The Spatial Distribution of Affordable Home Loan Purchases in Major Metropolitan Areas: Documentation and Analysis

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Abstract

Analysis of twenty large metropolitan areas shows that the spatial distribution of purchases made by Fannie Mae and Freddie Mac in support of the Low and Moderate- Income Housing Goal does not match the spatial distribution of low- and moderate-income households that apply for or take out a mortgage. Regression analysis then finds that both neighborhood traits and risk factors of goal-eligible applicants (or borrowers) are correlated with the degree of spatial mismatch between loan purchase activity and goal-eligible applications and originations. The most robust finding is consistent with a policy of the two GSEs targeting the purchase of Low and Moderate Income Housing Goal loans in relatively high income tracts. That is, the higher is a census tract's income relative to the median for its metropolitan area, the higher is the GSE purchase rate in the tract relative to that for the overall metropolitan area. Race effects are somewhat less robust across metropolitan areas, with the bulk of the evidence suggesting that suburban, not central city, tracts with relatively high concentrations of African-American households are more likely to have relatively low GSE purchase rates of Low and Moderate-Income Housing Goal loans. Finally, our analysis finds that a larger FHA presence is associated with a lower origination rate of conventional loans. We suspect that a stronger FHA presence increases the perceived risk of a neighborhood in most metropolitan areas, as FHA loans have a higher default risk.

1. Introduction

We document and analyze the intra-metropolitan distribution of single family mortgage purchases made by the Federal National Mortgage Association (FNMA or Fannie Mae) and the Federal Home Loan Mortgage Corporation (FHLMC or Freddie Mac) under three affordable housing goals set by the Department of Housing and Urban Development (HUD). The three goals are the Low- and Moderate-Income Housing Goal, the Geographically Targeted Housing Goal, and the Special Affordable Housing Goal. For brevity, they are referred to collectively as the affordable housing goals.

Recent research has increased our knowledge about how the two Government Sponsored Enterprises (GSEs) perform in aggregate with respect to fulfilling goal requirements (e.g., see Bunce and Scheessele (1996, 1998), Manchester (1998), and Manchester, *et. al*. (1998)). However, whether Fannie Mae and Freddie Mac meet their affordable housing goals with purchases proportional to the spatial distribution of low- and moderate-income mortgage applicants or borrowers remains unknown. The answer has important policy implications, as the interests of elected officials and taxpayers are involved (although their interests certainly need not coincide). For elected officials, the issue is how their constituencies fare with respect to the liquidity provided by the GSEs. For taxpayers, the issue is whether the GSEs are mitigating risks associated with the purchase of affordable housing goal loans by avoiding certain neighborhoods.

Our work is part of a growing literature on the geography of metropolitan opportunities (e.g., see Galster and Killen, 1995 and Abramson, et al, 1995). Within that body of research, there is an expanding set of analyses of the role neighborhood characteristics play in mortgage lending (e.g., Canner and Passmore, 1995a; Avery, et al, 1996; Van Order, 1996; MacDonald, 1996; Calem, 1996; Anseling and Can, 1998). These studies find that neighborhood characteristics, in addition to borrower-specific risks, are significantly correlated with mortgage origination. However, those studies do not directly examine the spatial distribution issues analyzed here.

We begin by comparing the intra-metropolitan spatial distribution of GSE affordable housing loan purchases with the analogous distributions for lower-income home mortgage applications and originations. The primary data sources for our investigation are the GSE Public Use Data Base and Home Mortgage Disclosure Act (HMDA) data, both over 1993-1996. The two data sets are merged at the census tract level and are used in conjunction with 1990 census data. These sources are employed in a detailed spatial analysis of over 20 large metropolitan areas that account for 31 percent of the nation's households in 1990, and 32 percent of GSE single family mortgage purchases in 1996.

Our analysis reveals a meaningful spatial mismatch in the sense that the intra-metropolitan area distributions of the GSEs' affordable loan purchases do not coincide with those for goal-eligible mortgage applicants or for goal-eligible originations.[1] We then try to identify factors that help account for why the GSEs do not purchase loans made in support of the Low and Moderate-Income Housing Goal in a manner that is spatially proportional either to the applications for or the originations of those loans.

Both neighborhood traits and the risk distribution among goal-eligible applicants (or borrowers) are found to help account for the spatial mismatch. The most robust finding is that the higher is the median income of a census tract relative to that for its metropolitan area, the greater is the degree of GSE mortgage purchase activity in that tract. That is, the GSEs help fulfill their low income housing goal requirements by purchasing eligible loans disproportionately from the stronger local housing markets of a metropolitan area. That this result holds with respect to the distributions of applications *and* originations suggests that the correlation is not driven primarily by lenders tending to originate low income loans in stronger local land markets.

Other local or neighborhood traits investigated include race and central city status. We find no substantial evidence that central city tracts with relatively high fractions of African-American households have relatively low rates of low income mortgage purchases by the GSEs. The racial impacts we do find exist primarily in suburban tracts. In the suburbs of most of the metropolitan areas studied, the purchase rate of low income loans is lower the higher the fraction of African-American households. On average in most metropolitan areas, there is not a significantly lower low income loan purchase rate in the typical central city tract. We also report evidence indicating that a larger FHA presence in a neighborhood is associated with a lower origination rate of conventional loans. While we cannot rule out other explanations, this result is consistent with a large FHA presence being associated with higher perceived risk on the part of conventional lenders.

Borrower-level risk controls such as household income also are found to influence materially the degree of spatial mismatch, with GSE purchase activity being greater the higher is mean borrower (or applicant) income in a tract. We also investigate the role of a number of proxies for supply and demand conditions. Those results suggest the GSEs prefer deeper markets and those with more owner-occupied housing.

The remainder of the paper focuses on our empirical work. Section 2 describes the three affordable housing goals. Section 3 then follows with an explanation of how we measure the spatial mismatch of affordable loan purchases and borrowers (or applicants). Sections 4

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[1] Our use of the term spatial mismatch obviously is in a different context from that of Kain (1962). We can think of no other term that better describes the focus of our analysis, and we trust that the terminology will not

and 5 detail the underlying estimations and results, respectively. A brief summary concludes the paper.

2. Affordable Housing Goals and Data

As GSEs, Fannie Mae and Freddie Mac are required to meet three affordable housing goals to serve lower income households and their communities. While our regression analysis concentrates on the Low and Moderate-Income Housing Goal described below, we provide summary statistics on all three goals to illustrate the scope of activity in support of affordable housing loan programs. In each case, our analysis focuses exclusively on the three goals as they relate to single family purchases. Very briefly, each goal can be described as follows. [See U.S. Department of Housing and Urban Development (1995) for detailed definitions.]

(1) Low- and Moderate-Income Goal. This goal applies to loans made on dwelling units for families whose incomes are less than or equal to their metropolitan area's median family income, and, hereafter, is referred to as Goal 1.

(2) Geographically Targeted Goal (for Central Cities, Rural Areas, and Other Underserved Areas). Within metropolitan areas, this goal (referred to as Goal 2) applies to loans made on dwelling units located in census tracts with: median income less than or equal to 90 percent of area median family income; or minority population share greater than or equal to 30 percent and median income less than or equal to 120 percent of area median family income. It is important to note that from 1993 to 1995, this goal was defined as a central city goal, which targeted mortgages made in central cities. In what follows, when we refer to "loans supporting Goal 2" we mean central city loans in 1993-1995 and loans supporting the goal based on its current definition in 1996.

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confuse readers familiar with Kain's hypothesis.

(3) Special Affordable Goal. This goal (Goal 3) applies to loans on dwelling units for families whose income is less than or equal to: 60 percent of area median income, or 80 percent of median income and who live in low-income areas (i.e., where the census tract median income also is no more than 80 percent of the area median).

Each of the goals is met through Freddie Mac's and Fannie Mae's secondary market purchases of home mortgages, and each goal is measured as a percentage of the total number of dwelling units financed by the GSEs (except for the multifamily component of the Special Affordable Goal, which is dollar value-based). One purchase can satisfy all three goals. However, when we report figures on aggregate GSE performance, we use the number of purchases that meets either of the three goals without double (or triple) counting.[2]

Three data sets are used in this research -- the GSE Public Use Database (PUDB) on loan purchases by the agencies, HMDA data on low- and moderate-income loan applicants and borrowers, and the 1990 Census. The PUDB is the primary source of information on single-family mortgage purchases by the GSEs, and includes cross sections of data from 1993-1996. The single family census tract loan level data of the GSE PUDB contain basic information about the borrowers, the location of the property, and demographic descriptors for the census tract. Aggregating the PUDB loan data at the census tract level, we can document the spatial distribution (within and across metropolitan areas) of GSE mortgage purchases in aggregate and for each affordable housing goal.

The HMDA data provide loan level application and origination information, including borrowers' demographic traits, loan type, loan amount, location of property, origination status

[2] To clarify, when reporting the number of loans supporting a particular goal, we count every purchase that meets the goal. However, when reporting the aggregate number of goal-supported loan purchases, a loan is counted only once even if it meets more than one goal's criteria.

and certain institutional variables. Aggregating the loan data at the census tract level, we can determine the number of loan applicants and originations in aggregate as well as the numbers of loan applicants and originations that meet the requirements for each affordable housing goal. In addition, we can determine the number of each type of affordable loan, average loan amount, and borrower's average income among other information.[3]

The limited number of census tract-level variables included in the PUDB and HMDA files make it useful to merge tract level data from the STF3 file of the 1990 census. Besides including a host of census tract-level data on household and housing stock characteristics, the STF3 files also provide each census tract with a place identifier that enables identification of the central cities of each metro area.

We then document and investigate loan purchase, applicant, and borrowing patterns in over twenty of the largest metropolitan areas in the nation. Because the house in which people hope to live need not be in the census tract in which they currently reside, our comparison of GSE purchase activity is not with the extant spatial distribution of low- and moderate-income households. This is not to suggest that it is uninteresting to know the extent to which the GSEs either do or do not provide liquidity in support of affordable housing goals in proportion to where lower income families currently live. However, we think it equally, if not more, interesting to know whether loan purchases are made in a spatially proportionate way with respect to where potential and actual low- and moderate-income owners ultimately decide to live.

Before getting to those issues of spatial mismatch, the first two tables report summary statistics on the three affordable housing goals. Table 1 lists the study areas and summarizes the

[3] The HMDA data also contain GSE purchase information, but merging the two data sets at the loan level is problematic. The coverage of GSE purchases in the HMDA files is not complete, as it has been estimated that the HMDA files contain only 70-75 percent of Freddie Mac's purchases (Berkovec and Zorn, 1996). In the results

basic information of GSE affordable loan purchases. In the 22 large metropolitan areas covered here, the total number of GSE loan purchases was over 870,000 in 1996, which accounts for about one third of total GSE loan purchases nationwide.[4] On average, nearly 49 percent of GSE loan purchases were used to support at least one of the affordable housing goals in these metro areas in 1996. Thirty-seven percent of the GSE loans meet Goal 1 requirements, 24 percent meet Goal 2 requirements, and 11 percent meet Goal 3 requirements. While nearly 50 percent of the GSE loans in these metro areas were made to support the affordable housing goals, there is a fairly wide cross-area spread. On average, the fraction of loan purchases in the studied metropolitan areas that meet the three goals is smaller than the national average by five percentage points.[5]

Table 2 shows that there was a steady increase in GSE purchases in terms of these goals from 1993 to 1996 in the study areas, which also is consistent with previously published work (see Bunce and Scheessele, 1996; 1998). In terms of the central city-suburban break down of those purchases, the changes tend to be smaller as shown in the bottom panel of the table. The one significant change in the central city share of affordable housing loans (a decline from 44 percent to 29 percent between 1995 and 1996) is due largely to the aforementioned change in Goal 2's definition.

3. Measuring the Spatial Mismatch of Affordable Loan Purchases and Goal-Eligible Borrowers

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reported below, we use the GSE PUDB as the primary source for GSE loan purchases. However, we did experiment with using HMDA on loan purchases. See the next section for the details.

[4] From 1993 to 1995, the number of GSE purchases in the studied areas declined 50%, with the number rising slightly in 1996. This pattern is consistent with the national trend. See Gyourko & Hu (1999) for detailed documentation of the purchases in years 1993-95.

[5] Fannie Mae's low income-related purchases for all three goals are about ten percent higher than Freddie Mac's in our metro areas, which is consistent with what has been found using national aggregate data (see Bunce & Scheessele, 1998). However, the difference between the two agencies in our studied areas is smaller than that at the national level.

We need to compare the spatial distribution of affordable loan purchases with those of goal-eligible applicants and/or borrowers to determine if there is a spatial mismatch between where affordable housing mortgage credit ends up being allocated and where potential or actual borrowers are within a metropolitan area. The ratio of a census tract's share of its metropolitan area's affordable housing loan purchases to its share of the metro area's goal-eligible mortgage applicants provides a measure of the extent to which the spatial distributions of loan purchases and potential borrowers differs. This ratio (SM^A for spatial mismatch with respect to goal-eligible applications) can be written as

$$SM_j^A = \frac{l_j}{\sum_{j=1}^{n} l_j} \bigg/ \frac{h_j}{\sum_{j=1}^{n} h_j}$$

where *l* and *h* respectively denote the number of loans purchased that support a housing goal and the number of loan applicants eligible for that goal, *j* subscripts census tracts, and *n* is the number of tracts in a metropolitan area.[6]

If a tract's SM_j^A value is less than one, then the tract's share of affordable housing loan purchases is less than its share of eligible applicants; if a tract's SM_j^A is greater than one, then its share of loans purchased exceeds its share of goal-eligible mortgage applicants. Another way to view this measure is as the ratio of the GSEs' purchase rate of affordable housing loans in a tract to the average purchase rate for the metropolitan area. If a tract's SM value is less

[6] In the empirical work reported below, this measure is created using the HMDA files for data on applications at the tract level and the PUDB files for data on GSE purchases across tracts. We do this because the HMDA files contain incomplete information on GSE purchases as stated in footnote 3. However, using data from two different sources can create problems of its own. Consequently, we also created an analogous mismatch measure with respect to applications that employed HMDA data on loan purchases. Our regression results are not materially different depending upon which of the two measures of spatial mismatch is employed. However, the R-square

than one, then the GSEs' affordable housing purchase activity in the tract is less than the average level in the metropolitan area.

A second spatial mismatch measure can be defined with respect to the GSE purchase rate of the loans actually originated by primary lenders in each tract. Analogous to SM_j^A above, we define SM_j^O,

$$SM_j^O = \frac{l_j}{\sum_{j=1}^{n} l_j} \Bigg/ \frac{o_j}{\sum_{j=1}^{n} o_j}$$

where a lower-case *o* denotes the number of goal-eligible loans that were originated by primary lenders.[7]

Values for SM_j^A and SM_j^O are calculated with respect to Goal 1 for each census tract.[8] Their means and standard deviations are reported in Table 3.[9] Note that the means of SM^A almost always are higher than those for SM^O, indicating that the degree of spatial mismatch is lower with respect to originations. As it is easy to show that a larger standard deviation implies a greater degree of spatial mismatch, this suggests that primary market lender behavior may account for at least some of the observed spatial mismatch with respect to applicants. This is an issue that will be explored more carefully in the empirical work below. Note also

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drops slightly when HMDA data are used both in the numerator and denominator of SM^A, so we report results using data on loan purchases are from the PUDB files.

[7] Once again, the HMDA files are the source for all tract-level originations, with the PUDB files providing the data on GSE purchases. We experimented with using HMDA data on loan purchases. As was the case with the SM^A measure, the results are substantially the same if this is done.

[8] We focus on Goal 1 for two reasons. Analysis of Goal 2 is not particularly interesting because it was purely center-city targeted before 1996. Hence, there is no analogous spatial mismatch measure for it. Goal 3-eligible borrowers are part of the Goal 1-eligible borrower pool, and tend to be more spatially concentrated than Goal 1-eligible applicants. Analysis of Goal 3 does not add much to what is presented below for Goal 1. However, all results for Goal 3 are available upon request.

that means and standard deviations tend to have risen since 1993. In addition, it is worth noting that there is considerable heterogeneity in the degree of spatial mismatch across metropolitan areas. Atlanta, Boston, and Miami tend to have the least spatial mismatch in recent times, while Cleveland, Dallas, Detroit, New York and Philadelphia have the highest degrees of mismatch.[10]

[add Table 3 here]

4. Model and Econometric Specifications

4.1. Introducing Neighborhood Traits into a Simple Spatial Model with Default Risk

In this subsection, we derive a specification that employs the spatial mismatch measures, SM_j^A and SM_j^O, as dependent variables in a regression involving a variety of variables that might reasonably be thought to influence the spatial distribution of purchase activity relative to the spatial distribution of origination or application activity. For simplicity we do not distinguish between primary market lenders and secondary market purchasers in this model.[11]

While it turns out to be relatively easy to motivate the regression model within a framework built around spatial differences in risk, we do not mean to imply that mitigation of localized (or neighborhood, in our terms) risk differences is the only possible explanation for observed GSE purchase behavior. Some of our key results will be consistent with that conjecture, but we caution that our analysis does not rule out other factors such as fundamental supply-demand interactions as being responsible for the spatial mismatches identified in our

[9] Each census tract is equally weighted in these calculations. This is necessary for the standard deviation to reflect variance across tracts and not across individual applicants or borrowers.

[10] Plots of the spatial mismatch measures based on 1996 data for each metropolitan area can be found in Gyourko & Hu (1999).

[11] Although one could argue that the GSEs influence the primary market lenders' behavior, we do not presume that it is the GSEs who are solely responsible for the observed spatial distributions of low-income loan purchases in the studied metropolitan areas. Another way to view the agnosticism of the model in this regard is that if the GSEs do not know location-specific information at loan purchase time, we effectively assume that the spatial distribution in the primary loan market is reflected in the secondary market.

data. In fact, we include a number of proxies for supply and demand conditions in the specifications reported.[12]

In general, neighborhood traits seem likely to matter for mortgage origination or purchase activity for various reasons. For example, properties in certain types of neighborhoods may have higher appreciation rates than similar properties in other neighborhoods (e.g., Archer, et al 1996). In a distressed area, the decline in housing value may be more severe, increasing the probability of negative equity which leads to higher credit risk. In addition, because individual traits such as income have limited variation within the pool of goal-eligible borrowers, lenders and GSEs rationally might use neighborhood characteristics to help mitigate the costs associated with potential defaults.

