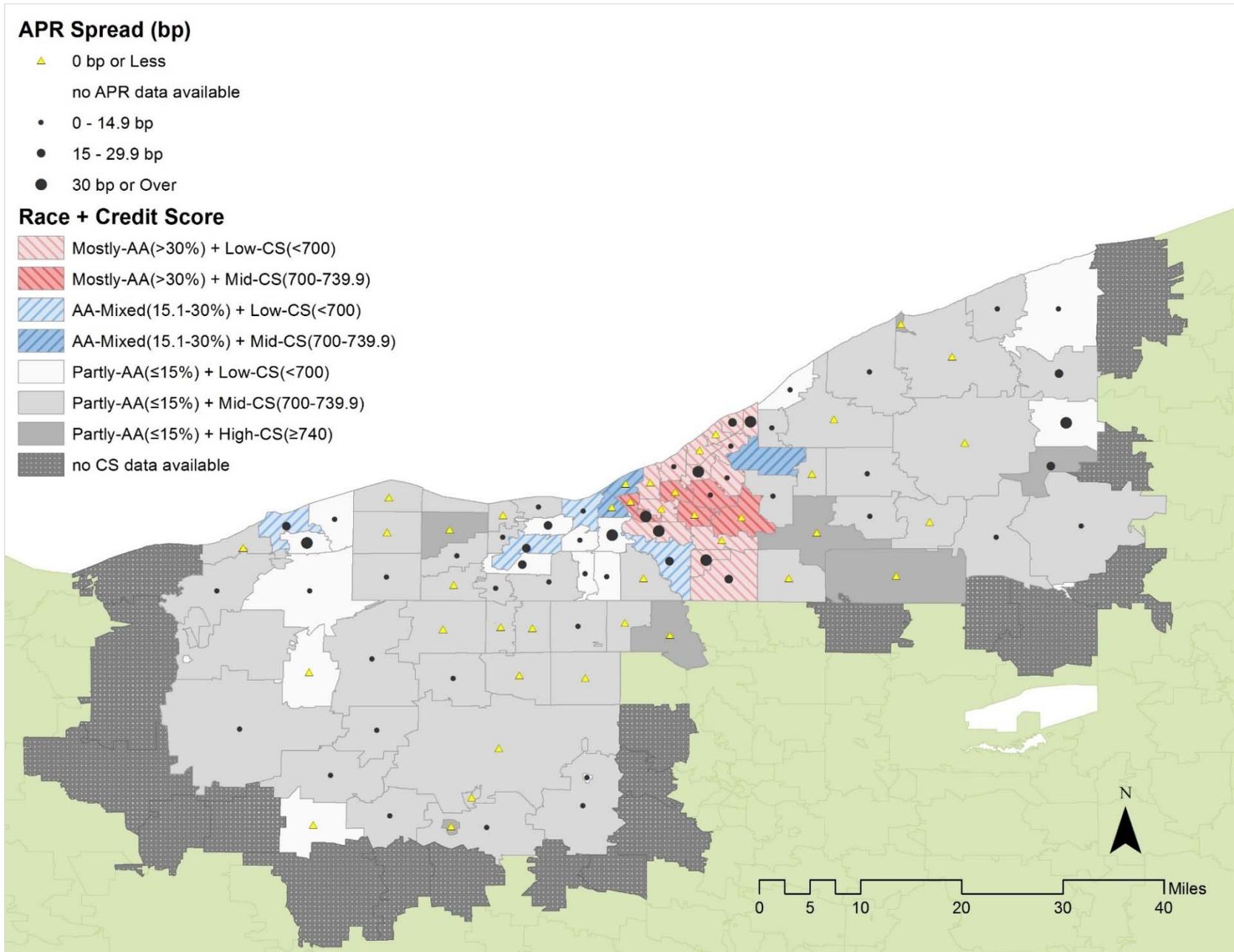
FHA share: a proportion of FHA-insured mortgage origination count of the total mortgage origination count in a neighborhood

6. Geography of the Share of FHA-insured Loans in Neighborhoods in the Cleveland MSA in Period 3 (2012-2015)



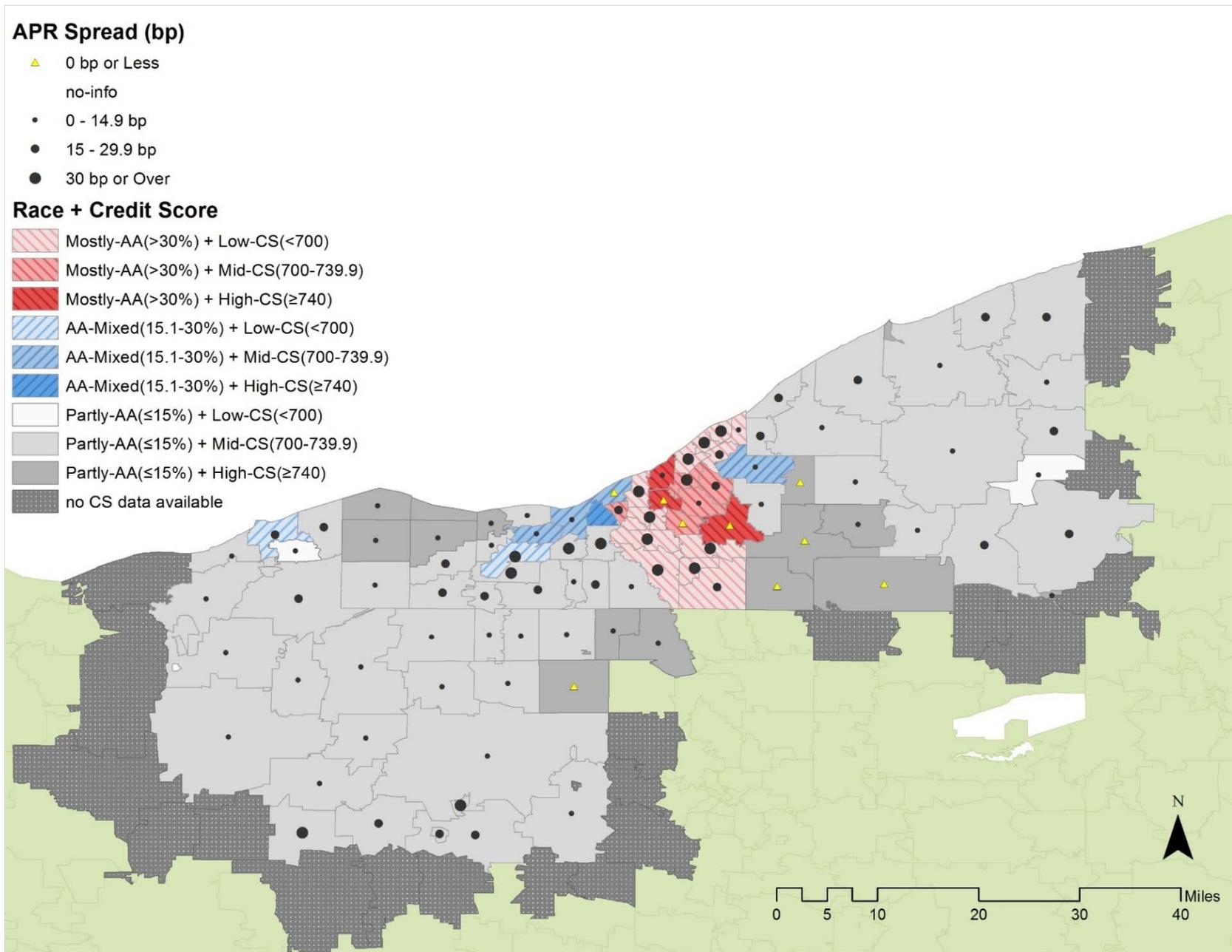
FHA share: a proportion of FHA-insured mortgage origination count of the total mortgage origination count in a neighborhood

7. **Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Cleveland MSA in Period 2 (2008-2011)**



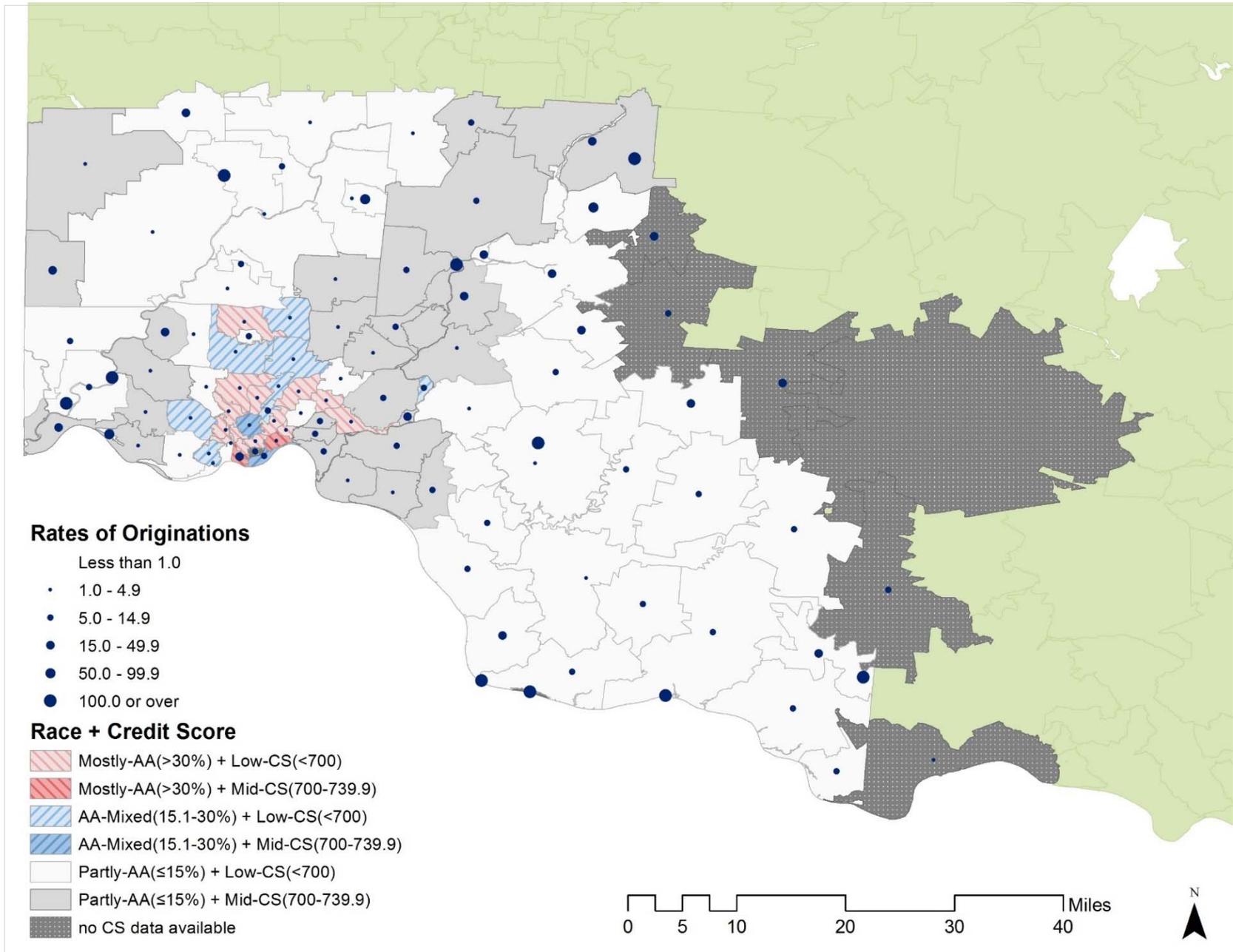
Median APR spread: neighborhood level median APR spread

8. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Cleveland MSA in Period 3 (2012-2015)



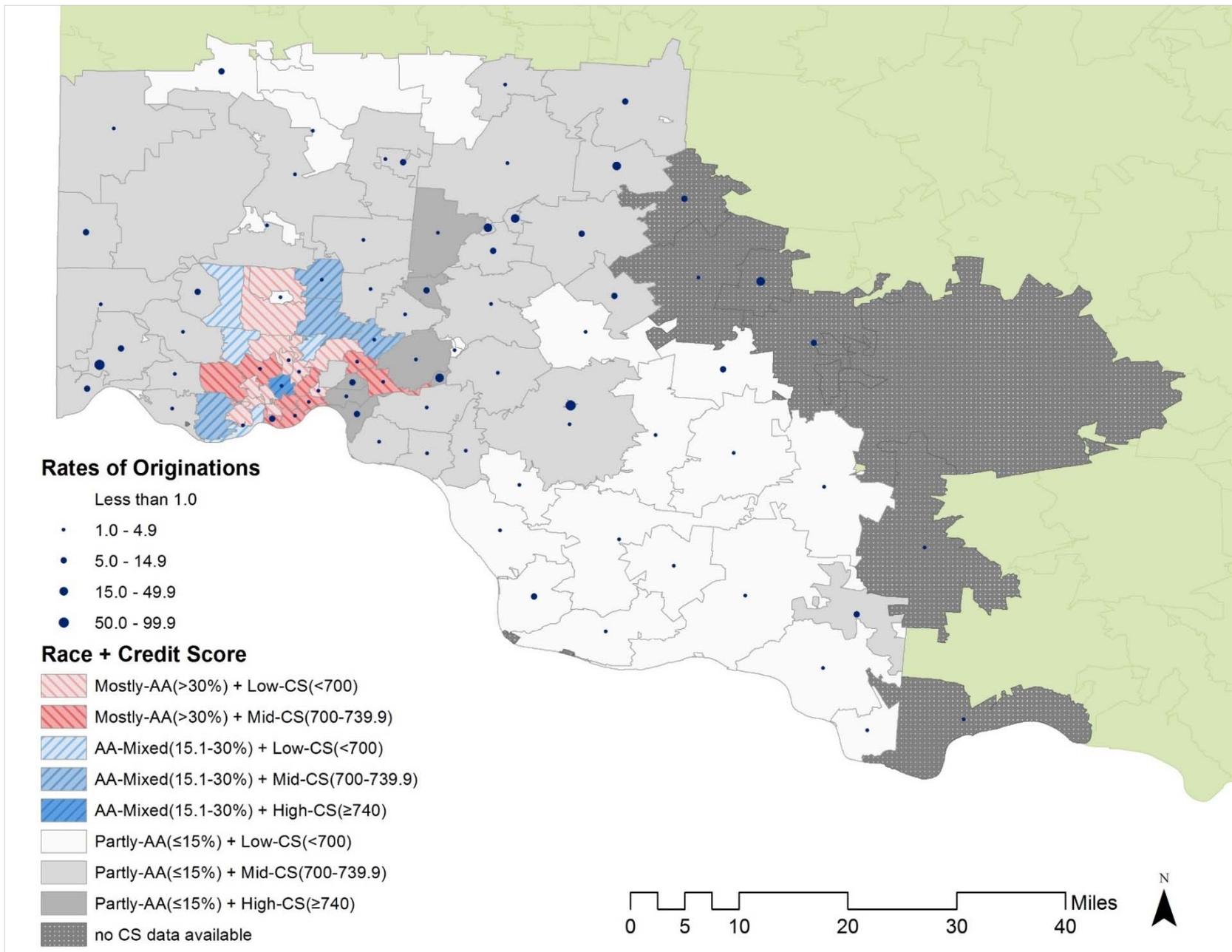
Median APR spread: neighborhood level median APR spread

9. Geography of Rate of Originations in Neighborhoods in the Cincinnati MSA in Period 1 (2004-2007)



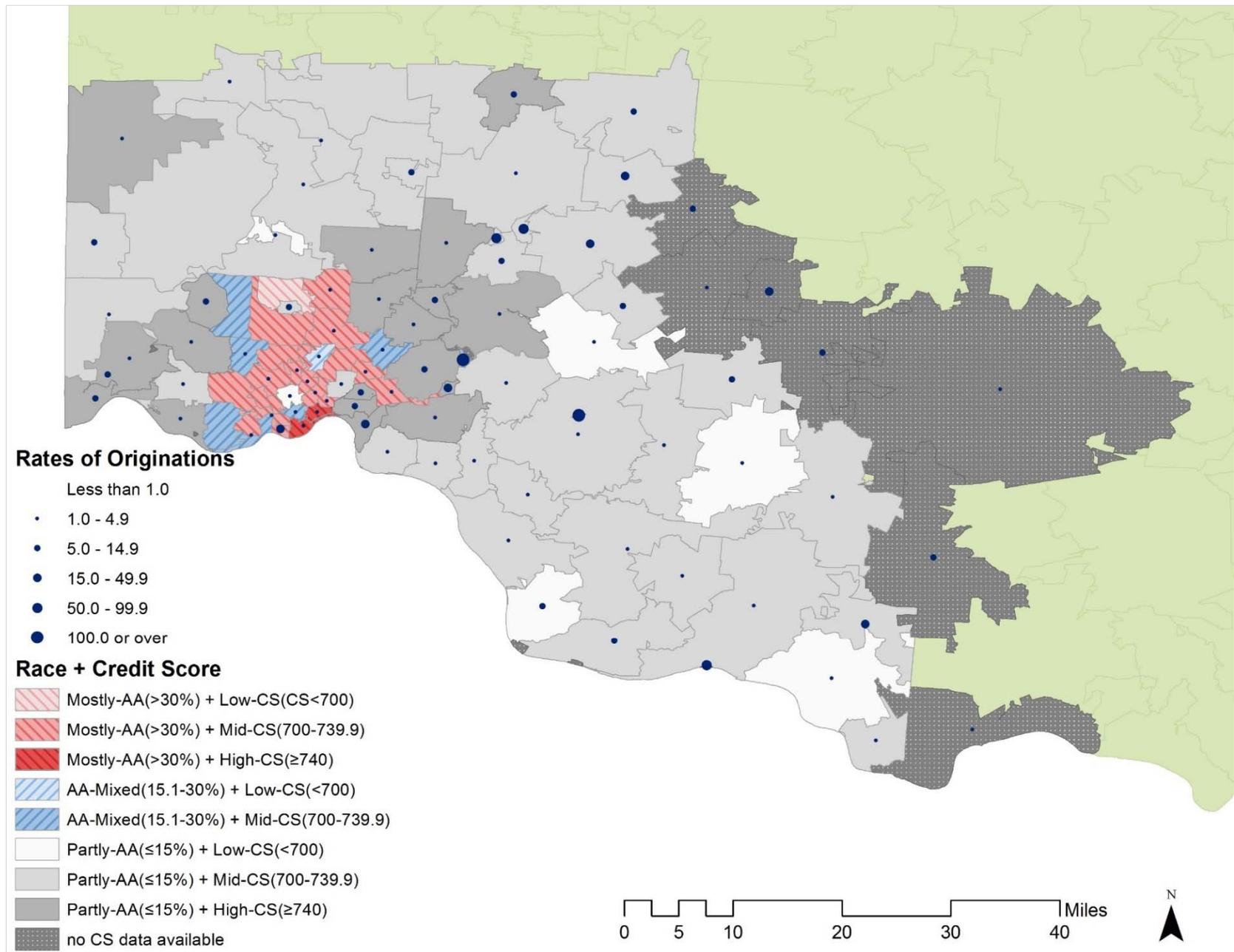
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

10. Geography of Rate of Originations in Neighborhoods in the Cincinnati MSA in Period 2 (2008-2011)



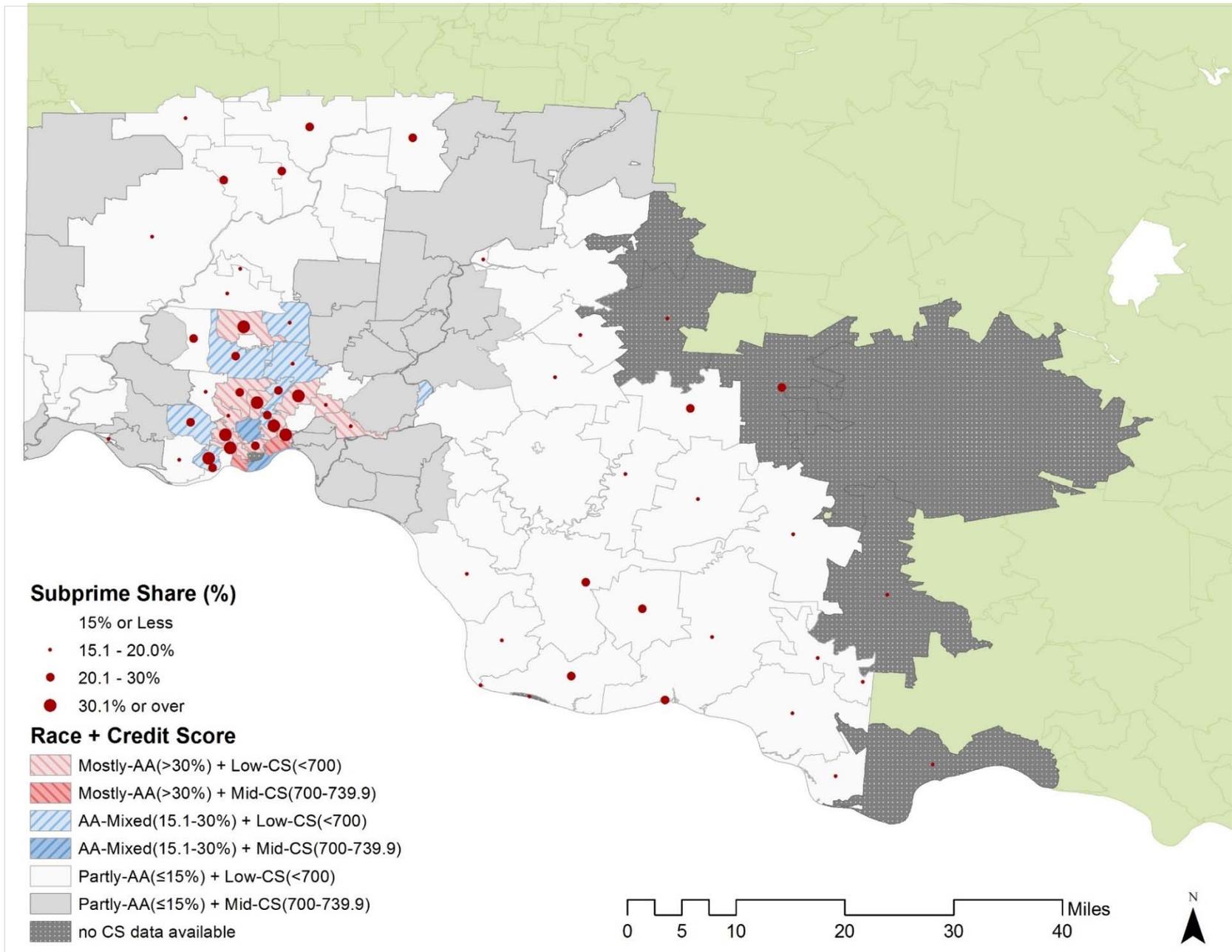
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

11. Geography of Rate of Originations in Neighborhoods in the Cincinnati MSA in Period 3 (2012-2015)



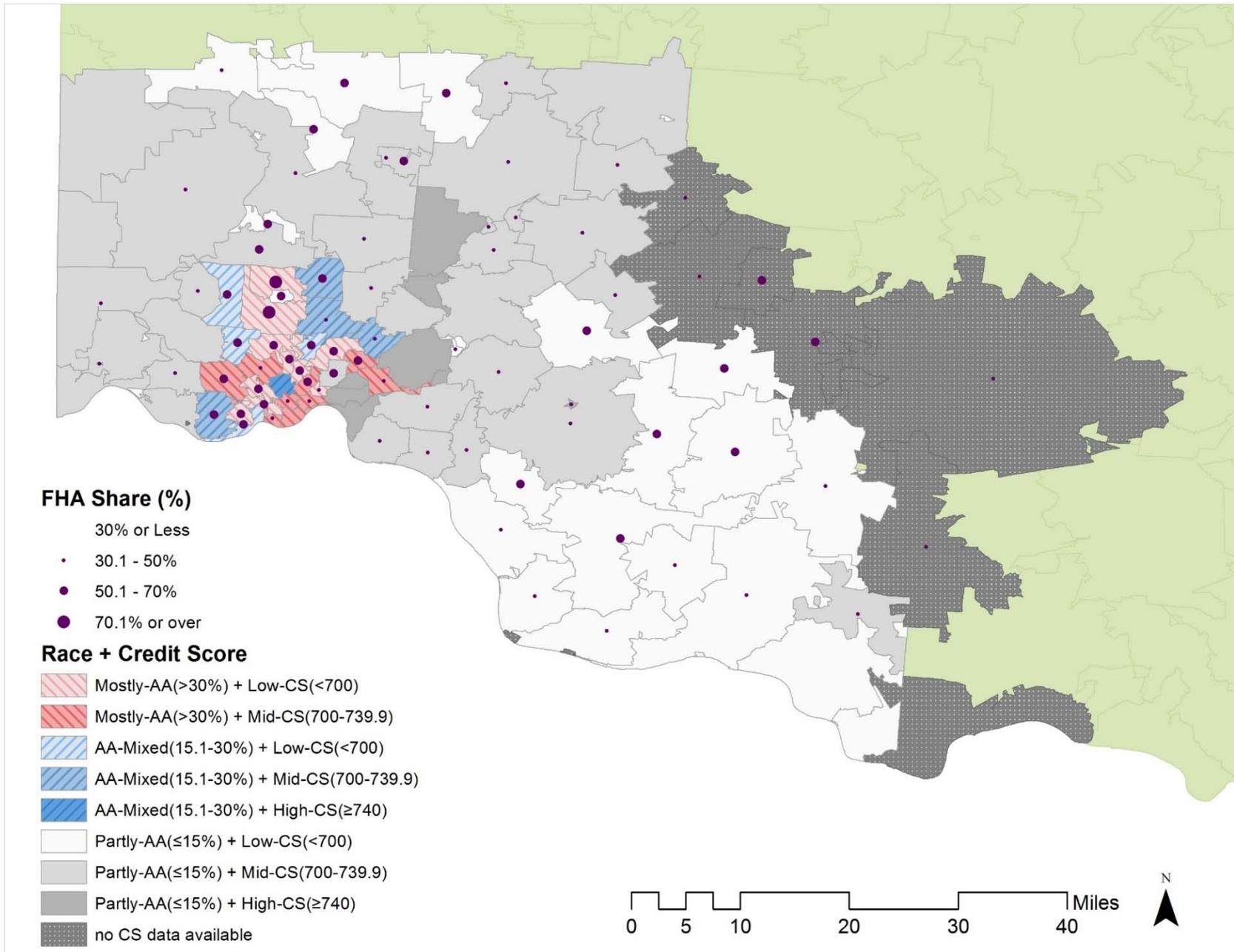
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

