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Concentrated poverty has been said to impose a double burden on those that confront it. In addition to an individual's own financial constraints, institutions and social networks of poor neighborhoods can further limit access to quality services and resources for those that live there. This study contributes to the characterization of the relationship between subprime lending and poor neighborhoods by including a spatial dimension to the analysis, in an attempt to capture social effect differences in poor and less poor neighborhoods. The analysis is applied to 2004-2006 census tract level data in Cuyahoga County, home to Cleveland, Ohio, a region that features urban neighborhoods highly segregated by income and race. The patterns found in poor neighborhoods suggest stronger social interaction effects inducing subprime lending in comparison to less poor neighborhoods.

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Francisca G.-C. Richter is a research economist in Community Development at the Federal Reserve Bank of Cleveland. She can be reached at francisca.g.richter@clev.frb.org. Ben Craig is a senior economic advisor in the Research Department of the Federal Reserve Bank of Cleveland. He can be reached at ben.r.craig@clev.frb.org.

1 Introduction

Concentrated poverty has been said to impose a double burden on those that confront it. One's own financial constraints may prevent or reduce access to good education, health, and financial services as well as good jobs. In addition, institutions and social networks of poor neighborhoods can further limit access to quality services and resources for those that live there. Less than four decades ago the institutional practice of redlining limited access to credit in poor neighborhoods. Redlining was a term to denote banks' unwillingness to lend to individuals based on where they lived and regardless of their own creditworthiness. Low income neighborhoods were red lined on a map signaling boundaries to the issuance of credit in these areas. During the 1970's, fair lending legislation was enacted to revert discriminatory practices and ensure fair and impartial access to credit [2]. With the recent expansion of mortgage credit and securitization, the relationship between neighborhood poverty and access to credit changed dramatically. Poorer neighborhoods throughout the nation, that during the redlining days would have had little to no credit availability, experienced a large drop in mortgage application denial rates and an expansion of subprime credit from 2002-2005, in the midst of relative income and employment declines[1] [7]. As was the case during the redlining era, these neighborhoods have been negatively impacted by the distinct borrowing and lending patterns they experienced. However, unlike the pre-70's case, characterizing the relationship between borrowing/lending and neighborhood poverty is more challenging than displaying evidence of red-lined maps. Calem, Hershaff, and Wachter [3] identify a positive relationship between high rates of subprime lending and characteristics of low

[1]Mian and Sufi [7] quantify this credit expansion paired with relative income and employment decline for what they call subprime zip codes. They define zip codes as subprime (prime) if their share of low-credit score consumers (FICO score below 660 as of 1991) is in the highest (lowest) quartile, within their respective county. Subprime zip codes, in comparison to prime ones, have lower median income, higher poverty rates, lower education levels, higher unemployment rates and a large fraction of minority population.

income neighborhoods in seven cities between 2002 and 2007. They point to the share of neighborhood minority and low educational level as consistently and negatively related to higher subprime shares, even when controlling for credit and equity risk. Squires, Hyra, and Renner [11] find that the level of racial segregation at the metropolitan level is positively related with the rate of subprime lending in 2006, even after controlling for percent minority, low credit scores, poverty, and median home value. They also suggest that general education levels seem to be an important protective factor against high rates of subprime lending. A qualitative study by Pittman [9] uses in-depth interviews to inquire why black borrowers tend to disproportionately hold higher priced mortgage products even when controlling for creditworthiness. Her work suggests borrowers' decisions were shaped by the informal and formal advice they received, and that social networks may be at play in determining different outcomes between borrowers.

This study contributes to the characterization of the relationship between subprime lending and poor neighborhoods by adding a spatial dimension to the analysis, in an attempt to capture social effect differences in poor and less poor neighborhoods. The focus is on non-depository subprime lending taking place in Cuyahoga County, home to Cleveland, Ohio during the 2004-2006 period. The region features a mix of neighborhoods, ranging from highly segregated and persistently poor, to those of mid to high income and racially diverse[2]. Non-depository subprime loans are subprime loans according to Home Mortgage Disclosure Act (HMDA) data that were issued by an independent mortgage company or a subsidiary of a bank, and likely facilitated by a mortgage broker. A 2004 Government Accounting Office report on consumer protection [12] concludes that much of the predatory lending problem lies with non-depository finance companies and that homebuyer education,

[2]In fact, a study by Sethi and Somanathan rank Cleveland third out of thirty major metropolitan areas in terms of a racial dissimilarity index that accounts for income differences [10].

counseling, and disclosures have limited effectiveness in deterring predatory lending.