This can be illustrated fairly simply if the true default risk, μ_{ij}, for borrower *i* in tract *j* is modeled as a function of individual traits (Z) and neighborhood traits (X). Lenders do not know true default risk with certainty, so they perceive default risk with error as described in equation (1),

$$(1) \qquad \tilde{\mu}_{ij} = E(\mu_{ij} \mid Z_{ij}, X_j) + \eta_{ij}$$

with η_{ij} the error term. Default costs themselves can vary by individual property and neighborhood. We define this cost as c_{ij} with the expected default cost (v_{ij}) given perceived default risk equal to

$$(2) \qquad v_{ij} = \tilde{\mu}_{ij} c_{ij} = v(Z_{ij}, X_j) .$$

[12] A referee also noted that differing regulatory environments between depository institutions and GSEs might at least partially account for some of the outcomes we document below. For example, the Community Reinvestment Act emphasizes geographic distribution of depository institution loans, while HUD rules for affordable housing loans tends to focus on borrower income. Thus, a differing regulatory impetus might also help account for a spatial purchase pattern that is different from the underlying origination pattern.

Theoretically, the true risk premium can be derived from option pricing models. In an efficient and complete market, the realized price of default risk should be the derived equilibrium price plus a white noise error term. However, markets often are not perfect or complete, making it difficult to price this risk in practice. In addition, legal and political considerations are relevant in this case, as the GSEs benefit financially from their special status and would put that status at risk if they were to perfectly price discriminate.

Absent the ability to easily price credit risks in mortgage rates, points, or fees, a lender's/purchaser's profit maximizing problem boils down to one of minimizing expected default costs, assuming other costs (e.g., cost of funds and transaction costs) are invariant across loans. In this situation, the v_{ij} term in equation (2) becomes central in determining if a low- and moderate-income applicant is funded or the mortgage purchased.

If we denote the marginal probability for a low-income mortgage application to be purchased by the GSEs in metropolitan area *c* as $prob_c$, the conditional probability for a lower income application *i* in tract *j* to be purchased, denoted as $prob(loan \mid i, j)$, then is a function of the expected default cost v_{ij} and $prob_c$,

(3) $$prob(loan \mid i, j) = g(v_{ij}) * prob_c, \; g \geq 0, \text{ and } g' \leq 0.$$

The marginal probability depends upon the relevant loan supply and demand conditions in a metropolitan area. One possible specification is as in (4),

(4) $$prob_c = \sum_{j=1}^{n} l_j \Big/ \sum_{j=1}^{n} h_j ,$$

where l_j is the number of affordable housing loans purchased from tract *j*, h_j is the number of low- or moderate-income loan applicants in tract *j* eligible under the affordable housing goals, and *n* is the number of tracts in any given metropolitan area.

The expected number of affordable housing loans purchased from the tract will equal

(5) $E(l_j) = h_j E[\text{Prob(Loan | i, j)}]$.

By assuming linearity in the functional forms of $v(Z_{ij}, X_j)$ and $g(v_{ij})$, Equation (5) becomes a function of neighborhood characteristics and the mean of the vector of borrowers' traits $\bar{Z}_j$. Rearranging equation (5) and substituting (1) - (4) into (5), we obtain

(6) $$\frac{E(l_j)}{h_j} \Bigg/ \frac{\sum_{j=1}^{n} l_j}{\sum_{j=1}^{n} h_j} = g(v_{ij}) = f(\bar{Z}_j, X_j).$$

where $\bar{Z}_j = E(Z_{ij})$. Following this, a linear form of $f(\bar{Z}_j, X_j)$ from equation (6) can be rewritten as

(7) $$\frac{E(l_j)}{h_j} \Bigg/ \frac{\sum_{j=1}^{n} l_j}{\sum_{j=1}^{n} h_j} = \alpha + \gamma \bar{Z}_j + \beta\ X_j + \varepsilon_j$$

where $\bar{Z}_j$ and X_j are vectors of goal-eligible applicants' risk variables and tract characteristics, respectively, and the dependent variable is the number of affordable housing loans per goal-eligible household in tract *j* normalized by the area mean. With a little rearrangement, the left-hand side can be written as $\frac{E(l_j)}{\sum_{j=1}^{n} l_j} \Bigg/ \frac{h_j}{\sum_{j=1}^{n} h_j}$. This is the tract share of affordable housing loans divided by the tract share of goal-eligible applicants. Thus, this dependent variable is identical to the measure of spatial mismatch (SM) that was defined in Section 3.

4.2 Econometric Specifications

Versions of equation (7) are estimated using census tract-level data from twenty metropolitan areas.[13] Given that Table 3's data suggested substantial heterogeneity in the degree of spatial mismatch across metropolitan areas, it is advisable to allow for different effects across metropolitan areas. Consequently, we estimate each specification by metropolitan area.[14] In addition, equation (7) is estimated using weighted ordinary least squares (WLS) at the census tract level, with the weighting variable based on the number of low income loan applications or borrowers (depending upon which dependent variable is used).[15]

Both SM_j^A and SM_j^O are used as dependent variables. The independent variables include a variety of tract traits, loan applicants' characteristics, and loan type information. Neighborhood, or tract-level, traits include whether the tract is in a central city of the metropolitan area (*C_CITY*), the fraction of tract population comprised of African-Americans (*BLCKRATE*), an interaction of central city with the black population share (*CC_BLCK*), the relative income of the tract as defined by the ratio of the tract's median income to that for the metropolitan area (*TR_RATIO*), the age distribution of household heads (HHR25LOW, *HHR2534*, *HHR3544*, *HHR4554*, *HHR5564*, HHR6574 (the omitted category), and *HHR75UP*), the number of owner-occupied homes in a tract (*U_OWNER*), the ownership rate in the tract (*R_OWNER*1), an indicator variable for whether the tract meets Goal 2 qualifying criteria (G2_DUMMY, the geographic targeting goal), and another variable measuring the proportion of loans purchased in the tract that meet Goal 3 criteria (*G3_PROP*).

[13] Two of the metropolitan areas listed in the tables above, Nassau-Suffolk and Riverside-San Bernardino, are dropped because they do not have traditional central cities, a trait we wish to control for in the regressions.
[14] The data support this approach. Pooling and restricting the coefficient vectors to be the same across metropolitan areas is easily rejected.
[15] While WLS does help with heteroskedasticity, results very similar to those reported below are obtained without weighting on a sample from which tracts with few applications (<20) are dropped.

This set of local traits is focused upon for a variety of reasons, data availability being one of them. While no structural interpretation can be attached to the resulting coefficients, some of the variables are likely to be more informative about the importance of local risk differentials, with others more likely to reflect supply and/or demand conditions. Some, such as the race and central city controls, have potentially widespread policy interest whatever underlying causal force might be behind any relation to the degree of spatial mismatch.

For example, the disparity in social and economic trends between central cities and their suburbs long has been discussed and debated, and purchase behavior in cities versus suburbs is important to a variety of policy makers. While various supply or demand factors potentially could explain why the GSEs might over- or under-weight purchases in cities relative to applications or originations in cities, it also could be that central city tracts are perceived as relatively risky. If so, the model above suggests these neighborhoods are more likely to be under-represented in terms of affordable housing loan purchases if the GSEs (or primary market originators) mitigate risk by using neighborhood traits as signals.[16]

Whether spatial mismatch is associated with the fraction of African-American population is of interest for obvious reasons. Racial differentials in mortgage lending in general are of widespread public policy interest (e.g., see Munnell, et al 1996; Ladd, 1998). And, racial segregation is a fact of life in most metropolitan areas. In terms of the local risk framework

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[16] To see this last point more clearly, returning to equations (3) and (6) shows that $\frac{\partial SM_j}{\partial v_{ij}} \leq 0$. Therefore, for a profit maximizing agent, we have $\frac{\partial SM_j}{\partial v_j}\frac{\partial v_j}{\partial x_j} \leq 0.$ where *x* is some variable from the Z or X vectors. That is, if lenders view certain neighborhood characteristics as risky, we should observe a negative correlation between that characteristic and our measure of the relative distribution of loan purchases, *ceteris paribus*.

outlined above, it might not be all that difficult for loan originators or purchasers to spatially target low income-related mortgages in a way that was correlated with race if the agencies suspected that default costs were higher in minority areas. If so, this would lead to a negative correlation between *BLCKRATE* and our spatial mismatch measures.[17] In addition, it is worthwhile to know if there is a difference in any African-American effect across central city and suburban areas. To find out, we include the interaction of *BLCKRATE* and *C_CITY* in the models estimated below.

The *TR_RATIO* variable is included to capture whether the GSEs are meeting affordable housing goal requirements by targeting loans made to goal-eligible borrowers in economically stronger neighborhoods or census tracts, as this variable proxies for the strength of the local housing market. While supply and demand conditions certainly could be correlated with the relative level of local income, we believe this variable serves as a very useful indicator of whether local risk differentials are playing any meaningful role in determining the degree of spatial mismatch. Simply put, since regulation forces the agencies to buy loans made to lower income borrowers, they may be able to mitigate risk by purchasing loans made in the strongest sub-markets. A significant positive partial correlation between this variable and the spatial mismatch measures would be consistent with this hypothesis; no correlation, or a significant negative correlation would leave considerable doubt in our minds as to whether local risk mitigation is a meaningful part of the story behind the spatial mismatch of loan purchase behavior and application/origination behavior.

The series of dummy variables that controls for the age distribution of household heads in each tract, the number of owners (*U_OWNER*), and the ownership rate (*R_OWNER*1) are

[17] Of course, other potential explanations exist for any racial differential found, discrimination among them.

included to help proxy for supply or demand conditions in the neighborhood. For example, housing liquidity that impacts both the supply of and demand for mortgages well could differ depending upon the age distribution, the size or depth of the local market (i.e., the number of owners in the area), and the local ownership rate.[18] In addition, we generally think it useful to see if central city, race, and income variables have any correlation with our spatial mismatch measure independent of the age distribution and ownership measures. The controls for whether a purchased loan meets other affordable housing goals (G2_DUMMY and *G3_PROP*) are included because the GSEs have an incentive to target loans that meet multiple criteria.

A second group of variables is included to control for the distribution of applicants' or borrowers' risk. To the extent possible, we would like to distinguish between the influences of neighborhood traits versus individual risk factors. However, because certain types of individuals tend to live near one another, some of the neighborhood and individual risk controls undoubtedly are correlated. In addition, because loan level data on risk factors such as loan-to-value (LTV), payment to income ratio (PTI), or credit history are not available in our data sources, we adopt a "mean household" approach. That is, we use the mean values of lower-income applicants' (or borrowers') traits in each tract to represent the tract value for each variable.

To approximate applicant (or borrower) risk, goal-eligible applicants' (borrowers') average income (denoted *LOGINCM*) and an estimated loan-to-value ratio (*LTV*) are employed as proxies, with the latter variable splined at the 80 percent cutoff for private mortgage insurance. Since the payment-to-income ratio (PTI) is directly related to applicants' (or borrowers') income

[18] The impact of the age distribution also can be interpreted as part of the local risk framework. For example, mobility differentials that impact returns to home owners might also be reflected in the coefficients on these variables.

or wealth, and credit score is significantly correlated with income, using these proxies should help control for differences in applicant (or borrower) risk across tracts.[19]

More specifically, *LOGINCM* is the log of lower income applicant (or borrower) average income in a tract. The *LTV* variable is constructed as the average loan amount in the tract divided by an estimated house value for lower-income home buyers in each tract. The estimated house value is based on the tract median value, adjusted by the loan applicant's (or (borrowers') income relative to tract median income. Appendix 1 provides more detail on the imputation of house value and LTV.[20] As just noted, a spline of this variable is estimated in the specifications we report. The transformation allows for differing effects above and below the 80 percent leverage amount. The impact for loans below the 80 percent cutoff is captured in the variable LTV_LE80; that for loans above 80 percent leverage is reflected in the coefficient on LTV_GT80.[21]

Two loan-type controls also are employed to help account for differences in applicant/borrower risk across census tracts. One is the fraction of so-called refinance loans, which is defined as the share of low- and moderate-income loan applications (or originations) made to refinance an existing loan (*REFI_RA*). In one sense, refinance loans typically have lower loan-to-value ratios which makes them less risky. However, they also may be less well

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[19] See Pennington-Cross (1999) for more on studies of the correlation between credit score with income.

[20] We also experimented with a loan-to-income (LTI) measure in lieu of the LTV variable. One potential advantage of using LTI is that is can be computed directly from the HMDA data so that no imputation is needed. However, this variable is not free of measurement error either, as we do not observe loan terms in the data. Thus, different underlying payment-to-income ratios can result from the same measured debt-to-income ratio. In addition, LTI proved strongly correlated with LOGINCM so that multicollinearity made it more difficult than usual to measure distinct income and leverage effects. For example, the coefficient on LTI often was positive. This impact almost certainly is unrelated to risk, and probably reflects a scale effect. That is, while borrower income (i.e., the denominator of LTI) effectively is being held constant via the LOGINCM variable, variance in LTI is due to variance in loan size (in the numerator of LTI). The results indicate the GSEs are purchasing bigger loans. While not uninteresting in its own right, we report results with LTV included in order to more clearly capture distinct leverage and income effects. In addition, our other key results are robust to the specification change (i.e., the coefficients on the other variables generally are unaffected).

[21] We also experimented with other transformations, including adding the interaction of the LTV measure with a dummy for whether leverage is above 80 percent. The results were essentially unchanged.

documented and appraisal values will be less accurate since there is no sale. In addition, the proportion of refinance loans may be influenced by the degree of housing market activity, with more stagnant markets having a relatively high share of these loans. Thus, the impact of this variable is uncertain. A second variable controls for so-called investor loans (*INV_RA*). This is defined as the fraction of low-income loan applications (or originations) that reflect an investment motive, not a desire of the borrower to occupy the home as a primary residence.[22]

Finally, we control for FHA/VA activity in a market. Specifically, we include the ratio of FHA/VA loans made in each tract to the number of goal-eligible loan applications (or originations) in each tract (*FHA_RA*). We do this so that our analysis is of loans available to be purchased by Fannie Mae and Freddie Mac. The GSEs generally do not purchase FHA/VA insured or guaranteed loans so that a large FHA/VA presence implies a smaller share of GSEs purchases. Hence, a negative sign is expected for the coefficient on this variable. However, our interest in the variable is not so much on its direct impact on the degree of spatial mismatch as in its role of controlling for potentially important specification bias. To see the latter point more clearly, consider how excluding this variable would cloud the interpretation regarding other right-hand side variables. For example, we will soon report a strong positive correlation of TR_RATIO with our spatial mismatch measure. Absent the FHA/VA control, the association could be due solely to a low FHA/VA market share. It is in this particular sense that it is important that we focus our analysis on loans available for purchase by the GSEs.[23]

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[22] DiVenti (1998) concludes there are different risk characteristics for such loans. Hence, we desire to control for the possibility.

[23] Whether high FHA/VA activity causes low conventional loan activity is another matter entirely. We provide some results on this matter in Section 5. In addition, the fact that the degree of FHA/VA activity could be endogenously determined led us to estimate equation (8) below with and without this variable. While we wish our analysis to focus on the loans available for purchase by the GSEs, the general tenor of the results is unaltered if this variable is not included. More specifically, the TR_RATIO variable still is quite robustly significant and the borrow risk controls behave in the same way. The largest impact of not controlling for FHA/VA activity is on the

Given this set of variables, the specifications estimated for Goal 1 loans take on the following form for loan applicants,

$$(8)\quad SM^{A}_{jct} = \alpha_{ct} + \beta_{1ct} * C\_CITY_{jct} + \beta_{2ct} * BLCKRATE_{jct} + \beta_{3ct} * CC\_BLCK_{jct} + \beta_{4ct} * TR\_RATIO_{jct}$$
$$+ \beta_{5ct} * FHA\_RA_{jct} + \beta_{6ct} * REFI\_RA_{jct} + \beta_{7ct} * INV\_RA_{jct} + \beta_{8ct} * LOGINCM_{jct}$$
$$+ \beta_{9ct} * LTV\_LE80_{jct} + \beta_{10ct} * LTV\_GT80_{jct} + \beta_{11ct} * G3\_prop_{jct} + \beta_{12ct} * G2\_dummy_{jct}$$
$$+ \beta_{13ct} * HHR24LOW_{jct} + \beta_{14ct} * HHR2534_{jct} + \beta_{15ct} * HHR3544_{jct} + \beta_{16ct} * HHR4554_{jct}$$
$$+ \beta_{17ct} * HHR5564_{jct} + \beta_{18ct} * HHR75UP_{jct} + \beta_{19ct} * U\_OWNER_{jct} + \beta_{20ct} * R\_OWNER_{jct}$$
$$+ \varepsilon_{jct}$$

with all variables as described above, and applications pertaining exclusively to Goal 1. The subscripts *c* and *t* denote MSA and year, respectively. As noted above, equation (8) is fully interacted by year and metropolitan area. A variable key, along with means and standard deviations, are reported in Table 4. Finally, an analogous equation is estimated with SM^{O}_{jct} as the dependent variable.

5. Results

Tables 5 and 6 present the results from estimating equation (8) on 1996 data using SM^{A}_{jct} and SM^{O}_{jct}, respectively, as the dependent variable. In terms of the vector of neighborhood controls, the most consistently significant result across metropolitan areas involves *TR_RATIO*, the ratio of tract-level family median income (for all families in the tract)

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center city control (C_CITY). In a handful of areas, the magnitude and significance of this variable's coefficient changes materially. This suggests that FHA/VA activity tends to be concentrated in central cities. In addition, the impact of whether the loan meets Goal 2 requirements also changes materially in certain areas. All results are available upon request.

to metropolitan area family median income (for all families in the metropolitan area). In both Tables 5 and 6, this variable is positively and statistically significantly related to our measures of spatial mismatch in all but one metropolitan area (Miami, FL). Thus, the GSEs disproportionately purchase Goal 1 loans in tracts with incomes that are high relative to the metro area median. While a causal interpretation cannot be convincingly applied here, this stylized fact suggests that future research should take into account the possibility that the GSEs are mitigating risk with regard to their affordable mortgage purchase requirements by targeting goal-eligible loans in the stronger local land markets. In addition, it is noteworthy that the positive correlation also exists in the loan origination regression (Table 6), indicating the finding in Table 5 is not driven solely by primary market originators only making affordable loans to qualified borrowers in higher income tracts.[24]

It also is noteworthy that relative tract income is economically, not just statistically, significant. Table 7 reports standardized marginal effects for this and select other variables based on the regression results from Table 5. The first column contains the standardized marginal effect for *TR_RATIO*—that is, the impact on the dependent variable of a one standard deviation change in *TR_RATIO*. Because the variance of SM^A differs so much across metropolitan areas, in the second column this standardized marginal effect is divided by the standard deviation of each area's SM^A measure. Thus, in Atlanta (top row), a one standard deviation increase in *TR_RATIO* is associated with a 0.38 increase in its SM^A. This impact is 43 percent of the standard deviation in SM^A for Atlanta. Gauged this way, the median-sized impact occurs in Tampa, where a one standard deviation increase in *TR_RATIO* is associated with a 0.46 standard deviation larger SM^A value. In Tampa's case, this implies an increase of

[24] Regression results for this and all other variables for 1993 are reported in the appendix Tables 3a and 3b. While there are some differences across years, the general nature of the results is similar to the findings for 1996.