12. Geography of the Share of Subprime Loans in Neighborhoods in the Cincinnati MSA in Period 1 (2004-2007)



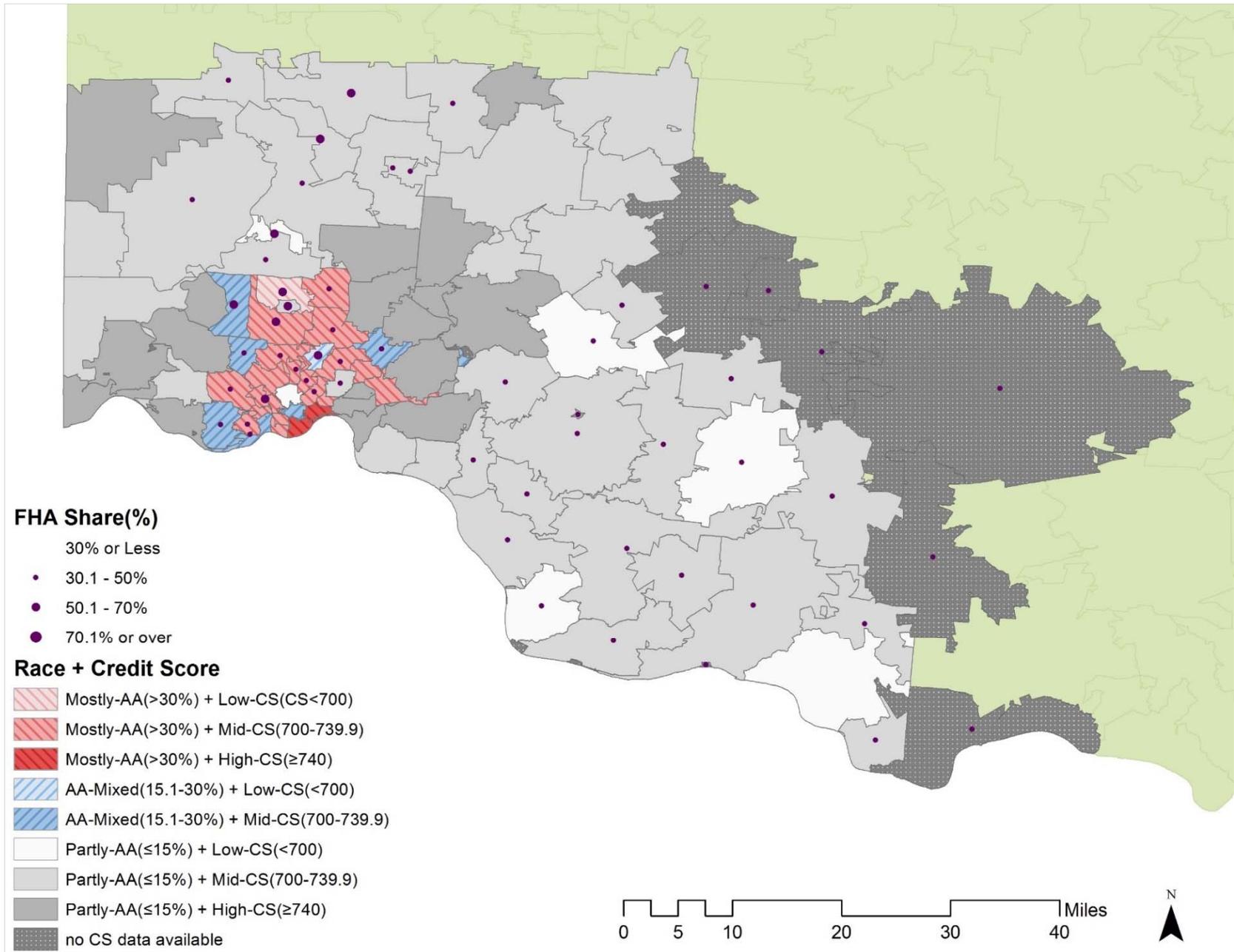
Subprime Share: a proportion of the subprime mortgage origination count of the total mortgage origination count in a neighborhood

13. Geography of the Share of FHA-insured Loans in Neighborhoods in the Cincinnati MSA in Period 2 (2008-2011)



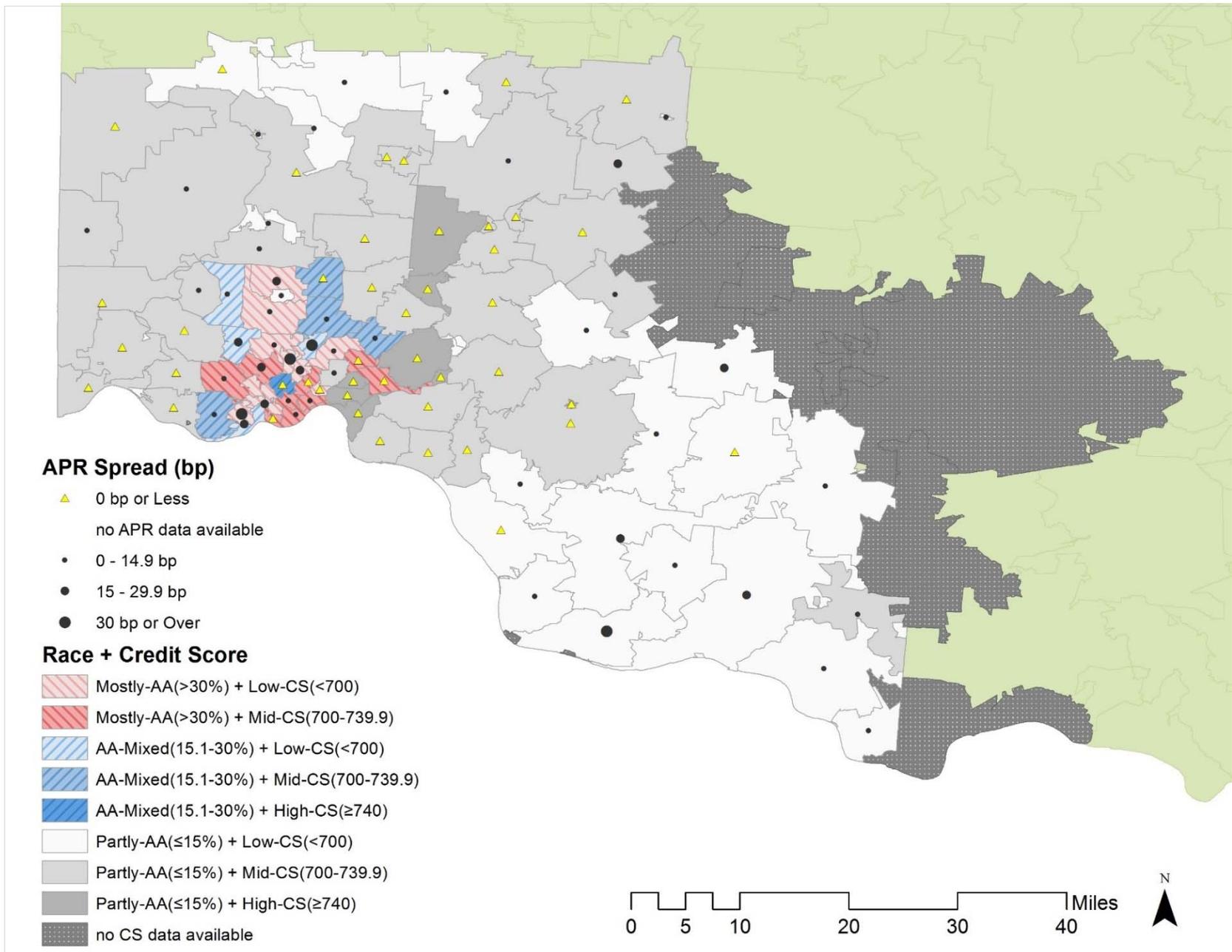
FHA share: a proportion of FHA-insured mortgage origination count of the total mortgage origination count in a neighborhood

14. Geography of the Share of FHA-insured Loans in Neighborhoods in the Cincinnati MSA in Period 3 (2012-2015)



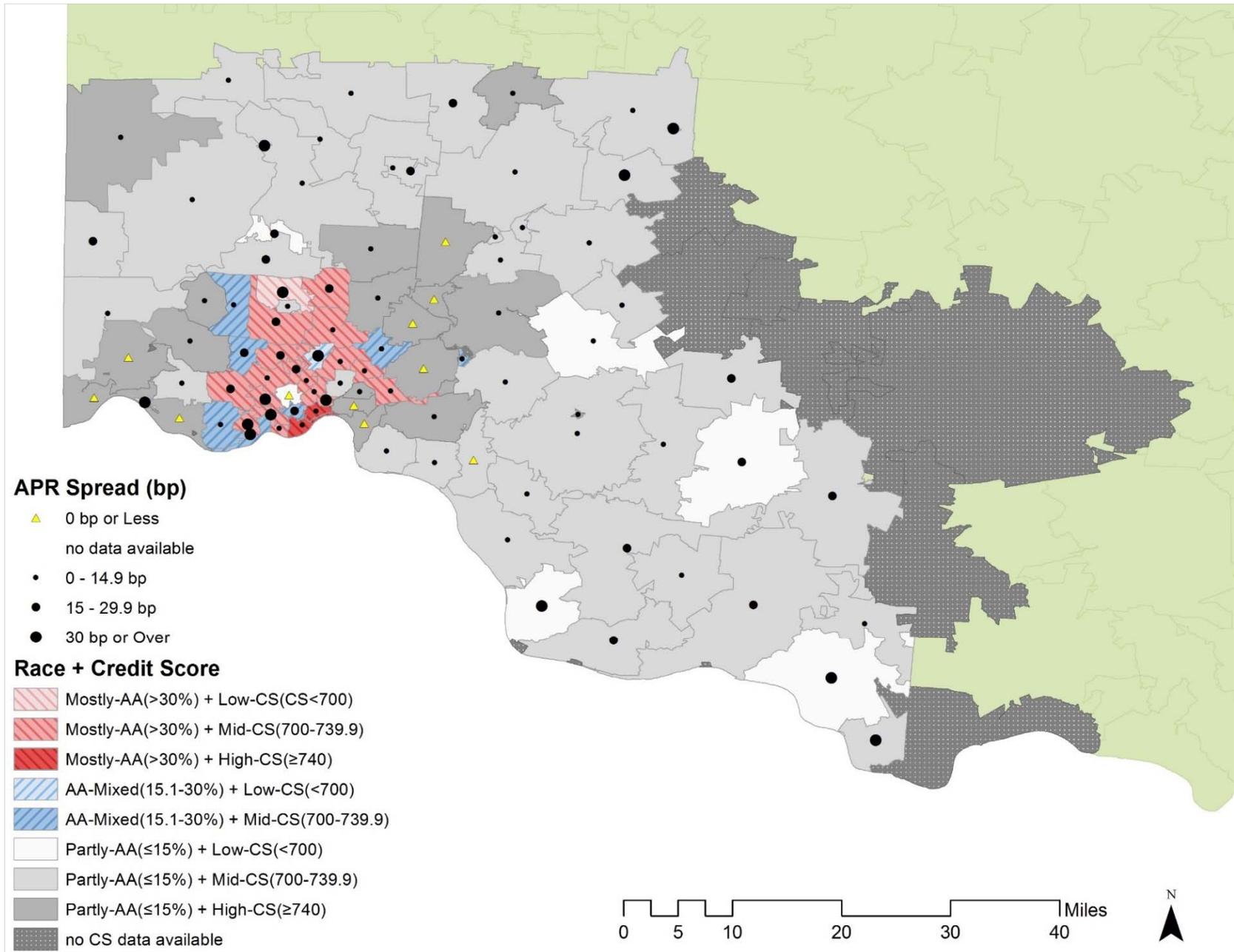
FHA share: a proportion of FHA-insured mortgage origination count of the total mortgage origination count in a neighborhood

15. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Cincinnati MSA in Period 2 (2008-2011)



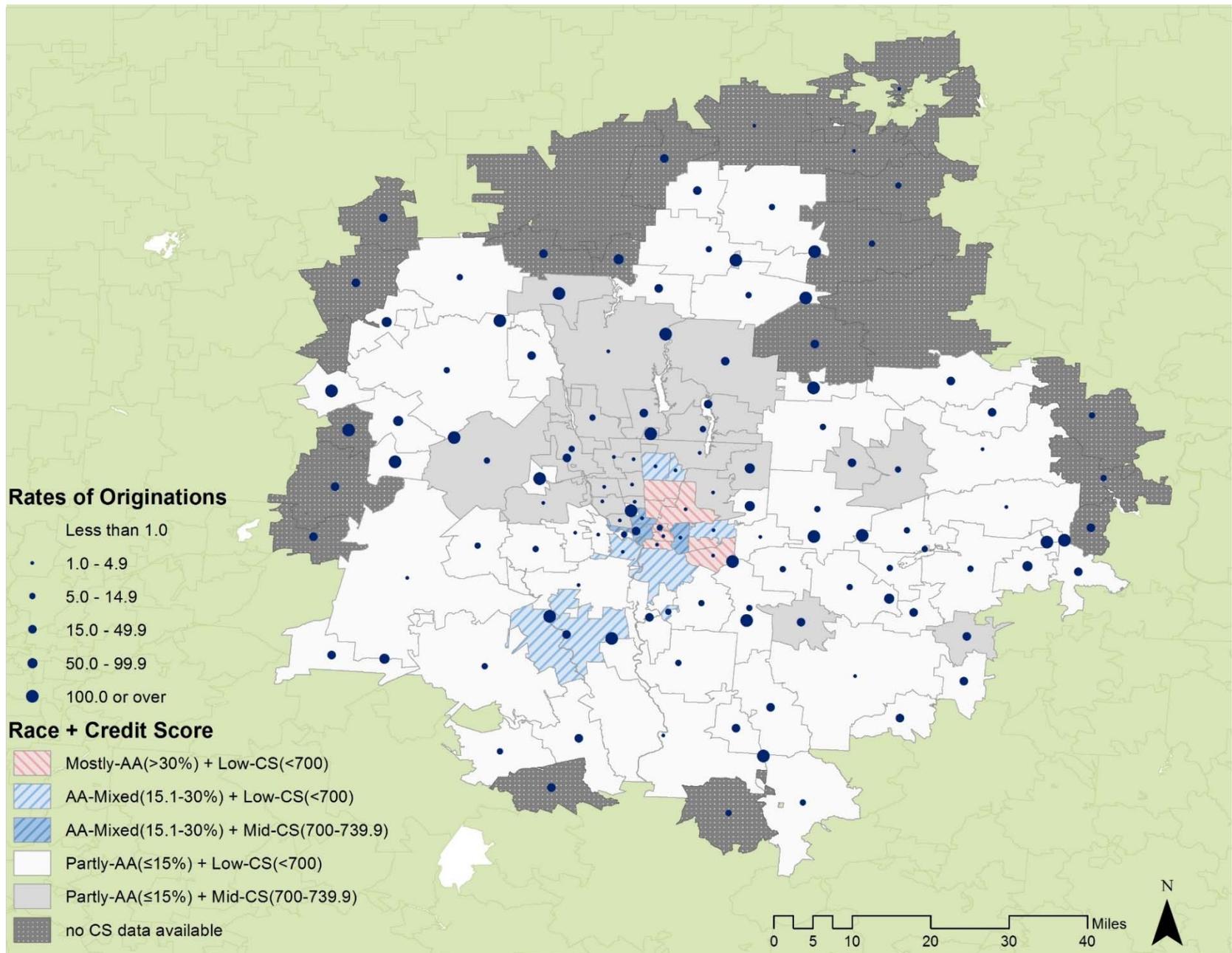
Median APR spread: neighborhood level median APR spread

16. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Cincinnati MSA in Period 3 (2012-2015)



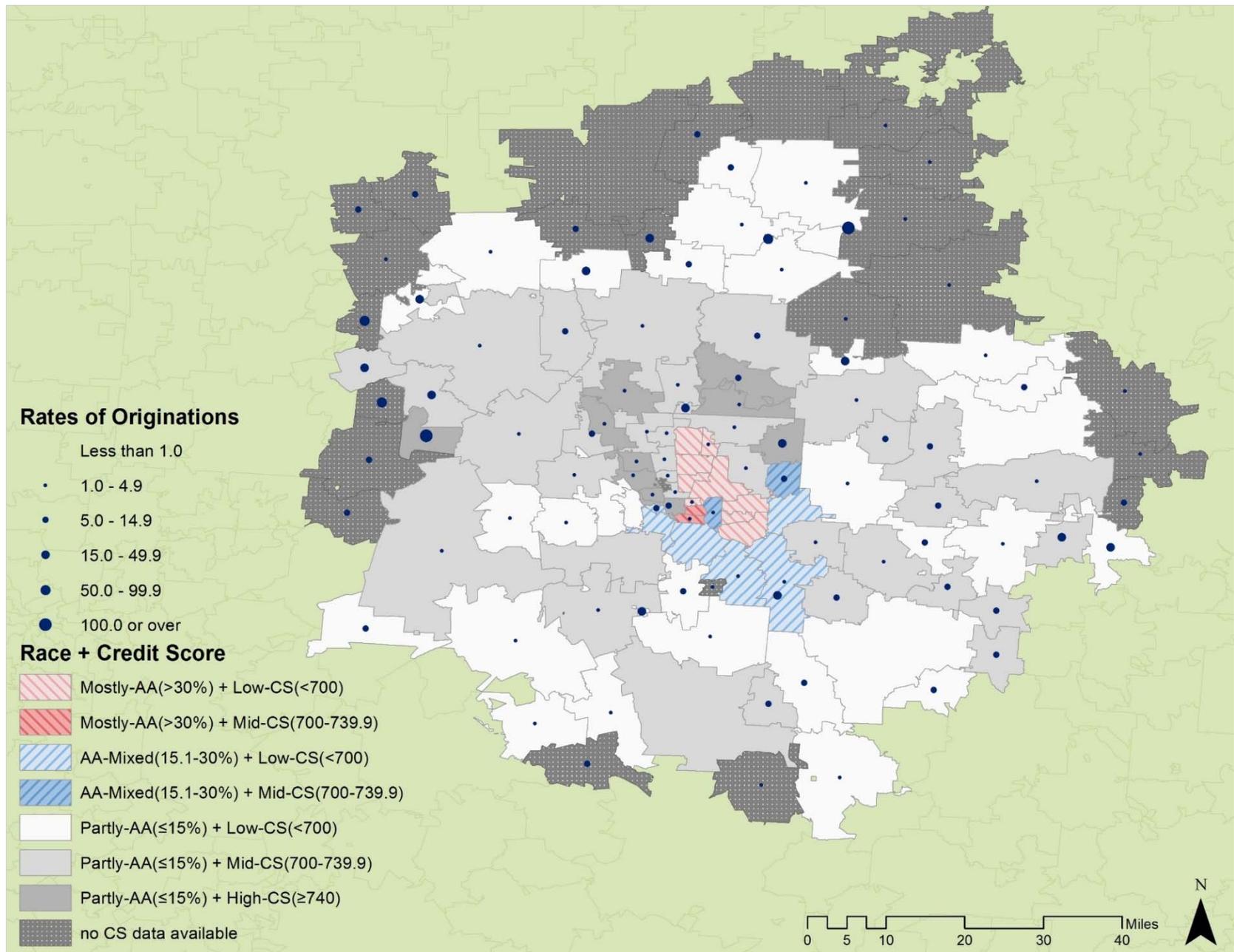
Median APR spread: neighborhood level median APR spread

17. Geography of Rate of Originations in Neighborhoods in the Columbus MSA in Period 1 (2004-2007)



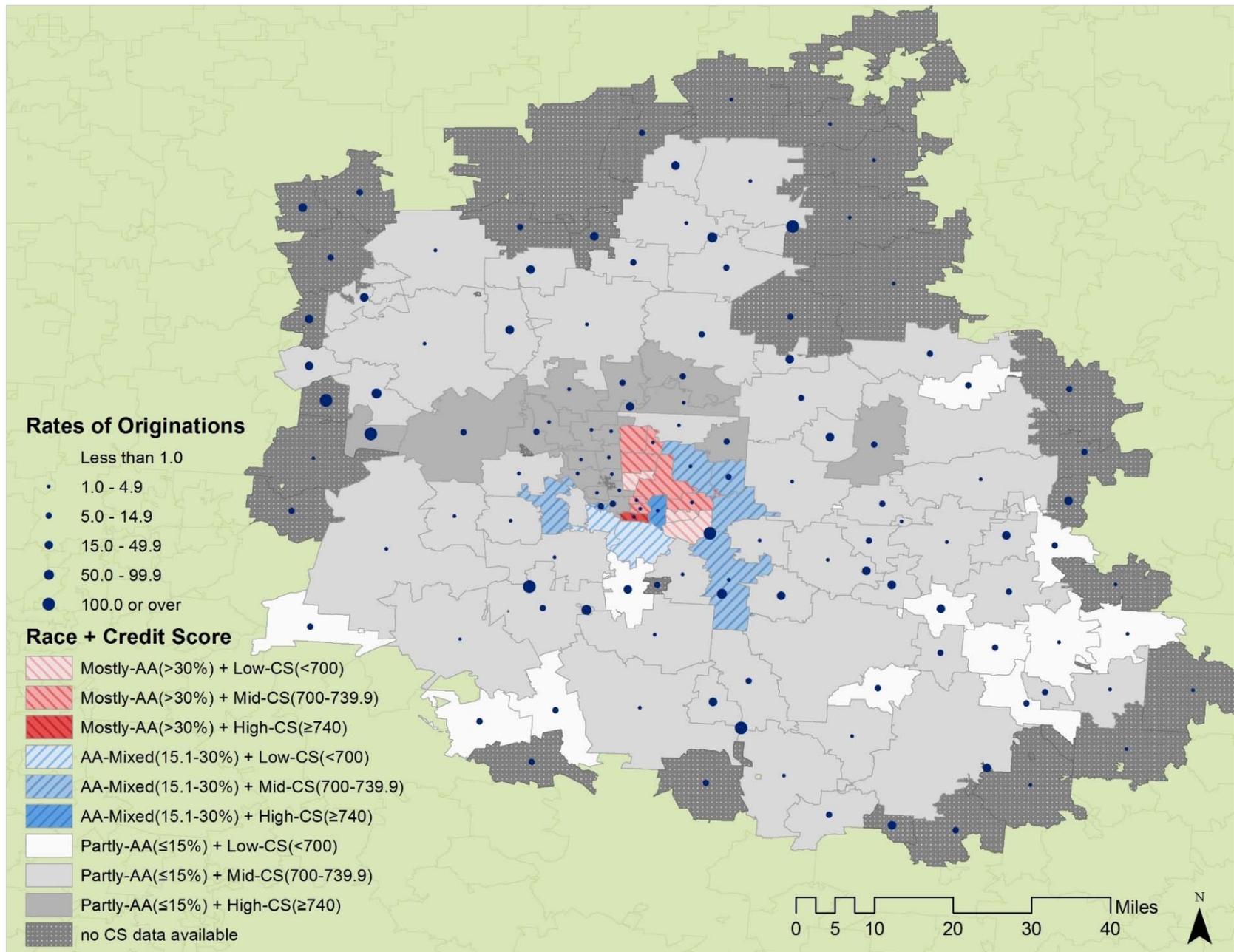
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

18. Geography of Rate of Originations in Neighborhoods in the Columbus MSA in Period 2 (2008-2011)



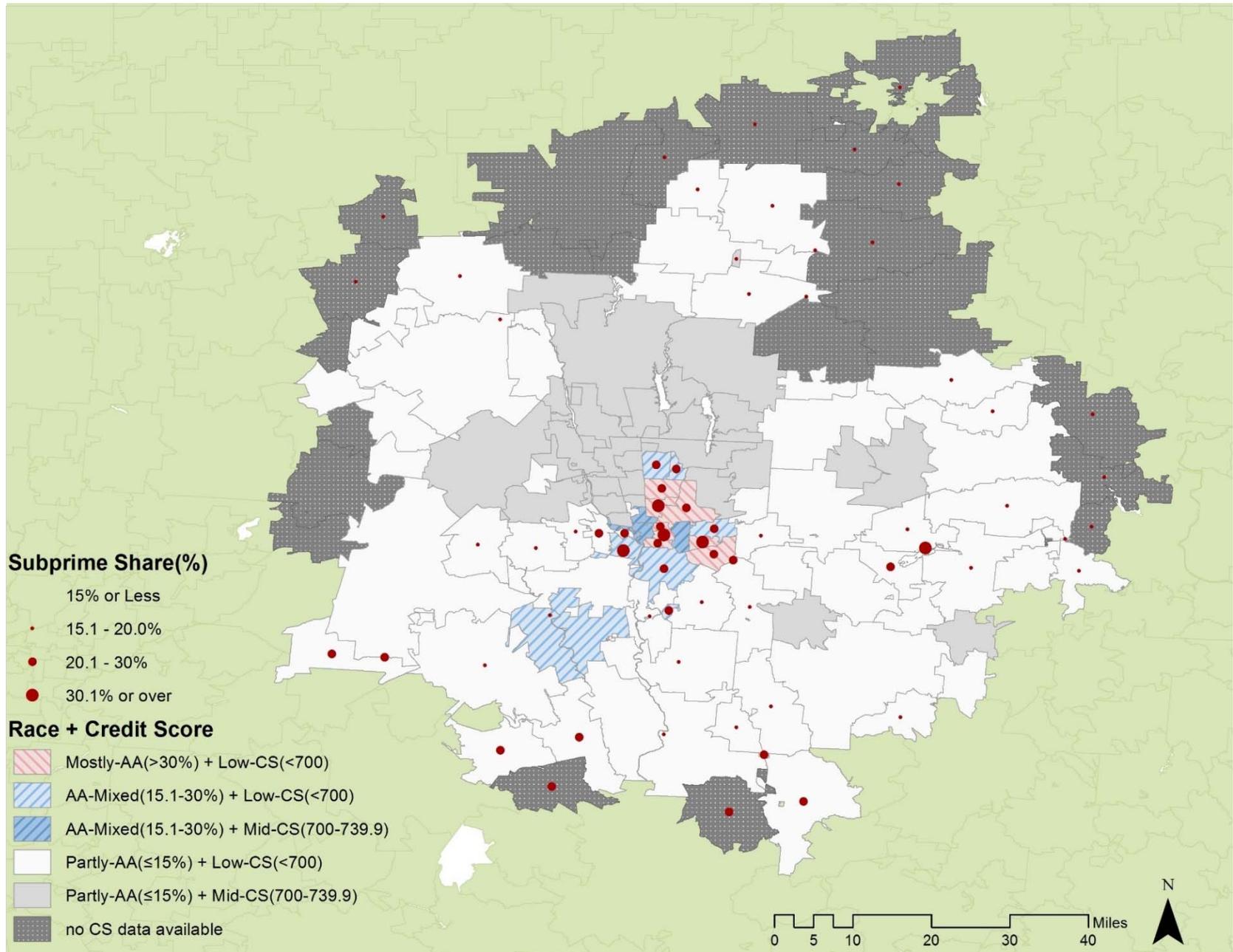
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

19. Geography of Rate of Originations in Neighborhoods in the Columbus MSA in Period 3 (2012-2015)



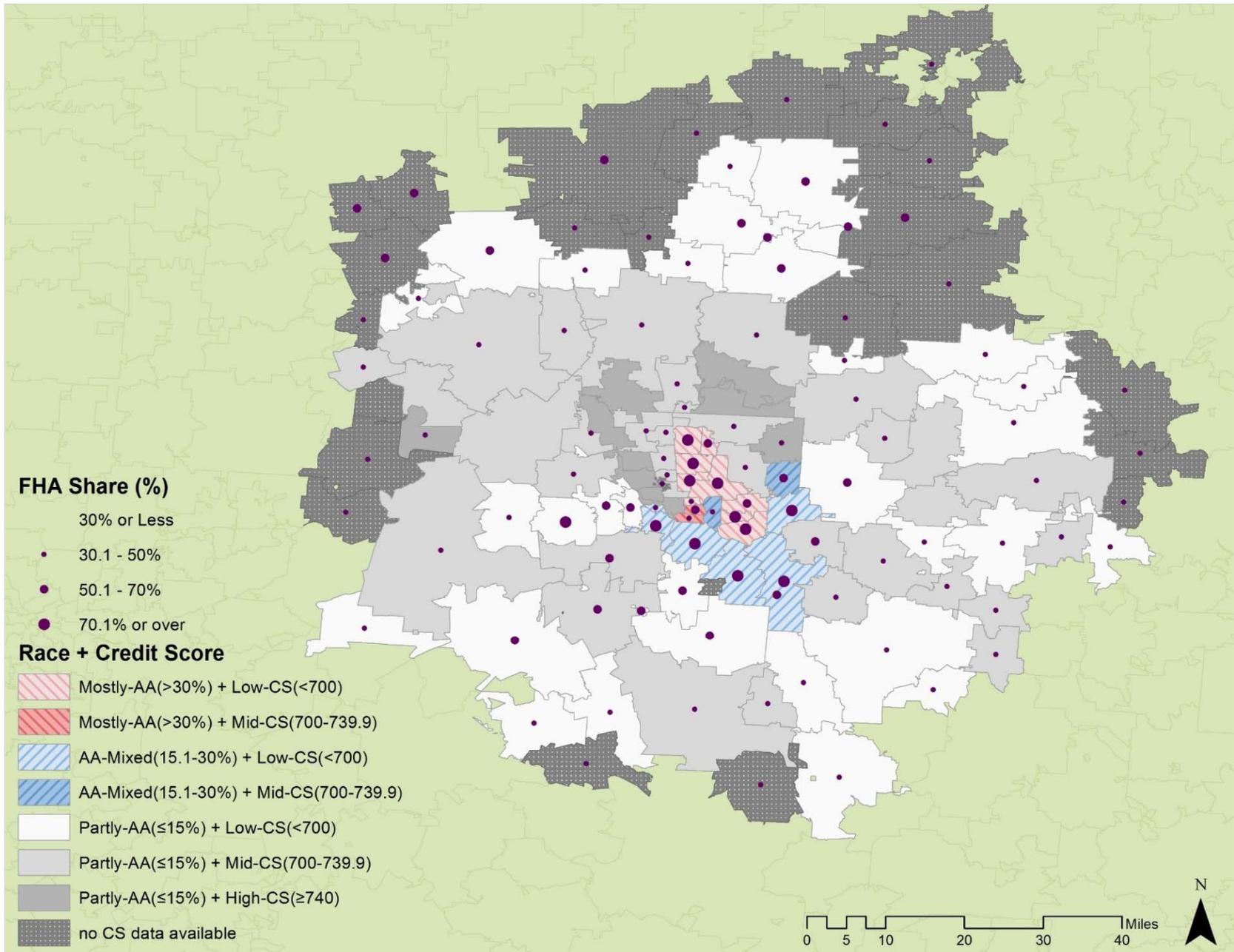
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