The paper proceeds by outlining a set of social and non-social hypotheses that may explain the spatial relationship between non-depository subprime lending and neighborhood poverty.[3] This is followed by the models and data section, which includes a discussion of issues and limitations encountered when working with aggregate data and the lack of social network data. Results are then presented followed by concluding remarks.

2 Neighborhood Poverty and Subprime Lending

People are connected to others through social links. These can originate in the family, neighborhood, work environment, or through their sense of affiliation to groups with common beliefs, ethnicity, status, etc. Since the poverty status of individuals is likely to influence social ties formation, the influence of social environments on individual decisions and group outcomes may differ among poor and non-poor groups. Over the past three decades, social science researchers have developed concepts and models to formally explore the effects of social interactions on individual behavior and outcomes. Manski's [6] non-exclusive hypotheses for why one might observe individuals in the same social environment behaving similarly have become standard and are used here to describe various hypotheses underlying the relationship between subprime lending rates and neighborhood poverty.

- Correlated effects (non-social): individuals in the same group tend to display similar borrowing outcomes because they have similar individual characteristics or face similar institutional environments. Income

[3] In what follows, 'subprime lending' will be used to refer to non-depository subprime lending.

and credit scores are examples of such characteristics. An individual's low credit scores and savings are likely to reduce access to prime products. Lack of access to good education is an institutional constraint likely to make for less sophisticated borrowers. These characteristics, more prevalent among the poor, may explain in part why similar borrowing/lending patterns are observed in poor neighborhoods.

- Exogenous or contextual interactions (social): the propensity of an individual to take out a subprime loan varies with the exogenous characteristics of the group. Independent of a particular borrower's income or education level, by living in a poor neighborhood (group income is low) he may likely have been more exposed to location or group-based marketing of subprime products. Visual ads in convenience stores, sales presentations by mortgage brokers in social gatherings are examples of contextual effects inducing similar borrowing behaviors.

- Endogenous interactions (social): all else equal, the propensity of an individual to take out a subprime loan varies with the borrowing behavior of the group. As peers make use of these mortgage products with seemingly positive results (in the short term), risk aversion toward these previously unfamiliar products drops, possibly inducing an increased demand[4]. A lower reliance on mainstream financial institutions by low income individuals may have contributed to strengthen this effect. Unlike the two previous types of effects, these interactions induce what is called a social multiplier effect. Assume persons 'J' and 'I' are socially linked. If person 'J' displays low risk aversion to a mortgage product, person 'I' may lower her own risk aversion to it. This in turn induces person's 'J' risk aversion to further decrease. Anecdotal evidence pointing to referrals as a way to broker high cost loans in poor

[4]Note that no matter how rich the data, risk aversion will be unobservable to the researcher.

neighborhoods illustrates a channel for the formation of endogenous interactions.

Thus, poverty may exert its influence on the propensity to take out a subprime loan through individual or social group effects. And as is evident now, high rates of subprime lending in poor neighborhoods have led to high foreclosure rates, devastation and wealth loss for borrowers and non-borrowers alike. Correlated individual effects, as well as social -exogenous and endogenous- effects may be apparent in poor neighborhoods. The individual effects are due to being poor whereas the social effects are directly related to living in a poor neighborhood, and speak of what has been termed the 'double burden' of concentrated poverty.

Ideally one would want to know in what ways did the concentration of poverty influence the high rates of subprime lending that these neighborhoods experienced. Is the decision or propensity of a person to take-up a subprime loan directly affected by the lending decisions of his peers in that respect? Are endogenous effects at play? That is, even after accounting for characteristics of the borrower and the people in his social network - such as income, education, credit scores - as well as neighborhood characteristics, do lending decisions of the latter affect those of the former? Unable to answer that, a less specific question is to ask whether social effects in general, a combination of endogenous and exogenous effects, induced higher rates of subprime lending. And whether lending in lower income neighborhoods exhibit stronger or weaker social interaction effects than in less poor areas. Is there any evidence that social interactions in poor neighborhoods facilitated the higher rates of subprime lending? If evidence exists, it provides important feedback that can serve to inform financial education efforts and consumer protection policies. It would also suggest revisiting the availability and accessibility of products in the traditional financial system that meet the needs of low income borrowers.