0.38 (see column one) to 1.53 about its mean SM^A of 1.15 (see Table 3). In other words, if a tract's *TR_RATIO* increases from the mean in Tampa of 1.01 to 1.37, the relative purchase rate of low income loans increases from a mean of 1.15 to 1.53.

The impact of race is not quite as robust across cities. In our specification, the impact of race on the degree of spatial mismatch can vary depending upon whether the tract is in a central city or the suburbs.[25] The impact in suburban tracts is reflected in the $\exists_{2ct}$ coefficient on *BLCKRATE*. The results indicate that a high fraction of African-American households in a suburban census tract generally is negatively correlated with our spatial mismatch measure for Goal 1. This is the case in 90 percent (18 of 20) metropolitan areas, both when the mismatch is measured with respect to applications (Table 5) and originations (Table 6). Table 5's results show that in most, but not all (12 of 18), of these metropolitan areas, a greater concentration of African-Americans in the tract is associated in a statistically significant way with a purchase rate of goal-eligible loans that is low relative to that for the overall metropolitan area. The results are quite similar when SM^O is the dependent variable (see Table 6).[26] In no case do we find a statistically significant positive correlation between *BLCKRATE* and the degree of spatial mismatch.

Standardized marginal effects tend to be smaller for this variable, but the implied suburban racial impacts still are statistically and economically meaningful in many

If anything, the impact of key variables such as TR_RATIO has become more robust over time.

[25]The impact of race is determined by the combination of coefficients on BLCKRATE and *CC_BLCK*. From equation (8), $\frac{\partial SM_{jct}}{\partial BLCKRATE_{jct}} = \beta_{2ct} + \beta_{3ct} * C\_CITY_{jct}$ where *C_CITY=1* if the tract is in a central city.

[26]There is only one case (Houston) in which the sign on *BLCKRATE* differs depending upon whether SM_j^A or SM_j^O is the dependent variable, and those coefficients are not statistically significant at anything close to standard confidence levels.

metropolitan areas. Effects analogous to those discussed above for *TR_RATIO* are reported in the third and fourth columns of Table 7. In Atlanta, Baltimore, Chicago, Cleveland, Detroit, and Washington, the implied marginal effects are close to or above one-third of a standard deviation in the spatial mismatch dependent variable. For Atlanta, the results imply that a one standard deviation increase in the fraction of a tract's population that is African-American (i.e., from the local mean of 31 percent to 66 percent) is associated with a decrease in Atlanta's SM^A of –0.29 from its mean value of 1.10. While this and other impacts are meaningful, we should emphasize that in other areas (e.g., Dallas, Denver, Houston, New York, and Oakland), there is virtually no effect, in either a statistical or economic sense. That suburban racial impacts differ so much across metropolitan areas clearly warrants future study. [27]

Consideration of the coefficients on the interaction of *BLCKRATE* with center city status (*C_CITY*) generally suggest that what racial impact exists generally is confined to the suburbs and is not present in the central city. That is, it typically is the case that when the coefficient on *BLCKRATE* is statistically significant and negative, the coefficient on the interaction term (*CC_BLCK*) is positive (sometimes significantly so). In general, we cannot reject the null that differences in the fraction of African-American households across central city tracts are uncorrelated with our measures of spatial mismatch (i.e., $\beta_{2ct} + \beta_{3ct} = 0$ for central city tracts).[28]

[27] We emphasize that these results should not be interpreted as evidence of racial discrimination on the part of the GSEs (or anybody else for that matter). Even if one thought only risk differentials mattered, our borrower risk controls are too crude to allow for any other conclusion. In addition, if there was any discrimination occurring, it could be exclusively in the primary market or the mortgage insurance market, neither of which we observe directly. Hence, the agencies may not be the causal force even if discrimination is present.

[28] This conclusion still holds if the G2_DUMMY and G3_PROP variables are dropped from the specification. We experimented with such a specification because race is part of the criteria for Goal 2 and Goal 3 loans. Essentially, the correlation at the tract level is not high enough to alter the findings in a material way.

Results on the impact of being in the central city are much more mixed across metropolitan areas. While there is no well-defined standardized marginal effect for this variable, the impacts of discretely changing a tract identity from suburban to central city status are reported in columns 5 and 6 of Table 7. In the few metropolitan areas for which the underlying regressions coefficients (on *C_CITY* and *CC_BLCK*) are statistically significant, GSE purchase rates tend to be low in central city tracts. However, there is little consistency across metropolitan areas, especially in comparison to income and race. A better understanding of this trait's role will require more detailed analysis of individual metropolitan areas. All that can be said now is that in some areas (e.g., Cleveland), Goal 1 loan purchase rates are relatively low in central city tracts. However, in others (e.g., Houston and New York), they tend to be relatively higher in central city tracts.

It is noteworthy that these local neighborhood effects hold controlling for the degree of FHA/VA activity. The coefficients on *FHA_RA* generally are negative and statistically significant at standard confidence levels, no matter whether SM_j^A or SM_j^O is the dependent variable. As expected, the greater the FHA/VA presence in a tract, the lower the GSE purchase rate in that tract because there are fewer loans that can be purchased by the GSEs in such areas. Marginal effects once again are reported in columns 7 and 8 of Table 7. On the whole, impacts are not as large as for relative income (*TR_RATIO*), but recall that it is important to account for this variable as it controls for potentially important specification bias, thereby permitting a much cleaner interpretation of other local effects.

The vector of borrower risk controls also clearly helps explain some of the spatial mismatch found in the data. It is not surprising to see the strong positive coefficients on the log of applicant or borrower income (*LOGINCM*) in Tables 5 and 6. Such income is highly correlated with credit scores, payment ability and several other lending criteria. The final columns of Table 7 show that a standard deviation higher mean income among lower income borrowers in the tract typically is associated with a 0.2 to 0.4 standard deviation higher loan purchase rate in the tract. These effects are on a par (in absolute value) with those found for race in the suburbs.

The impacts of the spline of the loan-to-value ratio are much more mixed. It is not possible to reject the null that there is no difference in effects above and below the spline breakpoint in most, but not all, cases. In addition there are significantly negative and significantly positive effects found for each component of the splined variable. It is possible that we are not capturing a more non-linear effect associated with default. However, experimentation with other specifications did not yield a meaningfully different pattern of results.

Somewhat surprisingly from our perspective, the *G2_DUMMY* control often is negative and statistically significant across our sample of cities. Except in Dallas and New York, the coefficients on this variable are negative, indicating that Goal 1 purchase rates tend to be lower if the loan also meets Goal 2 qualifying criteria. Why this is the case is not clear, but we suspect the variable must be proxying for some market fundamental or regulatory burden that makes such loans less attractive. The coefficients on *G3_PROP*, the proportion of loans that also meet Goal 3 qualifying criteria, are statistically significant in fewer cities. And, there are positive and negative impacts found across cities.

The results for the loan type variables also are mixed. The impact of the share of refinance loans (*REFI_RA*) is mixed, with statistically significant coefficients reported in nine areas. That some are positive and others negative suggests, as discussed above for this variable, that different factors are driving the results in different areas. The results also tend to be inconclusive for the investor loans (INV_RA). It could be that these variables are not especially good proxies for borrower risk differences across tracts or that other variables already control for these effects. Dropping these variables from the specification does not change the impacts of the other controls in any material sense.

Some of the age distribution controls are statistically significant across a wide variety of cities, while many others are not. It is difficult to put an interpretation on individual coefficients, as they can reflect varying forces in different cities depending upon how demographics and supply-demand fundamentals interact with one another in each area.

That statistical significance of the controls for size and depth of the local market (*U_OWNER* and *R_OWNER*) is mixed. However, U_OWNER generally is positively associated with the degree of spatial mismatch. [Dallas is the lone exception in which the variable's impact is both negative and statistically significant at conventional levels, and the estimated coefficient is quite small and is only marginally significant.] R_OWNER never has both a positive and statistically significant effect. While caution regarding interpretation always is in order, the tenor of these results suggests the GSEs prefer deeper markets and markets with more uniformly owner-occupied housing. Both traits probably are associated with lower risk.

In sum, a series of stylized facts emerge from our estimation of equation (8). Controlling for a variety of variables, GSE purchase rates of Goal 1 qualifying loans are systematically higher in tracts with incomes high relative to the metropolitan area median. Purchase rates also are uniformly higher the higher the income of low income borrowers in the tract. While we reemphasize that strict causal interpretations cannot be applied to the results of our specification, we believe these findings suggest that risk mitigation is likely to at least partially underpin the spatial purchase patterns documented in our data.

With respect to other patterns likely to be of interest to policy makers, differential race effects tend to be confined to suburban areas. Why this is so is not immediately clear, and it should be the subject of follow-on research. In addition, the results on how central city status is related to the degree of spatial mismatch are mixed. The heterogeneity in results across areas also warrants additional investigation.

5.1 More on a possible FHA externality

The dependent variables employed in the regressions above are based on all loans—conventional and FHA/VA—applied for or made. However, it is possible that FHA activity differentially influences the origination rate of conventional loans in a neighborhood. One possible reason is that, since FHA loans typically have a higher default rate, FHA activity may be associated with a negative spillover effect on the neighborhood. For example, conventional lenders might be scared away from neighborhoods in which there are more foreclosed properties. And, FHA loan activity and the foreclosure rate probably are positively correlated. Consequently, a more appropriate analysis of spatial mismatch may involve only conventional loans and/or loan applications.

Such an analysis requires the creation of new dependent variables, analogous to our SM_j^A and SM_j^O measures, but based only on conventional loan applications and originations. We define these new variables as SM_j^{CA} and SM_j^{CO}, as shown here

$$SM_j^{CA} = \frac{l_j}{\sum_{j=1}^{n} l_j} \bigg/ \frac{c_j}{\sum_{j=1}^{n} c_j}$$

and

$$SM_j^{CO} = \frac{l_j}{\sum_{j=1}^{n} l_j} \bigg/ \frac{co_j}{\sum_{j=1}^{n} co_j}$$

where the lower case *c* represents the number of conventional loan applications and lower case *co* represents the number of conventional originations in a tract.

Equation (8) is then rerun using SM_j^{CA} and SM_j^{CO} as dependent variables. The FHA/VA ratio variable still is included as an independent variable to test for whether there is any external impact of FHA activity on the perceived risk of a neighborhood. If so, we would anticipate a negative coefficient on *FHA_RA*.

Table 8 reports results using SM_j^{CA} as the dependent variable. Before getting to the FHA impact, it is worth noting that the findings for the other variables are little changed from what was presented in previous tables. With respect to FHA activity, *FHA_RA*'s coefficient is negative in 14 out of 20 metropolitan areas, and significantly so in twelve of those cases. Thus, in the bulk of metropolitan areas the results are consistent with a story in which a stronger FHA presence increases perceived riskiness by conventional lenders.[29] That said, there is a case (Pittsburgh) in which the coefficient is significantly positive. Once again, heterogeneity in results across cities suggests it may prove fruitful to more deeply scrutinize individual areas.

[29] When comparing the GSE purchases with conventional originations, the FHA_RA variable does not show a consistent pattern across metropolitan areas. Conditional on a loan being originated, the GSEs' purchase rate is actually slightly higher in a heavy FHA neighborhood. See Table A2 in Appendix. This suggests that the negative impact of FHA activity may arise mainly from primary market lender behavior.

6. Conclusion

Purchase patterns of Low- and Moderate-Income Housing Goal loans are documented for a variety of metropolitan areas across the United States. Measures are developed of how closely matched is the spatial distribution of GSE purchases of these loans with the analogous distributions of applications and originations of these loans. A simple regression model is estimated, with the degree of spatial mismatch serving as the dependent variable and a host of local and borrower traits on the right-hand side.

In terms of the Low and Moderate Income Housing Goal, the most robust finding is consistent with a policy of targeting loans in relatively higher income tracts. The higher is a census tract's income relative to the median for its metropolitan area, the higher is the GSE purchase rate in the tract relative to that for the overall metropolitan area. Race effects are slightly less robust across metropolitan areas, with the bulk of the evidence suggesting that suburban tracts with relatively high concentrations of African-American households are more likely to have relatively low GSE purchase rates. The findings for central city status are quite mixed. It seems clear that a more detailed look at individual metropolitan area behavior is needed to better understand this variable's influence. Finally, our analysis suggests that a stronger FHA presence raises the perceived risk of a neighborhood in most metropolitan areas. In these areas, a larger FHA presence reduces the origination rate of conventional loans.

While these conclusions are drawn from regressions in 20 large metropolitan areas, they are not entirely consistent across each of the 20 metropolitan areas studied here. For future research, we cannot overemphasize the need to exploit the heterogeneity in behaviors identified across metropolitan areas in helping understand what is driving the systematic patterns that we do find.

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Appendix 1. Imputation of House Value and LTV

In the HMDA data the loan amount is readily available, but not the house value for each loan application. Consequently, house value must be estimated to impute a LTV. We use the applicant's income to estimate house value. According to Mills (1999), the income elasticity of housing demand (house value) largely is invariant by income, and the elasticity is less than one. Assuming the income elasticity (denoted e_j) within a census tract is constant, we have the following relationship

$$\text{(A1)} \qquad \frac{HV_{ij} - MedHV_j}{MedHV_j} = e_j \frac{Incm_{ij} - MedIncm_j}{MedIncm_j}.$$

where HV_{ij} is the house value for each applicant that needs to be estimated, $Incm_{ij}$ is the applicant's income, $MedHV_j$ and $MedIncm_j$ are the tract median house value and median income, respectively. Because house value and location are closely correlated, the elasticity within one census tract should be smaller than the elasticity in general. In this paper, we use e_j=0.6.

In order to deal with the impacts of inflation and house price depreciation/appreciation, median income is deflated by the Urban Worker Consumer Price Index (CPI) and median house value by the Freddie Mac Repeat Sale Housing Index. After estimating each loan applicant's house value, the LTV is computed for each loan application. The tract mean for all lower income applicants' is then employed as the tract value.

Table 1: GSE Single-Family Mortgage Purchases Made in Support of the Three Housing Goals, Individually and in Aggregate: 1996

Metropolitan Area	Number of GSE Loan Purchases	Number of Purchases Supporting Either of the 3 Goals	As Percentage of Total Loan Purchases (%)	Goal 1 Loans As Percentage of Total Loan Purchases (%)	Goal 2 Loans As Percentage of Total Loan Purchases (%)	Goal 3 Loans As Percentage of Total Loan Purchases (%)
Atlanta, GA MSA	58,027	28,264	48.7	40.6	19.6	11.0
Baltimore, MD MSA	21,866	9,631	44.0	37.3	16.1	10.8
Boston--Lawrence--Salem, MA—NH NECMA	44,064	21,384	48.5	38.5	22.0	10.1
Chicago, IL PMSA	72,346	38,324	53.0	44.2	21.9	13.4
Cleveland, OH PMSA	16,301	7,385	45.3	39.5	14.9	11.1
Dallas, TX PMSA	31,003	10,414	33.6	26.9	15.1	8.4
Denver, CO PMSA	42,291	21,320	50.4	43.8	19.9	15.2
Detroit, MI PMSA	73,622	32,983	44.8	39.2	15.2	11.0
Houston, TX PMSA	36,024	15,337	42.6	29.6	26.6	9.6
Los Angeles, CA PMSA	65,452	37,502	57.3	31.5	45.3	9.5
Miami, FL PMSA	25,600	14,107	55.1	29.5	42.5	6.6
Minneapolis--St. Paul, MN--WI MSA	50,145	25,243	50.3	44.9	16.6	14.1
Nassau-Suffolk, NY PMSA	49,394	14,304	29.0	22.9	13.9	5.1
New York, NY--NJ PMSA	35,628	14,338	40.2	20.3	27.6	5.0
Oakland, CA PMSA	27,837	16,749	60.2	41.2	40.9	12.9
Philadelphia PA--NJ PMSA	42,534	17,791	41.8	35.8	17.5	11.0
Phoenix, AZ MSA	47,060	20,515	43.6	33.8	18.6	10.6
Pittsburgh PA PMSA	8,677	2,723	31.4	23.8	12.7	5.2
Riverside-San Bernardino, CA MSA	24,546	12,584	51.3	31.5	36.6	10.8
San Diego, CA MSA	27,333	11,947	43.7	29.6	26.5	8.5
Tampa--St. Petersburg—Clearwater, FL MSA	27,292	12,103	44.3	35.1	21.3	12.0
Washington, DC--MD--VA MSA	44,747	28,057	62.7	50.7	31.1	15.6
22 Metro Total and Weighted Averages	**871,789**	**372,845**	**48.7**	**37.2**	**24.4**	**11.0**
Fannie Mae	*519,552*	*260,242*	*50.1*	*38.1*	*26.0*	*11.6*
Freddie Mac	*352,237*	*164,633*	*46.7*	*35.9*	*22.1*	*10.2*
Nation-Wide Figures						
Fannie Mae	*1,548,414*			*45.4*	*28.2*	*17.4*
Freddie Mac	*1,178,349*			*41.3*	*25.0*	*14.2*

Note: National numbers are from Manchester (1998) and the HUD web site; the Metropolitan average is weighted by the number of GSE purchases.
For the number of loans supporting a single goal (columns 4, 5 and 6), we count every purchase that meets that goal's requirements. If one loan meets two or three goals' requirement, we count it once only in the number of purchases supporting any of the 3 goals (columns 1-2).