20. Geography of the Share of Subprime Loans in Neighborhoods in the Columbus MSA in Period 1 (2004-2007)



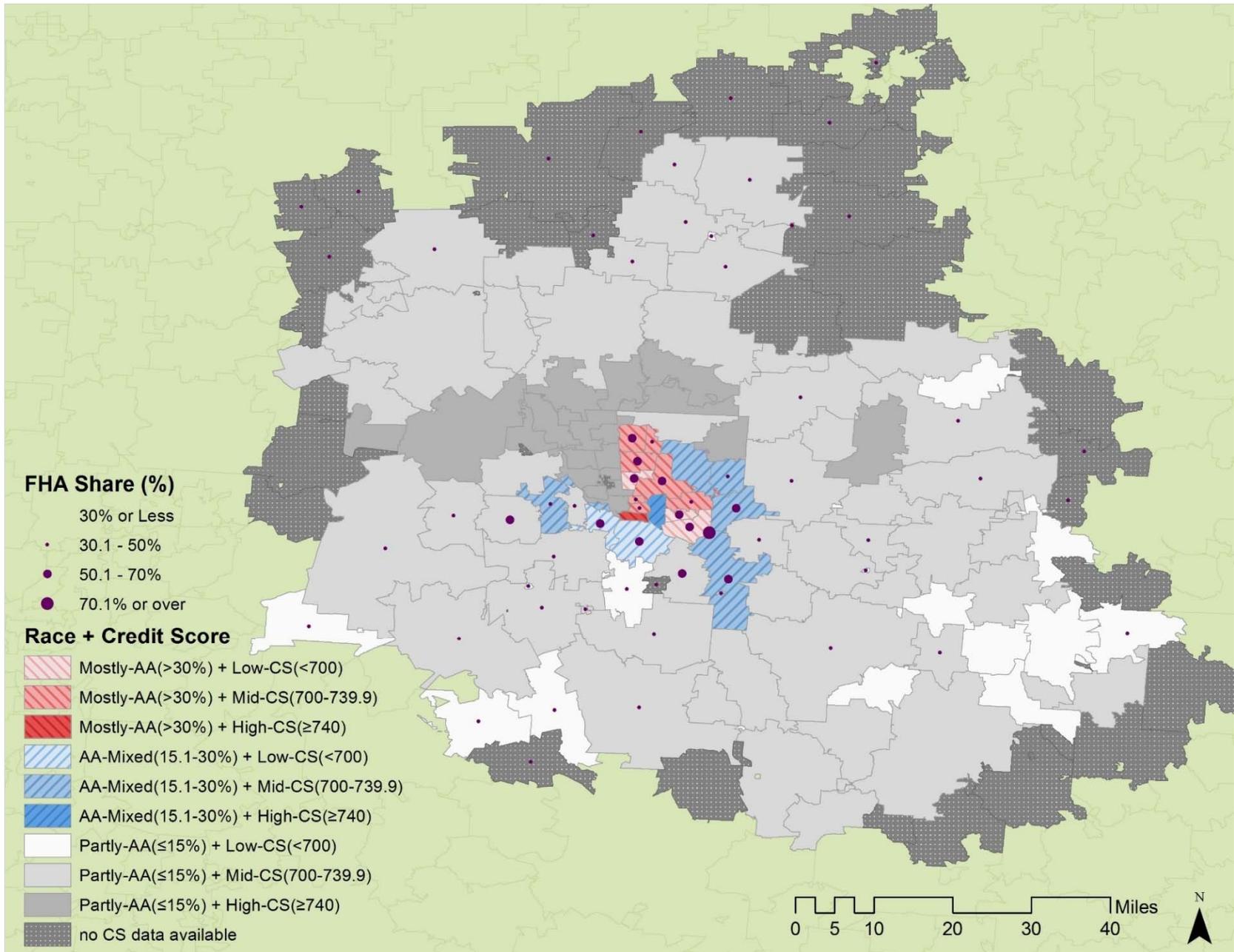
Subprime Share: a proportion of the subprime mortgage origination count of the total mortgage origination count in a neighborhood

21. Geography of the Share of FHA-insured Loans in Neighborhoods in the Columbus MSA in Period 2 (2008-2011)



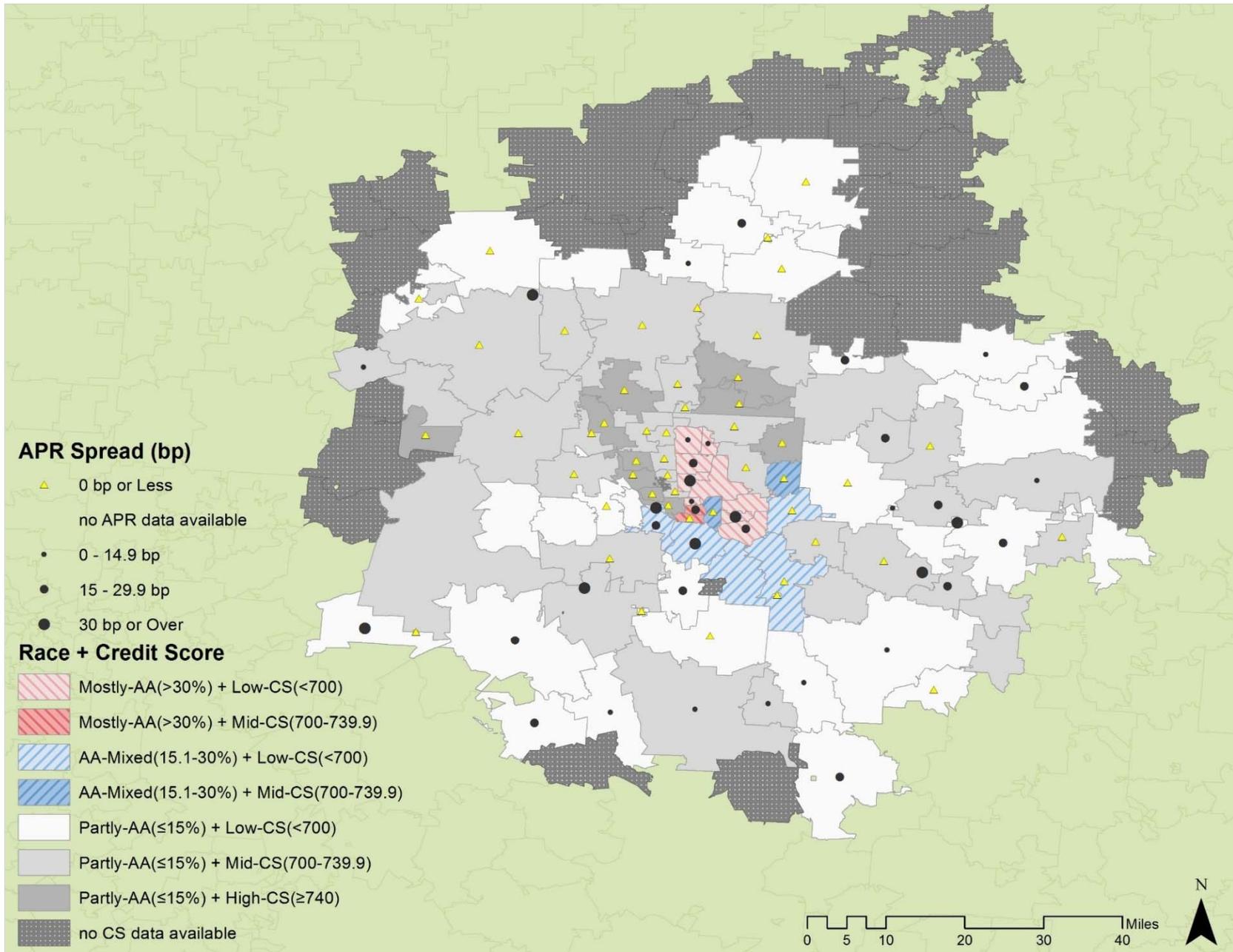
FHA share: a proportion of FHA-insured mortgage origination count of the total mortgage origination count in a neighborhood

22. Geography of the Share of FHA-insured Loans in Neighborhoods in the Columbus MSA in Period 3 (2012-2015)



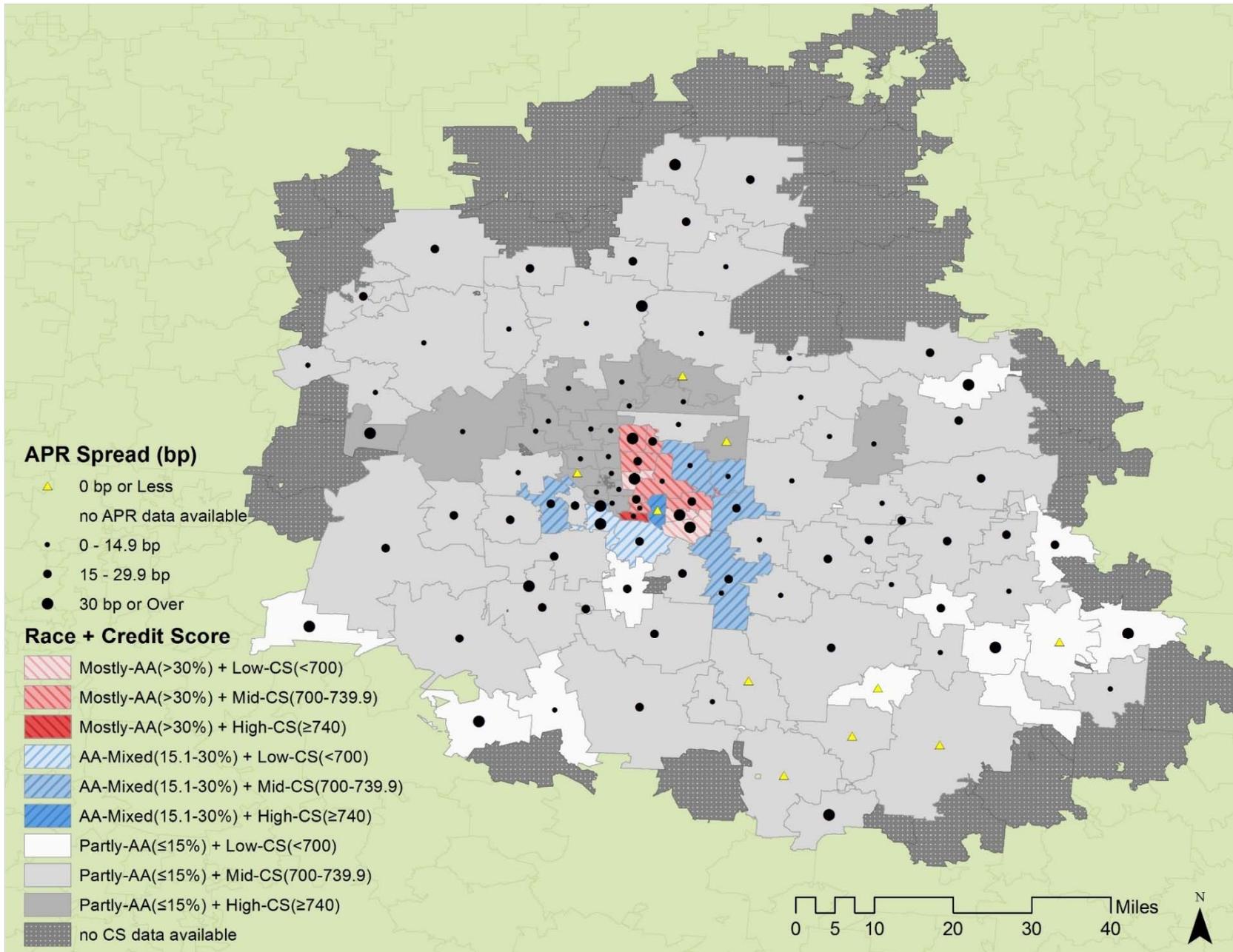
FHA share: a proportion of FHA-insured mortgage origination count of the total mortgage origination count in a neighborhood

23. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Columbus MSA in Period 2 (2008-2011)



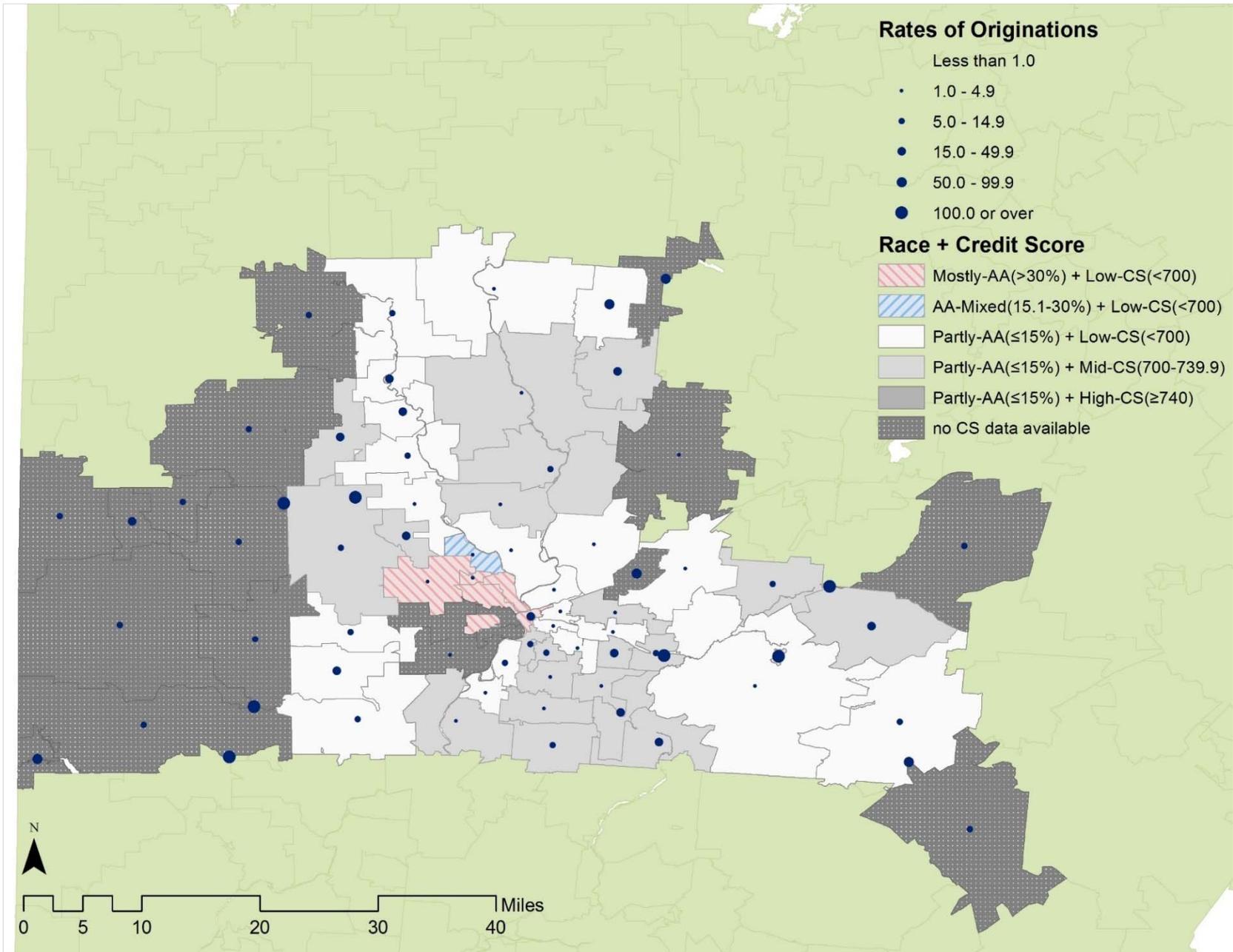
Median APR spread: neighborhood level median APR spread

24. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Columbus MSA in Period 3 (2012-2015)



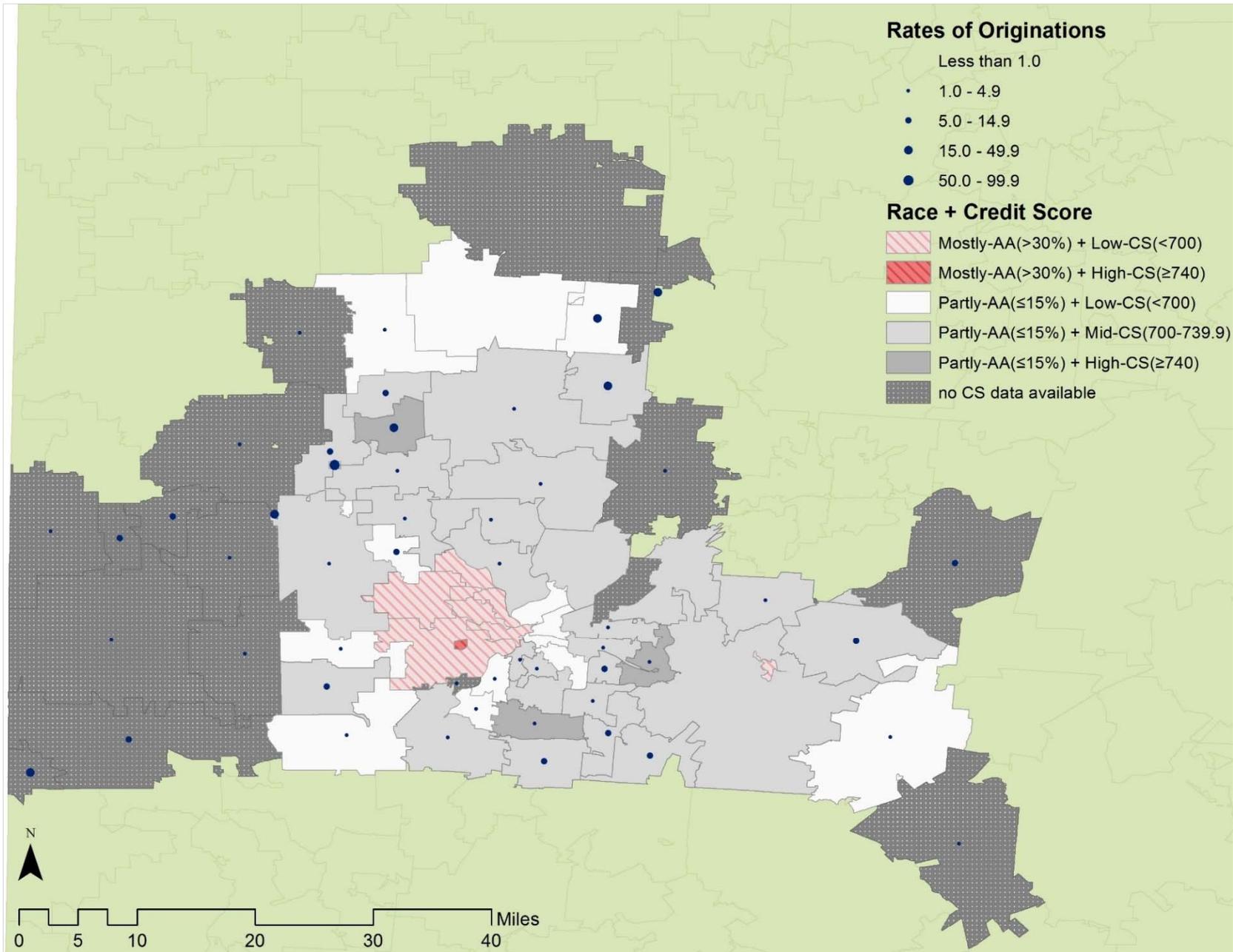
Median APR spread: neighborhood level median APR spread

25. Geography of Rate of Originations in Neighborhoods in the Dayton MSA in Period 1 (2004-2007)



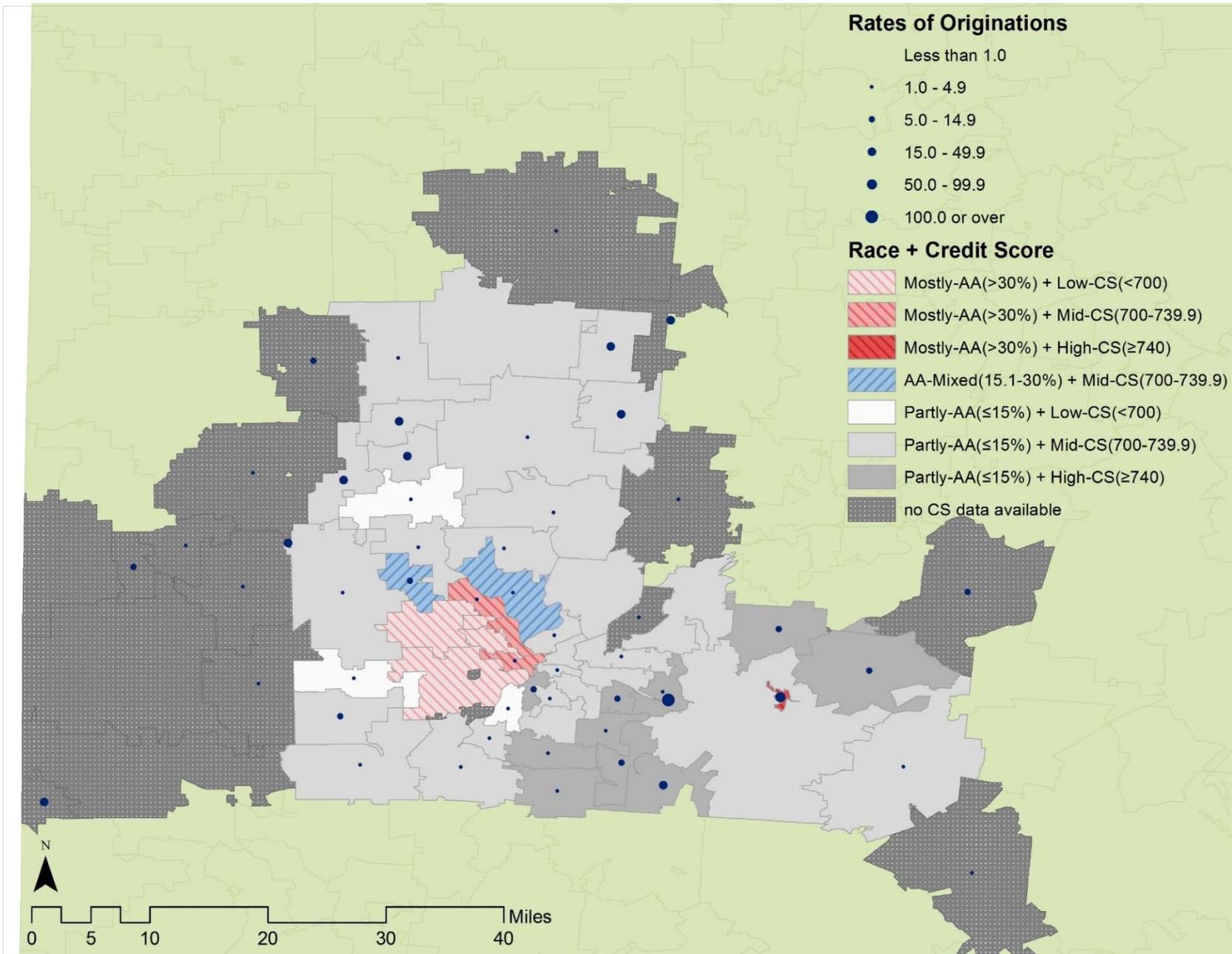
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

26. Geography of Rate of Originations in Neighborhoods in the Dayton MSA in Period 2 (2008-2011)



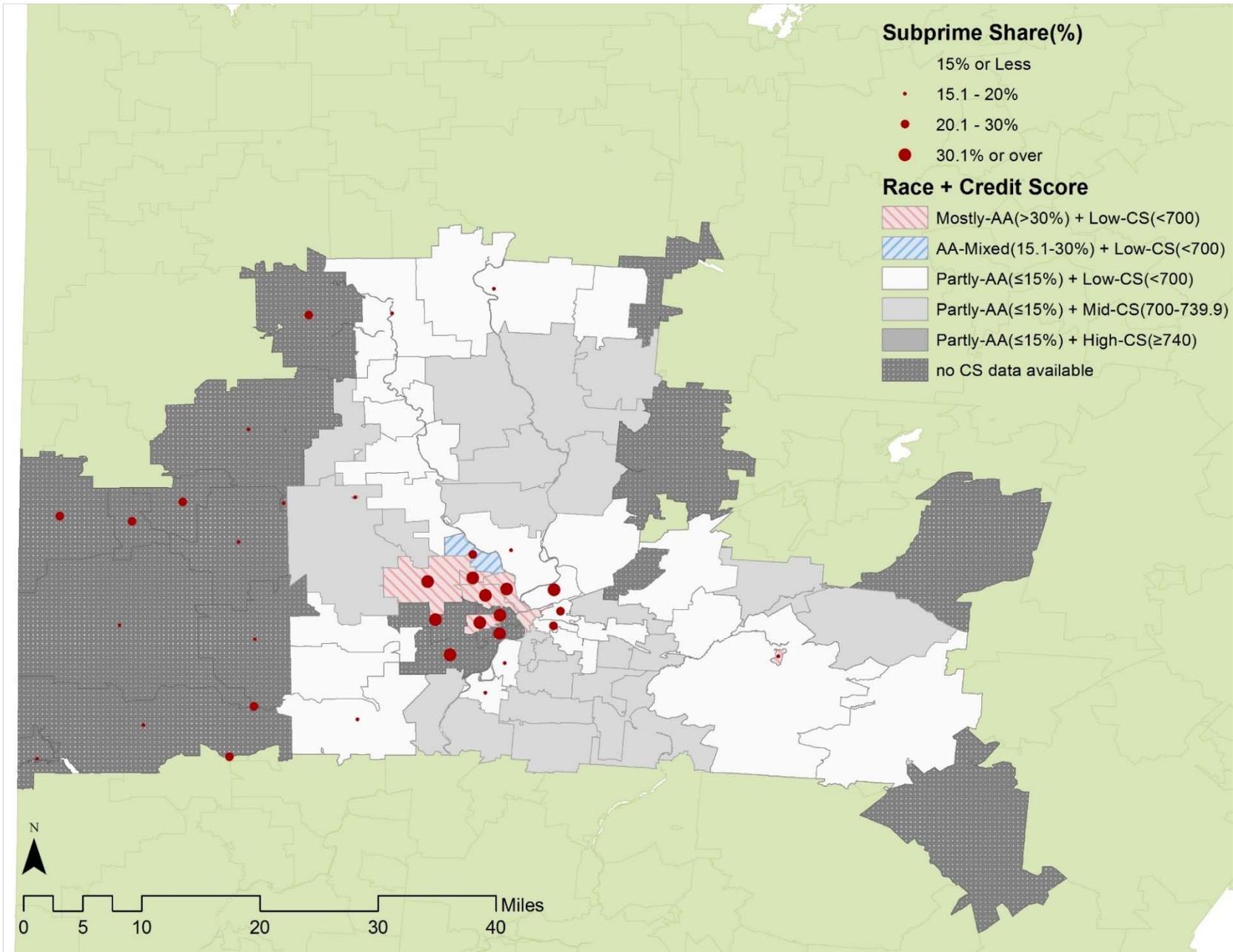
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