3 Models and Data

Much of the research on social interactions has focused on being able to identify endogenous effects when present, given that policy implementation may benefit from recognizing social multiplier effects. A typical example is to consider the effects of additional tutoring to a group of students in a classroom. Assume students are homogeneous in terms of family income, parental education, health, and other relevant exogenous factors, and education quality per student remains fixed. If in fact, there are endogenous interaction effects on student achievement, increased achievement by the tutored group would increase the achievement of the overall group and in turn, further increase the tutored group's achievement. Given the limitations of the data at hand, this study makes no attempt to isolate a social multiplier effect in subprime borrowing. Even if disaggregate or individual level data were available along with their respective social links, lack of data on unobservables such as risk aversion will prevent obtaining accurate estimates of social interaction effects. Cooley [4] shows this to be the case for student achievement peer effects, when peer achievement is proxying for unobservable effort.

The lack of social network data affects the analysis, whether it is performed at the aggregate or disaggregate level. Consider the case in which disaggregate or individual level data are available. When loans are refinances, location of the home allows linking a borrower with a geographic area such as the census tract[5] in which the home is located. Yet, it misses links taking place in other social spaces not related to the neighborhood. When loans are for a new home, location of the new home is not necessarily close to the borrower's previous neighborhood. Given the lack of specificity in the data, including a rather large geographic definition of neighborhood should be pre-

[5] Census tracts are small statistical subdivisions of a county, and are designed to be homogeneous in terms of population characteristics, economic status, and living conditions. There are 495 census tracts in Cuyahoga County.

ferred to a small one.[6]

In this section a spatial analysis is performed on rates of subprime lending and other characteristics at the census tract level. Since the analysis is done at the aggregate level, it is not able to identify a social interactions effect. However, the spatial patterns found in poor neighborhoods are consistent with stronger social interaction effects inducing subprime lending in comparison to less poor neighborhoods.

Assume disaggregate or borrower level data were available, including data on the social network of borrowers. A simple model of spatial interactions would be the following:

$$y = \rho W_d y + e, \tag{1}$$

with y being the observed individual's decision or propensity to take out a subprime loan, W_d a disaggregate spatial weights matrix with information of each individual's neighbors, and e a disturbance term. Then ρ is the spatial interaction parameter between peer and borrower decisions. If this model is extended to include a set of explanatory variables and its spatial lags, then even endogenous social interaction effects may be captured by the spatial parameter ρ. However, aggregating the data to the neighborhood level imposes strong restrictions on the interpretation of ρ as a social interaction parameter. The following procedure helps interpret the spatial interaction parameter under aggregation. Assume m neighborhoods, each of size n_i, $i = 1, \cdots, m$, $\sum n_i = N$. Pre-multiplying both sides of the disaggregate equation (1) by an averaging matrix $A_{m \times N} =$

[6] As will be detailed in the following sections, the model is estimated with data on home purchases, refinances and home improvement loans, as well as for refinances and home improvement loans only.

$$\begin{bmatrix} \frac{1}{n_1}1'_{n_1} & 0_{1\times n_2} & \cdots & 0_{1\times n_m} \\ 0_{1\times n_1} & \frac{1}{n_2}1'_{n_2} & \cdots & 0_{1\times n_m} \\ \vdots & & \ddots & \vdots \\ 0_{1\times n_1} & 0_{1\times n_2} & \cdots & \frac{1}{n_m}1'_{n_m} \end{bmatrix}$$

one obtains (2), which differs from the aggregate data model in equation (3). In words, the aggregate data model is not the same as the disaggregate model pre-multiplied by an aggregation matrix, and thus, spatial interaction parameters ρ and $\tilde{\rho}$ will not be comparable in general.

$$\begin{aligned} Ay &= \rho A W_d y + Ae, \quad (2) \\ Ay &= \tilde{\rho} W_a A y + Ae, \quad (3) \end{aligned}$$

However, if W_d and W_a are such that

$$AW_d y = W_a A y, \quad (4)$$

then $\rho = \tilde{\rho}$, so the spatial interaction parameters of both models are equal. The following row-standardized spatial contiguity matrices, $W_d := [diag(\breve{W}_d 1_N)]^{-1}\breve{W}_d$ and $W_a := A\breve{W}_d A'$ satisfy condition (4), where

$$\breve{W}_d = \begin{bmatrix} 0_{n_1} & \frac{1}{n_2}D_{n_1\times n_2} & \cdots & \frac{1}{n_m}D_{n_1\times n_m} \\ \frac{1}{n_1}D_{n_2\times n_1} & 0_{n_2} & \cdots & \frac{1}{n_m}D_{n_2\times n_m} \\ \vdots & & \ddots & \vdots \\ \frac{1}{n_1}D_{n_m\times n_1} & \frac{1}{n_2}D_{n_m\times n_2} & \cdots & 0_{n_m} \end{bmatrix}$$