Table 2: Breakdown of Low-Income Related Loan Purchases in the 22 Areas Over Time: 1993-1996

YEAR	Loans Supporting Either of the Three Goals as Percentage of Total Loans (%)	Loans Supporting Goal 1 As Percentage of Total Loans (%)	Loans Supporting Goal 2 As Percentage of Total Loans(%)	Loans Supporting Goal 3 As Percentage of Total Loans (%)
1993	43.3	28.3	20.9	6.3
1994	50.5	34.8	24.3	9.4
1995	50.8	36.4	23.4	10.8
1996	48.7	37.2	24.4	11.0

YEAR	Center Cities' Share of Low-Income Related Loans (%)	Center Cities' Share of Loans Supporting Goal 1 (%)	Center Cities' Share of Loans Supporting Goal 2 (%)	Center Cities' Share of Loans Supporting Goal 3 (%)
1993	44.9	21.4	89.8	29.6
1994	45.6	25.4	90.9	34.3
1995	43.8	25.6	90.5	34.7
1996	29.5	26.3	40.9	35.6

Note: These figures are weighted averages of the 22 metropolitan areas, with the weighting by the number of affordable housing loan purchases. For the number of loans supporting any one goal (columns 2-4), we count every purchase that meets the relevant goal. If a single loan meets two or three goals, we count it only once in the number of loans supporting any of the three goals (first column). Loans are single family mortgage loans purchased by the GSEs in each year.

Table 3: Summary Statistics on Spatial Mismatch Measures, 1993 & 1996
Means and Standard Deviations

Metropolitan Area		1993 SM^A	1993 SM^O	1996 SM^A	1996 SM^O
Atlanta	Mean	0.88	0.89	1.10	1.03
	Std. Dev.	*0.55*	*0.51*	*0.90*	*0.80*
Baltimore	Mean	0.92	0.90	1.16	1.12
	Std. Dev.	*0.71*	*0.65*	*1.01*	*1.00*
Boston	Mean	0.92	0.93	1.09	1.07
	Std. Dev.	*1.00*	*0.94*	*0.62*	*0.58*
Chicago	Mean	0.84	0.85	1.22	1.10
	Std. Dev.	*0.67*	*0.64*	*1.06*	*0.90*
Cleveland	Mean	0.90	0.86	1.31	1.17
	Std. Dev.	*0.72*	*0.64*	*1.26*	*1.13*
Dallas	Mean	1.03	1.01	1.31	1.29
	Std. Dev.	*0.96*	*0.89*	*1.34*	*1.59*
Denver	Mean	0.96	0.96	1.21	1.16
	Std. Dev.	*0.63*	*0.59*	*0.80*	*0.76*
Detroit	Mean	0.89	0.83	1.34	1.16
	Std. Dev.	*0.83*	*0.66*	*1.36*	*0.98*
Houston	Mean	0.90	0.87	1.24	1.10
	Std. Dev.	*0.92*	*0.77*	*1.28*	*1.08*
Los Angeles	Mean	1.02	1.01	1.26	1.32
	Std. Dev.	*0.54*	*0.57*	*0.89*	*1.01*
Miami	Mean	0.88	0.91	1.05	1.00
	Std. Dev.	*0.57*	*0.59*	*0.83*	*0.60*
Minneapolis	Mean	0.92	0.92	1.10	1.07
	Std. Dev.	*0.48*	*0.44*	*0.68*	*0.62*
New York	Mean	0.98	1.00	1.30	1.19
	Std. Dev.	*1.56*	*1.39*	*2.00*	*1.49*
Oakland	Mean	0.97	0.96	1.18	1.14
	Std. Dev.	*0.49*	*0.42*	*1.27*	*0.76*
Philadelphia	Mean	0.97	0.95	1.31	1.17
	Std. Dev.	*0.72*	*0.83*	*1.00*	*0.84*
Phoenix	Mean	0.96	0.94	1.13	1.09
	Std. Dev.	*0.71*	*0.66*	*1.22*	*0.81*
Pittsburgh	Mean	1.08	1.02	1.29	1.18
	Std. Dev.	*1.58*	*1.00*	*1.93*	*1.42*
San Diego	Mean	0.97	0.98	1.11	1.13
	Std. Dev.	*0.41*	*0.40*	*0.60*	*0.59*
Tampa	Mean	0.94	0.94	1.15	1.10
	Std. Dev.	*0.61*	*0.57*	*0.82*	*0.83*
Washington	Mean	0.95	0.96	1.25	1.22
	Std. Dev.	*0.52*	*0.49*	*0.97*	*0.96*

Table 4: Variable Key for Regressors

Variable	Definition	Mean		Std	
Neighborhood traits					
C_CITY	Center city dummy, 1 if a tract locates in a census designed center city, 0 otherwise;	0.484		0.5	
BLCKRATE	Ratio of African American households to total number of households in a tract;	0.196		0.307	
CC_BLCK	Interaction of *C_CITY* and *BLCKTATE*;	0.149		0.297	
TR_RATIO	Ration of tract family median income to the metropolitan area median;	1.019		0.487	
G3_PROP	Proportion of G3-eligible applicants (or originations) in G1_eligible applicants (or oiginations)	0.384		0.246	
G2_DUMMY	1 if the tract if Goal 2-eligible, 0 otherwise	0.44		0.48	
HHR24LOW	Ratio of household head age 24 or lower	0.048		0.046	
HHR2534	Ratio of household head age 25 to 34	0.088		0.062	
HHR3544	Ratio of household head age 35 to 44	0.227		0.071	
HHR4554	Ratio of household head age 45 to 54	0.161		0.061	
HHR5564	Ratio of household head age 55 to 64	0.136		0.054	
HHR75UP	Ratio of household head age 75 and up	0.087		0.063	
U_OWNER	Number of owner_occupied housing units	1019		697	
R_OWNER	Ratio of owner_occupied housing units in total housing unit	0.601		0.243	
		Application	Origination	Application	Origination
Loan type Information					
FHA_RA	Frequency of FHA/VA loans in all the lower income loan application or origination in a tract	0.144	0.153	0.132	0.176
INV_RA	Frequency of investor loans (non-owner occupied) in all the lower income loan application or origination in a tract	0.054	0.043	0.081	0.085
REFI_RA	Frequency of refinance loans in all the lower income loan applications or origination in a tract;	0.384	0.357	0.196	0.219
Borrower's risk distribution					
LOGINCM	mean income of lower income loan applications or origination, in log form	10.251	10.278	0.175	0.186
LTV	mean LTV of lower income loan applications or origination in a tract; the specification estimated employs a spline at 80 percent leverage	0.657	0.72	0.32	0.348

Note: Data are for the 20 metropolitan areas, 1996.

Table 5: Weighted Regression of (8): SM^A, 1996
Observations are weighted by number of low income applicants in each tract

MSA	INTERCEPT	C_CITY	BLCKRATE	CC_BLCK	TR_RATIO	FHA_RA	REFI_R	INV_RA	LOGINCM	LTV_LE80	LTV_GT80
Atlanta	-44.60	-0.12	-0.82	0.46	0.80	-1.88	-0.01	1.67	4.42	0.26	0.20
	(-7.84)**	(-1.07)	(-6.46)**	(2.62)**	(6.33)**	(-7.37)**	(-0.04)	(2.72)**	(8.02)**	(1.71)*	(2.25)**
Baltimore	-19.34	-0.23	-1.44	1.08	1.29	-1.88	-0.11	-1.09	1.99	-0.03	0.05
	(-3.69)**	(2.53)**	(-7.51)**	(5.13)**	(9.79)**	(-7.54)**	(-0.44)	(-1.40)	(3.97)**	(-0.20)	(0.50)
Boston	-29.45	0.04	-0.85	0.53	0.31	-1.12	0.10	0.32	2.93	-0.39	-0.10
	(-7.91)**	(0.92)	(-1.43)	(0.89)	(3.28)**	(-3.83)**	(0.69)	(0.82)	(8.28)**	(-2.26)**	(-1.10)
Chicago	-13.48	-0.17	-0.86	0.43	0.43	-2.19	-0.18	-0.83	1.47	-0.30	-0.18
	(-4.78)**	(-4.42)**	(-10.43)**	(5.17)**	(6.57)**	(-14.57)**	(-1.30)	(-2.18)**	(5.44)**	(-3.23)**	(-3.45)**
Cleveland	-16.91	-0.71	-1.15	0.98	0.36	-2.20	-0.60	-1.14	1.87	-0.03	0.01
	(-3.71)**	(-9.34)**	(-8.88)**	(7.66)**	(2.81)**	(-4.78)**	(-2.82)**	(-1.76)*	(4.20)**	(-0.13)	(0.06)
Dallas	-36.99	-0.11	-0.27	0.83	1.75	-0.75	2.65	0.60	3.62	0.54	0.28
	(-5.66)**	(-1.42)	(-0.71)	(2.18)**	(11.71)**	(-2.79)**	(4.11)**	(0.59)	(5.70)**	(2.43)**	(2.64)**
Denver	-30.43	0.10	-0.02	-0.09	1.42	-1.39	0.26	0.63	2.97	0.18	0.19
	(-4.71)**	(1.45)	(-0.04)	(-0.18)	(9.64)**	(-5.46)**	(1.01)	(0.64)	(4.71)**	(0.75)	(1.62)
Detroit	-5.02	-0.17	-1.10	0.60	1.12	-0.13	1.06	-3.33	0.69	0.55	0.20
	(-1.36)**	(-2.29)	(-6.66)**	(3.42)**	(9.92)**	(-0.70)	(6.31)**	(-4.39)**	(1.94)*	(3.96)**	(2.15)**
Houston	-40.98	0.31	0.01	-0.30	1.27	0.05	3.37	0.23	4.02	0.05	-0.17
	(-7.36)**	(4.84)**	(0.04)	(-1.03)	(9.96)**	(0.13)	(5.41)**	(0.26)	(7.42)**	(0.35)	(-2.21)**
Los Angeles	-6.64	0.06	-0.50	-0.07	0.13	-1.95	-0.54	-1.10	0.88	-0.16	-0.11
	(-2.57)**	(1.98)**	(-6.87)**	(-0.81)	(2.12)**	(-17.08)**	(-4.90)**	(-5.04)**	(3.54)**	(-2.00)**	(-2.54)**
Miami	-20.10	0.20	-0.46	-0.28	0.10	-1.63	-1.39	0.67	2.30	0.15	0.15
	(-2.68)**	(2.28)**	(-3.36)**	(-1.63)	(0.75)	(-4.49)**	(-6.29)**	(0.81)	(3.12)**	(0.70)	(1.36)
Minneapolis	-22.63	0.11	0.67	-0.73	1.32	-1.13	0.87	0.30	2.23	0.36	0.23
	(-5.33)**	(2.08)**	(0.48)	(-0.52)	(12.04)**	(-6.08)**	(4.35)**	(0.44)	(5.41)**	(1.89)*	(2.21)**
New York City	-13.48	0.88	-0.22	-0.46	0.70	-0.64	-0.65	0.01	1.31	0.03	0.09
	(-5.14)**	(10.30)**	(-0.84)	(-1.77)*	(8.41)**	(-2.64)**	(-5.99)**	(0.04)	(5.22)**	(0.18)	(1.05)
Oakland	-5.06	-0.18	-0.41	0.16	0.30	-2.01	0.02	-0.88	0.58	0.08	0.00
	(-1.14)	(-1.96)**	(-2.75)**	(0.86)	(2.33)**	(-8.37)**	(0.12)	(-2.08)**	(1.38)	(0.50)	(0.03)
Philadelphia	-7.80	0.02	-0.81	0.37	0.99	-2.43	-1.47	-0.45	0.88	-0.03	0.09
	(-3.14)**	(0.34)	(-6.77)**	(3.02)**	(11.11)**	(-12.48)**	(-8.89)**	(-1.93)*	(3.67)**	(-0.25)	(1.08)
Phoenix	-32.57	-0.20	-3.23	2.99	0.70	-1.85	0.38	1.33	3.28	0.42	0.26
	(-5.61)**	(-2.93)**	(-1.72)*	(1.59)	(6.04)**	(-8.25)**	(1.29)	(1.77)*	(5.81)**	(1.93)*	(2.62)**
Pittsburgh	-19.01	-0.40	-1.08	1.17	1.70	0.98	0.36	-0.30	1.95	-0.51	-0.20
	(-2.85)**	(-3.60)**	(-3.43)**	(3.33)**	(9.68)**	(1.85)*	(1.10)	(-0.32)	(2.97)**	(-1.93)*	(-1.51)
San Diego	-12.81	0.05	-0.66	0.33	0.42	-1.21	0.02	-0.71	1.36	0.24	0.16
	(-3.03)**	(1.06)	(-1.40)	(0.69)	(4.35)**	(-6.01)**	(0.10)	(-1.92)*	(3.36)**	(1.68)*	(2.19)**
Tampa	-31.55	-0.21	-0.23	0.42	1.09	-0.28	0.07	-0.73	3.27	0.18	0.21
	(-4.28)**	(-2.25)**	(-1.30)	(1.49)	(7.14)**	(-0.83)	(0.23)	(-0.78)	(4.49)**	(0.81)	(1.78)*
Washington	-27.19	-0.27	-0.97	0.65	0.51	-2.09	-0.27	-0.17	2.75	-0.13	-0.14
	(-7.66)**	(-2.93)**	(-11.97)**	(5.08)**	(5.07)**	(-12.52)**	(-1.53)	(-0.31)	(8.24)**	(-1.27)	(-2.55)**

Notes: [1]Underlying coefficients multiplied by 1,000; t-statistics reported in parentheses; ** denotes significance at the 5% level or better; * denotes significance at the 10% level

Table 5: Weighted Regression of (8): SM^A, 1996 (continued)

Observations are weighted by number of low income applicants in each tract

MSA	G3_Prop	G2_Dummy	HHR24LOW	HHR2534	HHR3544	HHR4554	HHR5564	HHR75UP	U_OWNER[1]	R_OWNER1	R-Square	# of Obs.
Atlanta	0.28	-0.04	-1.70	0.04	0.90	0.33	1.88	-0.36	0.08	-1.34	0.67	466
	(1.40)	(-0.65)	(-1.53)	(0.06)	(1.31)	(0.43)	(1.92)*	(-0.39)	"(2.94)**	(-3.81)**		
Baltimore	0.24	-0.10	-2.04	-0.92	0.98	-0.14	-1.24	1.09	0.05	-0.85	0.66	559
	(1.12)	(-1.51)	(-1.90)*	(-1.41)	(1.68)*	(-0.23)	(-1.55)	(1.50)	(1.22)	(-3.59)**		
Boston	0.11	-0.15	1.01	-0.21	-0.64	-0.95	0.30	-0.62	0.12	-0.20	0.47	613
	(0.79)	(-3.14)**	(1.59)	(-0.41)	(-1.54)	(-1.92)*	(0.54)	(-1.20)	(3.64)**	(-1.11)		
Chicago	-0.03	-0.22	-0.05	1.19	-0.05	-0.32	-0.02	0.27	0.09	-0.29	0.73	1454
	(-0.30)	(-6.22)**	(-0.08)	(3.17)**	(-0.17)	(-0.97)	(-0.06)	(0.71)	(4.35)**	(-2.38)**		
Cleveland	-0.16	-0.24	-1.54	0.56	0.89	0.42	-0.31	-0.59	0.04	-0.46	0.73	597
	(-0.83)	(-4.06)**	(-1.43)	(0.72)	(1.55)	(0.64)	(-0.44)	(-0.85)	(0.73)	(-2.02)**		
Dallas	0.79	0.02	-2.88	1.06	-0.05	-1.80	-1.61	0.24	-0.09	-0.98	0.55	527
	(3.49)**	(0.22)	(-2.77)**	(1.36)	(-0.07)	(-2.20)	(-1.46)	(0.24)	(-1.83)*	(-2.58)**		
Denver	0.51	-0.28	-0.70	1.23	0.32	0.25	-0.04	1.05	0.00	-1.08	0.68	406
	(2.58)**	(-3.89)**	(-0.69)	(2.10)**	(0.62)	(0.37)	(-0.06)	(1.49)	(0.05)	(-3.95)**		
Detroit	-0.75	-0.08	-3.04	-1.93	-1.36	-1.94	-1.08	-1.19	0.00	-1.09	0.59	1179
	(-4.28)**	(-1.63)	(-3.14)**	(-3.19)**	(-2.78)**	(-3.40)**	(-1.65)*	(-1.72)	(0.21)	(-4.66)**		
Houston	0.50	-0.04	-1.06	1.50	0.09	-0.38	-0.48	1.31	0.01	-0.90	0.61	666
	(2.31)**	(-0.59)	(-0.99)	(1.87)*	(0.14)	(-0.52)	(-0.47)	(1.36)	(0.20)	(-2.85)**		
Los Angeles	-0.42	-0.06	-0.76	-1.19	-0.38	-0.68	-0.88	-0.48	0.03	0.19	0.49	1607
	(-4.14)**	(-1.48)	(-1.31)	(-2.93)**	(-1.10)	(-1.83)*	(-2.06)**	(-1.11)	(1.23)	(1.35)		
Miami	-0.09	-0.25	-2.03	-0.26	-0.97	-1.26	-1.80	-2.07	0.01	-0.26	0.66	262
	(-0.33)	(-2.79)**	(-1.31)	(-0.28)	(-1.20)	(-1.67)*	(-1.77)*	(-2.75)**	(0.54)	(-0.86)		
Minneapolis	0.18	-0.03	-2.15	-0.27	-0.25	-1.01	-1.31	-0.72	0.05	-0.67	0.62	615
	(1.18)	(-0.64)	(-2.63)**	(-0.60)	(-0.56)	(-1.87)*	(-2.02)**	(-1.32)	(1.40)	(-3.04)**		
New York City	0.10	0.15	1.57	3.18	0.05	0.09	-0.72	0.40	0.32	-0.61	0.31	2216
	(0.69)	(2.70)**	(1.62)	(4.11)**	(0.11)	(0.20)	(-1.40)	(0.75)	(6.77)**	(-3.86)**		
Oakland	-0.09	-0.09	1.01	1.27	0.41	0.75	0.44	0.41	0.02	-0.39	0.55	453
	(-0.60)	(-1.68)*	(1.10)	(2.11)**	(0.80)	(1.26)	(0.61)	(0.61)	(0.68)	(-1.61)		
Philadelphia	0.00	-0.07	-0.31	2.13	0.46	0.36	-0.22	0.95	-0.01	-0.46	0.63	1209
	(-0.02)	(-1.73)*	(-0.42)	(4.39)**	(1.25)	(0.81)	(-0.45)	(2.02)**	(-0.30)	(-2.90)**		
Phoenix	0.23	-0.14	-0.92	0.00	0.58	-1.15	0.75	-0.22	0.17	-0.55	0.65	460
	(1.15)	(-2.21)**	(-1.06)	(0.00)	(1.08)	(-1.93)*	(0.93)	(-0.35)	(4.27)**	(-2.06)**		
Pittsburgh	-0.33	-0.08	0.59	2.62	0.60	-1.02	1.33	-1.51	0.10	-1.51	0.47	628
	(-1.27)	(-1.08)	(0.47)	(1.99)**	(0.57)	(-0.90)	(1.10)	(-1.39)	(1.48)	(-4.05)**		
San Diego	0.02	-0.20	0.40	-0.94	-0.31	-0.84	-1.64	-0.38	0.05	0.14	0.52	429
	(0.14)	(-4.04)**	(0.61)	(-1.50)	(-0.66)	(-1.56)	(-2.40)**	(-0.67)	(1.85)*	(0.67)		
Tampa	-0.02	-0.16	-3.26	-2.58	-1.05	-1.30	-0.54	-0.07	0.02	-0.45	0.58	405
	(-0.07)	(-2.32)**	(-2.57)**	(-3.07)**	(-1.37)	(-1.56)	(-0.55)	(-0.10)	(1.62)	(-1.58)		
Washington	0.22	-0.19	-0.77	0.33	0.91	0.00	0.27	0.49	0.05	-0.74	0.65	855
	(1.70)*	(-4.43)**	(-1.05)	(0.81)	(2.33)**	(0.00)	(0.56)	(0.91)	(2.11)	(-4.52)**		

Notes: [1]Underlying coefficients multiplied by 1,000; t-statistics reported in parentheses; ** denotes significance at the 5% level or better; * denotes significance at the 10% level.