27. Geography of Rate of Originations in Neighborhoods in the Dayton MSA in Period 3 (2012-2015)



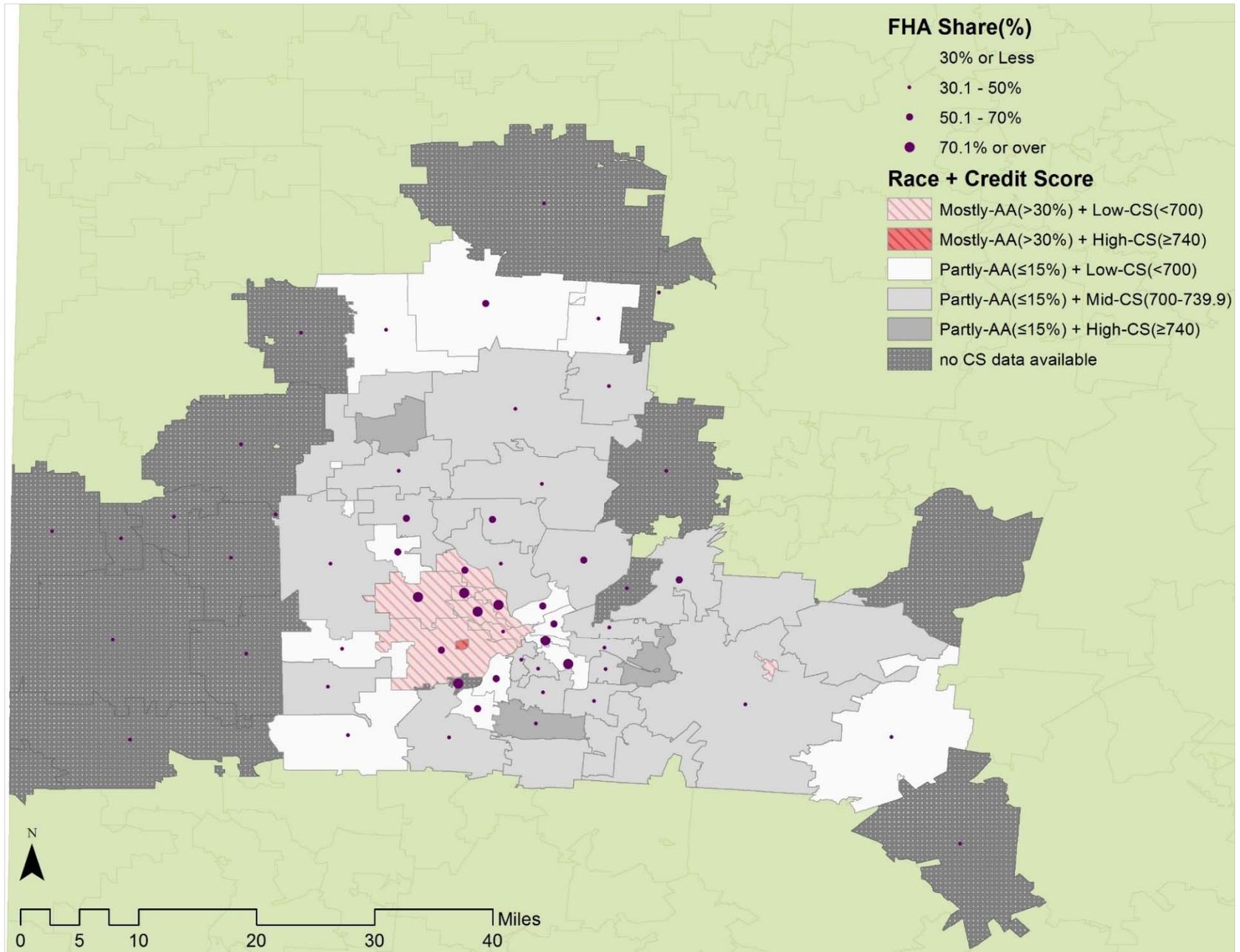
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

28. Geography of the Share of Subprime Loans in Neighborhoods in the Dayton MSA in Period 1 (2004-2007)



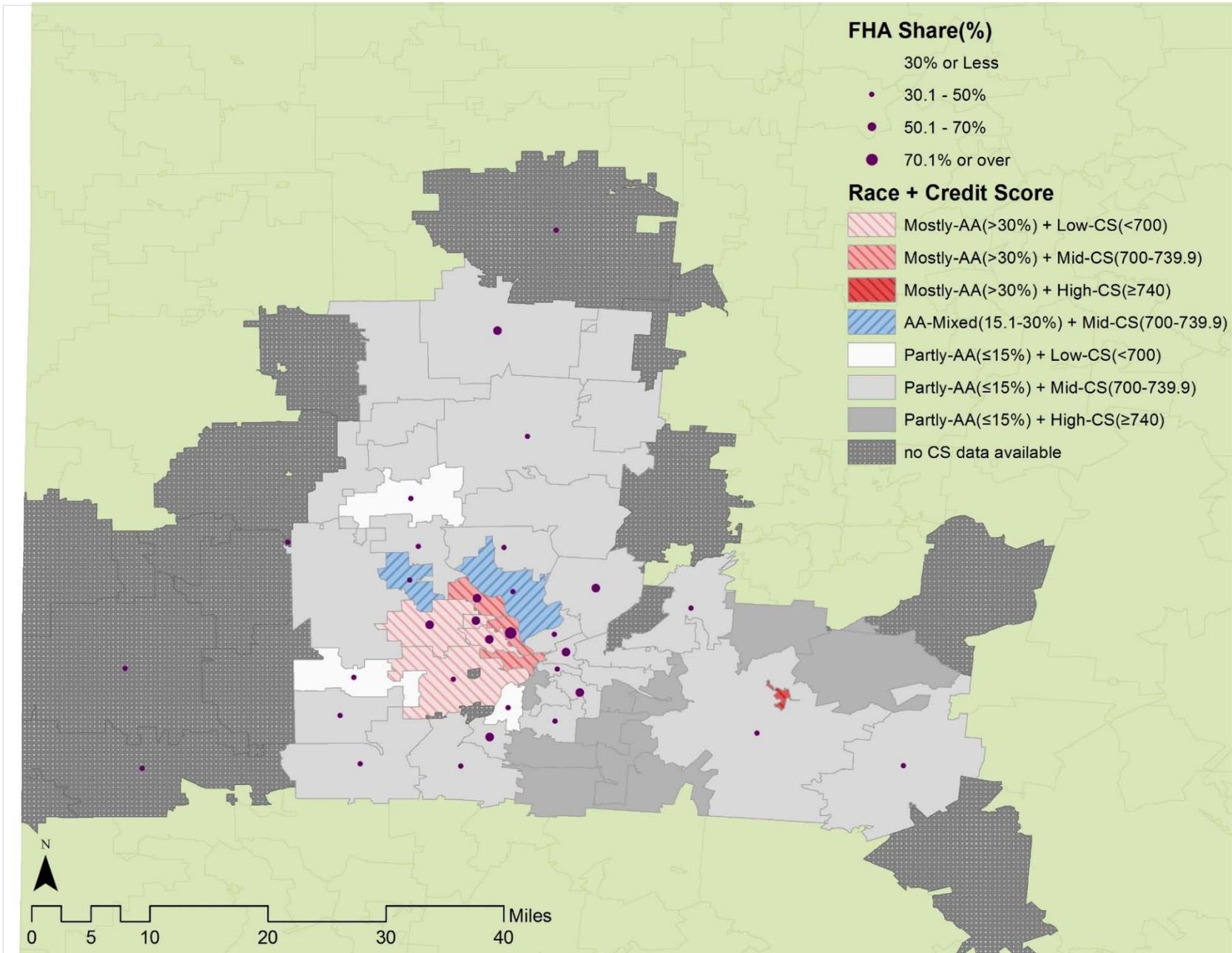
Subprime Share: a proportion of the subprime mortgage origination count of the total mortgage origination count in a neighborhood

29. Geography of the Share of FHA-insured Loans in Neighborhoods in the Dayton MSA in Period 2 (2008-2011)



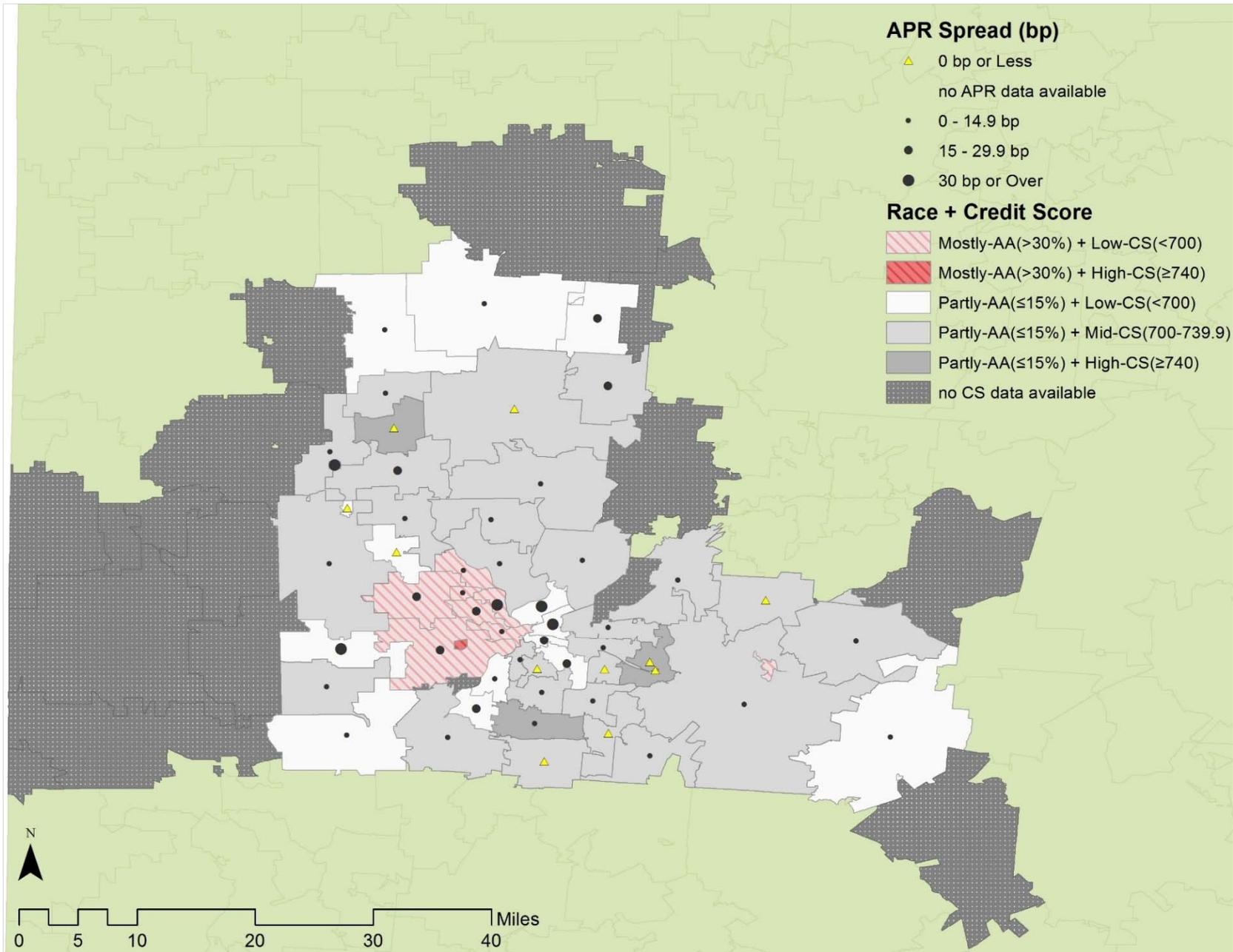
FHA share: a proportion of FHA-insured mortgage origination count of the total mortgage origination count in a neighborhood

30. Geography of the Share of FHA-insured Loans in Neighborhoods in the Dayton MSA in Period 3 (2012-2015)



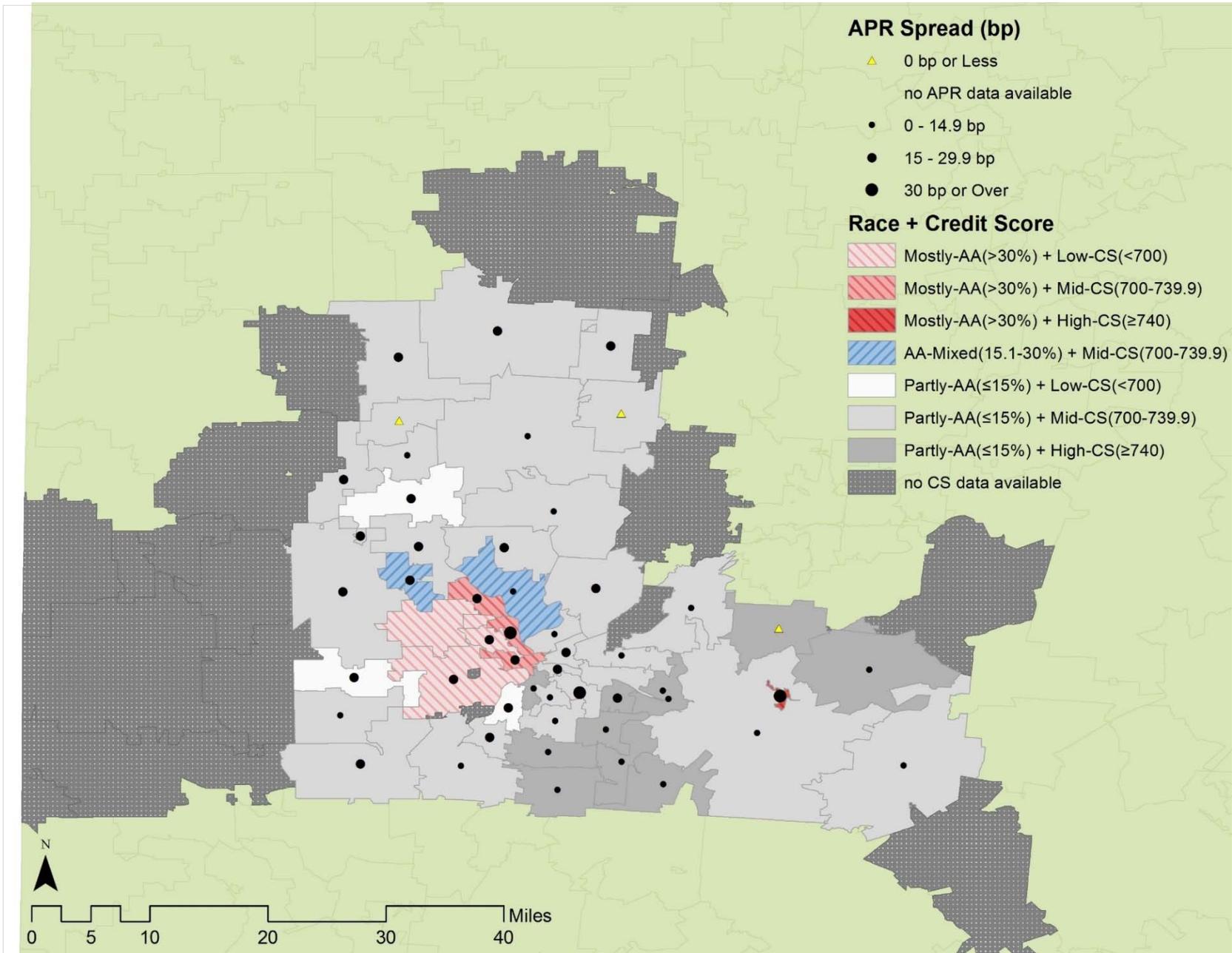
FHA share: a proportion of FHA-insured mortgage origination count of the total mortgage origination count in a neighborhood

31. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Dayton MSA in Period 2 (2008-2011)



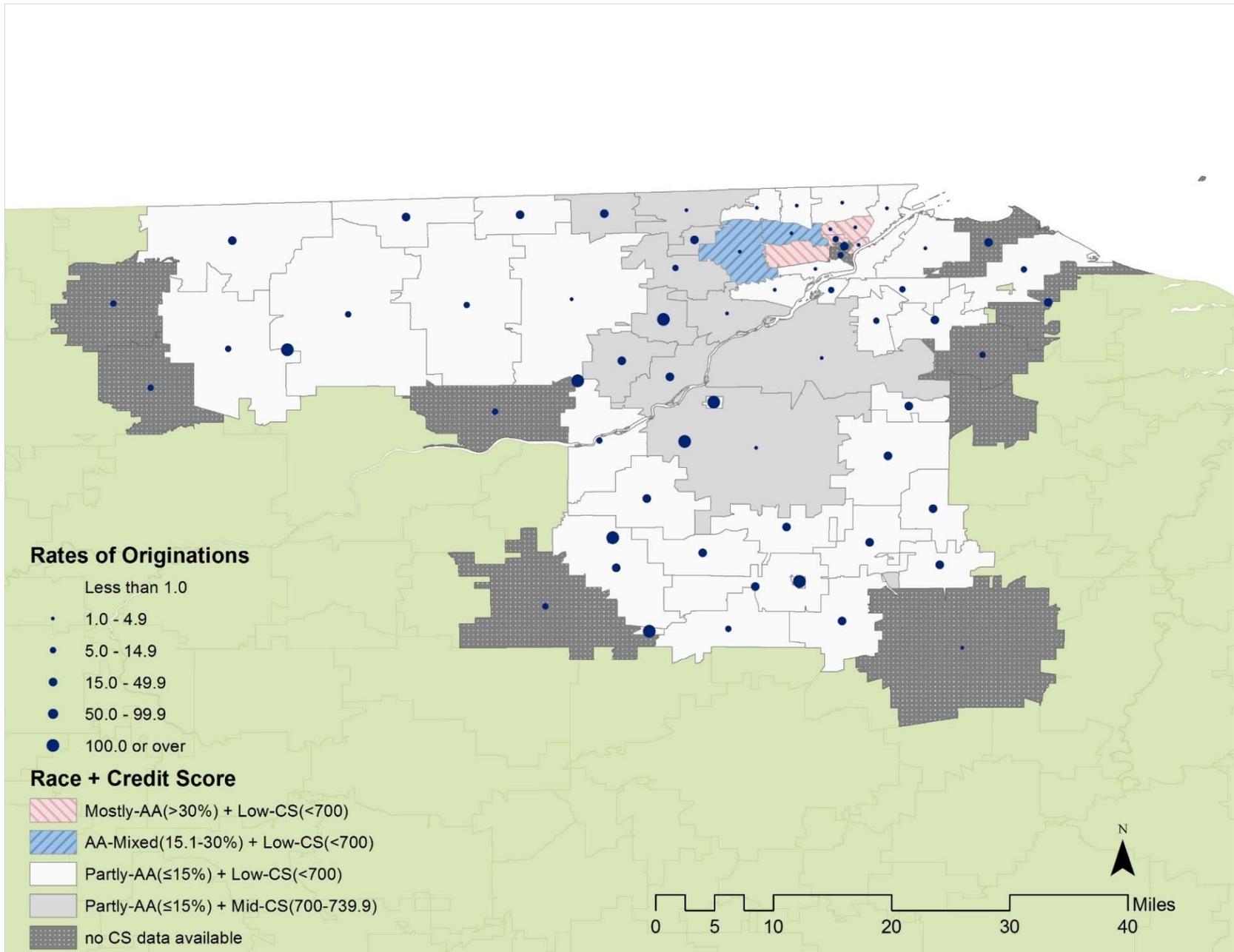
Median APR spread: neighborhood level median APR spread

32. Geography of Costlier Mortgages (Median APR Spread) in Neighborhoods in the Dayton MSA in Period 3 (2012-2015)



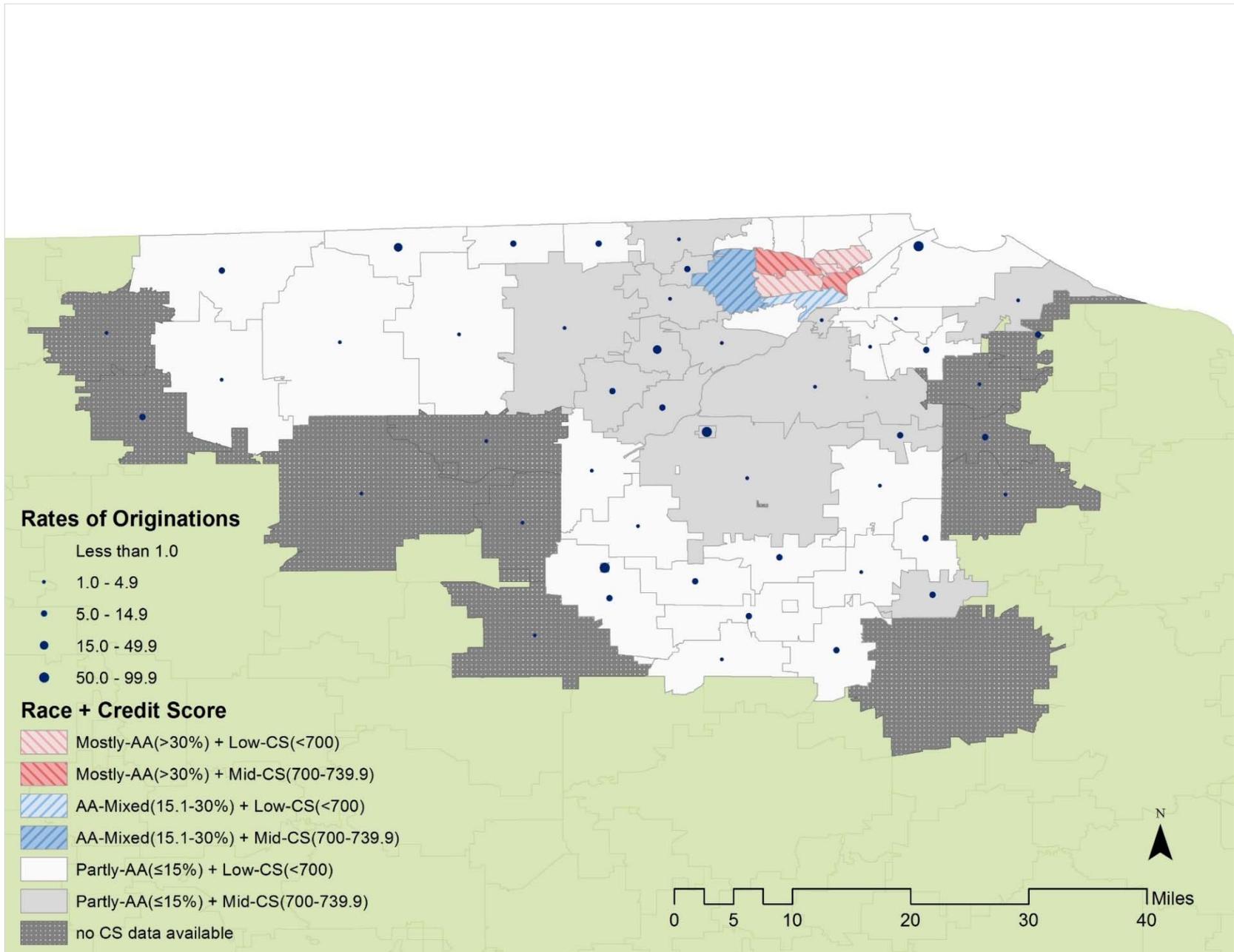
Median APR spread: neighborhood level median APR spread

33. Geography of Rate of Originations in Neighborhoods in the Toledo MSA in Period 1 (2004-2007)



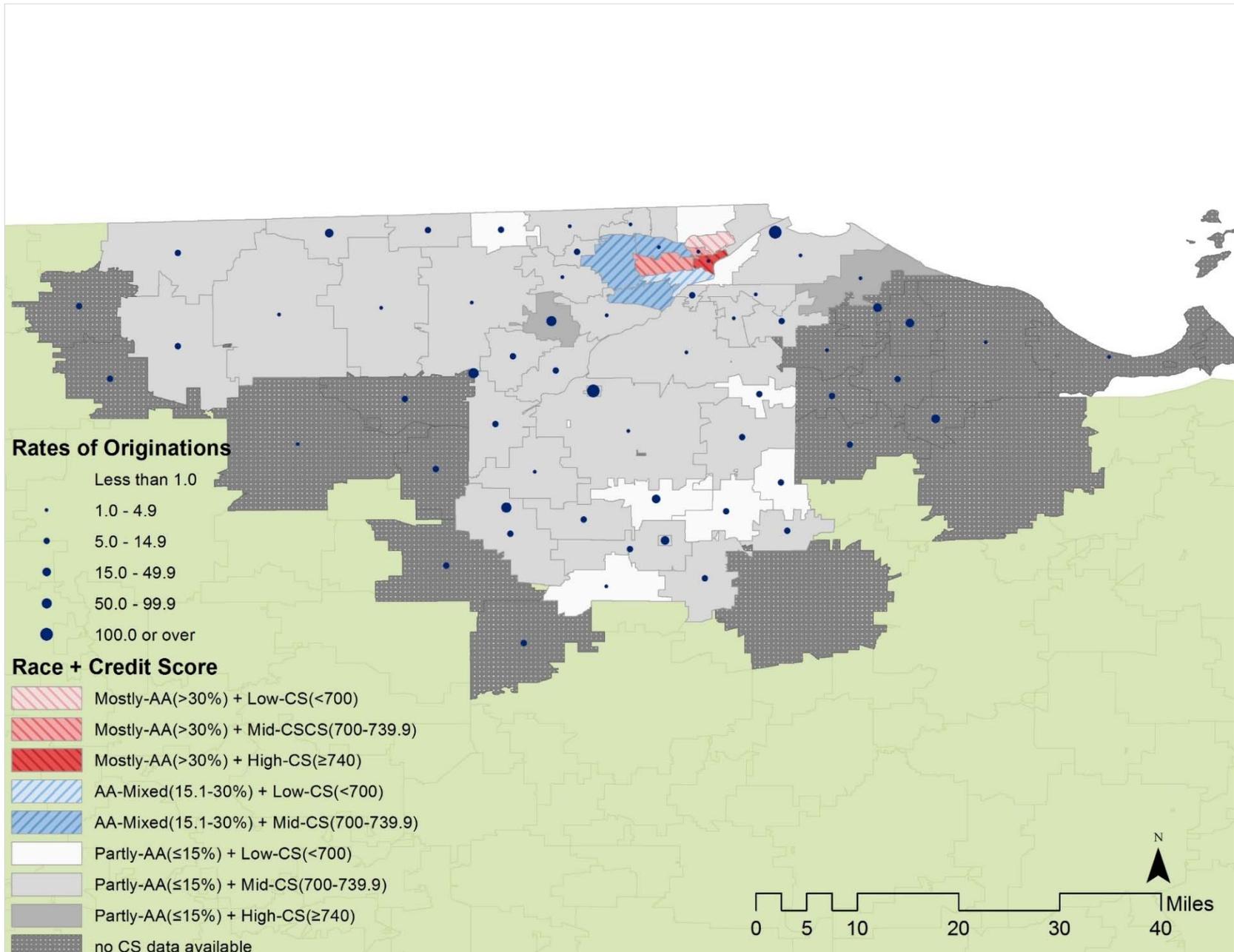
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