$$D_{n_i\times n_j} = \begin{cases} J_{n_i\times n_j}, & \text{neighborhoods } i \text{ and } j \text{ contiguous} \\ 0_{n_i\times n_j}, & \text{otherwise} \end{cases}$$

$$W_a = A\breve{W}_d A' = \begin{bmatrix} 0 & \frac{d_{12}}{d_{1.}} & \cdots & \frac{d_{1m}}{d_{1.}} \\ \frac{d_{21}}{d_{2.}} & 0 & \cdots & \frac{d_{2m}}{d_{2.}} \\ \vdots & & \ddots & \vdots \\ \frac{d_{m1}}{d_{m.}} & \frac{d_{m2}}{d_{m.}} & \cdots & 0 \end{bmatrix}$$

$$d_{ij} = \begin{cases} 1, & \text{neighborhoods } i \text{ and } j \text{ contiguous} \\ 0, & \text{otherwise} \end{cases}$$

$$d_{i.} = \sum_{j=1}^{m} d_{ij}, \text{ number of neighborhoods contiguous to } i$$

Here, W_a is the row-standardized spatial -neighborhood- contiguity matrix that would be used for the aggregated data model. But W_d, is not a typical spatial weights matrix for the disaggregate model. While it accounts for spatial contiguity between individuals in contiguous neighborhoods, it fails to capture within neighborhood spatial contiguity. Thus, the aggregate model will not be able to identify within neighborhood spatial interactions through the spatial parameter ρ, but does need to account for it with the use of other explanatory variables to reduce misspecification bias in ρ. If model (3) is extended by introducing a set of relevant aggregated borrower and neighborhood characteristics, as well as their spatial lags in the right hand side, then ρ should still be able to capture spatial effects in subprime lending due to endogenous and contextual social interactions taking place across neighborhoods.

In order to explore differences in lending patterns among poorer and less poor neighborhoods (census tracts for this analysis), these are classified into two categories according to the percentage of poor inhabitants. And with a dual-regime spatial model a spatial interaction parameter is estimated for each category, i.e., poorer (ρ_p) and less poor (ρ_{np}) neighborhoods. Models including spatially lagged dependent and independent variables are called Durbin models, so the following dual-regime spatial Durbin model with time fixed effects is estimated:

$$Y = \rho_p PWY + \rho_{np}(I - P)WY + \alpha P 1_{mT} + X\beta + WX\theta + \lambda_T \otimes 1_m + \epsilon \quad (5)$$

where $Y = [y_{11}, \cdots, y_{m1}, \cdots, y_{mT}]'$ is the stacked vector of $y_{it}'s$, the subprime lending rate in census tract i during year t. The data includes all tracts in Cuyahoga County, Ohio with more than 16 originations each year over the 2004-2006 period ($T = 3$), according to HMDA data. $W = I_T \otimes W_a$, with W_a being a row-standardized spatial weights matrix for the census tract level data. Year fixed effects are represented by λ_T and ϵ is an iid error term. $P = I_T \otimes diag(p_i)$, with p_i being a dummy for poverty in census tract i. Tracts are classified into the poorer group if $z\%$ of its population is below the official poverty line, according to the 2000 Census. Figure 1 shows the distribution of poverty rates in Cuyahoga County neighborhoods according to the 2000 Census. The model is estimated for z values of 20, 30, and 40 percent. Columns of X are yearly census tract data on credit scores and borrower income, as well as time-invariant data on race, and education from the Census. More specifically, explanatory variables are as follows. Data on the percent of the tract population with low credit scores are based on Equifax and Transunion scores.[7] Median borrower income from HMDA is

[7]The low credit score upper bound is an equivalent to a 600 FICO score. This corresponds to 490 for Transunion and 640 for Equifax. Equifax based rates are available for 2005 and 2006 while Transunion based rates are for 2004 and 2005. The 2004-2005 change in the percent of population with low credit scores from Transunion is applied to the 2005 Equifax based figure to obtain a 2004 estimate. That is $\hat{E_{2004}} = E_{2005}T_{2004}/T_{2005}$, where E_t is the percent of population in the tract with low credit score in year t based on Equifax

another time varying explanatory variable. Time fixed effects are important given the national trends in credit expansion and securitization taking place during the 2004-2006 period. Explanatory variables at the tract level that do not vary with time are the percent of the population without high school diploma, and the percent of African American population, both from the Census 2000. Finally, the spatial lags of these variables (WX) are also included, making it a spatial Durbin model. Elhorst [5] suggests using this model in the presence of endogenous, exogenous, and correlated effects. He argues that a Durbin model is more likely to produce unbiased coefficient estimates even if the true data generating process is a spatial lag, spatial error, or a combination of them.