Table 6: Weighted Regression of (8): SM^O, 1996
Observations are weighted by the number of low income originations in each tract.

MSA	INTERCEPT	C_CITY	BLCKRATE	CC_BLCK	TR_RATIO	FHA_RA	REFI_R	INV_RA	LOGINCM	LTV_LE80	LTV_GT80
Atlanta	-20.49	-0.07	-0.62	0.26	0.84	-1.43	-0.05	0.92	2.05	0.36	0.18
	(-4.55)**	(-0.71)	(-5.65)**	(1.71)*	(7.87)**	(-7.81)**	(-0.20)	(2.16)**	(4.74)**	(3.36)**	(2.72)**
Baltimore	-13.47	-0.13	-1.00	0.64	1.21	-1.95	-0.21	-1.05	1.41	-0.08	0.00
	(-3.20)**	(-1.64)	(-.578)**	(3.35)**	(10.45)**	(-10.35)**	(-.096)	(-1.74)*	(3.51)**	(-0.59)	(-0.01)
Boston	-23.69	0.04	-0.54	0.25	0.29	-0.80	0.37	0.03	2.36	-0.40	-0.10
	(-7.13)**	(0.88)	(-0.94)	(0.44)	(3.21)**	(-3.55)**	(2.66)**	(0.09)	(7.48)**	(-2.59)**	(-1.18)
Chicago	-13.03	-0.12	-0.69	0.22	0.39	-1.39	0.15	-0.83	1.37	0.03	-0.06
	(-5.47)**	(-3.60)**	(-8.92)**	(2.82)**	(6.86)**	(-13.60)**	(1.40)	(-2.71)**	(5.99)**	(0.47)	(-1.53)
Cleveland	-7.96	-0.49	-0.81	0.59	0.43	-1.19	0.25	-0.80	0.90	0.20	0.11
	(-2.13)**	(-7.21)**	(-6.74)**	(4.70)**	(3.61)**	(-4.33)**	(1.39)	(-1.74)*	(2.50)**	(1.32)	(1.10)
Dallas	-18.72	-0.12	-0.37	0.72	1.54	-1.02	1.39	-0.50	1.90	0.25	0.16
	(-3.65)**	(-1.78)*	(-1.03)	(1.95)*	(11.86)**	(-6.25)**	(3.13)**	(-0.78)	(3.82)**	(1.62)	(2.11)**
Denver	-17.62	0.09	0.35	-0.41	1.17	-2.10	-0.45	0.77	1.75	0.34	0.20
	(-3.30)**	(1.49)	(0.78)	(-0.87)	(8.97)**	(-9.89)**	(-1.88)*	(1.01)	(3.37)**	(2.19)**	(2.40)**
Detroit	14.54	-0.05	-0.84	0.23	1.17	-0.79	0.59	-2.65	-1.26	0.27	0.10
	(5.08)**	(-0.97)	(-6.11)**	(1.58)	(13.69)**	(-6.22)**	(4.22)**	(-5.56)**	(-4.58)**	(2.69)**	(1.63)
Houston	-21.14	0.05	-0.32	0.24	1.06	-0.87	1.01	0.43	2.17	-0.18	-0.15
	(-5.23)**	(0.90)	(-1.25)	(0.88)	(11.00)**	(-4.50)**	(2.74)**	(0.82)	(5.55)**	(-1.57)	(-2.71)**
Los Angeles	-5.50	0.07	-0.40	-0.09	0.20	-1.59	-0.22	-0.62	0.70	-0.02	-0.05
	(-2.41)**	(2.27)**	(-5.25)**	(-0.92)	(3.20)**	(-19.04)**	(-2.50)**	(-3.23)**	(3.23)**	(-0.25)	(-1.14)
Miami	-13.08	0.08	-0.52	-0.18	0.08	-1.25	-0.53	0.90	1.50	0.42	0.20
	(-2.33)**	(1.19)	(-4.33)	(-1.17)	(0.68)	(-5.46)**	(-2.76)**	(1.52)	(2.73)**	(2.55)**	(2.08)**
Minneapolis	-12.25	0.12	0.89	-0.98	1.12	-1.32	0.47	0.20	1.27	0.07	0.08
	(-3.45)**	(2.66)**	(0.72)	(-0.78)	(11.38)**	(-9.71)**	(2.73)**	(0.36)	(3.71)**	(0.59)	(1.10)
New York City	-5.98	0.68	-0.18	-0.32	0.51	-0.55	-0.32	-0.09	0.58	-0.19	-0.01
	(-3.14)**	(8.98)**	(-0.71)	(-1.22)	(6.90)**	(-3.61)**	(-3.97)**	(-0.42)	(3.22)**	(-1.55)	(-0.16)
Oakland	-4.38	-0.13	-0.30	0.11	0.35	-1.49	0.03	-0.14	0.49	0.14	0.03
	(-1.21)	(-1.49)	(-2.10)**	(0.61)	(2.89)**	(-8.74)**	(0.22)	(-0.38)	(1.43)	(1.08)	(0.43)
Philadelphia	-2.00	0.01	-0.58	0.17	0.83	-1.66	-0.65	-0.77	0.29	-0.25	-0.04
	(-1.04)	(0.14)	(-4.96)**	(1.47)	(10.62)**	(-13.62)**	(-4.98)**	(-3.59)**	(1.57)	(-2.27)**	(-0.64)
Phoenix	-16.40	-0.17	-2.03	1.72	0.78	-1.72	0.24	1.26	1.71	0.03	0.05
	(-3.58)**	(-2.79)**	(-1.27)	(1.07)	(7.34)**	(-11.04)**	(0.99)	(2.04)**	(3.85)**	(0.22)	(0.82)
Pittsburgh	-10.33	-0.40	-0.95	1.13	1.72	0.20	0.04	-1.12	1.04	-0.01	0.00
	(1.67)*	(-3.90)**	(-2.93)**	(3.06)**	(10.38)**	(0.55)	(0.15)	(-1.51)	(1.70)*	(-0.03)	(0.04)
San Diego	-10.58	0.03	-0.23	-0.06	0.49	-1.17	0.16	-0.13	1.10	0.09	0.07
	(-3.03)**	(0.81)	(-0.50)	(-0.13)	(5.23)**	(-8.24)**	(1.08)	(-0.45)	(3.31)**	(0.70)	(1.04)
Tampa	-8.40	-0.13	-0.37	0.28	1.24	-1.08	-0.10	-1.18	0.94	0.18	0.15
	(-1.50)	(-1.67)*	(-2.35)**	(1.12)	(9.21)**	(-4.89)	(-0.40)	(-1.83)*	(1.71)*	(1.25)	(1.75)*
Washington	-16.60	-0.32	-0.72	0.54	0.54	-1.75	0.10	-0.31	1.71	0.02	-0.07
	(-5.30)**	(-3.89)**	(-8.98)**	(4.52)**	(5.91)**	(-13.35)**	(0.66)	(-0.58)	(5.84)**	(0.25)	(-1.51)

Notes: [1]Underlying coefficients multiplied by 1,000; t-statistics reported in parentheses; ** denotes significance at the 5% level or better; * denotes significance at the 10% level.

Table 6: Weighted Regression of (8): SM^O, 1996 (continued)

Observations are weighted by the number of low income originations in each tract.

MSA	G3_Prop	G2_Dummy	HHR24LOW	HHR2534	HHR3544	HHR4554	HHR5564	HHR75UP	U_OWNER[1]	R_OWNER1	R-Square	# of Obs.
Atlanta	0.04	-0.03	-0.81	-0.02	0.97	-0.22	1.48	-0.63	0.08	-0.94	0.68	464
	(0.26)	(-0.59)	(-0.86)	(-0.03)	(1.64)	(-0.34)	(1.78)*	(-0,81)	(3.48)**	(-3.11)**		
Baltimore	0.32	-0.03	-1.53	-0.25	0.89	0.27	-1.19	0.79	0.04	-0.75	0.67	556
	(1.78)*	(-0.57)	(-1.63)	(-0.44)	(1.72)*	(0.49)	(-1.65)*	(1.22)	(1.14)	(-3.54)**		
Boston	0.20	-0.09	0.99	-0.69	-0.37	-0.90	-0.22	-0.59	0.11	-0.07	0.41	608
	(1.57)	(-2.00)**	(1.64)	(-1.40)	(-0.93)	(-1.89)*	(-0.41)	(-1.19)	(3.34)**	(-0.42)		
Chicago	0.01	-0.10	-0.45	0.96	0.26	-0.05	-0.04	0.39	0.07	-0.35	0.67	1433
	(0.15)	(-3.16)**	(-0.82)	(2.94)**	(0.97)	(-0.17)	(-0.11)	(1.13)	(3.74)**	(-3.10)**		
Cleveland	-0.26	-0.11	-1.56	0.65	0.75	0.44	-0.80	-0.17	0.05	-0.54	0.68	588
	(-1.67)*	(-2.09)**	(-1.57)	(0.95)	(1.45)	(0.74)	(-1.26)	(-0.26)	(0.98)	(-2.62)**		
Dallas	0.54	0.02	-2.20	0.30	-0.52	-1.85	-2.27	-0.27	-0.11	-0.62	0.53	514
	(2.75)**	(0.27)	(-2.32)**	(0.44)	(-0.72)	(-2.56)**	(-2.27)**	(-0.30)	(-2.46)**	(-1.78)*		
Denver	0.29	-0.17	0.24	1.79	0.60	0.65	0.66	1.07	-0.03	-0.94	0.68	403
	(1.73)*	(-2.73)**	(0.27)	(3.37)**	(1.30)	(1.10)	(0.98)	(1.70)*	(-0.61)	(-3.83)**		
Detroit	-0.81	0.00	-2.77	-0.80	-0.41	-1.75	-0.93	-0.90	0.00	-0.89	0.62	1170
	(-6.34)**	(0.08)	(-3.54)**	(-1.65)*	(-1.05)	(-3.96)**	(-1.76)*	(-1.67)*	(-0.28)	(-4.82)**		
Houston	0.28	-0.01	-1.69	0.89	-0.20	-0.38	-1.49	-0.02	-0.01	-0.97	0.54	657
	(1.76)*	(-0.18)	(-1.77)*	(1.36)	(-0.36)	(-0.61)	(-1.81)*	(-0.02)	(-0.55)	(-3.52)**		
Los Angeles	-0.28	-0.02	-0.78	-0.74	-0.03	0.27	-0.62	-0.05	0.03	-0.10	0.50	1582
	(-2.97)**	(-0.68)	(-1.36)	(-1.90)*	(-0.09)	(0.74)	(-1.45)	(-0.12)	(1.65)*	(-0.74)		
Miami	-0.12	-0.19	-1.99	0.80	0.03	-1.30	-0.99	-1.09	0.00	-0.46	0.66	261
	(-0.55)	(-2.52)**	(-1.53)	(1.01)	(0.05)	(-2.03)**	(-1.13)	(-1.71)*	(0.02)	(-1.80)*		
Minneapolis	0.00	-0.05	-1.62	0.08	-0.18	-0.68	-1.28	-0.77	0.03	-0.59	0.61	612
	(0.00)	(-1.11)	(-2.18)**	-0.19	(-0.44)	(-1.40)	(-2.20)**	(-1.56)	(0.94)	(-2.98)**		
New York City	-0.16	0.16	2.22	1.44	0.38	0.59	-0.70	0.39	0.23	-0.37	0.25	1894
	(-1.28)	(3.05)**	(2.32)**	(2.07)**	(0.82)	(1.29)	(-1.33)	(0.74)	(5.39)**	(-2.57)**		
Oakland	0.03	-0.03	0.44	1.31	0.29	1.12	0.13	0.19	-0.01	-0.35	0.50	449
	(0.19)	(-0.63)	(0.50)	(2.27)**	(0.59)	(1.90)*	(0.18)	(0.29)	(-0.25)	(-1.53)		
Philadelphia	0.02	0.00	0.03	1.92	0.65	0.33	-0.32	0.53	-0.03	-0.47	0.55	1197
	(0.17)	(-0.03)	(0.04)	(4.56)**	(1.92)*	(0.82)	(-0.69)	(1.24)	(-1.81)*	(-3.20)**		
Phoenix	0.24	-0.07	-0.64	0.25	0.54	-0.88	0.71	-0.77	0.12	-0.50	0.69	458
	(1.41)	(-1.19)	(-0.82)	(0.54)	(1.17)	(-1.67)*	(1.02)	(-1.45)	(3.40)**	(-2.12)**		
Pittsburgh	-0.23	-0.07	1.32	1.95	1.00	-1.32	1.67	-1.26	0.06	-1.25	0.44	623
	(-1.01)	(-0.88)	(0.90)	(1.59)	(1.01)	(-1.24)	(1.44)	(-1.17)	(1.04)	(-3.39)**		
San Diego	0.04	-0.09	0.78	-0.74	0.31	-0.46	-0.94	-0.03	0.05	0.03	0.56	424
	(0.27)	(-1.94)*	(1.33)	(-1.33)	(0.73)	(-0.94)	(-1.50)	(-0.07)	(2.14)**	(0.13)		
Tampa	-0.13	-0.08	-2.66	-1.28	-0.36	-1.60	0.24	-0.17	0.02	-0.74	0.60	403
	(-0.68)	(-1.41)	(-2.48)**	(-1.80)*	(-0.56)	(-2.29)**	(0.30)	(-0.30)	(2.34)	(-3.07)**		
Washington	0.13	-0.09	-0.72	0.19	1.21	0.19	-0.08	0.36	0.05	-0.66	0.64	850
	(1.15)	(-2.15)**	(-1.08)	(0.49)	(3.35)**	(0.50)	(-0.17)	(0.70)	(2.15)**	(-4.19)**		

Notes: [1]Underlying coefficients multiplied by 1,000; t-statistics reported in parentheses; ** denotes significance at the 5% level or better; * denotes significance at the 10% level

Table 7: Standardized Marginal Effects Based on Regression Results from Table 5

Metro Area	Standardized Marginal Effect TR_RATIO	Marginal Effect as Percentage of SM^A Std.Dev. TR_RATIO	Standardized Marginal Effect BLCKRATE	Marginal Effect as Percentage of SM^A Std.Dev. BLCKRATE	Standardized Marginal Effect Center City(1)	Marginal Effect as Percentage of SM^A Std.Dev. Center City(1)	Standardized Marginal Effect FHA/VA	Marginal Effect as Percentage of SM^A Std.Dev. FHA/VA	Standardized Marginal Effect LOGINCM	Marginal Effect as Percentage of SM^A Std.Dev. LOGINCM
Atlanta	0.39*	0.43	-0.29*	-0.32	0.02*	0.02	-0.20*	-0.23	0.41*	0.46
Baltimore	0.54*	0.54	-0.49*	-0.49	0.06	0.06	-0.25*	-0.25	0.22*	0.22
Boston	0.12*	0.19	-0.17	-0.27	0.09*	0.14	-0.07*	-0.12	0.24*	0.38
Chicago	0.20*	0.19	0.34*	-0.32	-0.05*	-0.05	-0.24*	-0.23	0.17*	0.16
Cleveland	0.18*	0.14	-0.42*	-0.34	-0.47	-0.38	-0.15*	-0.12	0.23*	0.18
Dallas	1.03*	0.77	-0.07	-0.05	0.04	0.03	-0.10*	-0.08	0.40*	0.30
Denver	0.57*	0.72	0.00	0.00	0.09*	0.12	-0.17*	-0.21	0.22*	0.28
Detroit	0.52*	0.38	-0.41*	-0.30	-0.03*	-0.02	-0.01	-0.01	0.09*	0.07
Houston	0.69*	0.54	0.00	0.00	0.24*	0.19	0.00	0.00	0.41*	0.32
Los Angeles	0.07*	0.08	-0.10*	-0.11	0.05*	0.06	-0.28*	-0.32	0.09*	0.10
Miami	0.06	0.08	-0.15*	-0.18	0.13*	0.15	-0.17*	-0.21	0.16*	0.20
Minneapolis	0.44*	0.64	0.07	0.11	0.07*	0.10	-0.12*	-0.18	0.19*	0.27
New York	0.40*	0.20	-0.07	-0.04	0.76*	0.38	-0.08*	-0.04	0.27*	0.13
Oakland	0.12*	0.09	-0.10*	-0.08	-0.16	-0.12	-0.21*	-0.16	0.05	0.04
Philadelphia	0.43*	0.43	-0.24*	-0.24	0.08*	0.08	-0.25*	-0.25	0.13*	0.13
Phoenix	0.32*	0.26	-0.23*	-0.19	-0.09*	-0.08	-0.27*	-0.22	0.30*	0.25
Pittsburgh	0.84*	0.43	-0.25*	-0.13	-0.27	-0.14	0.09*	0.05	0.27*	0.14
San Diego	0.17*	0.29	-0.06	-0.09	0.07*	0.11	-0.15*	-0.25	0.11*	0.18
Tampa	0.38*	0.46	-0.05	-0.06	-0.16*	-0.20	-0.02	-0.03	0.23*	0.28
Washington	0.21*	0.21	-0.33*	-0.33	-0.08	-0.08	-0.33*	-0.34	0.27*	0.28

Note: * indicates the variable is significant at the 10% level or better in the underlying regression (see Table 5)
Note: (1), for the central city control, C_CITY, the reported impact is for a discrete change from suburban to central city status. In addition, the result is based on the combination fo the C_CITY and CC_BLCK coefficients with all variables except G2_DUMMY and the LTV spline evaluated at their means. With respect to those two variables, we assume that the loan does not meet Goal 2 criteria and that it constitutes less than 80 percent of house value. Finally for this marginal impact, a * signifies that the coefficients on both C_CITY and CC_BLCK are significant at least at the 10% level.