34. Geography of Rate of Originations in Neighborhoods in the Toledo MSA in Period 2 (2008-2011)



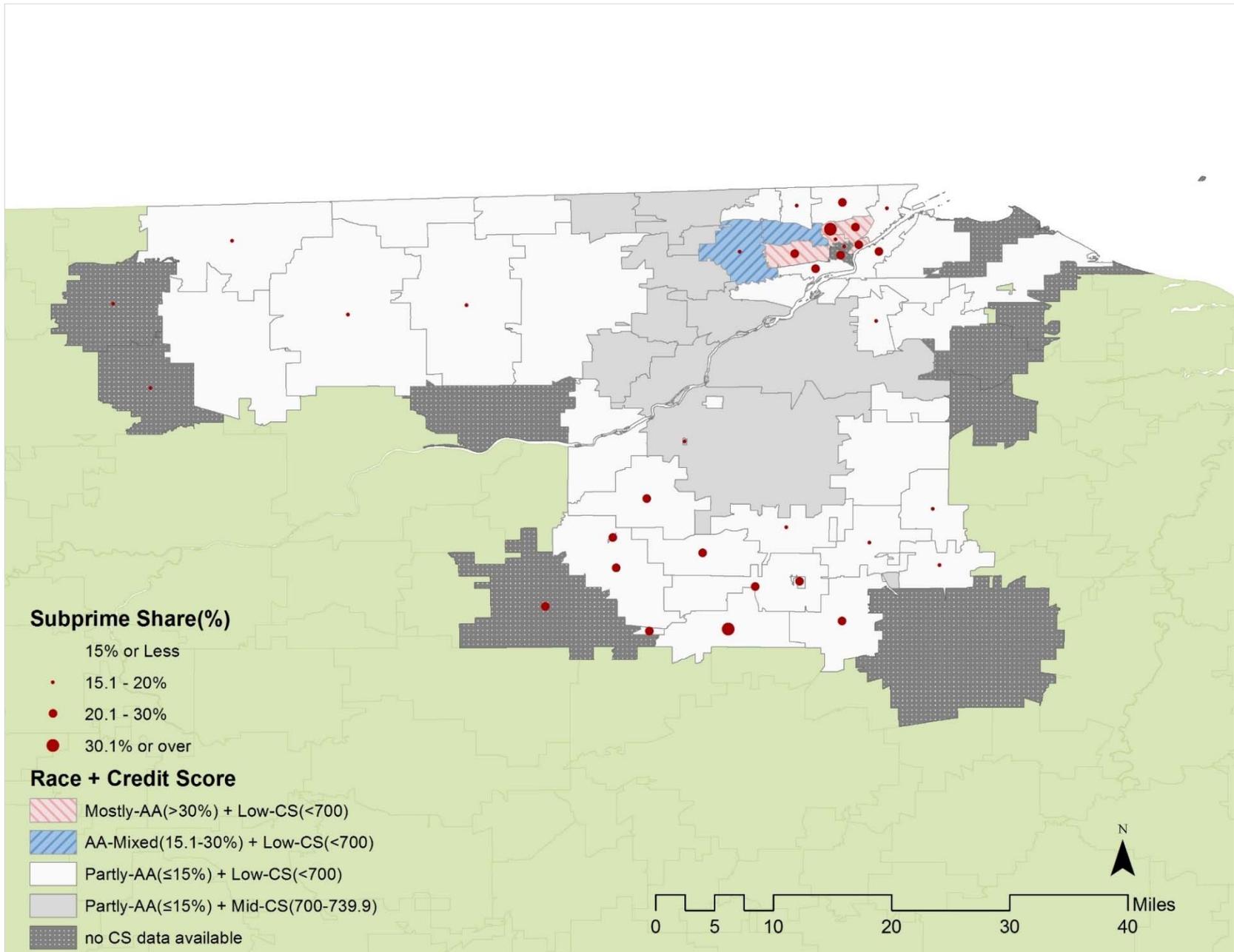
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

35. Geography of Rate of Originations in Neighborhoods in the Toledo MSA in Period 3 (2012-2015)



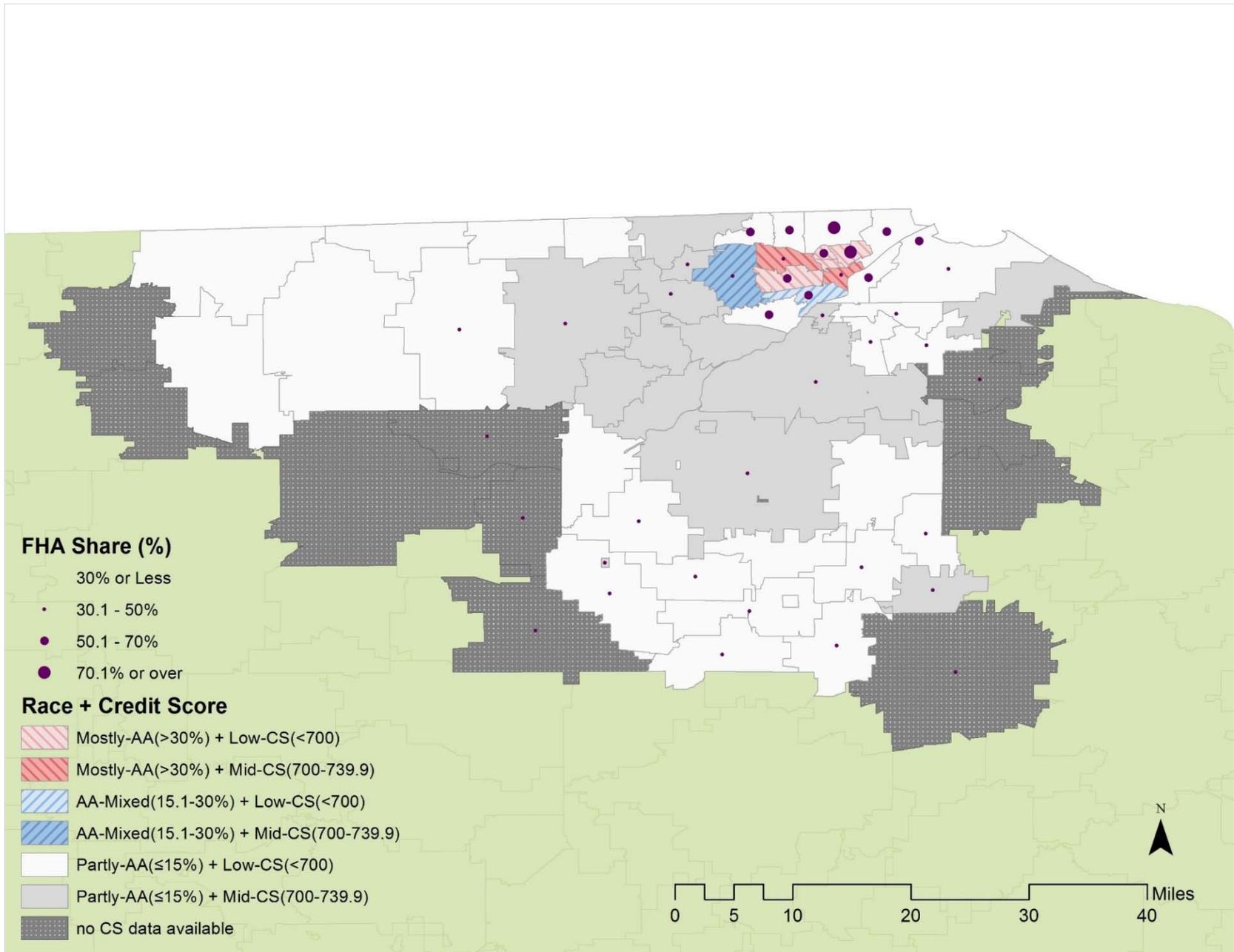
Rate of Originations: Conventional Loans per 100 Owner-Occupied Units in a Neighborhood

36. Geography of Shares of Subprime Loans in the Toledo MSA in Period 1 (2004-2007)



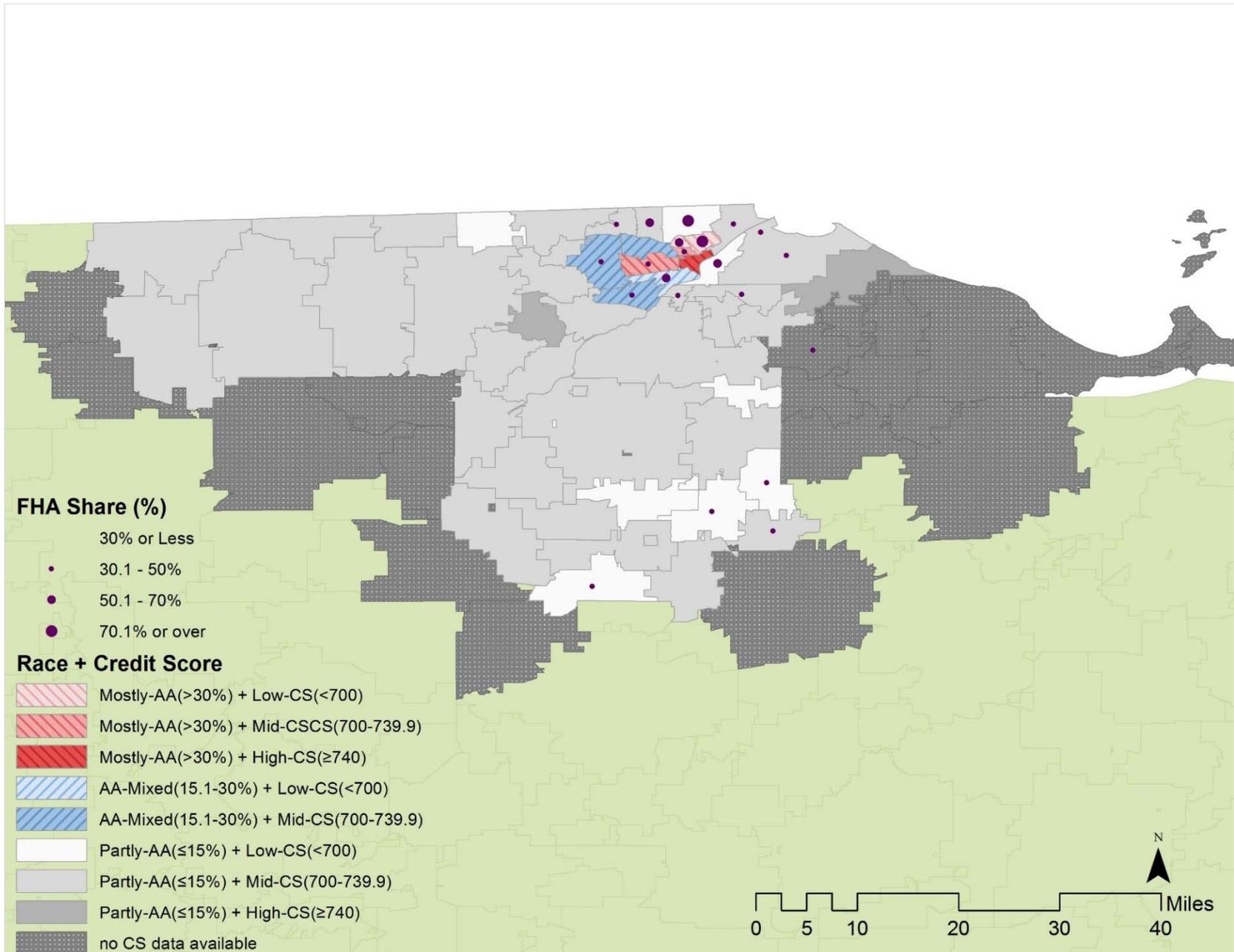
Subprime Share: a proportion of the subprime mortgage origination count of the total mortgage origination count in a neighborhood

37. Geography of Shares of FHA-insured Loans in the Toledo MSA in Period 2 (2008-2011)



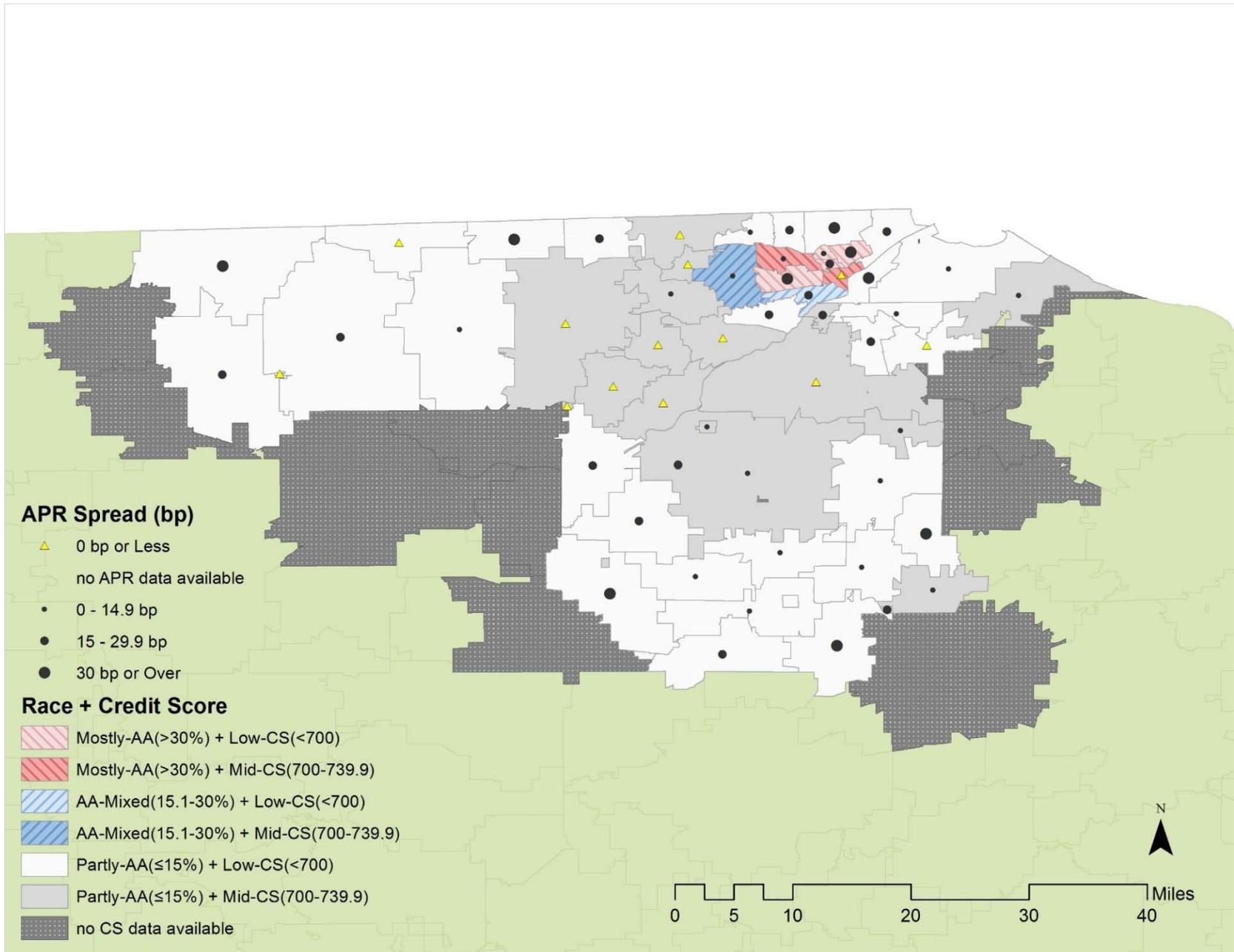
FHA share: a proportion of FHA-insured mortgage origination count of the total mortgage origination count in a neighborhood

38. Geography of Shares of FHA-insured Loans in the Toledo MSA in Period 3 (2012-2015)



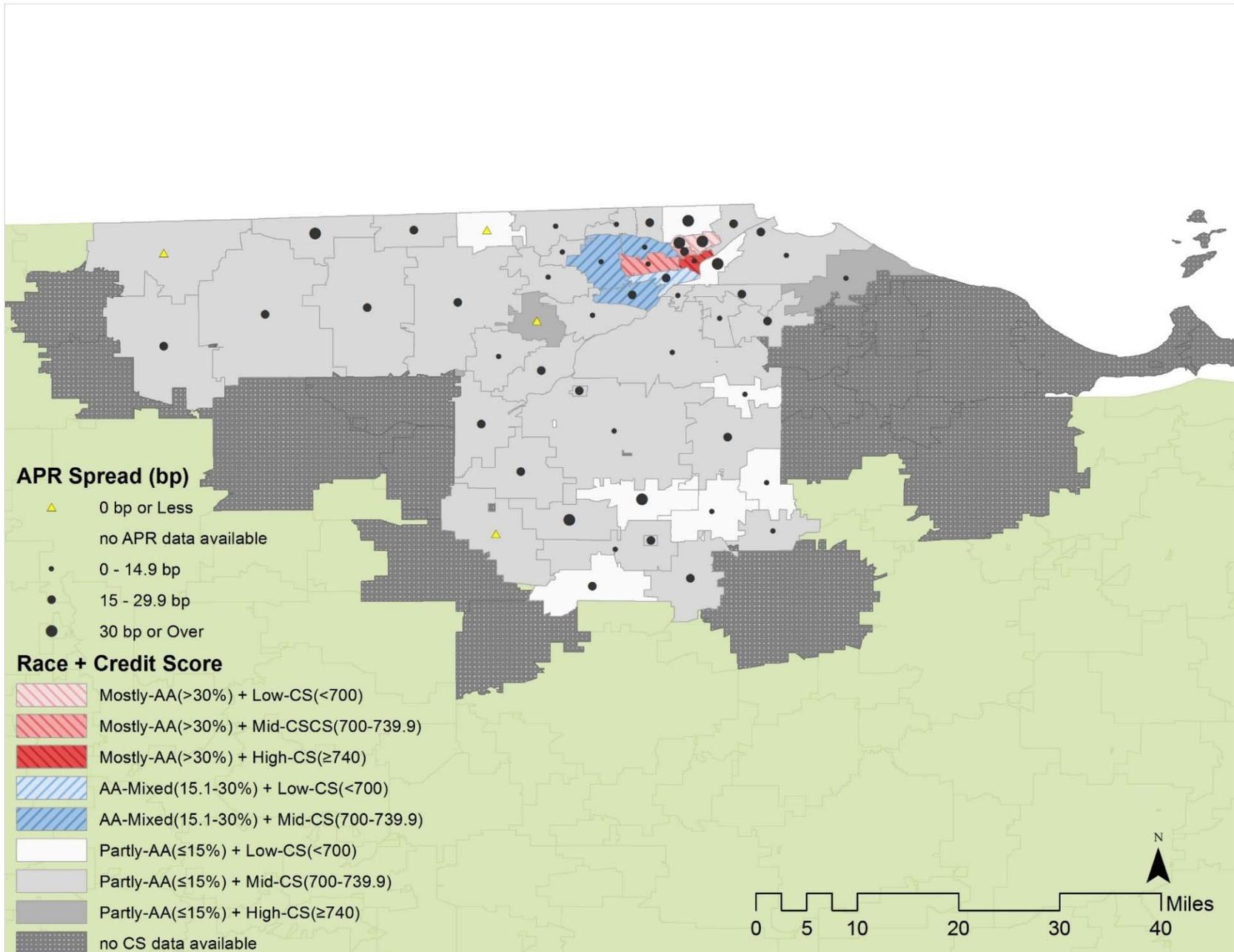
FHA share: a proportion of FHA-insured mortgage origination count of the total mortgage origination count in a neighborhood

39. Geography of Costlier Mortgages (APR Spread) in the Toledo MSA in Period 2 (2008-2011)



Median APR spread: neighborhood level median APR spread

40. Geography of Costlier Mortgages (APR Spread) in the Toledo MSA in Period 3 (2012-2015)



Median APR spread: neighborhood level median APR spread

Appendix C: Detailed Modeling Results of Multivariate Analysis of Patterns of Neighborhood Mortgage Lending, 2004-2015

—

1. Modelling Strategy..... 151

Results for Conventional Mortgage Originations in Period 1 (2004-2007)

2. Results for Conventional Mortgage Originations in the Cleveland MSA in Period 1 (2004-2007)... 152

3. Results for Conventional Mortgage Originations in the Cincinnati MSA in Period 1 (2004-2007) .. 153

4. Results for Conventional Mortgage Originations in the Columbus MSA in Period 1 (2004-2007)... 154

5. Results for Conventional Mortgage Originations in the Dayton MSA in Period 1 (2004-2007) .155

6. Results for Conventional Mortgage Originations in the Toledo MSA in Period 1 (2004-2007)..156

Results for Conventional Mortgage Originations in Period 2 (2008-2011)

7. Results for Conventional Mortgage Originations in the Cleveland MSA in Period 2 (2008-2011)... 157

8. Results for Conventional Mortgage Originations in the Cincinnati MSA in Period 2 (2008-2011) .. 158

9. Results for Conventional Mortgage Originations in the Columbus MSA in Period 2 (2008-2011)... 159

10. Results for Conventional Mortgage Originations in the Dayton MSA in Period 2 (2008-2011)..... 160

11. Results for Conventional Mortgage Originations in the Toledo MSA in Period 2 (2008-2011) .161

Results for Conventional Mortgage Originations in Period 3 (2012-2015)

12. Results for Conventional Mortgage Originations in the Cleveland MSA in Period 3 (2012-2015) .. 162

13. Results for Conventional Mortgage Originations in the Cincinnati MSA in Period 3 (2012-2015).. 163

14. Results for Conventional Mortgage Originations in the Columbus MSA in Period 3 (2012-2015).. 164

15. Results for Conventional Mortgage Originations in the Dayton MSA in Period 3 (2012-2015).165

16. Results for Conventional Mortgage Originations in the Toledo MSA in Period 3 (2012-2015) .166

Results for the Share of Subprime Mortgage in Period 1 (2004-2007)

17. Results for the Share of Subprime Mortgage in the Cleveland MSA in Period 1 (2004-2007) ...167

18. Results for the Share of Subprime Mortgage in the Cincinnati MSA in Period 1 (2004-2007) ..168

19. Results for the Share of Subprime Mortgage in the Columbus MSA in Period 1 (2004-2007)...169

20. Results for the Share of Subprime Mortgage in the Dayton MSA in Period 1 (2004-2007)170

21. Results for the Share of Subprime Mortgage in the Toledo MSA in Period 1 (2004-2007).....171

Results for the Share of FHA Mortgage in Period 2 (2008-2011)

22.Results for the Share of FHA Mortgage in the Cleveland MSA in Period 2 (2008-2011) 172

23.Results for the Share of FHA Mortgage in the Cincinnati MSA in Period 2 (2008-2011) 173

24.Results for the Share of FHA Mortgage in the Columbus MSA in Period 2 (2008-2011) 174

25.Results for the Share of FHA Mortgage in the Dayton MSA in Period 2 (2008-2011) 175

26.Results for the Share of FHA Mortgage in the Toledo MSA in Period 2 (2008-2011) 176

Results for the Share of FHA Mortgage in Period 3 (2012-2015)

27.Results for the Share of FHA Mortgage in the Cleveland MSA in Period 3 (2012-2015) 177

28.Results for the Share of FHA Mortgage in the Cincinnati MSA in Period 3 (2012-2015) 178

29.Results for the Share of FHA Mortgage in the Columbus MSA in Period 3 (2012-2015) 179

30.Results for the Share of FHA Mortgage in the Dayton MSA in Period 3 (2012-2015) 180

31.Results for the Share of FHA Mortgage in the Toledo MSA in Period 3 (2012-2015) 181

Results for the APR Spread for Conventional Mortgages in Period 2 (2007-2011)

32.Results for the APR Spread for Conventional Mortgages in the Cleveland MSA in Period 2 (2007-2011) 182

33.Results for the APR Spread for Conventional Mortgages in the Cincinnati MSA in Period 2 (2007-2011) 183

34.Results for the APR Spread for Conventional Mortgages in the Columbus MSA in Period 2 (2007-2011) 184

35.Results for the APR Spread for Conventional Mortgages in the Dayton MSA in Period 2 (2007-2011) 185

36.Results for the APR Spread for Conventional Mortgages in the Toledo MSA in Period 2 (2007-2011) 186

Results for the APR Spread for Conventional Mortgages in Period 3 (2012-2015)

37.Results for the APR Spread for Conventional Mortgages in the Cleveland MSA in Period 3 (2012-2015) 187

38.Results for the APR Spread for Conventional Mortgages in the Cincinnati MSA in Period 2 (2007-2011) 188

39.Results for the APR Spread for Conventional Mortgages in the Columbus MSA in Period 2 (2007-2011) 188

40.Results for the APR Spread for Conventional Mortgages in the Dayton MSA in Period 2 (2007-2011) 189

41.Results for the APR Spread for Conventional Mortgages in the Toledo MSA in Period 2 (2007-2011) 189

1. Modelling Strategy

First, we tested two models (1) a base model (**Base Model**) including only three main variables – credit score, income, and proportion of African-Americans, and (2) an unconstrained model (**Full Model**) including all variables. Next, we ran a number of models with stepwise regression analysis and looked at Bayesian Information Criterion (BIC) for each model. BIC is used for model selection, and the smaller the BIC, the better fitted model. BIC is particularly suitable to find an efficient model because including numerous (less necessary) parameters (variables) into a model may cause of the risk of over-fitting model. Once finding a fitted model with lower BIC (**Reduced Model**), we added interaction terms including either credit score or income or both and proportions of African-Americans in a neighborhood. In the main paper, we introduced two models; (1) a model commonly having lower BIC across five MSAs (**Model A**) and (2) the model with interaction terms (**Model B**). Base models (**Base Model**) for the APR spread in Period 3 tended to have the lower BIC. In this case, we simply introduced those models as **Model A** and **B**. In addition to this, in cases where proportions of African-Americans and income are highly correlated, thus influencing the model, we added an interaction term between income and the proportion African-American in all models. Here, in Appendix, we introduce all models including, a base model (**Base Model**), a base model with an interaction term for models whose dependent variable is APR spread (**Base Model 2**), efficient model (**Reduced Model 1**) and efficient model with interaction terms (**Reduced Model 2**), both of which were mostly **Model A** and **B** introduced in the main paper, and an unconstrained model (**Full Model 1**) and an unconstrained model with interaction terms (**Full Model 2 or 3**).