Characteristics measured in X affect lending and borrowing at the individual and neighborhood level, so the parameters in β clearly confound the individual and contextual effects of these variables in the aggregate model.[8] Parameters in θ control for additional contextual effects taking place across adjacent neighborhoods. Parameters in λ_T control for correlated effects not explicitly entered in the model. With these controls in place, it is of interest to see whether spatial interactions (WY) have a positive and larger impact in poor neighborhoods as opposed to less poor ones, even after accounting for within and across neighborhood characteristics, and exogenous factors correlated with borrowing and lending patterns (X, WX, and time fixed effects). Such findings would be consistent with stronger social interaction effects on subprime lending operating in poorer neighborhoods. Even when

data, and T_t is the corresponding measure based on Transunion data. The variables used in the model are $\hat{E}_{2004}$, E_{2005}, and E_{2006}.

[8]In other words, β_{income} may capture individual and contextual effects of neighborhood income on subprime rates: individual characteristics, such as low income, may limit the borrower to qualifying for products that she can -at least initially- afford, such as ones with no down payment or a low teaser rate. Additionally, lenders and brokers may have marketed their subprime products in low income neighborhoods, attracting clients regardless of their income (a contextual effect).

no direct inferences from the model can be made at the borrower level, this analysis adds to the understanding of the consumer credit market in areas of concentrated poverty.

The model is estimated via maximum likelihood both, for raw rates (linear probability model) and for the log odds ratio of subprime lending.[9] The advantage of estimating with the log odds transformed data (besides avoiding predicted rates outside the $(0, 1)$ range) is that their distribution is closer to normality, an assumption of maximum likelihood estimation. As expected, the Jarque-Bera test rejects the null hypothesis of normality for the raw, but not the transformed data. On the other hand, the advantage of the linear probability model is that interpretation and comparison of parameter estimates are straightforward. Thus we present the results for the linear probability model only, since models lead to the same overall results (estimations under both specifications are consistent in terms of parameter signs and significance for the exogenous and spatially lagged dependent variables).
Figure 2 shows the distribution of subprime lending in census tracts in the three year period, for various slices of the data according the mentioned poverty levels. Clearly, most of the higher rates are in the tracts with poverty levels between 20% and 40%. The maps in figure 3 provide a clear picture of the spread of subprime lending that took place in the 2004-2006 period.

4 Results

The main model is estimated with 2004-2006 HMDA loan data for home purchases, refinances and home improvement, for 1-4 family units, and secured by first lien. A restricted model for refinances and home improvement loans only is also estimated. The advantage of restricting the data to refinances

[9] Maximum likelihood estimation of the model is performed using a Matlab routine provided by P. Elhorst and available on his website `http://www.regroningen.nl/elhorst/software.shtml`