Table 8: Weighted Regression of (8): SM^{CA}, 1996
Observations are weighted by the number of low income conventional applications in each tract.

MSA	INTERCEPT	C_CITY	BLCKRATE	CC_BLCK	TR_RATIO	FHA_RA	REFI_R	INV_RA	LOGINCM	LTV_LE80	LTV_GT80
Atlanta	-47.95	-0.21	-0.63	0.59	0.61	-0.99	-0.08	-1.09	4.77	0.38	0.24
	(-9.33)**	(-2.13)**	(-5.35)**	(3.82)**	(5.52)**	(-6.38)**	(-0.38)	(-1.85)*	(9.56)**	(2.49)**	(2.80)**
Baltimore	-16.85	-0.25	-1.21	0.98	1.27	-0.56	-0.23	-0.74	1.71	0.51	0.37
	(-3.47)**	(-2.94)**	(-6.52)**	(4.81)**	(10.35)**	(-3.56)**	(-1.17)	(-1.22)	(3.70)**	(2.79)**	(3.51)**
Boston	-27.40	0.03	-0.59	0.27	0.28	-0.22	0.09	0.15	2.73	-0.30	-0.08
	(-7.64)**	(0.76)	(-0.99)	(0.45)	(3.02)**	(-0.95)	(0.62)	(0.39)	(8.02)	(-1.76)*	(-0.85)
Chicago	-12.64	-0.15	-0.82	0.39	0.34	-0.75	-0.20	-0.58	1.37	-0.19	-0.12
	(-4.72)**	(-4.12)**	(-10.88)**	(4.86)**	(5.47)**	(-7.25)**	(-1.70)*	(1.80)*	(5.32)**	(-2.05)**	(-2.33)**
Cleveland	-14.11	-0.73	-1.10	0.97	0.33	-0.81	-0.48	-0.84	1.58	0.15	0.08
	(-3.22)**	(-9.56)**	(-8.62)**	(7.62)**	(2.62)**	(-2.69)**	(-2.43)**	(-1.40)	(3.68)**	(0.72)	(0.66)
Dallas	-35.05	-0.10	-0.04	0.68	1.53	0.20	1.60	0.64	3.41	0.68	0.37
	(-5.64)**	(-1.34)	(-0.11)	(1.88)*	(10.79)**	(1.12)	(3.07)**	(0.78)	(5.68)**	(2.96)**	(3.32)**
Denver	-29.01	0.09	-0.06	0.01	1.21	-0.33	-0.02	0.30	2.84	0.45	0.33
	(-5.03)**	(1.41)	(-0.13)	(0.03)	(9.09)**	(-1.67)**	(-0.13)	(0.44)	(5.05)**	(2.21)**	(3.24)**
Detriot	-4.45	-0.20	-1.02	0.57	0.86	-0.21	0.94	-2.59	0.64	0.78	0.34
	(-1.30)	(-2.70)**	(-6.57)**	(3.43)**	(8.26)**	(-1.36)	(6.26)**	(-4.07)**	(1.96)**	(5.33)**	(3.82)**
Houston	-42.75	0.32	0.14	-0.38	1.20	0.25	2.89	0.49	4.20	0.08	-0.14
	(-7.74)**	(4.94)**	(0.49)	(-1.27)	(9.32)**	(1.03)	(4.97)**	(0.60)	(7.80)**	(0.50)	(-1.60)
Los Angeles	-3.63	0.07	-0.45	-0.07	0.07	-0.40	-0.44	-0.78	0.54	-0.05	-0.05
	(-1.60)	(2.38)**	(-6.73)**	(-0.80)	(1.22)	(-5.43)**	(-5.15)**	(-4.59)**	(2.50)**	(-0.62)	(-1.24)
Miami	-17.78	0.25	-0.46	-0.31	0.05	0.05	-1.20	0.69	2.06	0.19	0.17
	(-2.65)**	(2.96)**	(-3.35)**	(-1.83)*	(0.36)	(0.91)	(-6.41)**	(0.99)	(3.11)**	(0.95)	(1.62)
Minneapolis	-23.13	0.09	1.47	-1.53	1.19	-0.26	0.40	0.10	2.26	0.84	0.49
	(-5.78)**	(1.81)*	(1.06)	(-1.09)	(11.49)**	(-2.14)**	(2.56)**	(0.19)	(5.84)**	(4.95)**	(5.14)**
New York City	-16.42	0.84	-0.21	-0.42	0.62	0.06	-0.65	-0.08	1.59	0.10	0.15
	(-5.79)**	(10.11)**	(-0.84)	(-1.66)*	(7.55)**	(0.36)	(6.06)**	(-0.30)	(5.89)**	(0.71)	(1.71)*
Oakland	-3.49	-0.14	-0.38	0.15	0.22	-0.67	-0.10	-0.64	0.43	0.11	0.02
	(-0.90)	(-1.78)*	(-2.87)**	(0.89)	(2.02)**	(-4.45)**	(-0.60)	(-1.89)*	(1.17)	(0.80)	(0.33)
Philadelphia	-7.10	0.01	-0.76	0.34	0.87	-0.66	-1.21	-0.18	0.78	0.22	0.21
	(-3.10)**	(0.22)	(-6.47)**	(2.92)**	(10.44)**	(-5.06)**	(8.68)**	(-0.85)	(3.56)**	(1.79)*	(2.80)**
Phoenix	-27.04	-0.21	-3.36	3.12	0.42	-0.64	-0.01	0.82	2.74	0.63	0.33
	(-5.18)**	(-3.29)**	(-1.84)*	(1.71)**	(4.20)**	(-4.72)**	(-0.06)	(1.52)	(5.37)**	(3.20)**	(3.91)**
Pittsburgh	-18.47	-0.40	-1.14	1.25	1.65	1.12	0.20	-0.13	1.92	-0.45	-0.18
	(-2.82)**	(-3.61)**	(-3.60)**	(3.47)**	(9.65)**	(2.87)**	(0.67)	(-0.17)	(2.97)**	(-1.76)*	(-1.36)
San Diego	-10.87	0.03	-0.70	0.39	0.36	-0.06	-0.04	-0.61	1.16	0.33	0.22
	(-2.83)**	(0.79)	(-1.46)	(0.81)	(3.87)**	(-0.50)	(-0.27)	(-2.06)**	(3.16)**	(2.29)**	(2.85)**
Tampa	-30.70	-0.22	-0.29	0.39	1.07	0.19	0.20	-0.52	3.16	0.43	0.32
	(-4.42)**	(-2.44)**	(-1.72)*	(1.41)	(7.40)**	(0.69)	(0.74)	(-0.66)	(4.60)**	(2.11)**	(2.91)**
Washington	-22.43	-0.29	-0.88	0.67	0.29	-0.67	-0.33	-0.22	2.28	0.20	0.03
	(-7.20)**	(-3.49)**	(-11.08)**	(5.97)**	(3.20)**	(-5.86)**	(-2.52)**	(-0.52)	(7.78)**	(1.71)*	(0.56)

Notes: [1]Underlying coefficients multiplied by 1,000; t-statistics reported in parentheses; ** denotes significance at the 5% level or better; * denotes significance at the 10% level

Table 8: Weighted Regression of (8): SM^{CA}, 1996 (continued)

Observations are weighted by the number of low income conventional applications in each tract.

MSA	G3_Prop	G2_Dummy	HHR24LOW	HHR2534	HHR3544	HHR4554	HHR5564	HHR75UP	U_OWNER[1]	R_OWNER1	R-Square	# of Obs.
Atlanta	0.33	-0.05	-2.07	0.14	0.58	-0.02	1.68	-0.42	0.07	-1.31	0.70	464
	(1.81)*	(-1.01)	(-2.12)**	-0.21	(0.97)	(-0.02)	(1.94)	(-0.54)	(2.89)**	(-4.23)**		
Baltimore	0.13	-0.10	-1.89	-0.26	0.67	-0.40	-1.46	0.74	0.05	-0.96	0.66	556
	(0.61)	(-1.59)	(-1.81)*	(-0.40)	(1.20)	(-0.67)	(-1.92)(	(1.05)	(1.41)	(-4.25)**		
Boston	0.10	-0.15	0.86	-0.15	-0.59	-0.93	0.21	-0.66	0.13	-0.24	0.44	608
	(0.75)	(-3.23)**	(1.38)	(-0.29)	(-1.42)	(-1.88)*	(0.38)	(-1.28)	(3.73)	(-1.34)		
Chicago	-0.09	-0.22	0.11	1.69	-0.04	-0.24	0.03	0.23	0.10	-0.32	0.72	1434
	(-0.83)	(-6.10)**	(0.19)	(4.63)**	(-0.13)	(-0.76)	(0.07)	(0.63)	(4.68)**	(-2.69)**		
Cleveland	-0.28	-0.21	-1.44	0.80	0.78	0.17	-0.42	-0.51	0.05	-0.44	0.73	588
	(-1.50)	(-3.65)**	(-1.34)	(-1.04)	(1.39)	(0.27)	(-0.61)	(-0.74)	(0.84)	(-1.97)**		
Dallas	0.55	-0.02	-2.80	1.59	0.69	-1.79	-1.16	0.34	-0.07	-1.18	0.56	514
	(2.46)**	(-0.20)	(-2.73)**	(2.03)**	(0.88)	(-2.21)**	(-1.05)	(0.35)	(-1.27)	(-3.09)**		
Denver	0.42	-0.28	-1.10	1.54	0.20	0.08	-0.05	0.85	0.01	-1.10	0.69	403
	(2.20)**	(-4.08)**	(-1.13)	(2.85)**	(0.42)	(0.13)	(-0.07)	(1.29)	(0.15)	(-4.37)**		
Detriot	-0.94	-0.05	-3.27	-1.82	-1.57	-2.26	-0.91	-1.26	0.01	-0.93	0.60	1171
	(-5.53)**	(-1.06)	(-3.35)**	(-3.21)**	(-3.40)**	(-4.18)**	(-1.46)	(-1.89)*	(0.62)	(-4.17)**		
Houston	0.52	-0.10	-1.19	2.32	0.32	-0.56	-0.58	1.11	0.02	-0.99	0.62	657
	(2.40)**	(-1.61)	(-1.11)	(2.81)**	(0.47)	(-0.75)	(-0.57)	(1.15)	(0.55)	(-3.13)**		
Los Angeles	-0.40	-0.04	-0.73	-0.81	-0.32	-0.53	-0.91	-0.48	0.03	0.17	0.39	1584
	(-4.41)**	(-1.01)	(-1.33)	(-2.01)**	(-0.98)	(-1.53)	(-2.25)**	(-1.17)	(1.66)*	(1.32)		
Miami	-0.14	-0.28	-1.98	0.26	-1.44	-1.17	-2.13	-2.26	0.01	-0.21	0.69	261
	(-0.56)	(-3.32)**	(-1.31)	(0.29)	(-1.81)*	(-1.61)	(-2.18)**	(-3.13)**	(0.55)	(-0.75)		
Minneapolis	0.16	-0.04	-2.20	-0.13	-0.19	-0.92	-1.10	-0.88	0.05	-0.76	0.62	612
	(1.09)	(-0.82)	(-2.81)**	(-0.29)	(-0.45)	(-1.78)*	(-1.76)*	(-1.67)*	(1.62)	(-3.65)**		
New York City	0.11	0.13	1.93	2.74	0.03	0.07	-0.82	0.47	0.29	-0.45	0.32	1896
	-0.71	(2.40)**	(1.95)*	(3.58)**	(0.07)	(0.15)	(-1.57)	(0.88)	(6.24)**	(-2.84)**		
Oakland	-0.14	-0.10	0.66	1.50	0.22	0.68	0.20	0.14	0.03	-0.36	0.54	449
	(-0.97)	(-2.13)**	(0.82)	(2.76)**	(0.48)	(1.27)	(0.31)	(0.23)	(0.99)	(-1.67)*		
Philadelphia	-0.14	-0.07	-0.25	2.47	0.37	0.32	-0.23	0.90	0.01	-0.51	0.63	1197
	(-1.05)	(-1.57)	(-0.35)	(5.28)**	(1.04)	(0.76)	(-0.50)	(1.99)**	(0.40)	(-3.36)**		
Phoenix	-0.03	-0.18	-0.91	0.35	0.71	-0.75	0.64	-0.20	0.14	-0.56	0.61	458
	(-0.14)	(-3.03)**	(-1.17)	(0.73)	(1.49)	(-1.44)	(0.88)	(-0.38)	(3.94)**	(-2.33)**		
Pittsburgh	-0.41	-0.08	0.25	2.55	0.37	-1.18	1.20	-1.62	0.08	-1.48	0.46	623
	(-1.60)	(-1.05)	(0.20)	(1.96)*	(0.35)	(-1.04)	(0.99)	(-1.50)	(1.16)	(-3.99)**		
San Diego	-0.03	-0.18	0.38	-0.48	-0.30	-1.06	-1.59	-0.41	0.04	0.12	0.46	424
	(-0.21)	(-3.76)**	(0.59)	(-0.78)	(-0.67)	(-2.03)**	(-2.39)**	(-0.77)	(1.81)*	(0.56)		
Tampa	-0.02	-0.17	-3.38	-2.12	-0.72	-1.32	-0.67	0.10	0.02	-0.58	0.59	403
	(-0.10)	(-2.41)**	(-2.73)**	(-2.61)**	(-0.97)	(-1.60)	(-0.71)	(0.15)	(1.93)*	(-2.05)**		
Washington	0.09	-0.22	-0.94	0.31	0.77	-0.13	0.07	0.06	0.07	-0.63	0.64	851
	(0.69)	(-5.28)**	(-1.35)	(0.81)	(2.04)**	(-0.35)	(0.13)	(0.13)	(2.86)**	(-4.12)**		

Notes: [1]Underlying coefficients multiplied by 1,000; t-statistics reported in parentheses; ** denotes significance at the 5% level or better; * denotes significance at the 10% level

Table A1: Weighted Regression of (8): SM^{CO}, 1996

Observations are weighted by the number of low income conventional originations in each tract.