2. Results for Conventional Mortgage Originations in the Cleveland MSA in Period 1 (2004-2007)

- Proportion of African-Americans is significantly and negatively associated with conventional mortgage origination: The higher the proportion of African-Americans in a neighborhood, the fewer the conventional mortgage originations. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 0.7 percentage points.
- Neighborhood credit score and income are, on the other hand, positively associated with conventional mortgage origination: the higher the credit score and income, the higher the conventional mortgage originations.
- The median age of housing units and the self-employment rate are also negatively associated with the originations: The higher the median age of housing unit and the higher the self-employment rate in a neighborhood, the fewer the conventional mortgage originations.
- The relationship between debt-to-income ratio (DTI) and lending is different at or under 34% and over 34%. If DTI is less than 34%, DTI is positively associated with conventional mortgage originations; meanwhile, if DTI is 34% or higher, DTI is negatively associated with originations.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient
Credit Score	0.006	1.006 **	0.009	1.009 ***	0.011	1.011 ***	0.012	1.012 ***	0.013	1.013 ***
Proportion AA	-0.010	0.990 ***	-0.007	0.993 ***	0.065	1.067 *	-0.007	0.993 ***	0.051	1.053
Log Income	1.150	3.158 ***	0.987	2.683 ***	0.905	2.471 ***	0.899	2.456 **	0.925	2.521 **
DTI-conv (Low)			0.113	1.120 ***	0.167	1.181 ***	0.159	1.172 ***	0.197	1.218 ***
DTI-conv (High)			-0.075	0.928 **	-0.129	0.879 ***	-0.120	0.887 ***	-0.159	0.853 ***
DTI-conv (intersect)			-0.483	0.617 ***	-0.596	0.551 ***	-0.481	0.618 ***	-0.577	0.562 ***
House Age			-0.016	0.984 ***	-0.015	0.985 **	-0.017	0.983 ***	-0.015	0.985 **
Selfemployment			-0.029	0.972 *	-0.032	0.969 **	-0.037	0.964 **	-0.038	0.962 **
House Price Change							-2E-04	1.000	-6E-05	1.000
Bank Ratio							-0.011	0.989	-0.011	0.989
LTV-conv							0.011	1.011	0.008	1.008
CS×AA					-1E-04	1.000 **			-9E-05	1.000
Owner-Occupied	1E-05	1.000	2E-05	1.000	2E-05	1.000	1E-05	1.000	1E-05	1.000
Constant	-11.741	8E-06 ***	-14.387	6E-07 ***	-16.957	4E-08 ***	-17.921	2E-08 ***	-19.907	2E-09 ***
n		94		94		94		94		94
Log pseudolikelihood		-507.91		-496.69		-495.10		-493.01		-492.12
BIC		1043.08		1043.36		1044.73		1049.63		1052.38

Note 1. Model: Piecewise Negative Binomial Regression

2. DTI (Low/High): Knot at 34%

3. *** (**) (*): Significant at the 99% (95%) (90%) level

3. Results for Conventional Mortgage Originations in the Cincinnati MSA in Period 1 (2004-2007)

- Proportion of African-Americans is significantly and negatively associated with conventional mortgage origination: The higher the proportion of African-Americans in a neighborhood, the fewer the conventional mortgage originations. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 1.4 percentage points.
- Neighborhood credit score and income are, on the other hand, positively associated with conventional mortgage origination: The higher the credit score and income, the higher the conventional mortgage originations.
- The median age of housing units is negatively associated with conventional mortgage origination: The higher the median age of housing unit in a neighborhood, the fewer the conventional mortgage originations.
- The relationship between DTI and lending is different at or under 34% and over 34%. If DTI is less than 34%, DTI is positively associated with conventional mortgage originations; meanwhile, if DTI is 34% or higher, DTI is negatively associated with originations.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient
Credit Score	0.008	1.008 ***	0.008	1.008 ***	0.008	1.008 ***	0.008	1.008 ***	0.008	1.008 ***
Proportion AA	-0.016	0.984 ***	-0.014	0.986 ***	-0.018	0.982	-0.013	0.987 ***	-0.034	0.967
Log Income	0.677	1.967 ***	0.665	1.945 ***	0.672	1.959 ***	0.577	1.780 **	0.583	1.792 **
DTI-conv (Low)			0.149	1.160 ***	0.149	1.161 ***	0.149	1.161 ***	0.150	1.161 ***
DTI-conv (High)			-0.115	0.892 ***	-0.115	0.891 ***	-0.112	0.894 ***	-0.111	0.895 ***
DTI-conv (intersect)			0.238	1.269	0.236	1.266	0.154	1.167	0.154	1.166
House Age			-0.009	0.991 ***	-0.009	0.991 ***	-0.010	0.991 **	-0.010	0.990 **
Selfemployment			-0.013	0.987	-0.013	0.987	-0.016	0.984	-0.015	0.985
House Price Change							-4E-04	1.000	-0.001	0.999
Bank Ratio							0.006	1.006	0.006	1.006
LTV-conv							-0.018	0.982	-0.017	0.983
CS×AA					7E-06	1.000			3E-05	1.000
Owner-Occupied	2E-05	1.000	1E-05	1.000	1E-05	1.000	1E-05	1.000	1E-05	1.000
Constant	-7.202	0.001 ***	-12.131	5E-06 ***	-12.141	5E-06 ***	-9.692	6E-05 ***	-1E+01	0.000 ***
n		97		97		97		97		97
Log pseudolikelihood		-568.59		-562.70		-551.75		-549.59		-549.53
BIC		1164.63		1153.82		1158.39		1163.22		1167.67

- Note 1. Model: Piecewise Negative Binomial Regression
 2. DTI (Low/High) : Knot at 34%
 3. *** (**)(*) :Significant at the 99% (95%) (90%) level

4. Results for Conventional Mortgage Originations in the *Columbus* MSA in Period 1 (2004-2007)

- Proportion of African-Americans is negatively associated with conventional mortgage origination at 90% confidence level: The higher the proportion of African-Americans in a neighborhood, the fewer the conventional mortgage originations. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 0.6 percentage points.
- Neighborhood credit score and income are, on the other hand, significantly and positively associated with conventional mortgage origination: The higher the credit score and income, the higher the conventional mortgage originations.
- The median age of housing units is negatively associated with the originations: The higher the median age of housing unit in a neighborhood, the fewer the conventional mortgage originations.
- The relationship between DTI and lending is different at or under 36.2% and over 36.2%. If DTI is less than 36.2%, DTI is negatively associated with conventional mortgage originations; meanwhile, if DTI is 36.2% or higher, DTI has no significance to the conventional mortgage originations.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient
Credit Score	0.005	1.005 **	0.005	1.005 ***	0.004	1.004 *	0.005	1.005 ***	0.004	1.004 **
Proportion AA	-0.004	0.996	-0.006	0.994 *	-0.155	0.856 *	-0.005	0.995 *	-0.141	0.869 *
Log Income	1.536	4.646 ***	1.017	2.764 ***	1.043	2.837 ***	0.973	2.647 ***	1.015	2.760 ***
DTI-conv (Low)			-0.069	0.934 **	-0.069	0.933 ***	-0.048	0.953 **	-0.050	0.951 **
DTI-conv (High)			0.050	1.051	0.051	1.052	0.023	1.023	0.026	1.026
DTI-conv (intersect)			0.261	1.298 **	0.284	1.328 **	0.240	1.271 **	0.269	1.308 **
House Age			-0.015	0.985 ***	-0.015	0.985 ***	-0.015	0.985 ***	-0.015	0.985 ***
Selfemployment			0.001	1.001	4E-04	1.000	0.002	1.002	0.002	1.002
House Price Change							-0.002	0.998	-0.002	0.998
Bank Ratio							-0.002	0.998	-0.003	0.997
LTV-conv							-0.015	0.985 *	-0.011	0.989
CS×AA					2E-04	1.000 *			2E-04	1.000 *
Owner-Occupied	2E-05	1.000 **	-5E-05	1.000 ***	-5E-05	1.000 ***	-5E-05	1.000 ***	-5E-05	1.000 ***
Constant	-7.202	0.001 ***	-5.991	0.003 **	-5.467	0.004 **	-4.956	0.007 *	-5E+00	0.007 *
n		111		111		111		111		111
Log pseudolikelihood		-675.43		-659.59		-659.59		-657.28		-657.62
BIC		1379.12		1375.69		1375.69		1380.49		1382.68

Note 1. Model: Piecewise Negative Binomial Regression

2. DTI (Low/High) : Knot at 36.2%

3. *** (**) (*): Significant at the 99% (95%) (90%) level

5. Results for Conventional Mortgage Originations in the Dayton MSA in Period 1 (2004-2007)

- Proportion of African-Americans is significantly and negatively associated with conventional mortgage origination: The higher the proportion of African-Americans in a neighborhood, the fewer the conventional mortgage originations. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 1.6 percentage points.
- Neighborhood income is significantly and positively associated with conventional mortgage origination: The higher the credit score and income, the higher the conventional mortgage originations.
- However, a negative binomial regression model does not capture the significance of credit score for conventional mortgage originations in this period: Piecewise negative binomial regression worked instead (see Table 3 in the main paper).
- The median age of housing units and self-employment rate are negatively associated with the originations: The higher the median age of housing unit and the higher the self-employment rate in a neighborhood, the fewer the conventional mortgage originations.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient
Credit Score	-0.005	0.995	5E-05	1.000	-0.001	0.999	0.002	1.002	0.002	1.002
Proportion AA	-0.019	0.981 ***	-0.016	0.984 ***	-0.046	0.955	-0.018	0.982 ***	0.011	1.011
Log Income	2.043	7.716 ***	1.621	5.058 ***	1.638	5.145 ***	1.689	5.414 ***	1.663	5.275 ***
DTI-conv (Low)			0.033	1.033	0.027	1.027	0.039	1.040 *	0.043	1.044 *
DTI-conv (High)			0.006	1.006	0.012	1.012	-0.009	0.991	-0.011	0.989
DTI-conv (intersect)			0.062	1.064	0.056	1.058	0.051	1.053	0.050	1.051
House Age			-0.012	0.988 **	-0.013	0.987 **	-0.016	0.984 ***	-0.016	0.984 ***
Selfemployment			-0.027	0.974 **	-0.026	0.974 **	-0.034	0.967 ***	-0.035	0.966 ***
House Price Change							0.004	1.004 ***	0.004	1.004 ***
Bank Ratio							-0.007	0.993 *	-0.007	0.993 *
LTV-conv							0.024	1.024 *	0.024	1.024 *
CS×AA					5E-05	1.000			-5E-05	1.000
Owner-Occupied	4E-05	1.000 **	2E-05	1.000 **	2E-05	1.000	3E-05	1.000	3E-05	1.000 *
Constant	-13.897	9E-07 ***	-12.935	2E-06	-12.543	4E-06 ***	-16.898	5E-08 ***	-17.197	3E-08 ***
n		55		55		55		55		55
Log pseudolikelihood		-294.61		-289.68		-289.13		-282.36		-282.25
BIC		613.27		617.41		620.74		620.82		624.60

Note 1. Model: Piecewise Negative Binomial Regression

2. DTI (Low/High) : Knot at 36.2%

3. *** (**) (*): Significant at the 99% (95%) (90%) level

6. Results for Conventional Mortgage Originations in the Toledo MSA in Period 1 (2004-2007)

- Proportion of African-Americans and credit score are not significant to conventional mortgage origination in the negative binomial regression model: Piecewise negative binomial regression model shows that proportion of African-Americans is significantly and negatively associated with conventional mortgage origination (please see Table 3 in a main paper).
- Neighborhood income is significantly and positively associated with conventional mortgage origination: The higher the credit score and income, the higher the conventional mortgage originations.
- Loan-to-value ratio (LTV) is positively associated with conventional mortgage origination. One possible explanation is due to GSE Act that requires government sponsored enterprises (GSEs), Fannie Mae and Freddie Mac, to expand their business for underserved areas, such as lower income neighborhoods (An & Bostic, 2008).
- The relationship between DTI and lending is different at or under 34% and over 34%. If DTI is less than 34%, DTI is positively associated with conventional mortgage originations; meanwhile, if DTI is 34% or higher, DTI is negatively associated with originations.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient
Credit Score	0.006	1.007	0.005	1.005	0.005	1.006 *	0.006	1.006 *	0.007	1.007 **
Proportion AA	-0.005	0.995	-0.005	0.995	0.067	1.069	-0.002	0.998	0.092	1.097
Log Income	1.624	5.074 **	1.456	4.288 **	1.375	3.954 **	1.737	5.683 ***	1.658	5.249 ***
DTI-conv (Low)			0.303	1.354 ***	0.295	1.343 ***	0.329	1.389 ***	0.320	1.377 ***
DTI-conv (High)			-0.292	0.747 ***	-0.281	0.755 ***	-0.318	0.728 ***	-0.306	0.737 ***
DTI-conv (intersect)			-1.250	0.287 ***	-1.248	0.287 ***	-1.212	0.298 ***	-1.205	0.300 ***
House Age			-0.008	0.992	-0.008	0.992	-0.011	0.989	-0.011	0.989 *
Selfemployment			-0.012	0.988	-0.009	0.991	-0.010	0.990	-0.007	0.993
House Price Change							-0.002	0.998	-0.002	0.998
Bank Ratio							0.003	1.003	0.003	1.003
LTV-conv							0.032	1.032 ***	0.034	1.034 ***
CS×AA					-1E-04	1.000			-0.007	0.993
Owner-Occupied	2E-05	1.000	2E-05	1.000	2E-05	1.000	5E-06	1.000	1E-05	1.000
Constant	-16.883	5E-08 ***	-22.583	2E-10 ***	-21.980	3E-10 ***	-29.822	1E-13 ***	-29.692	1E-13 ***
n		55		55		55		55		55
Log pseudolikelihood		-305.75		-298.71		-293.10		-293.10		-292.42
BIC		635.54		641.49		642.29		642.29		644.96

Note 1. Model: Piecewise Negative Binomial Regression

2. DTI (Low/High) : Knot at 34%

3. *** (**) (*): Significant at the 99% (95%) (90%) level

7. Results for Conventional Mortgage Originations in the Cleveland MSA in Period 2 (2008-2011)

- Proportion of African-Americans is significantly and negatively associated with conventional mortgage origination: The higher the proportion of African-Americans in a neighborhood, the fewer the conventional mortgage originations. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 0.6 percentage points.
- Neighborhood credit score and income are, on the other hand, positively associated with conventional mortgage origination: The higher the credit score and income, the higher the conventional mortgage originations.
- The median age of housing units is negatively associated with the conventional mortgage originations: The higher the median age of housing unit in a neighborhood, the fewer the conventional mortgage originations.
- The relationship between debt-to-income ratio (DTI) and lending is different at or under 38% and over 38%. If DTI is less than 38%, DTI has no significance to the conventional mortgage originations; meanwhile, if DTI is 38% or higher, DTI is negatively associated with conventional mortgage originations.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Exponentiated		Exponentiated		Exponentiated		Exponentiated		Exponentiated	
	Coefficient	Coefficient								
Credit Score	0.013	1.013 ***	0.014	1.014 ***	0.012	1.012 **	0.014	1.014 **	0.013	1.013 *
Proportion AA	-0.010	0.990 ***	-0.006	0.994 **	-0.061	0.941	-0.006	0.994 **	-0.051	0.950
Log Income	1.502	4.492 ***	1.027	2.792 ***	1.086	2.963 ***	0.946	2.576 ***	0.993	2.700 ***
DTI-conv (Low)			-0.001	0.999	-2E-04	1.000	0.009	1.009	0.009	1.009
DTI-conv (High)			-0.104	0.901 **	-0.105	0.900 **	-0.121	0.886 ***	-0.119	0.888 ***
DTI-conv (intersect)			0.271	1.311	0.289	1.334	0.236	1.267	0.245	1.277
House Age			-0.021	0.979 ***	-0.022	0.978 ***	-0.023	0.977 ***	-0.023	0.977 ***
Selfemployment							0.012	1.012	0.013	1.013
House Price Change							-0.003	0.997	-0.002	0.998
LTV-conv							-0.014	0.986	-0.009	0.991
Bank Ratio							-0.014	0.986	-0.014	0.986
CS×AA					8E-05	1.000			7E-05	1.000
Owner-Occupied	3E-05	1.000 ***	3E-05	1.000 ***	3E-05	1.000 ***	3E-05	1.000 **	3E-05	1.000 **
Constant	-21.667	4E-10 ***	-16.700	6E-08 ***	-15.942	1E-07 ***	-14.818	4E-07 ***	-14.791	4E-07 ***
n		94		94		94		94		94
Log pseudolikelihood		-415.59		-403.81		-403.45		-402.31		-402.10
BIC		858.44		853.06		856.88		868.22		872.34

Note 1. Model: Piecewise Negative Binomial Regression

2. DTI (Low/High) : 38%

3. *** (**)(*) :Significant at the 99% (95%) (90%) level

8. Results for Conventional Mortgage Originations in the Cincinnati MSA in Period 2 (2008-2011)

- Proportion of African-Americans is significantly and negatively associated with conventional mortgage origination in Base Model and Full Model 1, while other models cannot show the significance of proportion of African-Americans. In these two models, the higher the proportion of African-Americans in a neighborhood, the fewer the conventional mortgage originations. In Full Model 1, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 0.6 percentage points.
- Neighborhood credit score and income are, on the other hand, positively associated with conventional mortgage origination: the higher the credit score and income, the higher the conventional mortgage originations.
- The median age of housing units is negatively associated with the conventional mortgage originations: The higher the median age of housing unit in a neighborhood, the fewer the conventional mortgage originations.
- The relationship between DTI and lending is different at or under 38% and over 38%. If DTI is less than 38%, DTI is positively associated with conventional mortgage originations; meanwhile, if DTI is 38% or higher, DTI is negatively associated with originations.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Exponentiated		Exponentiated		Exponentiated		Exponentiated		Exponentiated	
	Coefficient	Coefficient								
Credit Score	0.018	1.018 ***	0.018	1.018 ***	0.021	1.021 ***	0.014	1.014 **	0.022	1.022 ***
Proportion AA	-0.016	0.984 ***	-0.007	0.993 *	0.136	1.146 *	-0.006	0.994 **	0.145	1.157 *
Log Income	0.676	1.967 ***	0.623	1.865 ***	0.526	1.693 **	0.946	2.576 ***	0.535	1.708 **
DTI-conv (Low)			0.109	1.115 **	0.122	1.130 **	0.009	1.009	0.125	1.133 **
DTI-conv (High)			-0.180	0.835 ***	-0.190	0.827 ***	-0.121	0.886 ***	-0.186	0.831 **
DTI-conv (intersect)			-0.057	0.945	-0.065	0.937	0.236	1.267	-0.063	0.939
House Age			-0.021	0.980 ***	-0.020	0.980 ***	-0.023	0.977 ***	-0.020	0.980 ***
Selfemployment							0.012	0.997	-0.008	0.992
House Price Change							-0.003	0.986	0.003	1.003
LTV-conv							-0.014	0.986	-0.004	0.996
Bank Ratio							-0.014	1.000	-0.006	0.994
CS×AA					-2E-04	1.000 *			-2E-04	1.000 **
Owner-Occupied	3E-05	1.000 **	3E-07	1.000	-6E-07	1.000	3E-05	4E-07 **	-4E-08	1.000
Constant	-15.653	2E-07 ***	-17.591	2E-08 ***	-19.210	5E-09 ***	-14.818	1.000 ***	-19.826	2E-09 ***
n		91		91		91		91		91
Log pseudolikelihood		-471.42		-453.99		-453.00		-456.71		-452.03
BIC		969.90		953.08		955.63		969.45		971.72

Note 1. Model: Piecewise Negative Binomial Regression

2. DTI (Low/High) : 38%

3. *** (**)(*) :Significant at the 99% (95%) (90%) level

9. Results for Conventional Mortgage Originations in the Columbus MSA in Period 2 (2008-2011)

- Proportion of African-Americans is significantly and negatively associated with conventional mortgage origination in Model B and Full Model 2 that include an interaction term (CS×AA). Thus, neighborhood racial composition only matters for conventional mortgage origination when credit scores are considered in tandem with racial composition. Accounting for an interaction term between the proportions of African-Americans and median credit scores, generally when African-American comprise more of the neighborhood, fewer conventional mortgages were originated.
- Neighborhood credit score and income are significantly and positively associated with conventional mortgage origination: the higher the credit score and income, the higher the conventional mortgage originations.
- The median age of housing units is negatively associated with the conventional mortgage originations: The higher the median age of housing unit in a neighborhood, the fewer the conventional mortgage originations.
- Bank brunch numbers per housing unit in a neighborhood is negatively associated with conventional mortgage origination, while this generally happens in the neighborhoods with lower income level, accounting for the interaction term between bank ratio and income.
- The relationship between DTI and lending is different at or under 37% and over 37%. If DTI is less than 37%, DTI has no significance to the conventional mortgage originations; meanwhile, if DTI is 37% or higher, DTI is negatively associated with conventional mortgage originations.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient
Credit Score	0.010	1.010 **	0.016	1.016 ***	0.013	1.014 **	0.015	1.015 ***	0.012	1.012 **
Proportion AA	-4E-04	1.000	-0.002	0.998	-0.305	0.737 **	-0.004	0.996	-0.302	0.740 **
Log Income	1.826	6.209 ***	1.071	2.919 ***	1.045	2.844 ***	0.750	2.117 **	0.765	2.149 **
DTI-conv (Low)			-0.035	0.965	-0.040	0.961	-0.006	0.994	-0.014	0.986
DTI-conv (High)			-0.192	0.825 **	-0.169	0.844 **	-0.202	0.817 **	-0.179	0.836 **
DTI-conv (intersect)			0.563	1.756 **	0.549	1.731 **	0.302	1.352	0.308	1.361
House Age			-0.021	0.980 ***	-0.021	0.979 ***	-0.021	0.979 ***	-0.022	0.978 ***
Selfemployment							0.001	1.001	-0.003	0.997
House Price Change							-0.004	0.996	-0.002	0.998
LTV-conv							0.009	1.009	0.006	1.006
Bank Ratio							-0.729	0.482 **	-0.711	0.491 **
Inc×Bank Ratio							0.064	1.066 **	0.062	1.064 **
CS×AA					4E-04	1.000 **			4E-04	1.000 **
Owner-Occupied	1E-06	1.000	-1E-05	1.000	-1E-05	1.000	-1E-05	1.000	-1E-05	1.000
Constant	-22.753	1E-10 ***	-16.485	7E-08 ***	-14.404	6E-07 ***	-13.775	1E-06 ***	-11.460	1E-05 **
n		99		99		99		99		99
Log pseudolikelihood		-529.60		-511.43		-509.60		-504.76		-503.08
BIC		1086.77		1068.82		1069.60		1078.45		1079.68

Note 1. Model: Piecewise Negative Binomial Regression

2. DTI (Low/High) : 37%

3. *** (**)(*) :Significant at the 99% (95%) (90%) level

10. Results for Conventional Mortgage Originations in the Dayton MSA in Period 2 (2008-2011)

- Proportion of African-Americans is significantly and negatively associated with conventional mortgage origination: The higher the proportion of African-Americans in a neighborhood, the fewer the conventional mortgage originations. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 2.2 percentage points.
- However, negative binomial regression models do not indicate the significance of credit score and income on conventional mortgage originations at a neighborhood level in this period.
- The median age of housing units is also negatively associated with the originations: The higher the median age of housing unit in a neighborhood, the fewer the conventional mortgage originations.
- The relationship between debt-to-income ratio (DTI) and lending is different at or under 34% and over 34%. If DTI is less than 34%, DTI is positively associated with conventional mortgage originations; meanwhile, if DTI is 34% or higher, DTI is negatively associated with originations.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient
Credit Score	-2E-04	1.000	0.003	1.003	0.001	1.001	0.005	1.005	0.003	1.003
Proportion AA	-0.017	0.983 ***	-0.022	0.978 ***	-0.186	0.831	-0.021	0.980 ***	-0.228	0.796
Log Income	1.737	5.679 ***	0.756	2.131 *	0.818	2.266 *	0.522	1.686	0.577	1.781
DTI-conv (Low)			0.135	1.144 **	0.134	1.144 **	0.128	1.137 **	0.129	1.138 **
DTI-conv (High)			-0.196	0.822 **	-0.189	0.828 **	-0.207	0.813 **	-0.200	0.819 **
DTI-conv (intersect)			-0.311	0.733	-0.371	0.690 *	-0.286	0.751	-0.360	0.697 *
House Age			-0.018	0.982 ***	-0.019	0.981 ***	-0.021	0.979 **	-0.022	0.978 ***
Selfemployment							0.032	0.999	0.034	1.034
House Price Change							-0.001	1.028	-0.001	0.999
LTV-conv							0.027	1.008	0.029	1.029
Bank Ratio							0.008	1.000	0.006	1.006
CS×AA					2E-04	1.000			3E-04	1.000
Owner-Occupied	4E-05	1.000 **	-4E-06	1.000	-1E-05	1.000	1E-05	3E-05	7E-06	1.000
Constant	-14.864	4E-07 ***	-9.225	1E-04 **	-8.244	3E-04 **	-10.590	1.000 ***	-9.538	7E-05 **
n		53		53		53		53		53
Log pseudolikelihood		-250.25		-240.66		-240.06		-238.43		-237.43
BIC		524.33		521.02		523.80		532.45		534.41

Note 1. Model: Piecewise Negative Binomial Regression

2. DTI (Low/High) : 34%

3. *** (**) (*): Significant at the 99% (95%) (90%) level

11. Results for Conventional Mortgage Originations in the Toledo MSA in Period 2 (2008-2011)

- Proportion of African-Americans is significantly and negatively associated with conventional mortgage origination in Model B and Full Model 2 that include an interaction term (CS×AA): Neighborhood racial composition only matters for conventional mortgage origination when credit scores are considered in tandem with racial composition. Accounting for an interaction term between the proportions of African-Americans and median credit scores, generally when African-American comprise more of the neighborhood, fewer conventional mortgages were originated.
- Neighborhood income is significantly and positively associated with conventional mortgage origination: the higher the credit score and income, the higher the conventional mortgage originations.
- However, models do not indicate the significance of credit score for conventional mortgage originations at a neighborhood level in this period.
- The median age of housing units is negatively associated with the conventional mortgage originations: The higher the median age of housing unit in a neighborhood, the fewer the conventional mortgage originations.
- The relationship between DTI and lending is different at or under 34% and over 34%. If DTI is less than 34%, DTI is positively associated with conventional mortgage originations; meanwhile, if DTI is 34% or higher, DTI is negatively associated with originations.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient
Credit Score	0.006	1.006	0.003	1.003	-0.001	0.999	-0.002	0.998	-0.008	0.992
Proportion AA	-0.006	0.994	-0.004	0.996	-0.216	0.806 **	-8E-05	1.000	-0.273	0.761 ***
Log Income	2.571	13.079 ***	2.262	9.598 ***	2.375	10.755 ***	2.365	10.640 ***	2.546	12.759 ***
DTI-conv (Low)			0.123	1.130 ***	0.131	1.139 ***	0.108	1.114 ***	0.119	1.126 ***
DTI-conv (High)			-0.103	0.902 **	-0.110	0.896 **	-0.079	0.924 *	-0.083	0.920 **
DTI-conv (intersect)			-0.332	0.717 *	-0.370	0.691 **	-0.289	0.749 *	-0.362	0.697 **
House Age			-0.014	0.987 **	-0.015	0.985 **	-0.018	0.982 ***	-0.020	0.980 ***
Selfemployment							0.003	1.003	-0.007	0.993
House Price Change							2E-04	1.000	0.003	1.003
LTV-conv							-0.005	0.995	-0.008	0.993
Bank Ratio							0.026	1.027	0.030	1.031 *
Inc×Bank Ratio										
CS×AA					3E-04	1.000 **			4E-04	1.000 ***
Owner-Occupied	1E-05	1.000	-7E-06	1.000	-6E-06	1.000	-1E-05	1.000	-3E-06	1.000
Constant	-28.341	5E-13 ***	-25.975	5E-12 ***	-24.628	2E-11 ***	-23.097	9E-11 ***	-21.163	6E-10 ***
n		49		49		49		49		49
Log pseudolikelihood		-217.31		-209.69		-207.67		-206.16		-202.96
BIC		457.97		458.29		458.93		466.81		464.30

Note 1. Model: Piecewise Negative Binomial Regression

2. DTI (Low/High) : 34%

3. *** (**)(*) :Significant at the 99% (95%) (90%) level

12. Results for Conventional Mortgage Originations in the Cleveland MSA in Period 3 (2012-2015)

- Proportion of African-Americans is significantly and negatively associated with conventional mortgage origination: The higher the proportion of African-Americans in a neighborhood, the fewer the conventional mortgage originations. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 1.2 percentage points.
- Neighborhood credit score and income are, on the other hand, significantly and positively associated with conventional mortgage origination: the higher the credit score and income, the higher the conventional mortgage originations.
- The median age of housing units is also negatively associated with the originations: The higher the median age of housing unit in a neighborhood, the fewer the conventional mortgage originations.
- Housing price change from 2011 to 2015 is positively associated with the originations: The higher the housing price changes from 2011 to 2015 in a neighborhood, the higher the conventional mortgage origination.
- The relationship between DTI and lending is different at or under 32% and over 32%. If DTI is less than 32%, DTI is positively associated with conventional mortgage originations; meanwhile, if DTI is 32% or higher, DTI is negatively associated with originations.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Exponentiated		Exponentiated		Exponentiated		Exponentiated		Exponentiated	
	Coefficient	Coefficient								
Credit Score	0.018	1.019 ***	0.018	1.018 ***	0.017	1.017 ***	0.018	1.018 ***	0.017	1.017 ***
Proprtion AA	-0.016	0.984 ***	-0.012	0.988 ***	-0.035	0.966	-0.012	0.988 ***	-0.039	0.962
Log Income	1.227	3.411 ***	0.662	1.938 ***	0.674	1.961 ***	0.697	2.007 ***	0.708	2.031 ***
DTI-conv (Low)			0.086	1.089 ***	0.087	1.091 ***	0.101	1.106 ***	0.103	1.109 ***
DTI-conv (High)			-0.127	0.881 ***	-0.129	0.879 ***	-0.148	0.863 ***	-0.150	0.861 ***
DTI-conv (intersect)			-0.113	0.893	-0.110	0.896	-0.110	0.896	-0.108	0.897
House Age			-0.021	0.979 ***	-0.021	0.979 ***	-0.020	0.980 ***	-0.020	0.980 ***
House Price Change			0.010	1.010 ***	0.010	1.010 ***	0.009	1.009 ***	0.009	1.009 ***
Selfemployment							-0.013	0.988	-0.012	0.988
LTV-conv							-0.003	0.997	-0.003	0.997
Bank Ratio							0.008	1.008	0.009	1.009
CS×AA					3E-05	1.000			4E-05	1.000
Owner-Occupied	2E-05	1.000 **	2E-05	1.000 **	1E-05	1.000 **	8E-06	1.000	8E-06	1.000
Constant	-22.423	2E-10 ***	-17.166	4E-08 ***	-16.826	5E-08 ***	-17.782	2E-08 ***	-17.399	3E-08 ***
n		92		92		92		92		92
Log pseudolikelihood		-423.03		-398.93		-398.84		-397.53		-397.40
BIC		873.19		847.60		851.94		858.36		862.64