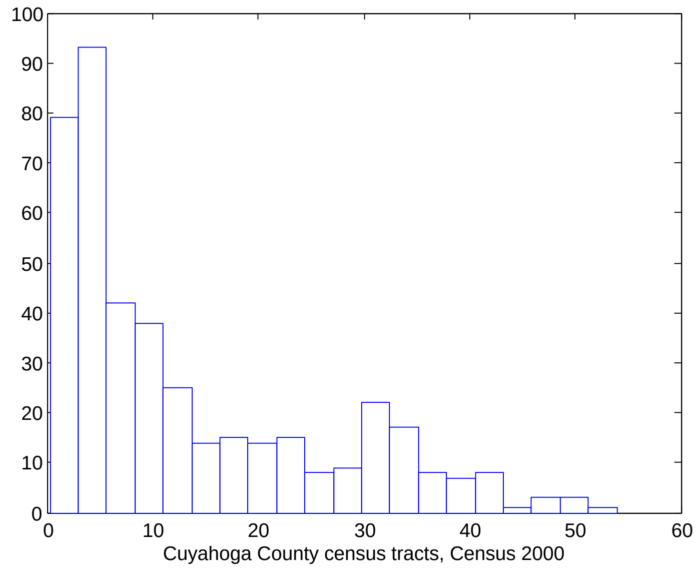

Figure 1: Distribution of % population below poverty line

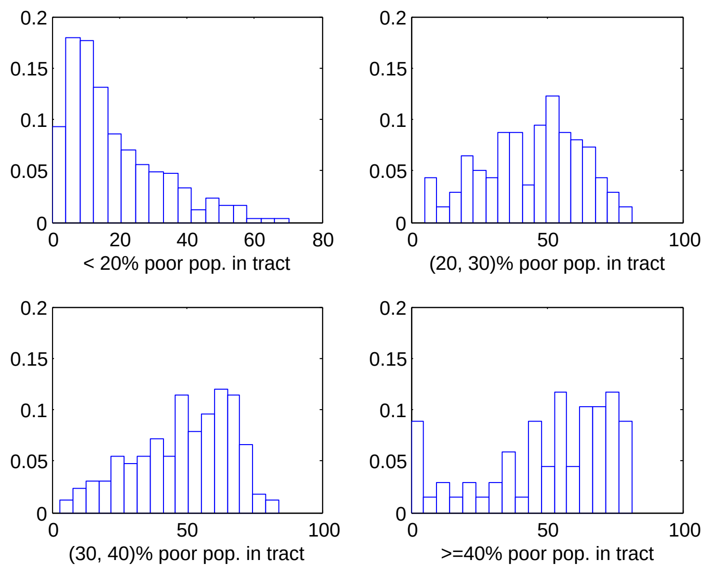

Figure 2: Relative frequency histograms of non-depository subprime lending rates by % population below poverty line

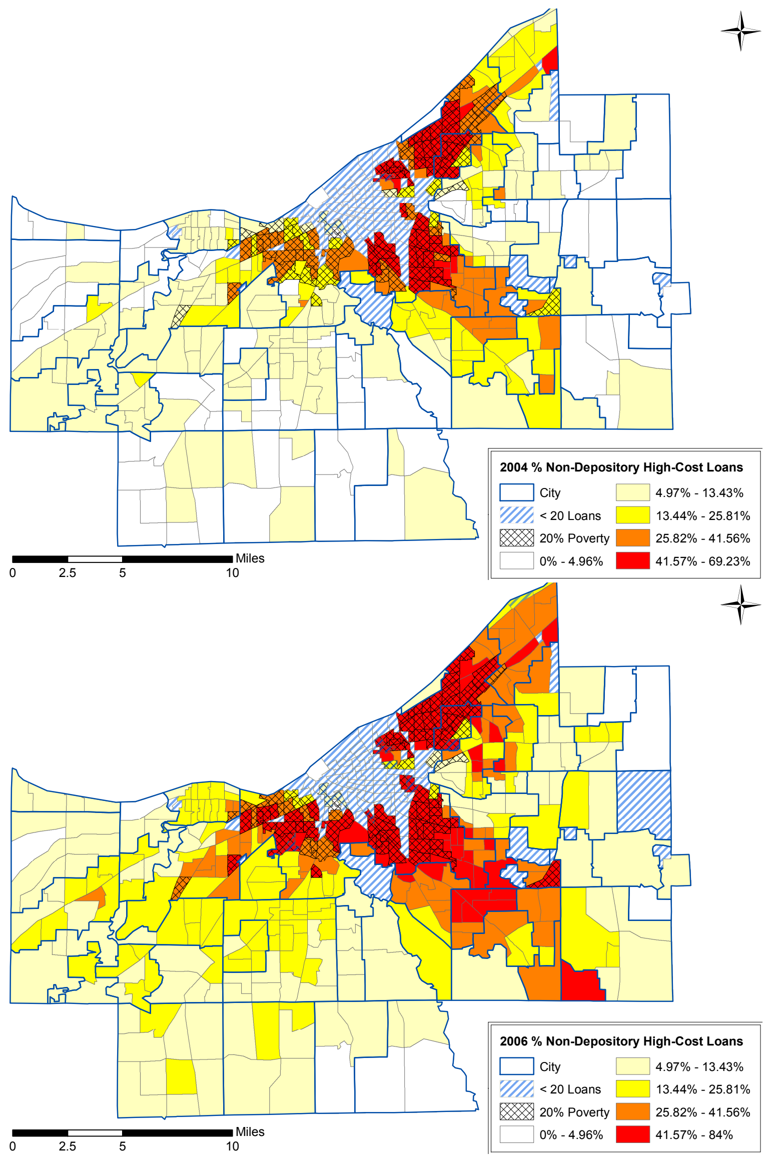

Figure 3: Non-depository subprime lending rates in Cuyahoga County, OH - 2004 and 2006

and home improvement loans is that borrowers' neighborhood location is more likely to be that of the mortgaged property (recorded in HMDA) at the time the decision to take out a loan is being made. However, social interactions between borrowers refinancing a mortgage and those buying a home may also induce subprime activity, and these interactions would not be captured by the spatial parameters of the restricted model. This is a significant disadvantage of the restricted model. Table 1 shows that on average, about half of all loans in the dataset are refinance or home improvement loans. It is also clear that the share of home purchase loans increased year by year throughout this period. For the model including all loan types, tracts with less than 16 loans on a given year are excluded from the analysis. With this condition, the main model is estimated on 422 tracts, excluding mainly the downtown, industrial, and predominantly rental areas. The restricted model is estimated on 408 tracts, including only those with more than 8 loans on any given year.