MSA	INTERCEPT	C_CITY	BLCKRATE	CC_BLCK	TR_RATIO	FHA_RA	REFI_R	INV_RA	LOGINCM	LTV_LE80	LTV_GT80
Atlanta	-3.24	-0.13	-0.53	0.34	0.67	-0.22	0.12	-0.64	0.41	0.11	0.06
	(-3.14)**	(-1.56)	(-5.09)**	(2.47)**	(6.84)**	(-1.46)	(0.76)	(-1.51)	(4.06)**	(0.70)	(0.79)
Baltimore	0.46	-0.21	-0.86	0.71	1.11	-0.09	-0.29	-0.34	0.03	0.16	0.23
	(0.40)	(-2.80)**	(-4.94)**	(3.79)**	(10.02)**	(-0.64)	(-1.91)*	(-0.80)	(0.30)	(1.00)	(2.21)**
Boston	0.38	0.03	-0.56	0.18	0.30	-0.06	0.37	-0.16	0.05	-0.20	-0.03
	(0.35)	(0.69)	(-0.94)	(0.30)	(3.20)**	(-0.23)	(2.69)**	(-0.43)	(0.50)	(-1.12)	(-0.29)
Chicago	0.12	-0.10	-0.76	0.24	0.27	-0.16	0.08	-0.65	0.10	-0.20	-0.14
	(0.17)	(-3.05)**	(-9.39)**	(3.06)**	(4.96)**	(-1.61)	(0.86)	(-2.50)**	(1.45)	(-2.16)**	(-2.74)**
Cleveland	2.26	-0.61	-0.81	0.67	0.38	-0.05	0.19	-0.58	-0.11	0.58	0.17
	(2.09)**	(-8.74)**	(-6.70)**	(5.51)**	(3.30)**	(-0.17)	(1.10)	(-1.39)	(-1.02)	(2.64)**	(1.36)
Dallas	0.35	-0.15	-0.24	0.66	1.16	0.24	0.59	-0.15	0.03	0.55	0.28
	(0.41)	(-2.57)**	(-0.83)	(2.21)**	(10.71)**	(1.77)*	(2.10)**	(-0.39)	(0.40)	(3.47)**	(2.99)**
Denver	-3.60	0.07	0.12	-0.12	0.84	-0.42	-0.52	0.27	0.40	0.28	0.23
	(-3.13)**	(1.26)	(0.28)	(-0.25)	(6.96)**	(-2.44)**	(-3.20)**	(0.58)	(3.45)**	(1.78)*	(2.56)**
Detroit	-1.69	-0.07	-0.45	0.15	0.87	0.01	0.08	-1.92	0.30	0.41	0.15
	(-2.32)**	(-1.39)	(-3.49)**	(1.15)	(10.78)**	(0.11)	(0.67)	(-5.24)**	(4.18)**	(2.97)**	(1.87)*
Houston	-2.20	-0.03	-0.21	0.16	0.81	0.37	0.94	0.44	0.36	-0.30	-0.25
	(-3.12)**	(-0.53)	(-0.88)	(0.63)	(8.67)**	(1.97)**	(3.14)**	(1.03)	(5.21)**	(-2.01)**	(-3.03)**
Los Angeles	4.24	0.07	-0.40	-0.11	0.09	-0.09	-0.23	-0.57	-0.28	-0.13	-0.09
	(7.89)**	(2.67)**	(-5.99)**	(-1.29)	(1.59)	(-1.21)	(-3.61)**	(-4.25)**	(-5.49)**	(-1.49)	(-1.69)*
Miami	-0.76	0.11	-0.47	-0.24	0.06	0.48	-0.35	0.60	0.29	0.06	0.19
	(-0.61)	(1.55)	(-4.00)**	(-1.60)	(0.53)	(2.25)**	(-2.15)**	(1.26)	(2.41)**	(0.31)	(1.76)*
Minneapolis	-1.99	0.06	0.20	-0.19	0.96	0.00	0.24	0.12	0.25	0.35	0.27
	(-2.14)**	(1.42)	(0.16)	(-0.15)	(10.32)**	(-0.04)	(2.00)**	(0.32)	(2.76)**	(2.42)**	(2.98)**
New York City	3.25	0.66	-0.31	-0.28	0.40	0.40	-0.40	-0.14	-0.33	-0.01	-0.05
	(5.33)**	(9.14)**	(-1.23)	(-1.11)	(5.77)**	(2.14)**	(-5.37)**	(-0.67)	(-5.77)**	(-0.06)	(-0.58)
Oakland	5.05	-0.10	-0.40	0.07	0.24	-0.50	-0.06	-0.50	-0.41	-0.09	-0.05
	(4.43)**	(-1.26)	(-2.77)**	(0.39)	(2.11)**	(-3.13)**	(-0.50)	(-1.63)	(-3.81)**	(-0.62)	(-0.62)
Philadelphia	1.94	-0.02	-0.61	0.28	0.79	-0.13	-0.52	-0.70	-0.14	0.19	0.13
	(2.84)**	(-0.45)	(-5.21)**	(2.40)**	(11.02)**	(-1.12)	(-5.13)**	(-4.10)**	(-2.11)**	(1.62)	(1.75)*
Phoenix	-2.89	-0.16	-0.92	0.61	0.49	-0.36	-0.11	0.71	0.39	0.10	0.05
	(-2.69)**	(-3.04)**	(-0.58)	(0.38)	(5.54)**	(-2.95)**	(-0.71)	(1.83)*	(3.66)**	(0.64)	(0.61)
Pittsburgh	1.87	-0.47	-1.20	1.31	1.68	1.44	-0.08	-0.98	-0.19	0.31	0.03
	(1.28)	(-4.54)**	(-3.56)**	(3.47)**	(10.47)**	(3.82)**	(-0.32)	(-1.51)	(-1.32)	(1.31)	(0.24)
San Diego	2.56	0.01	-0.60	0.27	0.45	0.18	0.02	-0.30	-0.19	0.10	0.13
	(2.84)**	(0.15)	(-1.26)	(0.58)	(5.28)**	(1.47)	(0.16)	(-1.30)	(-2.19)**	(0.83)	(1.62)
Tampa	-2.05	-0.16	-0.37	0.20	1.16	0.32	-0.13	-0.72	0.30	0.29	0.16
	(-1.82)*	(-2.11)**	(-2.55)**	(0.84)	(9.58)**	(1.48)	(-0.67)	(-1.45)	(2.62)**	(1.59)	(1.52)
Washington	0.40	-0.27	-0.74	0.57	0.30	-0.09	0.01	-0.19	0.08	-0.16	-0.10
	(0.40)	(-3.87)**	(-9.05)**	(5.73)**	(3.72)**	(-0.82)	(0.09)	(-0.55)	(1.07)	(-1.44)	(-1.65)*

Notes: [1]Underlying coefficient multiplied by 1,000; t-statistics in parentheses; ** denotes significance at the 5% level or better; * denotes significance at the 10% level

Table A1: Weighted Regression of (8): SM^{CO}, 1996

Observations are weighted by the number of low income conventional originations in each tract.

MSA	G3_Prop	G2_Dummy	HHR24LOW	HHR2534	HHR3544	HHR4554	HHR5564	HHR75UP	U_OWNER[1]	R_OWNER1	R-Square	# of Obs
Atlanta	-0.25	-0.02	-1.17	0.10	0.83	-0.45	1.24	-0.72	0.09	-0.88	0.65	464
	(-1.81)*	(-0.51)	(-1.39)	(0.19)	-1.58	(-0.76)	(1.63)	(-1.05)	(4.02)**	(-3.21)**		
Baltimore	-0.27	-0.03	-1.76	0.09	0.61	0.18	-1.23	0.45	0.04	-0.82	0.62	555
	(-1.80)*	(-0.47)	(-1.88)*	(0.16)	(1.21)	(0.34)	(-1.79)*	(0.72)	(1.29)	(-4.01)**		
Boston	-0.34	-0.06	1.24	-0.46	-0.17	-0.75	0.20	-0.40	0.10	-0.17	0.28	607
	(-2.83)**	(-1.27)	(1.99)**	(-0.87)	(-0.39)	(-1.50)	(0.35)	(-0.77)	(3.09)**	(-0.94)		
Chicago	-0.33	-0.10	-0.57	1.52	0.46	0.14	0.19	0.45	0.07	-0.46	0.63	1430
	(-3.95)**	(-3.03)**	(-1.07)	(4.66)**	(1.81)*	(0.46)	(0.55)	(1.35)	(4.06)**	(-4.35)**		
Cleveland	-0.62	-0.09	-1.65	1.01	0.85	0.36	-0.61	-0.12	0.04	-0.62	0.68	587
	(-4.26)**	(-1.75)*	(-1.71)*	(1.50)	(1.70)*	(0.61)	(-0.98)	(-0.20)	(0.75)	(-3.10)**		
Dallas	-0.12	-0.04	-1.75	0.70	0.18	-1.77	-1.82	-0.14	-0.08	-0.76	0.53	509
	(-0.83)	(-0.62)	(-2.10)**	(1.17)	(0.30)	(-2.85)**	(-2.09)**	(-0.18)	(-2.11)**	(-2.55)**		
Denver	-0.09	-0.12	0.12	1.99	0.75	0.53	0.76	1.02	-0.06	-0.69	0.64	403
	(-0.67)	(-1.98)**	(0.14)	(4.24)**	(1.81)*	(1.00)	(1.24)	(1.79)*	(-1.52)	(-3.04)**		
Detroit	-0.38	-0.07	-1.28	-0.04	-0.45	-1.07	-0.67	-0.40	-0.01	-0.65	0.59	1170
	(-3.47)**	(-2.01)**	(-1.74)*	(-0.09)	(-1.25)	(-2.62)**	(-1.37)	(-0.79)	(-0.77)	(-3.84)**		
Houston	-0.26	-0.08	-1.00	1.49	-0.24	-0.27	-1.36	0.30	0.00	-1.02	0.58	655
	(-1.93)*	(-1.65)*	(-1.09)	(2.42)**	(-0.47)	(-0.47)	(-1.75)*	(0.40)	(-0.15)	(-4.03)**		
Los Angeles	-0.54	-0.02	-0.75	-0.68	0.04	0.17	-0.61	-0.21	0.04	-0.05	0.28	1576
	(-7.59)**	(-0.68)	(-1.43)	(-1.79)*	(0.13)	(0.57)	(-1.60)	(-0.55)	(1.86)*	(-0.42)		
Miami	-0.46	-0.20	-2.13	1.50	0.16	-1.07	-0.68	-0.88	0.01	-0.65	0.67	260
	(-2.64)**	(-2.93)**	(-1.66)*	(2.00)**	(0.23)	(-1.77)*	(-0.81)	(-1.43)	(0.87)	(-2.73)**		
Minneapolis	-0.28	-0.04	-1.08	0.39	0.09	-0.24	-1.10	-0.74	0.03	-0.64	0.56	611
	(-2.61)**	(-0.95)	(-1.53)	(1.01)	(0.23)	(-0.51)	(-1.98)**	(-1.56)	(1.14)	(-3.50)**		
New York City	-0.53	0.12	2.65	1.83	0.33	0.65	-0.64	0.40	0.21	-0.46	0.23	1866
	(-4.88)**	(2.34)**	(2.83)**	(2.69)**	(0.72)	(1.42)	(-1.23)	(0.76)	(5.29)**	(-3.29)**		
Oakland	-0.26	-0.06	0.53	1.67	0.28	0.89	0.04	0.13	0.00	-0.35	0.38	449
	(-2.13)**	(-1.31)	(0.65)	(3.01)**	(0.61)	(1.60)	(0.05)	(0.21)	(0.05)	(-1.62)		
Philadelphia	-0.17	-0.02	0.00	1.86	0.56	0.17	-0.55	0.54	-0.02	-0.43	0.50	1194
	(-1.62)	(-0.57)	(0.00)	(4.62)**	(1.73)*	(0.45)	(-1.22)	(1.31)	(-1.28)	(-3.11)**		
Phoenix	-0.20	-0.09	-0.38	0.60	0.69	-0.42	0.45	-0.58	0.07	-0.40	0.55	457
	(-1.40)	(-1.77)*	(-0.55)	(1.47)	(1.71)*	(-0.92)	(0.74)	(-1.31)	(2.29)**	(-1.95)*		
Pittsburgh	-0.71	-0.03	1.49	2.17	0.98	-1.24	1.78	-1.21	0.04	-1.31	0.44	621
	(-3.55)**	(-0.41)	(1.03)	(1.81)*	(0.99)	(-1.17)	(1.55)	(-1.13)	(0.75)	(-3.57)**		
San Diego	-0.23	-0.10	0.58	-0.76	0.28	-0.77	-1.24	-0.42	0.05	0.07	0.38	424
	(-2.08)**	(-2.20)**	(1.01)	(-1.39)	(0.68)	(-1.61)	(-2.04)**	(-0.87)	(2.02)**	(0.36)		
Tampa	-0.25	-0.06	-2.30	-0.81	-0.24	-1.24	0.59	-0.34	0.03	-0.78	0.62	403
	(-1.58)	(-1.09)	(-2.27)**	(-1.21)	(-0.40)	(-1.88)*	(0.78)	(-0.68)	(2.76)**	(-3.45)**		
Washington	-0.35	-0.13	-0.94	-0.06	1.22	-0.01	-0.32	-0.01	0.06	-0.51	0.54	849
	(-3.59)**	(-3.21)**	(-1.46)	(-0.16)	(3.55)**	(-0.02)	(-0.71)	(-0.01)	(2.91)**	(-3.48)**		

Notes: [1]Underlying coefficient multiplied by 1,000; t-statistics in parentheses; ** denotes significance at the 5% level or better; * denotes significance at the 10% level

Table A2: Weighted Regression of (8): SM^{A}, 1993

Observations are weighted by the number of low income applications in each tract.

MSA	INTERCEPT	C_CITY	BLCKRATE	CC_BLCK	TR_RATIO	FHA_RA	REFI_R	INV_RA	LOGINCM	LTV_LE80	LTV_GT80
Atlanta	-16.44	0.00	-0.24	-0.02	-0.03	-1.51	0.39	-2.37	1.76	0.09	0.04
	(-3.62)**	(0.01)	(-2.19)**	(-0.15)	(-0.31)	(-7.63)**	(1.64)	(-3.87)**	(4.01)**	(0.87)	(0.58)
Baltimore	-8.94	-0.05	-0.52	0.31	0.34	-0.82	1.10	-0.35	0.94	0.02	0.01
	(-2.45)**	(-0.81)	(-3.55)**	(1.87)*	(4.26)**	(-5.24)**	(5.73)**	(-0.48)	(2.69)**	(0.15)	(0.10)
Boston	-9.88	0.15	-1.91	1.46	0.05	-0.36	0.92	-0.32	0.91	-0.18	-0.11
	(-1.44)	(1.92)*	(-1.89)*	(1.42)	(0.40)	(-0.58)	(3.43)**	(-0.37)	(1.40)	(-0.64)	(-0.72)
Chicago	-5.82	-0.10	-0.32	0.19	0.03	-1.32	0.20	-0.66	0.66	-0.09	-0.04
	(-2.25)**	(-3.28)**	(-3.69)**	(2.17)**	(0.61)	(-12.54)**	(1.62)	(-1.50)	(2.66)**	(-1.34)	(-1.19)
Cleveland	-8.27	-0.39	-0.69	0.51	0.13	-0.72	0.17	0.58	0.94	-0.07	-0.02
	(-2.21)**	(-6.90)**	(-6.23)**	(4.58)**	(1.60)	(-2.50)**	(0.96)	(1.30)	(2.60)**	(-0.50)	(-0.21)
Dallas	-20.25	-0.07	-0.46	0.41	0.42	-1.19	1.90	-1.05	2.14	0.03	-0.01
	(-5.08)**	(-1.22)	(-1.41)	(1.21)	(4.65)**	(-8.12)**	(6.95)**	(-1.41)	(5.58)**	(0.24)	(-0.17)
Denver	-19.72	0.05	-0.23	0.16	0.59	-1.40	0.79	0.49	1.95	0.32	0.12
	(-4.63)**	(0.99)	(-0.66)	(0.43)	(6.74)**	(-9.09)**	(3.55)**	(0.61)	(4.71)**	(2.97)**	(2.20)**
Detroit	-8.19	0.05	-0.25	0.15	0.31	-0.40	1.60	-2.40	0.86	0.09	0.00
	(-3.09)**	(1.12)	(-2.15)**	(1.19)	(5.32)**	(-3.63)**	(12.23)**	(-4.09)**	(3.34)**	(1.15)	(0.08)
Houston	-15.76	0.06	-0.24	0.18	0.24	-1.03	1.92	-0.23	1.61	0.09	-0.01
	(-5.07)**	(1.16)	(-0.88)	(0.63)	(2.99)**	(-6.31)**	(8.08)**	(-0.46)	(5.37)**	(0.80)	(-0.09)
Los Angeles	-12.83	0.01	-0.50	0.03	-0.02	-1.15	0.53	-0.06	1.37	-0.26	-0.19
	(-5.74)**	(0.36)	(-8.27)**	(0.41)	(-0.54)	(-10.01)**	(4.63)**	(-0.26)	(6.36)**	(-3.76)**	(-5.12)**
Miami	-16.76	0.26	-0.33	-0.34	0.16	-0.44	0.25	1.05	1.86	0.22	0.11
	(-2.79)**	(3.26)**	(-2.11)**	(-1.61)	(1.55)	(-1.77)*	(1.12)	(1.42)	(3.13)**	(1.21)	(1.01)
Minneapolis	-17.48	0.02	0.52	-0.47	0.46	-0.94	0.44	-2.82	1.81	-0.02	0.02
	(-5.38)**	(0.46)	(0.48)	(-0.44)	(6.17)**	(-7.98)**	(2.87)**	(-2.93)**	(5.78)**	(-0.19)	(0.34)
New York City	-4.59	0.13	-0.45	-0.03	-0.40	-0.71	0.20	0.24	0.50	0.61	0.35
	(-1.87)*	(1.72)*	(-1.65)*	(-0.11)	(-5.72)**	(-2.83)**	(1.82)*	(0.71)	(2.16)**	(4.01)**	(4.39)**
Oakland	-14.57	-0.06	-0.54	0.09	-0.11	-1.25	0.78	-0.30	1.43	-0.02	-0.02
	(-4.35)**	-0.90	(-5.04)**	(0.65)	(-1.42)	(-6.02)**	(4.85)**	(-0.83)	(4.53)**	(-0.25)	(-0.41)
Philadelphia	-12.31	-0.17	-0.36	0.17	0.22	-1.27	0.24	0.42	1.30	-0.01	-0.04
	(-4.90)**	(-3.84)**	(-2.65)**	(1.22)	(3.29)**	(-8.22)**	(1.44)	(0.65)	(5.40)**	(-0.10)	(-0.55)
Phoenix	-21.60	0.06	-0.28	-0.29	0.30	-1.47	1.25	2.35	2.22	0.09	0.12
	(-4.27)**	(0.88)	(-0.12)	(-0.13)	(3.04)**	(-9.18)**	(5.64)**	(2.29)**	(4.52)**	(0.69)	(1.76)*
Pittsburgh	-24.62	-0.17	-0.45	0.74	1.18	0.10	0.86	-0.71	2.45	0.67	0.36
	(-4.62)**	(-1.74)*	(-1.50)	(2.22)**	(9.26)**	(0.35)	(2.85)**	(-0.68)	(4.71)**	(3.11)**	(3.34)**
San Diego	-14.31	-0.02	-1.05	0.68	0.04	-0.82	0.85	-0.45	1.51	0.19	0.13
	(-4.07)**	(-0.52)	(-2.76)**	(1.77)*	(0.61)	(-5.07)**	(5.60)**	(-1.29)	(4.45)**	(1.71)*	(2.16)**
Tampa	-11.82	0.03	-0.20	0.32	0.68	-0.21	1.46	-0.86	1.20	0.23	0.11
	(-2.26)**	(0.46)	(-1.27)	(1.24)	(6.20)**	(-0.90)	(5.64)**	(-1.65)*	(2.31)**	(1.52)	(1.40)
Washington	-19.23	-0.06	-0.31	0.12	-0.07	-1.47	0.44	-0.73	1.95	0.06	-0.01
	(-8.76)**	(-1.27)	(-5.79)**	(1.45)	(-1.17)	(-18.01)**	(4.39)**	(-2.08)**	(9.60)**	(0.96)	(-0.30)

Notes: [1]Underlying coefficients multiplied by 1,000; t-statistics reported in parentheses; ** denotes significance at the 5% level or better; * denotes significance at the 10% level

Table A2: Weighted Regression of (8): SM^{A}, 1993 (continued)

Observations are weighted by the number of low income applications in each tract.