Note 1. Model: Piecewise Negative Binomial Regression

2. DTI (Low/High) : 32%

3. *** (**)(*) :Significant at the 99% (95%) (90%) level

13. Results for Conventional Mortgage Originations in the Cincinnati MSA in Period 3 (2012-2015)

- Proportion of African-Americans is not significantly associated with conventional mortgage origination, unlike other MSAs.
- Neighborhood credit score and income are, on the other hand, still significantly and positively associated with conventional mortgage origination: the higher the credit score and income, the higher the conventional mortgage originations.
- The median age of housing units is negatively associated with the originations: The higher the median age of housing unit in a neighborhood, the fewer the conventional mortgage originations.
- Housing price change from 2011 to 2015 is positively associated with the originations: The higher the housing price changes from 2011 to 2015, the higher the conventional mortgage origination.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient
Credit Score	0.011	1.011 **	0.009	1.009 **	0.007	1.007	0.007	1.007	0.005	1.005
Proprtion AA	-0.003	0.997	0.008	1.008	-0.076	0.926	0.007	1.007	-0.088	0.916
Log Income	1.349	3.853 ***	1.360	3.897 ***	1.411	4.099 ***	1.289	3.628 ***	1.342	3.828 ***
DTI-conv (Low)			0.058	1.060 **	0.059	1.061 **	0.057	1.058 **	0.058	1.059 **
DTI-conv (High)			-0.059	0.943	-0.061	0.940	-0.073	0.930	-0.075	0.928
DTI-conv (intersect)			-0.292	0.747	-0.306	0.736	-0.300	0.741	-0.318	0.728
House Age			-0.018	0.982 ***	-0.018	0.982 ***	-0.017	0.983 ***	-0.018	0.983 ***
House Price Change			0.018	1.018 **	0.017	1.017 **	0.019	1.019 **	0.018	1.018 **
Selfemployment							0.018	1.018	2E-02	1.020
LTV-conv							-0.004	0.996	-0.004	0.996
Bank Ratio							0.010	1.010	0.010	1.010
CS×AA					1E-04	1.000			1E-04	1.000
Owner-Occupied	2E-05	1.000	3E-06	1.000	3E-06	1.000	2E-06	1.000	3E-06	1.000
Constant	-18.218	1E-08 ***	-17.808	2E-08 ***	-17.153	4E-08 ***	-15.627	2E-07 ***	-14.719	4E-07 ***
n		92		92		92		92		92
Log pseudolikelihood		-504.10		-479.19		-478.98		-478.23		-477.97
BIC		1035.32		1008.11		1012.22		1019.77		1023.76

Note 1. Model: Piecewise Negative Binomial Regression

2. DTI (Low/High) : 36%

3. *** (**)(*) :Significant at the 99% (95%) (90%) level

14. Results for Conventional Mortgage Originations in the Columbus MSA in Period 3 (2012-2015)

- Proportion of African-Americans is significantly and negatively associated with conventional mortgage origination: The higher the proportion of African-Americans in a neighborhood, the fewer the conventional mortgage originations. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 1.3 percentage points. However, an interaction term (CS×AA) indicates that the negative impact of proportion of African-Americans is improved by higher credit score. In other words, lower credit scores as the proportion of African-Americans increased in neighborhoods reduced the origination counts
- Neighborhood credit score and income are positively associated with conventional mortgage origination: the higher the credit score and income, the higher the conventional mortgage originations.
- The median age of housing units is negatively associated with the originations: The higher the median age of housing unit in a neighborhood, the fewer the conventional mortgage originations.
- Bank brunch numbers per housing unit in a neighborhood is negatively associated with conventional mortgage origination, which is also seen in Period 2. This generally happens in the neighborhoods with lower credit score level, accounting for the interaction term between bank ratio and credit score (CS×Bank).

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient
Credit Score	0.007	1.007 **	0.010	1.010 **	0.005	1.005	0.013	1.013 ***	0.004	1.004
Proprtion AA	-0.010	0.990 **	-0.013	0.987 ***	-0.473	0.623 ***	-0.013	0.987 ***	-0.478	0.620 ***
Log Income	1.232	3.428 ***	0.927	2.528 ***	0.926	2.524 ***	0.974	2.647 ***	0.883	2.419 ***
DTI-conv			0.012	1.012	0.011	1.011	0.010	1.010	0.013	1.013
House Age			-0.011	0.989 **	-0.014	0.986 ***	-0.013	0.987 ***	-0.016	0.984 ***
House Price Change			-0.010	0.990 *	-0.008	0.992	-0.012	0.988 **	-0.010	0.990 *
Selfemployment							0.004	1.004	0.008	1.008
LTV-conv							0.015	1.015 *	0.017	1.018 **
Bank Ratio							-0.027	0.974 ***	-0.624	0.536 *
CS×Bank									0.001	1.001 *
CS×AA					0.001	1.001 ***			0.001	1.001 ***
Owner-Occupied	2E-05	1.000 *	1E-05	1.000	1E-05	1.000	1E-05	1.000	2E-05	1.000 *
Constant	-14.026	8E-07 ***	-13.003	2E-06 ***	-8.564	2E-04 ***	-16.074	1E-07 ***	-9.164	1E-04 ***
n		98		98		98		98		98
Log pseudolikelihood		-533.39		-526.66		-518.58		-521.39		-509.22
BIC		1094.29		1094.59		1083.01		1097.81		1091.79

Note 1. Model: Negative Binomial Regression

2. *** (**) (*): Significant at the 99% (95%) (90%) level

15. Results for Conventional Mortgage Originations in the Dayton MSA in Period 3 (2012-2015)

- Proportion of African-Americans is significantly and negatively associated with conventional mortgage origination: The higher the proportion of African-Americans in a neighborhood, the fewer the conventional mortgage originations. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 1.2 percentage points.
- Neighborhood income are significantly and positively associated with conventional mortgage origination: the higher the neighborhood income, the higher the conventional mortgage originations.
- However, a negative binomial regression model does not capture the significance of credit score for conventional mortgage originations in this period: Piecewise negative binomial regression worked instead (see Table 9 in a main paper).
- The median age of housing units is also negatively associated with the originations: The higher the median age of housing unit in a neighborhood, the fewer the conventional mortgage originations.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient
Credit Score	0.005	1.005	0.008	1.009 *	0.004	1.004	0.010	1.010	0.007	1.007
Proprtion AA	-0.012	0.988 ***	-0.012	0.988 ***	-0.186	0.830	-0.011	0.989 **	-0.185	0.831
Log Income	1.413	4.109 ***	0.739	2.093 **	0.956	2.601 ***	0.523	1.687	0.796	2.218 **
DTI-conv (Low)			0.094	1.099 *	0.086	1.090	0.090	1.094 **	0.079	1.082 *
DTI-conv (High)			-0.117	0.890 *	-0.102	0.903	-0.081	0.922 *	-0.070	0.932
DTI-conv (intersect)			-0.088	0.916	-0.099	0.906	-0.179	0.836	-0.166	0.847
House Age			-0.013	0.987 **	-0.013	0.987 **	-0.014	0.986 ***	-0.014	0.986 **
House Price Change			0.006	1.006	0.004	1.004	0.003	1.003	-3E-04	1.000
Selfemployment							0.035	1.035	0.035	1.036
LTV-conv							-0.005	0.995	0.002	1.002
Bank Ratio							0.023	1.023	9E-06	1.000
CS×AA					2E-04	1.000			2E-04	1.000
Owner-Occupied	2E-05	1.000	-9E-06	1.000	8E-06	1.000	2E-06	1.000	9E-06	1.000
Constant	-14.535	5E-07 ***	-12.130	5E-06 ***	-12.342	4E-06 ***	-10.157	4E-05	-11.374	1E-05 *
n		50		50		50		50		50
Log pseudolikelihood		-244.85		-236.19		-234.98		-233.39		-232.20
BIC		513.16		515.41		516.90		521.56		523.08

Note 1. Model: Piecewise Negative Binomial Regression

2. DTI (Low/High) : 32%

3. *** (**)(*) :Significant at the 99% (95%) (90%) level

16. Results for Conventional Mortgage Originations in the Toledo MSA in Period 3 (2012-2015)

- Proportion of African-Americans is significantly and negatively associated with conventional mortgage origination: The higher the proportion of African-Americans in a neighborhood, the fewer the conventional mortgage originations. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 1.0 percentage points. However, an interaction term (CS×AA) indicates that the negative impact of proportion of African-Americans is improved by higher credit score. In other words, lower credit scores as the proportion of African-Americans increased in neighborhoods reduce the origination counts
- Neighborhood credit score and income are, on the other hand, positively associated with conventional mortgage origination: The higher the credit score and income, the higher the conventional mortgage originations.
- The median age of housing units is negatively associated with the originations: The higher the median age of housing unit in a neighborhood, the fewer the conventional mortgage originations.
- The relationship between DTI and lending is different at or under 32% and over 32%. If DTI is less than 32%, DTI is negatively associated with conventional mortgage originations; meanwhile, if DTI is 32% or higher, DTI has no significance to the conventional mortgage originations.

	Base Model		Model A		Model B		Full Model 1		Full Model 2	
	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient	Coefficient	Exponentiated Coefficient
Credit Score	0.015	1.015 ***	0.013	1.013 ***	0.012	1.012 ***	0.013	1.013 ***	0.012	1.012 ***
Proprtion AA	-0.011	0.989 ***	-0.010	0.990 ***	-0.131	0.877 **	-0.011	0.989 ***	-0.148	0.863 **
Log Income	2.098	8.149 ***	1.745	5.723 ***	1.788	5.979 ***	1.783	5.950 ***	1.840	6.298 ***
DTI-conv (Low)			0.064	1.066 ***	0.063	1.065 ***	0.070	1.072 ***	0.070	1.072 ***
DTI-conv (High)			-0.029	0.971	-0.029	0.972	-0.031	0.969	-0.032	0.968
DTI-conv (intersect)			-0.399	0.671 **	-0.411	0.663 ***	-0.428	0.652 ***	-0.441	0.644 ***
House Age			-0.017	0.984 ***	-0.016	0.984 ***	-0.016	0.984 ***	-0.016	0.984 ***
House Price Change			-0.010	0.990 *	-0.010	0.990	-0.010	0.990 *	-0.010	0.990
Selfemployment							-0.009	0.991	-0.008	0.992
LTV-conv							-0.004	0.996	-0.003	0.997
Bank Ratio							-0.004	0.996	-0.006	0.994
CS×AA					2E-04	1.000 **			2E-04	1.000 **
Owner-Occupied	2E-06	1.000	-1E-05	1.000	-1E-05	1.000	-2E-05	1.000	-2E-05	1.000
Constant	-29.408	2E-13 ***	-25.331	1E-11 ***	-25.033	1E-11 ***	-25.370	1E-11 ***	-25.297	1E-11 ***
n		49		49		49		49		49
Log pseudolikelihood		-228.52		-219.28		-218.84		-218.98		-218.44
BIC		480.38		481.37		484.39		492.45		495.26

Note 1. Model: Piecewise Negative Binomial Regression

2. DTI (Low/High) : 32%

3. *** (**) (*) :Significant at the 99% (95%) (90%) level

17. Results for the Share of Subprime Mortgage in the Cleveland MSA in Period 1 (2004-2007)

- Proportion of African-Americans is significantly and positively associated with the share of loans being a subprime: The higher the proportion of African-Americans in a neighborhood, the higher the share of subprime loans. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to increase the conventional mortgage origination count by 0.15 percentage points. However, an interaction term (**CS×AA**) indicates that the positive impact of proportion of African-Americans is improved by higher credit score. In other words, lower credit scores as the proportion of African-Americans increased in neighborhoods increase the share of loans being a subprime.
- Neighborhood credit score is, on the other hand, negatively associated with the share of subprime loans: the higher the credit score and income in a neighborhood, the lower the share of loans being a subprime.
- Turnover rate is positively associated with the subprime share, while this generally happens in a neighborhood where housing price declines from 1990 to 2000, accounting for the interaction term between housing price change and turnover rate (**HPC×Turnover**).
- Bank brunch numbers per housing unit in a neighborhood is positively associated with the share of loans being a subprime. This means that the more bank branches in a neighborhood, the higher the subprime share.

	Basic Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.334 ***	-0.332 ***	-0.295 ***	-0.370 ***	-0.316 ***
Proprtion AA	0.157 ***	0.149 ***	2.095 ***	0.135 ***	2.086 ***
Log Income	1.499	-1.017	-1.831	-2.593	-2.104
House Price Change		2E-04	0.006	0.002	0.007 *
DTI-all		-0.099	-0.060	-0.116	0.061
Turnover		4.309 ***	4.812 ***	5.314 ***	5.034 ***
HPC×Turnover		-0.109 **	-0.151 ***	-0.137 ***	-0.166 ***
Bank Ratio		0.110 **	0.184 ***	0.156 ***	0.227 ***
House Age				-0.044	0.039
Selfemployment				0.331 **	0.266 *
CS×AA			-0.003 ***		-0.003 ***
Constant	227.861 ***	257.382 ***	239.107 ***	299.461 ***	247.787 ***
n	94	94	94	94	94
adjusted R ²	0.8794	0.9063	0.9247	0.9103	0.9267
BIC	578.16	571.79	554.70	574.48	558.91

Note 1. Model: OLS Regression

2. *** (**)(*) :Significant at the 99% (95%) (90%) level

18. Results for the Share of Subprime Mortgage in the Cincinnati MSA in Period 1 (2004-2007)

- Proportion of African-Americans is significantly and positively associated with the share of loans being a subprime: The higher the proportion of African-Americans in a neighborhood, the higher the share of subprime loans. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to increase the conventional mortgage origination count by 0.09 percentage points.
- Interaction term (**CS×AA**) indicates that the positive impact of proportion of African-Americans is improved by higher neighborhood credit score, while another interaction term (**Inc×AA**) indicates that the positive impact of proportion of African-Americans is magnified by higher neighborhood income. In other words, higher incomes as the proportion of African-Americans increased in neighborhoods increase the share of loans being a subprime.
- Neighborhood credit score and income themselves are, on the other hand, significantly and negatively associated with the share of subprime loans: the higher the credit score and income, the lower the share of loans being a subprime.
- DTI is positively associated with the share of subprime loans, while Turnover rate is negatively associated with the share of subprime loans.

	Basic Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.133 ***	-0.124 ***	-0.070 **	-0.118 ***	-0.062 **
Proprtion AA	0.122 ***	0.090 ***	1.345 **	0.097 ***	1.357 ***
Log Income	-2.483	-6.322 **	-11.513 ***	-6.162 **	-11.497 **
House Price Change		-0.015 ***	-0.001	-0.015 ***	-0.002
DTI-all		0.784 ***	0.601 ***	0.751 **	0.588 **
Turnover		-2.063 **	-1.737 **	-2.008 *	-1.744 **
Bank Ratio				0.011	0.016
House Age				-0.029	-0.031
Selfemployment				-0.210	-0.207
Inc×AA			0.124 ***		0.126 ***
CS×AA			-0.004 ***		-0.004 ***
Constant	132.164 ***	139.795 ***	165.287 ***	137.830 ***	163.058 ***
n	98	98	98	98	98
adjusted R ²	0.5763	0.7561	0.8016	0.7553	0.8033
BIC	612.22	568.68	555.44	579.45	564.97

Note 1. Model: OLS Regression

2. *** (**) (*): Significant at the 99% (95%) (90%) level

19. Results for the Share of Subprime Mortgage in the Columbus MSA in Period 1 (2004-2007)

- Proportion of African-Americans is significantly and positively associated with the share of loans being a subprime: The higher the proportion of African-Americans in a neighborhood, the higher the share of subprime loans. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to increase the share of loans being subprime by 0.16 percentage points. However, the interaction term (CS×AA) indicates that the positive impact of proportion of African-Americans is mitigated by higher neighborhood credit score.
- Neighborhood credit score and income themselves are, on the other hand, significantly and negatively associated with the share of subprime loans: the higher the credit score and income, the lower the share of loans being a subprime.

	Basic Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.108 ***	-0.110 ***	-0.078 ***	-0.107 ***	-0.075 **
Proprtion AA	0.173 ***	0.161 ***	3.685 ***	0.166 ***	3.687 ***
Log Income	-5.801 *	-6.474 **	-7.474 ***	-6.403 **	-7.263 **
House Price Change		0.004	0.005	0.000	0.001
DTI-all		0.374 *	0.327 *	0.356	0.310
Turnover		-0.076	-0.076	-0.114	-0.117
Bank Ratio				-0.009	-0.004
House Age				0.018	0.023
Selfemployment				0.138 *	0.132 *
CS×AA			-0.005 ***		-0.005 ***
Constant	150.1 ***	144.314 ***	135.978 ***	140.595 ***	130.380 ***
n	112	112	112	112	112
adjusted R ²	0.6202	0.6407	0.7203	0.6396	0.6902
BIC	682.29	687.10	666.33	698.34	685.00

Note 1. Model: OLS Regression

2. *** (**)(*) :Significant at the 99% (95%) (90%) level

20. Results for the Share of Subprime Mortgage in the Dayton MSA in Period 1 (2004-2007)

- Proportion of African-Americans is significantly and positively associated with the share of loans being a subprime: The higher the proportion of African-Americans in a neighborhood, the higher the share of subprime loans. In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to decrease the conventional mortgage origination count by 0.23 percentage points. However, the interaction term (**Inc×AA**) indicates that the positive impact of proportion of African-Americans is expected to be lowered by higher neighborhood income.
- Neighborhood credit score and income themselves are, on the other hand, significantly and negatively associated with the share of subprime loans: the higher the credit score and income, the lower the share of loans being a subprime.
- Housing price change and turnover rate are negatively associated with the share of subprime loans: The higher the housing price changes and the turnover rate, the lower the share of loans being a subprime.

	Basic Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.091 *	-0.115 ***	-0.172 ***	-0.147 ***	-0.208 ***
Proprtion AA	0.219 ***	0.231 ***	2.768 ***	0.230 ***	2.492 ***
Log Income	-17.592 ***	-15.987 ***	-7.986 **	-13.928 ***	-4.640 ***
House Price Change		-0.056 ***	-0.046 ***	-0.068 ***	-0.057 ***
DTI-all		0.385 *	-0.026	0.377 *	-0.102
Turnover		-1.657 ***	-1.416 ***	-1.687 ***	-1.486 ***
Bank Ratio				-0.011	-0.027
House Age				0.050	0.071
Selfemployment				0.319 *	0.246
Inc×AA			-0.246 ***		-0.267 ***
CS×AA			0.000		-0.001
Constant	266.3 ***	255.748 ***	223.168 ***	251.272 ***	239.560 ***
n	55	55	55	55	55
adjusted R ²	0.8325	0.9069	0.9282	0.9299	0.9345
BIC	335.75	312.14	303.57	316.92	306.78

Note 1. Model: OLS Regression

2. *** (**) (*): Significant at the 99% (95%) (90%) level

21. Results for the Share of Subprime Mortgage in the Toledo MSA in Period 1 (2004-2007)

- Proportion of African-Americans is significantly and positively associated with the share of loans being a subprime: However, the interaction term (CS×AA) indicates that the positive impact of proportion of African-Americans is expected to be mitigated by higher neighborhood credit score.
- Neighborhood credit score and income themselves are, on the other hand, significantly and negatively associated with the share of subprime loans: the higher the credit score and income, the lower the share of loans being a subprime.

	Basic Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.101 ***	-0.105 **	-0.084 **	-0.133 ***	-0.113 **
Proprtion AA	-0.020	-0.048	1.910 **	-0.040	1.741 **
Log Income	-13.485 ***	-15.532 ***	-17.647 ***	-11.842 *	-14.118 **
House Price Change		0.002	-0.003	0.013	0.008
DTI-all		0.255	0.244	0.316	0.303
Turnover		-0.261	-0.453	-0.088	-0.269
HPC×Turnover					
Bank Ratio				0.077 *	0.070 *
House Age				-0.058	-0.057
Selfemployment				-0.468	-0.432
Inc×AA					
CS×AA			-0.003 **	***	-0.003 **
Constant	229.4 ***	244.719 ***	254.898 ***	226.318 ***	238.214 ***
n	58	58	58	58	58
adjusted R ²	0.6235	0.6294	0.6490	0.6418	0.6578
BIC	354.992	362.94	362.69	369.62	369.82

Note 1. Model: OLS Regression

2. *** (**) (*):Significant at the 99% (95%) (90%) level

22. Results for the Share of FHA Mortgage in the Cleveland MSA in Period 2 (2008-2011)

- Proportion of African-Americans is significantly and negatively associated with the share of loans being FHA-insured: However, an interaction term (**Inc×AA**) indicates that the negative impact of proportion of African-Americans is expected to be lowered by higher neighborhood income in Model A and Full Model 1 and 2. In other words, higher incomes as the proportion of African-Americans increased in neighborhoods increase the share of loans being a FHA-insured.
- Neighborhood credit score itself is significantly and negatively associated with the FHA share: the higher the credit score, the lower the share of loans being a FHA-insured.
- Self-employment rate and Turnover rate are negatively associated with FHA shares: The higher the self-employment rate and turnover rate in a neighborhood, the lower the loans being FHA-insured.

	Base Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.885 ***	-0.854 ***	-0.929 ***	-0.723 ***	-0.791 ***
Proportion AA	-4.391 ***	-3.514 ***	-4.165 ***	-3.640 ***	-4.163 ***
Log Income	-2.008	4.140	8.068	4.309	8.018
Selfemployment		-0.902 ***	-0.888 ***	-0.890 ***	-0.884 ***
Turnover		-0.531 **	-0.517 **	-0.716 ***	-0.695 ***
House Price Change				0.090	0.098
DTI-all				1.226 **	1.198 *
Bank Ratio				-0.238	-0.218
House Age				0.200 **	0.211 **
Inc×AA	0.394 ***	0.311 ***	0.243 *	0.323 ***	0.262 **
CS×AA			0.002		0.002
Constant	694.040 ***	614.006 ***	623.079 ***	464.525 ***	471.372 ***
n	93	93	93	93	93
adjusted R ²	0.7898	0.8258	0.8260	0.8364	0.8361
BIC	693.58	683.05	686.39	690.88	694.48

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

23. Results for the Share of FHA Mortgage in the Cincinnati MSA in Period 2 (2008-2011)

- Proportion of African-Americans is positively associated with the share of loans being a FHA-insured: In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to increase the FHA share by 0.19 %.
- Neighborhood credit score is significantly and negatively associated with the FHA share: the higher the credit score and income, the lower the share of loans being a FHA-insured.

	Base Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.451 ***	-0.430 ***	-0.376 ***	-0.382 ***	-0.306 **
Proportion AA	0.213 ***	0.194 ***	2.821	0.160 *	3.124 *
Log Income	3.786	3.472	1.813	-0.702	-2.959
Selfemployment		-0.490	-0.504	-0.401	-0.411
Turnover		0.004	-0.008	-0.045	-0.058
House Price Change				-0.093 *	-0.087
DTI-all				0.899	1.066
Bank Ratio				0.182	0.168
House Age				-0.013	-0.004
CS×AA			-0.004		-0.004
Constant	318.698 ***	311.544 ***	291.874 ***	291.892 ***	257.426 ***
n	92	92	92	92	92
adjusted R ²	0.5723	0.5744	0.5812	0.5906	0.6006
BIC	693.44	699.93	701.89	710.06	711.19

Note 1. Model: OLS Regression

2. *** (**) (*): Significant at the 99% (95%) (90%) level

24. Results for the Share of FHA Mortgage in the Columbus MSA in Period 2 (2008-2011)

- Proportion of African-Americans is significantly and positively associated with the share of loans being a FHA-insured: In Reduced Model 1, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to increase the FHA share by 0.27 %.
- Once a model includes interaction terms, proportion of African-Americans turns to be negatively associated with the share of loans being a FHA-insured; however, an interaction term (**Inc×AA**) indicates that the negative impact of proportion of African-Americans is expected to be lowered by higher neighborhood income in Model A and B. In other words, higher incomes as the proportion of African-Americans increased in neighborhoods increase the share of loans being a FHA-insured.
- Another interaction term (**CS×AA**) indicates that the negative impact of proportion of African-Americans to the FHA share is expected to be magnified by higher neighborhood credit score in Model B and Full Model 2
- Neighborhood credit score is significantly and negatively associated with the FHA share: the higher the credit score and income, the lower the share of loans being a FHA-insured.
- The median age of housing units is negatively associated with FHA shares: The higher the median age of housing unit in a neighborhood, the lower the loans being FHA-insured. However, in this period, the median age of housing units is also negatively associated with conventional mortgage originations. These results imply that the higher median age of housing units in a neighborhood seems to be a serious impact on mortgage lending in the Columbus MSA during Period 2.

	Base Model Coefficient	Reduced Model 1 Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.375 ***	-0.447 ***	-0.413 ***	-0.349 ***	-0.401 ***	-0.329 ***
Proportion AA	0.320 ***	0.268 ***	-7.144 ***	-2.122	0.210 **	-1.223
Log Income	0.648	5.458	-3.669	-4.961	-4.219	-10.561 **
Selfemployment		-1.359 ***	-0.913 ***	-0.826 ***	-1.276 ***	-0.838 ***
Turnover		0.016	0.017	0.010	0.001	0.008
House Price Change					-0.200 ***	-0.093
DTI-all					0.114	0.111
Bank Ratio					-0.089	0.004
House Age					-0.261 ***	-0.217 ***
Inc×AA			0.708 ***	0.782 ***		0.641 ***
CS×AA				-0.008 **		-0.008 **
Constant	301.416 ***	312.063 ***	383.268 ***	351.913 ***	397.021 ***	406.254 ***
n	97	97	97	97	97	97
adjusted R ²	0.4877	0.5840	0.6780	0.6968	0.6628	0.7142
BIC	759.57	746.42	725.06	722.72	739.97	727.38

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

25. Results for the Share of FHA Mortgage in the Dayton MSA in Period 2 (2008-2011)

- Proportion of African-Americans is significantly and negatively associated with the share of loans being a FHA-insured: However, the interaction term (**Inc×AA**) indicates that the negative impact of the proportion of African-Americans to the FHA share is expected to be lowered by higher neighborhood income.
- Neighborhood credit score and income are significantly and negatively associated with the FHA share: the higher the credit score and income, the lower the share of loans being a FHA-insured.
- Self-employment rate and Turnover rate are also negatively associated with FHA shares: The higher the self-employment rate and turnover rate in a neighborhood, the lower the loans being FHA-insured.