Table 1: Number of Loans by Census Tract - Descriptive Statistics

	All loans			Refi, HI only			Ratio Refi/All		
year	2004	2005	2006	2004	2005	2006	2004	2005	2006
tracts	487	486	486	483	475	476	483	475	476
p10	18	17	12	10	11	7	0.46	0.40	0.34
p25	51	49	36	30	26	18	0.52	0.47	0.39
p50	93	87	68	56	46	32	0.58	0.52	0.47
p75	146	133	102	83	69	46	0.64	0.58	0.54
p90	188	176	138	105	92	62	0.71	0.65	0.60
p100	407	492	295	219	206	142	1.00	1.00	1.00
mean	101.93	95.23	72.22	58.72	49.98	33.63	0.58	0.52	0.47
stdev	68.16	64.28	48.59	37.29	31.85	21.46	0.12	0.11	0.13

Table 2 displays estimated parameters for the main model. Poverty thresholds z are set at 20, 30 and 40 percent. Thus, tracts are classified into the 'poorer' group if z% of its population falls below the poverty line. When the threshold is set at 20 percent, the rate of non-depository subprime lending taking place in the poorer tracts (those with more than a 20% poverty rate) is significantly higher than that in the less poor tracts. However the statistical significance of the parameter $P_{\geq z}$ fades when the threshold is moved to 30 and above percent poverty, that is, when comparing tracts with more than a 30% poverty rate to those with 30% or lower poverty rate, and controlling for all model variables. This effect also holds for the refi only model 3. For all models, higher subprime rates are significantly related to a higher percent of tract population with low credit score and no high school diploma, as well as with lower medium borrower income. Even after accounting for all these effects, the percent of African Americans in the tract is positively and significantly related to higher rates of non-depository subprime lending for all models.

The coefficients for the spatial lags of the exogenous variables (slags) are for the most part statistically insignificant. Coefficient signs for this set of variables suggest a competitive-type relationship taking place across neighboring tracts. Once tract characteristics are accounted for, the same characteristics that result in higher rates of subprime lending for the tract are associated with lower subprime lending rates in neighboring tracts. Negative spatial correlation patterns across geographies arise in models of regional investment, for instance. Brown, Florax, and McNamara [1] find that regional characteristics such as market structure, labor supply, infrastructure, among others, attract investment opportunities to the region and away from its neighbors. Similarly, one could argue that tracts with higher rates of subprime borrowers (low credit scores, low income and education levels) were attractors of subprime business, although no attempt to test this hypothesis is made here. However, according to Pace and LeSage [8], including the spatial lags of the exogenous variables may diminish omitted variable bias when the data generating process is characterized by spatial dependence in the endogenous, exogenous, and residual terms.

The focus is on seeing whether there are differences in spatial interaction effects in subprime lending in poor as compared to less poor areas, once relevant exogenous factors and their spatial lags are taken into account. And this is in fact the case for both models, suggesting that endogenous or contextual social interactions play a smaller role in subprime lending in less poor versus poorer neighborhoods. Model estimates of ρ_{np} and ρ_p are denoted by slag $y_{<z}$ and slag $y_{\geq z}$ respectively in tables 2 and 3. Estimates of spatial effects are both positive, with statistically larger spatial effects taking place in poorer neighborhoods, irregardless of the poverty benchmark. For the 20% benchmark, according to the main model (all loans), spatial interactions across poorer neighborhoods add about half a percentage point of non-depository high cost lending, as compared to less than a third point in less poor areas.