MSA	G3_Prop	HHR24LOW	HHR2534	HHR3544	HHR4554	HHR5564	HHR75UP	U_OWNER[1]	R_OWNER1	R-Square	# of Obs.
Atlanta	-0.24	-1.27	0.85	1.14	-0.08	0.91	-0.12	0.13	-1.22	0.56	467
	(-1.51)	(-1.34)	(1.44)	(2.03)**	(-0.13)	(1.11)	(-0.17)	(5.92)**	(-4.24)**		
Baltimore	-0.24	-0.08	0.42	0.71	-0.31	-0.11	-0.28	0.06	-0.63	0.63	559
	(-1.55)	(-0.10)	(0.91)	(1.67)*	(-0.69)	(-0.18)	(-0.53)	(2.30)**	(-3.60)**		
Boston	-0.24	2.55	2.39	1.47	1.63	1.80	1.82	0.39	-1.47	0.22	618
	(-1.09)	(2.26)**	(2.86)**	(2.16)**	(2.09)**	(1.95)*	(2.18)**	(7.66)**	(-5.03)**		
Chicago	-0.30	0.95	0.43	0.39	-0.11	-0.09	0.32	0.16	-0.05	0.59	1448
	(-2.88)**	(1.79)*	(1.39)	(1.49)	(-0.36)	(-0.26)	(0.97)	(9.27)**	(-0.46)		
Cleveland	-0.60	-2.10	0.27	0.59	0.64	0.22	-0.15	0.23	-0.68	0.70	595
	(-3.43)**	(-2.38)**	(0.48)	(1.40)	(1.34)	(0.41)	(-0.29)	(5.86)**	(-3.95)**		
Dallas	0.06	-1.86	-0.79	-0.04	-1.74	-1.48	-0.89	0.08	-0.45	0.61	523
	(0.30)	(-2.27)**	(-1.31)	(-0.07)	(-2.79)**	(-1.69)*	(-1.12)	(2.09)**	(-1.51)		
Denver	0.13	0.63	0.68	0.61	-0.43	0.05	0.03	0.18	-0.42	0.75	407
	(0.85)	(0.81)	(1.55)	(1.59)	(-0.91)	(0.08)	(0.05)	(5.78)**	(-2.13)**		
Detroit	-0.12	-2.63	-0.03	0.24	-0.47	-0.62	-0.50	0.08	-0.52	0.68	1163
	(-1.09)	(-4.35)**	(-0.09)	(0.84)	(-1.48)	(-1.60)	(-1.25)	(4.75)**	(-3.87)**		
Houston	-0.23	0.62	1.02	0.73	0.27	0.07	0.29	0.09	-0.57	0.64	662
	(-1.38)	(0.70)	(1.66)*	(1.44)	(0.48)	(0.09)	(0.38)	(4.69)**	(-2.15)**		
Los Angeles	-0.50	0.06	-0.11	-0.17	-0.48	0.40	-0.75	0.10	-0.10	0.39	1606
	(-5.97)**	(0.12)	(-0.33)	(-0.61)	(-1.64)	(1.19)	(-2.18)**	(6.20)**	(-0.96)		
Miami	-0.48	-2.88	-1.04	-0.59	-1.19	-0.54	-1.86	0.13	-0.98	0.59	257
	(-1.70)*	(-2.33)**	(-1.21)	(-0.70)	(-1.57)	(-0.54)	(-2.49)**	(7.05)**	(-3.44)**		
Minneapolis	-0.06	-1.47	-0.37	0.32	-0.84	-0.60	-0.68	0.18	-0.61	0.62	617
	(-0.47)	(-2.39)**	(-1.03)	(0.94)	(-2.09)**	(-1.22)	(-1.61)	(7.28)**	(-3.57)**		
New York City	-0.49	0.36	2.91	1.19	0.57	-0.02	-0.03	0.25	0.10	0.15	2191
	(-3.18)**	(0.37)	(3.88)**	(2.53)**	(1.19)	(-0.04)	(-0.06)	(6.07)**	(0.64)		
Oakland	-0.06	0.56	0.74	0.68	0.46	0.34	0.19	0.15	-0.21	0.60	451
	(-0.58)	(0.84)	(1.88)*	(1.98)**	(1.21)	(0.70)	(0.42)	(6.81)**	(-1.35)		
Philadelphia	-0.15	-0.72	1.60	0.75	-0.20	-0.44	0.06	0.08	-0.47	0.49	1211
	(-1.13)	(-1.02)	(3.86)**	(2.06)**	(-0.48)	(-0.88)	(0.14)	(4.81)**	(-3.04)**		
Phoenix	-0.09	-1.29	0.17	0.45	0.38	-0.65	0.61	0.17	-0.78	0.61	460
	(-0.41)	(-1.51)	(0.34)	(0.93)	(0.71)	(-0.84)	(1.11)	(4.60)**	(-3.09)**		
Pittsburgh	-0.24	-0.90	0.09	1.23	-1.29	0.79	-0.23	0.08	-1.26	0.51	633
	(-1.08)	(-0.74)	(0.09)	(1.47)	(-1.41)	(0.80)	(-0.25)	(1.55)	(-3.97)**		
San Diego	-0.24	-0.52	-0.45	-1.10	-1.06	-1.63	-1.51	0.09	0.07	0.50	431
	(-1.94)*	(-1.00)	(-0.97)	(-3.15)**	(-2.62)**	(-3.06)**	(-3.56)**	(4.80)**	(0.42)		
Tampa	-0.48	-2.09	-0.40	0.86	0.17	-1.21	1.07	0.05	-0.70	0.59	406
	(-2.57)**	(-1.98)**	(-0.60)	(1.39)	(0.26)	(-1.55)	(2.01)**	(4.92)**	(-3.13)**		
Washington	-0.09	-0.20	0.58	0.69	-0.27	0.48	-0.04	0.12	-0.52	0.69	857
	(-1.02)	(-0.42)	(2.14)**	(2.75)**	(-1.03)	(1.32)	(-0.10)	(8.70)**	(-4.49)**		

Notes: [1]Underlying coefficients multiplied by 1,000; t-statistics reported in parentheses; ** denotes significance at the 5% level or better; * denotes significance at the 10% level

Table A3: Weighted Regression of (8): SM^O, 1993

Observations are weighted by the number of low income originations in each tract.

MSA	INTERCEPT	C_CITY	BLCKRATE	CC_BLCK	TR_RATIO	FHA_RA	REFI_R	INV_RA	LOGINCM	LTV_LE80	LTV_GT80
Atlanta	-12.24	-0.01	-0.15	0.05	0.01	-1.35	0.26	-1.47	1.35	-0.06	-0.01
	(-3.62)**	(0.01)	(-2.19)**	(-0.15)	(-0.31)	(-7.63)**	(1.64)	(-3.87)**	(4.01)**	(0.87)	(0.58)
Baltimore	-13.51	-0.04	-0.25	0.05	0.33	-1.06	0.61	0.34	1.38	-0.05	-0.01
	(-2.45)**	(-0.81)	(-3.55)**	(1.87)*	(4.26)**	(-5.24)**	(5.73)**	(-0.48)	(2.69)**	(0.15)	(0.10)
Boston	-2.00	0.15	-1.69	1.19	0.02	-0.09	0.90	-0.01	0.15	-0.13	-0.08
	(-1.44)	(1.92)*	(-1.89)*	(1.42)	(0.40)	(-0.58)	(3.43)**	(-0.37)	(1.40)	(-0.64)	(-0.72)
Chicago	-6.70	-0.05	-0.15	0.08	0.03	-1.17	0.19	-0.22	0.72	-0.01	-0.01
	(-2.25)**	(-3.28)**	(-3.69)**	(2.17)**	(0.61)	(-12.54)**	(1.62)	(-1.50)	(2.66)**	(-1.34)	(-1.19)
Cleveland	-5.51	-0.29	-0.47	0.29	0.15	-0.41	0.20	1.46	0.63	0.02	0.00
	(-2.21)**	(-6.90)**	(-6.23)**	(4.58)**	(1.60)	(-2.50)**	(0.96)	(1.30)	(2.60)**	(-0.50)	(-0.21)
Dallas	-15.64	-0.02	-0.33	0.15	0.41	-1.34	0.85	-0.73	1.71	-0.09	-0.04
	(-5.08)**	(-1.22)	(-1.41)	(1.21)	(4.65)**	(-8.12)**	(6.95)**	(-1.41)	(5.58)**	(0.24)	(-0.17)
Denver	-13.75	0.01	-0.34	0.36	0.64	-1.48	0.42	-0.54	1.39	0.22	0.07
	(-4.63)**	(0.99)	(-0.66)	(0.43)	(6.74)**	(-9.09)**	(3.55)**	(0.61)	(4.71)**	(2.97)**	(2.20)**
Detroit	-9.22	0.05	-0.17	0.00	0.35	-0.39	0.90	-0.98	0.95	0.00	-0.03
	(-3.09)**	(1.12)	(-2.15)**	(1.19)	(5.32)**	(-3.63)**	(12.23)**	(-4.09)**	(3.34)**	(1.15)	(0.08)
Houston	-9.33	0.00	-0.29	0.23	0.19	-1.05	1.06	-0.10	1.01	-0.02	-0.04
	(-5.07)**	(1.16)	(-0.88)	(0.63)	(2.99)**	(-6.31)**	(8.08)**	(-0.46)	(5.37)**	(0.80)	(-0.09)
Los Angeles	-7.66	0.03	-0.29	-0.10	-0.11	-0.95	0.45	0.04	0.83	-0.07	-0.07
	(-5.74)**	(0.36)	(-8.27)**	(0.41)	(-0.54)	(-10.01)**	(4.63)**	(-0.26)	(6.36)**	(-3.76)**	(-5.12)**
Miami	-3.87	0.19	-0.23	-0.29	0.16	-0.56	0.51	-0.21	0.52	0.05	0.02
	(-2.79)**	(3.26)**	(-2.11)**	(-1.61)	(1.55)	(-1.77)*	(1.12)	(1.42)	(3.13)**	(1.21)	(1.01)
Minneapolis	-12.31	0.02	1.24	-1.26	0.45	-1.12	0.18	-2.36	1.32	-0.03	0.00
	(-5.38)**	(0.46)	(0.48)	(-0.44)	(6.17)**	(-7.98)**	(2.87)**	(-2.93)**	(5.78)**	(-0.19)	(0.34)
New York City	-3.27	0.12	-0.06	-0.13	-0.30	-0.31	0.33	0.36	0.38	0.37	0.19
	(-1.87)*	(1.72)*	(-1.65)*	(-0.11)	(-5.72)**	(-2.83)**	(1.82)*	(0.71)	(2.16)**	(4.01)**	(4.39)**
Oakland	-10.97	-0.05	-0.41	0.06	-0.15	-1.06	0.35	-0.16	1.10	-0.05	-0.02
	(-4.35)**	-0.90	(-5.04)**	(0.65)	(-1.42)	(-6.02)**	(4.85)**	(-0.83)	(4.53)**	(-0.25)	(-0.41)
Philadelphia	-12.78	-0.12	-0.31	0.14	0.22	-0.91	0.11	0.56	1.34	-0.09	-0.07
	(-4.90)**	(-3.84)**	(-2.65)**	(1.22)	(3.29)**	(-8.22)**	(1.44)	(0.65)	(5.40)**	(-0.10)	(-0.55)
Phoenix	-13.79	0.09	0.66	-1.16	0.32	-1.42	0.80	1.07	1.45	0.20	0.13
	(-4.27)**	(0.88)	(-0.12)	(-0.13)	(3.04)**	(-9.18)**	(5.64)**	(2.29)**	(4.52)**	(0.69)	(1.76)*
Pittsburgh	-11.39	-0.17	-0.48	0.58	1.17	-0.06	0.54	-0.01	1.17	0.67	0.34
	(-4.62)**	(-1.74)*	(-1.50)	(2.22)**	(9.26)**	(0.35)	(2.85)**	(-0.68)	(4.71)**	(3.11)**	(3.34)**
San Diego	-7.77	-0.03	-0.80	0.63	0.00	-0.94	0.66	-0.03	0.88	0.05	0.05
	(-4.07)**	(-0.52)	(-2.76)**	(1.77)*	(0.61)	(-5.07)**	(5.60)**	(-1.29)	(4.45)**	(1.71)*	(2.16)**
Tampa	-6.41	0.09	-0.22	0.15	0.66	-0.36	1.01	-1.13	0.68	0.09	0.06
	(-2.26)**	(0.46)	(-1.27)	(1.24)	(6.20)**	(-0.90)	(5.64)**	(-1.65)*	(2.31)**	(1.52)	(1.40)
Washington	-16.92	-0.08	-0.16	0.11	-0.06	-1.49	0.18	0.46	1.74	0.09	0.00
	(-8.76)**	(-1.27)	(-5.79)**	(1.45)	(-1.17)	(-18.01)**	(4.39)**	(-2.08)**	(9.60)**	(0.96)	(-0.30)

Notes: [1]Underlying coefficients multiplied by 1,000; t-statistics in parentheses; ** denotes significance at the 5% level or better; * denotes significance at the 10% level

Table A3: Weighted Regression of (8): SM^O, 1993 (continued)

Observations are weighted by the number of low income originations in each tract.

MSA	G3_Prop	HHR24LOW	HHR2534	HHR3544	HHR4554	HHR5564	HHR75UP	U_OWNER[1]	R_OWNER1	R-Square	# of Obs
Atlanta	-0.20	-1.34	0.64	1.05	-0.23	0.76	-0.26	0.12	-1.10	0.49	466
	(-1.51)	(-1.34)	(1.44)	(2.03)**	(-0.13)	(1.11)	(-0.17)	(5.92)**	(-4.24)**		
Baltimore	-0.06	0.61	0.72	0.61	-0.02	-0.02	0.43	0.07	-0.53	0.60	559
	(-1.55)	(-0.10)	(0.91)	(1.67)*	(-0.69)	(-0.18)	(-0.53)	(2.30)**	(-3.60)**		
Boston	-0.21	2.67	2.54	1.64	1.77	2.01	2.01	0.38	-1.47	0.18	616
	(-1.09)	(2.26)**	(2.86)**	(2.16)**	(2.09)**	(1.95)*	(2.18)**	(7.66)**	(-5.03)**		
Chicago	-0.23	1.01	0.44	0.58	0.14	0.05	0.45	0.14	-0.10	0.52	1424
	(-2.88)**	(1.79)*	(1.39)	(1.49)	(-0.36)	(-0.26)	(0.97)	(9.27)**	(-0.46)		
Cleveland	-0.64	-1.34	0.56	0.81	0.99	0.51	0.14	0.22	-0.74	0.62	587
	(-3.43)**	(-2.38)**	(0.48)	(1.40)	(1.34)	(0.41)	(-0.29)	(5.86)**	(-3.95)**		
Dallas	-0.03	-1.45	-0.62	-0.09	-1.22	-1.50	-1.09	0.07	-0.49	0.58	512
	(0.30)	(-2.27)**	(-1.31)	(-0.07)	(-2.79)**	(-1.69)*	(-1.12)	(2.09)**	(-1.51)		
Denver	0.15	0.58	0.59	0.64	-0.75	0.26	-0.02	0.13	-0.36	0.73	406
	(0.85)	(0.81)	(1.55)	(1.59)	(-0.91)	(0.08)	(0.05)	(5.78)**	(-2.13)**		
Detroit	-0.12	-2.17	0.35	0.57	-0.16	-0.37	-0.15	0.08	-0.55	0.61	1158
	(-1.09)	(-4.35)**	(-0.09)	(0.84)	(-1.48)	(-1.60)	(-1.25)	(4.75)**	(-3.87)**		
Houston	-0.33	0.72	0.53	0.83	0.15	-0.40	-0.28	0.07	-0.47	0.57	652
	(-1.38)	(0.70)	(1.66)*	(1.44)	(0.48)	(0.09)	(0.38)	(4.69)**	(-2.15)**		
Los Angeles	-0.36	0.27	0.32	0.34	0.07	0.56	-0.36	0.09	-0.23	0.30	1600
	(-5.97)**	(0.12)	(-0.33)	(-0.61)	(-1.64)	(1.19)	(-2.18)**	(6.20)**	(-0.96)		
Miami	-0.49	-1.40	-0.22	0.73	-0.89	0.35	-0.16	0.12	-1.11	0.57	256
	(-1.70)*	(-2.33)**	(-1.21)	(-0.70)	(-1.57)	(-0.54)	(-2.49)**	(7.05)**	(-3.44)**		
Minneapolis	-0.07	-1.40	-0.18	0.23	-0.83	-0.47	-0.74	0.16	-0.60	0.59	615
	(-0.47)	(-2.39)**	(-1.03)	(0.94)	(-2.09)**	(-1.22)	(-1.61)	(7.28)**	(-3.57)**		
New York City	-0.28	0.05	1.64	0.80	0.25	-0.33	0.01	0.22	0.02	0.09	1959
	(-3.18)**	(0.37)	(3.88)**	(2.53)**	(1.19)	(-0.04)	(-0.06)	(6.07)**	(0.64)		
Oakland	-0.04	0.92	0.83	0.99	0.61	0.76	0.32	0.11	-0.23	0.50	449
	(-0.58)	(0.84)	(1.88)*	(1.98)**	(1.21)	(0.70)	(0.42)	(6.81)**	(-1.35)		
Philadelphia	-0.04	-0.47	1.12	0.88	-0.12	-0.52	0.07	0.07	-0.38	0.37	1204
	(-1.13)	(-1.02)	(3.86)**	(2.06)**	(-0.48)	(-0.88)	(0.14)	(4.81)**	(-3.04)**		
Phoenix	0.01	-1.10	0.27	0.67	0.57	-0.38	0.48	0.16	-0.85	0.57	460
	(-0.41)	(-1.51)	(0.34)	(0.93)	(0.71)	(-0.84)	(1.11)	(4.60)**	(-3.09)**		
Pittsburgh	-0.44	-2.28	-0.16	1.50	-1.59	1.04	-0.84	0.03	-1.40	0.49	617
	(-1.08)	(-0.74)	(0.09)	(1.47)	(-1.41)	(0.80)	(-0.25)	(1.55)	(-3.97)**		
San Diego	-0.17	-0.54	-0.08	-0.63	-0.85	-1.37	-1.30	0.07	0.01	0.45	430
	(-1.94)*	(-1.00)	(-0.97)	(-3.15)**	(-2.62)**	(-3.06)**	(-3.56)**	(4.80)**	(0.42)		
Tampa	-0.43	-2.11	0.37	1.00	0.52	-0.38	1.25	0.05	-1.05	0.54	403
	(-2.57)**	(-1.98)**	(-0.60)	(1.39)	(0.26)	(-1.55)	(2.01)**	(4.92)**	(-3.13)**		
Washington	-0.03	-0.19	0.43	0.60	-0.42	0.46	-0.23	0.12	-0.41	0.67	856
	(-1.02)	(-0.42)	(2.14)**	(2.75)**	(-1.03)	(1.32)	(-0.10)	(8.70)**	(-4.49)**		

Notes: [1]Underlying coefficients multiplied by 1,000; t-statistics in parentheses; ** denotes significance at the 5% level or better; * denotes significance at the 10% level