	Base Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.283 **	-0.280 **	-0.237 **	-0.332 ***	-0.282 **
Proportion AA	-10.896 ***	-10.521 ***	-6.436 *	-9.839 **	-6.079 *
Log Income	-16.751 *	-19.481 **	-20.325 **	-17.352 **	-18.949 **
Selfemployment		-0.945 **	-1.071 ***	-0.956 *	-1.060 **
Turnover		-0.286 ***	-0.292 ***	-0.300 ***	-0.301 ***
House Price Change				-0.137	-0.135
DTI-all				-0.411	-0.253
Bank Ratio				-0.193	-0.217
House Age				-0.117	-0.126
Log Inc×AA	1.046 ***	0.998 ***	0.914 ***	0.931 **	0.856 ***
CS×AA			-0.005		-0.004
Constant	427.2 ***	467.5 ***	447.981 ***	503.817 ***	483.053 ***
n	51	51	51	51	51
adjusted R ²	0.5567	0.7239	0.7275	0.7138	0.7154
BIC	399.66	381.11	383.20	393.80	396.16

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

26. Results for the Share of FHA Mortgage in the Toledo MSA in Period 2 (2008-2011)

- Proportion of African-Americans is significantly and positively associated with the share of loans being FHA-insured: In Model A, a one-percentage-point increases in the proportion of African-Americans in a neighborhood is expected to increase the FHA share by 0.34%. However, an interaction term ($CS \times AA$) indicates that the positive impact of proportion of African-Americans to the FHA share is expected to be lowered by higher neighborhood credit score in Model B.
- Neighborhood credit score is significantly and negatively associated with the FHA share: the higher the credit score and income, the lower the share of loans being a FHA-insured.
- Self-employment rate and Turnover rate are also negatively associated with FHA shares: The higher the self-employment rate and turnover rate in a neighborhood, the lower the loans being FHA-insured.

	Base Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.259 ***	-0.249 ***	-0.128	-0.229 **	-0.108
Proportion AA	0.228	0.338 ***	3.794 **	0.357 ***	3.736 *
Log Income	-6.183	16.117 *	9.050	13.604	8.091
Selfemployment		-3.349 ***	-3.214 ***	-3.295 ***	-3.161 ***
Turnover		-0.533 ***	-0.512 ***	-0.551 ***	-0.518 ***
House Price Change				0.088	0.031
DTI-all				0.157	0.078
Bank Ratio				-0.024	-0.108
House Age				-0.035	0.010
CS \times AA			-0.005 **		-0.005
Constant	284.552 ***	61.862	54.779	69.775	47.922
n	51	51	51	51	51
adjusted R ²	0.3441	0.5918	0.6103	0.5605	0.5743
BIC	419.68	401.14	401.56	415.89	416.94

Note 1. Model: OLS Regression

2. *** (**) (*): Significant at the 99% (95%) (90%) level

27. Results for the Share of FHA Mortgage in the Cleveland MSA in Period 3 (2012-2015)

- Proportion of African-Americans is significantly and negatively associated with the share of loans being a FHA-insured: However, the interaction term (**Inc×AA**) indicates that the negative impact of proportion of African-Americans to the FHA share is expected to be lowered by higher neighborhood income. In other words, higher incomes as the proportion of African-Americans increased in neighborhoods increase the share of loans being a FHA-insured.
- Neighborhood credit score is significantly and negatively associated with the FHA share: the higher the credit score, the lower the share of loans being a FHA-insured.
- Self-employment rate is also negatively associated with FHA shares: The higher the self-employment rate and turnover rate in a neighborhood, the lower the loans being FHA-insured.
- DTI is positively associated with FHA share: The higher the DTI, the higher the FHA share.
- Turnover rate is negatively associated with FHA shares: On the other hand, the interaction term (**Turnover×House Age**) indicates that this trend cannot be seen in neighborhoods with higher median age of housing units.

	Base Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.675 ***	-0.412 **	-0.152	-0.564 ***	-0.389 **
Proportion AA	-4.085 ***	-4.820 ***	-2.012	-3.945 ***	-2.394 *
Log Income	-11.591	-12.368 *	-23.581 **	-5.114	-12.296
Selfemployment		-1.235 ***	-1.250 ***	-1.173 ***	-1.202 ***
House Price Change		-0.296 *	-0.319 **	-0.179 *	-0.213 *
DTI-all		1.164 **	1.190 **	1.024 ***	0.998 **
House Age				-0.075	-0.043
Bank Ratio				-10.509	-17.866
Turnover				-2.281 **	-1.829 **
Turnover×House Age				0.052 ***	0.042 ***
Inc×AA	0.388 ***	0.456 ***	0.653 ***	0.377 ***	0.497 ***
CS×AA			-0.007 *		-0.004
Constant	648.96 ***	434.29 ***	371.32 ***	472.87 ***	426.2 ***
n	93	93	93	93	93
adjusted R ²	0.7008	0.7796	0.8118	0.8427	0.8508
BIC	729.6	711.6	700.3	693.8	692.3

Note 1. Model: OLS Regression

2. *** (**) (*): Significant at the 99% (95%) (90%) level

28. Results for the Share of FHA Mortgage in the Cincinnati MSA in Period 3 (2012-2015)

- Proportion of African-Americans is positively associated with the share of loans being a FHA-insured in a model where the interaction term (**CS×AA**) is included. This indicates that the positive impact of proportion of African-Americans to the FHA share is expected to be lowered by higher neighborhood credit score. In other words, higher credit scores as the proportion of African-Americans increased in neighborhoods decrease the share of loans being a FHA-insured.
- Neighborhood credit score itself is significantly and negatively associated with the FHA share: the higher the credit score, the lower the share of loans being a FHA-insured.
- Housing price change from 2011 to 2015 and turnover rate are also negatively associated with FHA shares: The higher the housing price change and turnover rate in a neighborhood, the lower the loans being FHA-insured.
- DTI is positively associated with FHA share: The higher the DTI, the higher the FHA share.

	Base Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.611 ***	-0.514 ***	-0.452 ***	-0.511 ***	-0.432 ***
Proportion AA	0.033	0.086	3.290 **	0.071	3.856 **
Log Income	-3.867	-0.201	-1.790	-1.684	-3.826
Selfemployment		-0.322	-0.345	-0.316	-0.340
House Price Change		-0.286 **	-0.257 **	-0.220 *	-0.178
DTI-all		0.897 **	0.843 **	0.894 ***	0.857 **
House Age				-0.005	0.004
Bank Ratio				12.312	9.941
Turnover				-0.072 **	-0.083 ***
CS×AA			-0.004 **		-0.005 **
Constant	517.90 ***	376.43 ***	351.07 ***	390.71 ***	359.15 ***
n	91	91	91	91	91
adjusted R ²	0.7060	0.7547	0.7622	0.7625	0.7742
BIC	650.3	644.1	644.7	651.4	650.2

Note 1. Model: OLS Regression

2. *** (**)(*): Significant at the 99% (95%) (90%) level

29. Results for the Share of FHA Mortgage in the Columbus MSA in Period 3 (2012-2015)

- In Model A and Full Model 1, proportion of African-Americans is significantly and negatively associated with the share of loans being FHA-insured: however, interaction terms (**Inc×AA**) in the both model indicate that higher income is expected to lower the magnitude of proportion of African-Americans. In other words, higher incomes as the proportion of African-Americans increased in neighborhoods increase the share of loans being a FHA-insured.
- Another interaction term (**CS×AA**) indicates that the negative impact of proportion of African-Americans to the FHA share is expected to be magnified by higher neighborhood credit score in Model B and Full Model 2: The higher the credit score in African-American neighborhoods, the lower the FHA share.
- Neighborhood credit score itself is significantly and negatively associated with the FHA share: the higher the credit score and income, the lower the share of loans being a FHA-insured.
- Housing price change from 2011 to 2015 is also negatively associated with FHA shares: The higher the housing price change, the lower the loans being FHA-insured.
- DTI is positively associated with FHA share: The higher the DTI, the higher the FHA share.

	Base Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.377 ***	-0.329 ***	-0.256 ***	-0.348 ***	-0.282 ***
Proportion AA	-4.306 ***	-3.767 **	3.960 *	-3.697 ***	3.335 *
Log Income	-4.162	-2.450	-4.696	-6.993	-8.079
Selfemployment		-0.226	-0.099	-0.236	-0.137
House Price Change		-0.216 *	-0.261 ***	-0.208	-0.251 **
DTI-all		0.913 **	0.472	0.939 **	0.551
House Age				-0.100	-0.067
Bank Ratio				20.879	21.028
Turnover				-0.050	-0.046
Inc×AA	0.441 ***	0.386 ***	0.495 ***	0.374 ***	0.476 ***
CS×AA			-0.013 ***		-0.011 ***
Constant	344.44 ***	260.03 ***	247.777 ***	327.83 ***	304.16 ***
n	101	101	101	101	101
adjusted R ²	0.6250	0.6515	0.7032	0.6803	0.7231
BIC	749.0	752.3	739.59	754.1	743.1

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

30. Results for the Share of FHA Mortgage in the Dayton MSA in Period 3 (2012-2015)

- Proportion of African-Americans is significantly and negatively associated with the share of loans being FHA-insured: However, the interaction term (**Inc×AA**) indicates that the negative impact of proportion of African-Americans to the FHA share is expected to be lowered by higher neighborhood income. In other words, higher incomes as the proportion of African-Americans increased in neighborhoods increase the share of loans being a FHA-insured.
- Neighborhood credit score and income are significantly and negatively associated with the FHA share: the higher the credit score, the lower the share of loans being a FHA-insured.
- Self-employment rate is negatively associated with FHA shares: The higher the self-employment rate and turnover rate in a neighborhood, the lower the loans being FHA-insured.

	Base Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.255 ***	-0.385 ***	-0.364 ***	-0.398 ***	-0.407 ***
Proportion AA	-9.423 ***	-6.969 ***	-6.594 ***	-6.742 ***	-6.899 ***
Log Income	-25.406 ***	-15.572 ***	-16.437 ***	-12.663 **	-12.243 *
Selfemployment		-1.118 ***	-1.111 ***	-0.938 **	-0.942 **
House Price Change		-0.185	-0.183	-0.135	-0.136
DTI-all		-0.391	-0.338	-0.336	-0.361
House Age				0.068	0.067
Bank Ratio				-31.536	-32.761
Turnover				-0.315	-0.319
Inc×AA	0.900 ***	0.659 ***	0.665 ***	0.636 ***	0.632 ***
CS×AA			-0.001		0.000
Constant	497.24 ***	506.12 ***	499.08 ***	480.83 ***	483.75 ***
n	50	50	50	50	50
adjusted R ²	0.6655	0.7513	0.7456	0.7068	0.7438
BIC	371.6	365.1	368.9	373.31	377.2

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

31. Results for the Share of FHA Mortgage in the Toledo MSA in Period 3 (2012-2015)

- Proportion of African-Americans is significantly and negatively associated with the share of loans being FHA-insured: However, the interaction term (**Inc×AA**) indicates that the negative impact of proportion of African-Americans to the FHA share is expected to be lowered by higher neighborhood income. In other words, higher incomes as the proportion of African-Americans increased in neighborhoods increase the share of loans being a FHA-insured.
- Neighborhood credit score and income are significantly and negatively associated with the FHA share: the higher the credit score, the lower the share of loans being a FHA-insured.
- Self-employment rate is negatively associated with FHA shares: The higher the self-employment rate and turnover rate in a neighborhood, the lower the loans being FHA-insured.

	Base Model Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.166 *	-0.175 **	-0.034	-0.206 **	-0.031
Proportion AA	-12.035 ***	-10.436 ***	2.918	-9.240 **	2.614
Log Income	-29.425 ***	-23.905 ***	-25.418 ***	-9.591	-21.206 ***
Selfemployment		-1.238 **	-1.230 **	-1.555 **	-1.704 **
House Price Change		-0.022	-0.114	-0.240	-0.120
DTI-all		0.586	0.619	0.372	0.543
House Age				0.272 *	0.166
Bank Ratio				43.335	46.115
Turnover				0.080 *	0.011
Inc×AA	1.170 ***	1.016 ***	0.644 ***	0.907 **	0.686 ***
CS×AA			-0.013 ***		0.000 ***
Constant	469.65 ***	403.59 ***	319.009 ***	258.59 **	264.77 ***
n	52	52	52	52	52
adjusted R ²	0.6001	0.6308	0.7187	0.5619	0.7217
BIC	403.3	407.6	396.2	414.0	403.7

Note 1. Model: OLS Regression

2. *** (**) (*): Significant at the 99% (95%) (90%) level

32. Results for the APR Spread for Conventional Mortgages in the Cleveland MSA in Period 2 (2007-2011)

- Proportion of African-Americans is significantly and negatively associated with the share of loans being FHA-insured: However, the interaction term (CS×AA) indicates that the negative impact of proportion of African-Americans to the APR spread is expected to be lowered by higher neighborhood credit score in Model B and Full Model 2. In other words, higher credit scores as the proportion of African-Americans increase in neighborhoods increase the APR spread.
- Neighborhood credit score itself is significantly and negatively associated with APR spread: The lower the credit score, the higher the APR spread.
- Bank brunch numbers per housing unit in a neighborhood is negatively associated with conventional mortgage origination. This means that the more bank branches in a neighborhood, the lower the APR spread (Model A). Particularly, this can be seen in neighborhoods with higher proportion of African-Americans (Model B). In other words, access to bank is important in African-American neighborhoods for costs of mortgages.

	Base Model 1 Coefficient	Base Model 2 Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.555 **	-0.831 ***	-0.363	-0.662 ***	-0.321	-0.610 ***
Proportion AA	-0.293 *	-7.404 *	-0.372 **	-12.341 **	-0.338 **	-13.441 ***
Log Income	9.270	17.096	13.502	14.144	17.149	21.483
Turnover			-1.407 **	-0.733	-0.970	-0.391
House Age			0.315	0.195	0.344	0.376 *
DTI-conv			0.239	0.455	0.033	0.239
Bank Ratio			-1.581 ***	-0.289	-1.571 **	0.036
Bank×AA				-0.098 **		-0.112 **
House Price Change					0.036	0.327
LTV-conv					-0.003	0.195
Selfemployment					-0.900	-1.105
CS×AA		0.011 *		0.018 **		0.020 ***
Constant	297.657 ***	405.111 ***	109.293	299.012 **	50.868	166.112
n	94	94	94	94	94	94
adjusted R ²	0.0850	0.1313	0.1898	0.3070	0.1724	0.3128
BIC	893.8	892.4	896.2	888.4	908.5	897.8

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

33. Results for the APR Spread for Conventional Mortgages in the Cincinnati MSA in Period 2 (2007-2011)

- Proportion of African-Americans has no association with APR spread.
- Neighborhood credit score is significantly and negatively associated with APR spread: the higher the credit score, the lower the APR spread.
- The median age of housing units is also positively associated with the APR spreads: The higher the median age of housing unit in a neighborhood, the higher the APR spreads.

	Base Model 1 Coefficient	Base Model 2 Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.421 ***	-0.466 ***	-0.320 ***	-0.326 ***	-0.369 ***	-0.388 ***
Proportion AA	-0.030	-2.332	-0.156 *	-0.355	-0.169	-0.814
Log Income	-4.896	-3.606	-5.469	-5.284	-6.095	-5.515
Turnover			-0.025	-0.024	-0.081	-0.076
House Age			0.342 ***	0.342 ***	0.330 ***	0.330 ***
DTI-conv			1.402 *	1.393 *	1.312 *	1.284 *
Bank Ratio			0.157	0.158	0.149	0.152
House Price Change					-0.026	-0.027
LTV-conv					-0.208	-0.217
Selfemployment					0.586	0.589
CS×AA		0.003		0.000		0.001 ***
Constant	357.907 ***	375.165 ***	231.014 ***	233.107 ***	289.125 ***	297.944 ***
n	91	91	91	91	91	91
adjusted R ²	0.3936	0.3933	0.5497	0.5443	0.5523	0.5472
BIC	742.1	745.6	728.8	733.3	738.4	742.8

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

34. Results for the APR Spread for Conventional Mortgages in the Columbus MSA in Period 2 (2007-2011)

- Proportion of African-Americans is significantly and positively associated with APR spread: the higher the proportion of African-Americans the higher the APR spread. However, the interaction term (CS×AA) indicates that the positive impact of proportion of African-Americans to the APR spread is expected to be lowered by higher neighborhood credit score. In other words, lower credit scores as the proportion of African-Americans increased in neighborhoods increase the APR spread.
- Neighborhood credit score itself is significantly and negatively associated with APR spread: The higher the credit score, the lower the APR spread.
- Turnover rate is negatively associated with APR spread: The higher the turnover rate in a neighborhood, the lower the APR spread.
- DTI is positively associated with APR spread: The higher the DTI, the higher the APR spread.

	Base Model 1 Coefficient	Base Model 2 Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.359 ***	-0.258 ***	-0.401 ***	-0.293 ***	-0.382 ***	-0.244 ***
Proportion AA	0.012	9.016 **	-0.007	9.982 ***	-0.045	11.301 ***
Log Income	-12.992 ***	-14.583 ***	-5.969	-6.721	-8.856	-10.143 *
Turnover			-0.148 ***	-0.153 ***	-0.153 **	-0.164 ***
House Age			0.145	0.172 *	0.128	0.155 *
DTI-conv			0.695 *	0.781 **	0.645	0.763 **
Bank Ratio			-0.226	-0.182	-0.235	-0.200
House Price Change					-0.153 *	-0.199 **
LTV-conv					-0.044	0.068
Selfemployment					-0.016	0.064
CS×AA		-0.013 **		-0.014 ***		-0.016 ***
Constant	401.762 ***	348.671 ***	327.987 ***	257.079 ***	356.472 ***	260.491 ***
n	99	99	99	99	99	99
adjusted R ²	0.4975	0.5420	0.5823	0.6399	0.5934	0.6685
BIC	780.2	774.6	776.0	764.8	783.8	767.1

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

35. Results for the APR Spread for Conventional Mortgages in the Dayton MSA in Period 2 (2007-2011)

- Proportion of African-Americans is not significant and has no association with APR spread.
- Among all variables, only neighborhood credit score is significantly and negatively associated with APR spread: The higher the credit score, the lower the APR spread.

	Base Model 1 Coefficient	Base Model 2 Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.370 ***	-0.403 ***	-0.351 ***	-0.385 ***	-0.300 ***	-0.331 ***
Proportion AA	-0.094	-3.733	-0.063	-3.656	-0.048	-3.972 *
Log Income	-10.519	-9.475	-12.373	-10.524	-14.160	-12.541
Turnover			0.109	0.111	0.075	0.075
House Age			-0.059	-0.046	0.003	0.016
DTI-conv			-0.178	-0.164	-0.380	-0.376
Bank Ratio			0.209	0.129	0.188	0.111
House Price Change					0.149	0.153
LTV-conv					0.295	0.331
Selfemployment					-0.175	-0.139
CS×AA		0.005		0.005		0.006
Constant	387.174 ***	398.753 ***	400.774 ***	402.682 ***	364.015 ***	364.025 ***
n	53	53	53	53	53	53
adjusted R ²	0.4748	0.4810	0.4545	0.4595	0.4453	0.4538
BIC	413.6	415.9	427.0	429.3	436.2	438.0

Note 1. Model: OLS Regression

2. *** (**) (*): Significant at the 99% (95%) (90%) level

36. Results for the APR Spread for Conventional Mortgages in the Toledo MSA in Period 2 (2007-2011)

- Proportion of African-Americans is significantly and positively associated with APR spread: the higher the proportion of African-Americans the higher the APR spread. However, the interaction term (CS×AA) indicates that the positive impact of proportion of African-Americans to the APR spread is expected to be lowered by higher neighborhood credit score. In other words, lower credit scores as the proportion of African-Americans increased in neighborhoods increase the APR spread.
- Neighborhood credit score itself is significantly and negatively associated with APR spread: the higher the credit score, the lower the APR spread.
- Loan-to-value ratio is positively associated with APR spread: The higher the LTV ratio, the higher the APR spread.

	Base Model 1 Coefficient	Base Model 2 Coefficient	Model A Coefficient	Model B Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.597 ***	-0.420 ***	-0.566 ***	-0.360 ***	-0.465 ***	-0.255 **
Proportion AA	0.138	5.299 ***	0.104	5.363 ***	0.194	5.854 ***
Log Income	1.121	-6.134	0.480	-4.877	2.503	-5.436
Turnover			-0.405	-0.380	-0.471	-0.392
House Age			-0.172	-0.057	-0.220	-0.101
DTI-conv			0.072	-0.037	0.177	0.063
Bank Ratio			-0.844	-0.912	-0.685	-0.789
House Price Change					0.077	0.009
LTV-conv					0.720 **	0.723 **
Selfemployment					-0.084	0.402
CS×AA		-0.008 ***		-0.008 ***		-0.008 ***
Constant	416.770 ***	373.977 ***	417.697 ***	331.712 ***	260.182 *	197.510
n	49	49	49	49	49	49
adjusted R ²	0.4636	0.4901	0.5045	0.5334	0.5467	0.5809
BIC	418.5	418.8	425.6	425.3	429.2	427.9

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

37. Results for the APR Spread for Conventional Mortgages in the Cleveland MSA in Period 3 (2012-2015)

- Proportion of African-Americans is significantly and positively associated with APR spread: the higher the proportion of African-Americans the higher the APR spread. However, the interaction term (CS×AA) indicates that the positive impact of proportion of African-Americans to the APR spread is expected to be lowered by higher neighborhood credit score. In other words, lower credit scores as the proportion of African-Americans increased in neighborhoods increase the APR spread
- Neighborhood credit score and income are significantly and negatively associated with APR spread: the higher the credit score, the lower the APR spread.

	Model A	Model B	Reduced Model 1	Reduced Model 2	Full Model 1	Full Model 2
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Credit Score	-0.458 ***	-0.262 **	-0.375 ***	-0.196 *	-0.379 ***	-0.162
Proportion of AA	0.042	4.104 ***	0.063	3.898 ***	0.038	4.138 ***
Log Income	-4.706	-9.187 **	-6.404 *	-10.229 **	-9.518 **	-12.083 ***
LTV-conv			0.396	0.412	0.394	0.367
DTI-conv			0.430	0.214	0.255	0.024
Turnover					-0.337	-0.298
House Price Change					-0.051	-0.082
Bank Ratio					-0.158	-0.296
House Age					-0.065	0.000
Selfemployment					0.550	0.357
CS×AA		-0.006 ***		-0.005 ***		-0.006 ***
Constant	396.769 ***	305.652 ***	-308.361 ***	-227.413 ***	352.256 ***	234.204 *
n	92	92	92	92	92	92
adjusted R ²	0.5716	0.6189	0.5847	0.6253	0.5769	0.6213
BIC	697.44	690.16	701.51	695.48	720.32	713.50

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

38. Results for the APR Spread for Conventional Mortgages in the Cincinnati MSA in Period 2 (2007-2011)

- Proportion of African-Americans is not significant and has no association with APR spread.
- Neighborhood credit score and income is significantly and negatively associated with APR spread: the higher the credit score, the lower the APR spread.

	Model A Coefficient	Model B Coefficient	Reduced Model 1 Coefficient	Reduced Model 2 Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.248 ***	-0.253 **	-0.227 ***	-0.213 **	-0.198 **	-0.191 *
Proportion of AA	-0.102	-0.276	-0.085	0.447	-0.065	0.231
Log Income	-18.523 ***	-18.415 ***	-16.429 ***	-16.723 ***	-14.826 ***	-15.005 **
LTV-conv			0.479 *	0.488 *	0.517 *	0.522 *
DTI-conv			-0.524	-0.522	-0.473	-0.471
Turnover					-0.053 *	-0.053 *
House Price Change					-0.037	-0.034
Bank Ratio					-0.209	-0.206
House Age					-0.045	-0.044
Selfemployment					-0.233	-0.237
CS×AA		2E-04		-0.001		0.000
Constant	399.535 ***	401.322 ***	336.918 ***	329.570 ***	298.918 ***	295.243 ***
n	92	92	92	92	92	92
adjusted R ²	0.5416	0.5363	0.5808	0.5761	0.5685	0.5632
BIC	687.07	691.58	685.78	690.23	705.52	710.03

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

39. Results for the APR Spread for Conventional Mortgages in the Columbus MSA in Period 2 (2007-2011)

- Proportion of African-Americans is not significant and has no association with APR spread.
- Neighborhood credit score and income are significantly and negatively associated with APR spread: the higher the credit score, the lower the APR spread.

	Model A Coefficient	Model B Coefficient	Reduced Model 1 Coefficient	Reduced Model 2 Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.300 **	-0.249	-0.210 *	-0.169	-0.243 **	-0.197 *
Proportion of AA	-0.038	4.012	-0.028	3.447	0.072	4.267
Log Income	-10.165	-11.020 *	-11.535 **	-12.280 **	-8.621	-8.700
LTV-conv			0.554 *	0.528	0.464	0.427
DTI-conv			0.973	0.979	0.946	0.950
Turnover					0.029	0.030
House Price Change					0.197	0.175
Bank Ratio					-0.043	-0.031
House Age					0.119	0.140 *
Selfemployment					0.604	0.613
CS×AA		-0.006		-0.005		-0.006
Constant	346.955 ***	320.021 ***	217.676 ***	198.345 ***	207.032 ***	177.397 **
n	98	98	98	98	98	98
adjusted R ²	0.3295	0.3344	0.4096	0.4122	0.4208	0.4276
BIC	783.63	786.44	778.22	781.31	793.79	796.10

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

40. Results for the APR Spread for Conventional Mortgages in the Dayton MSA in Period 2 (2007-2011)

- Proportion of African-Americans is not significant and has no association with APR spread.
- Among all variables, only neighborhood credit score is significantly and negatively associated with APR spread: the higher the credit score, the lower the APR spread.

	Model A Coefficient	Model B Coefficient	Reduced Model 1 Coefficient	Reduced Model 2 Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.214 ***	-0.246 ***	-0.167	-0.245 *	-0.113	-0.183
Proportion of AA	0.142	-1.076	0.152	-2.988	0.109	-3.571
Log Income	-2.967	-1.675	1.346	5.425	-7.211	-1.581
LTV-conv			0.548	0.630	0.566	0.726 *
DTI-conv			-0.430	-0.528	-0.387	-0.495
Turnover					-0.190	-0.238
House Price Change					-0.202	-0.254
Bank Ratio					0.492	0.285
House Age					-0.197	-0.200
Selfemployment					0.721	0.752
CS×AA		0.002		0.004		0.005
Constant	198.629 ***	207.357 ***	83.667	90.934	138.627	117.479
n	50	50	50	50	50	50
adjusted R ²	0.2845	0.2718	0.3195	0.3238	0.3547	0.3640
BIC	383.07	386.77	386.16	388.61	397.04	398.93

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level

41. Results for the APR Spread for Conventional Mortgages in the Toledo MSA in Period 2 (2007-2011)

- Proportion of African-Americans is not significant and has no association with APR spread.
- Among all variables, only neighborhood credit score is significantly and negatively associated with APR spread: the higher the credit score, the lower the APR spread.

	Model A Coefficient	Model B Coefficient	Reduced Model 1 Coefficient	Reduced Model 2 Coefficient	Full Model 1 Coefficient	Full Model 2 Coefficient
Credit Score	-0.299 **	-0.134	-0.301	-0.152	-0.628 **	-0.369
Proportion of AA	0.069	11.387 *	0.036	11.069 *	0.196	11.826 **
Log Income	-8.147	-14.827 *	-9.924	-16.503	-9.606	-26.347 **
LTV-conv			-0.082	-0.142	-0.453	-0.223
DTI-conv			-0.381	-0.211	-0.687	-0.425
Turnover					0.142 **	0.036
House Price Change					0.257	0.474 *
Bank Ratio					0.779	0.877 *
House Age					-0.049	-0.197
Selfemployment					0.177	-0.047
CS×AA		-0.016 *		-0.016 *		-0.017 **
Constant	321.944 ***	278.342 ***	362.628 *	329.095 **	629.122 **	612.999 ***
n	49	49	49	49	49	49
adjusted R ²	0.2012	0.3250	0.1829	0.3010	0.3197	0.4181
BIC	409.24	403.79	415.91	411.00	420.34	415.27

Note 1. Model: OLS Regression

2. *** (**) (*) :Significant at the 99% (95%) (90%) level