5 Conclusions

It may not come as a surprise that poorer neighborhoods in Cuyahoga, those with at least 20% of its population falling below the poverty line, experienced higher rates of subprime lending facilitated by mortgage brokers, as compared to less poor neighborhoods. But given that the region features urban neighborhoods highly segregated by income and race, it is of interest to further understand the effects of concentrated poverty on subprime lending. This study contributes to the characterization of the relationship between subprime lending and poor neighborhoods by adding a spatial dimension to the analysis, in an attempt to capture social effect differences in poorer as compared to less poor neighborhoods. After controlling for other relevant factors, the model finds stronger spatial interactions for poorer neighborhoods, suggesting that social effects related to poverty may have facilitated the higher rates of subprime lending. It is important to note that social effects can results from demand and supply side events. On the demand side, borrowers may have become less risk averse to subprime mortgages, as their peers purchased these products with seemingly positive results. On the supply side, borrowers living in a poorer neighborhood may have been more exposed to the marketing of these products. While the analysis is not able to separate between these two social hypotheses, they can both be traced to the effects of living in poor neighborhoods. This finding should provide important feedback to those involved in financial education efforts and consumer protection, and suggests revisiting the availability of products in the traditional financial system that meet the needs of low income borrowers.

Table 2: Two-Regime Spatial Durbin Models for Various Poverty Thresholds - Purchase and Refi Loans

Dependent variable y: Non-depository high cost lending rate

Poverty threshold (z)									
% poor population in tract	20%			30%			40%		
Variable	Coefficient	t-stat	z-prob.	Coefficient	t-stat	z-prob.	Coefficient	t-stat	z-prob.
$P_{\geq z}$	0.029	3.200	0.001	0.002	0.189	0.850	0.006	0.328	0.743
% lowcred	0.400	10.736	0.000	0.404	10.662	0.000	0.399	10.503	0.000
% afamerican	0.158	12.965	0.000	0.164	13.229	0.000	0.167	13.437	0.000
% nohschool	0.381	9.771	0.000	0.453	11.834	0.000	0.466	12.815	0.000
borr. income	-0.056	-5.476	0.000	-0.0475	-4.616	0.000	-0.045	-4.427	0.000
slag lowcred	-0.096	-1.263	0.207	-0.083	-1.091	0.275	-0.120	-1.564	0.118
slag afamerican	-0.277	-1.295	0.195	-0.018	-1.090	0.275	-0.009	-0.406	0.684
slag nohschool	-0.249	-4.114	0.000	-0.214	-3.467	0.001	-0.198	-3.218	0.001
slag borr. income	-0.001	-1.154	0.248	-0.003	-0.404	0.687	-0.007	-0.981	0.326
slag $y_{<z}$	0.281	7.296	0.000	0.284	7.389	0.000	0.309	8.247	0.000
slag $y_{\geq z}$	0.487	9.723	0.000	0.472	7.547	0.000	0.567	4.346	0.000
Δ slag y	-0.201	-5.338		-0.188	-3.597		-0.256	-2.053	
R^2	0.862			0.857			0.856		
σ^2	0.0057			0.0059			0.0059		
tracts	422								
years (fixed effects)	3								

Table 3: Two-Regime Spatial Durbin Models for Various Poverty Thresholds - Refinance and Home Improvement Only

Dependent variable y: Non-depository high cost lending rate

Poverty threshold (z) % poor population in tract	20%			30%			40%		
Variable	Coefficient	t-stat	z-prob	Coefficient	t-stat	z-prob	Coefficient	t-stat	z-prob
cp dummy	0.215	2.290	0.022	-0.010	-0.917	0.359	-0.023	-1.131	0.258
% lowcred	0.286	7.609	0.000	0.281	4.962	0.000	0.277	7.310	0.000
% afamerican	0.135	10.752	0.000	0.279	7.346	0.000	0.143	11.357	0.000
% nohschool	0.292	7.042	0.000	0.366	9.085	0.000	0.366	9.505	0.000
borr. income	-0.042	-4.124	0.000	-0.035	-3.475	0.001	-0.035	-3.498	0.000
slag lowcred	0.172	2.182	0.029	0.185	2.341	0.019	0.167	2.130	0.033
slag afamerican	-0.033	-1.500	0.133	-0.027	-1.212	0.226	-0.021	-0.949	0.343
slag nohschool	-0.234	-3.723	0.000	-0.213	-3.357	0.001	-0.206	-3.260	0.001
slag borr. income	0.004	0.512	0.609	0.010	1.339	0.181	0.009	0.199	0.230
slag $y_{<z}$	0.105	2.359	0.018	0.108	2.431	0.015	0.121	2.749	0.006
slag $y_{\geq z}$	0.277	4.360	0.000	0.267	3.330	0.001	0.490	2.696	0.007
Δ slag y	-0.172	-3.172		-0.159	-2.206		-0.369	-2.068	
R^2	0.780				0.776		0.776		
σ^2	0.0057				0.0058		0.0058		
tracts	408								
years (fixed effects)	3								

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