Measuring Neighborhood Quality With Survey Data: A Bayesian Approach

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Abstract

Although neighborhood quality is important for shaping public policy, it is also difficult to quantify. This study measured subjective neighborhood quality using data from two sources: (1) the 2002 American Housing Survey (AHS) and (2) the U.S. Department of Housing and Urban Development's (HUD's) Customer Satisfaction Survey (CSS) of Section 8 Housing Choice Voucher Program (HCVP) households. Survey responses were analyzed regarding neighborhood quality, home quality, and crime perceptions. Tract-level Bayesian estimates were computed using AHS metropolitan-level data and CSS census tract data.

The new Bayesian estimates have fewer outliers than the original CSS data, and the use of prior information allows for estimation for tracts with lower sample sizes than would be practical to estimate using only CSS data.

I compared the CSS and Bayesian estimates with other measures of neighborhood quality, such as poverty rates, median income, and indicators for tracts receiving low-income housing tax credits. The CSS and Bayesian indicators are highly correlated, and both the CSS and Bayesian estimates correlate well with the auxiliary variables used in this study. For tracts with large differences between the CSS and Bayesian estimates, correlations are much stronger for the Bayesian estimates.

Introduction

Measuring neighborhood quality is important for shaping many public policies. For instance, the U.S. Department of Housing and Urban Development's (HUD's) Housing Choice Voucher Program (HCVP) is intended to expand social and economic opportunities "outside areas of poverty or minority concentration" (HUD 2008: ch. 2, p. 2-1). In other words, the program is designed to promote access to decent and affordable housing in higher quality neighborhoods compared with neighborhoods of traditional public housing projects.

Despite its importance to policymakers, neighborhood quality is inherently complex and difficult to measure. Data are available on a wide variety of neighborhood characteristics, such as poverty rates, income, crime rates, and school test scores. Although many policymakers and researchers rely on such indicators, they may have limited ability to measure the quality of neighborhood life as rated by residents (Buron and Patrabansh, 2008).

Survey data are available that measure residents' subjective perceptions of their neighborhoods. The study described in this article analyzed neighborhood quality perception data from two surveys: (1) the American Housing Survey (AHS) and (2) HUD's Customer Satisfaction Survey (CSS). The AHS collects a large amount of information on housing conditions of American households.[1] The AHS is actually composed of two surveys, metropolitan and national, each taking place in different years. I employed 2002 metropolitan data for this study.

HUD's CSS was a 3-year survey of HCVP households.[2] Conducted between 2000 and 2002, its main objective was to provide independent housing quality data to public housing agencies. About 460,000 responses were collected.

Although the AHS and CSS contain many related questions, survey design differences make the direct comparison of AHS and CSS data difficult.[3] For a subset of data items, however, estimates from both surveys correlate well. For instance, despite substantial differences in question wording, Mast (2009a) reported similar crime perception estimates based on CSS and 2001 AHS data.

Two similar questions on each survey ask CSS and AHS respondents to rank both their home and neighborhood on a scale of 1 to 10. Estimates for HCVP households from the CSS and 2001 AHS are very close (Mast 2009b). Although many studies have examined differences in estimates from independent surveys, few researchers have attempted to combine information from independent surveys with Bayesian methods. This study attempted to extend this literature by using Bayesian methods to produce neighborhood quality indicators based on both the AHS and CSS.

CSS data pose several problems for measuring neighborhood quality. First, the neighborhood and home ratings are subjective ordinal ratings on a 1 to 10 scale. Although we could compute a mean rating, for ordinal data it is customary to compute only order statistics such as the median or other percentiles. The data do not easily lend themselves to standard statistical models that analyze the mean.

[1] AHS data and information are available at http://www.huduser.org/datasets/ahs.html.

[2] See Mast (2009b) and Gray, Haley, and Mast (2009) for more CSS information.

[3] See Gray, Haley, and Mast (2009) and Buron, Kaul, and Patterson (2003) for discussions of differences between the AHS and CSS.

Instead of analyzing raw ordinal ratings, I computed a binary (good or bad) neighborhood indicator by treating scores of at least 8 as high quality. If enough responses (at least 5) existed in each category for a neighborhood, the mean proportion followed an approximately normal distribution.

For most census tracts not nearly enough CSS responses existed to treat the tract distribution as normal, however. Even when combining CSS data for all 3 years of the survey, most census tracts have 4 or fewer CSS responses; this small number poses a second problem, because most statistical models for survey data assume normality of the sample mean. Instead of assuming normality, I treated the tract distributions as binomial data.

In addition to having small samples, many tracts have highly skewed distributions, with most or all households in the same binary category; this skewness poses a third problem. I proposed addressing the issue with a Bayesian model using prior information for the AHS. By drawing strength from the AHS, Bayesian methods can produce more reasonable estimates for many tracts with highly skewed CSS distributions.

Although sharp ideological differences exist between Bayesian and classical (or frequentist) statistics, in practice the most important difference concerns the use of prior information.[4] Although classical methods tend to let the data "speak for themselves," Bayesian estimates always condition on prior information. For this study, I started with prior information from the AHS and updated these estimates with CSS data.

I employed a particular Bayesian approach, referred to as a Bayesian Hierarchical Model, using metropolitan-level AHS data and CSS census tract data. Compared with tract estimates based only on CSS data, the Bayesian estimates have fewer outliers with very low or very high estimated quality.

To validate my estimates, I examined correlation of the CSS and Bayesian estimates with other measures of neighborhood quality, such as median income, poverty rates, and indicators for tracts receiving low-income housing tax credits (LIHTCs). The Bayesian estimates tend to correlate more strongly with these auxiliary variables, and the differences are more apparent for tracts with larger differences between the CSS and Bayesian estimates.

The remainder of the article proceeds as follows:

- A review of relevant studies.
- The survey data description.
- An explanation of the model.
- The empirical results.
- The estimates compared with other tract-level measures of neighborhood quality.
- A summary of the results.

[4] "Bayesians view statistical inference as a problem in belief dynamics, or use of evidence about a phenomenon to revise and update our knowledge about it." From course description at http://volgenau.gmu.edu/~klaskey/SYST664/SYST664.html. See Lee (2004) for an introduction to Bayesian methods.

Literature Review

In this section, I review two bodies of relevant literature. I start with a discussion of neighborhood quality studies. I then review past studies that have compared estimates from independent surveys.

Measuring Neighborhood Quality

Neighborhood quality is a difficult concept to quantify. According to Dubin (1992), measurement error is a likely cause for the lack of consistent effects of neighborhood quality indicators in hedonic housing price regressions.

The stalwarts of neighborhood quality measurement have traditionally been data on income, race, ethnicity, and poverty. Although, until recently, reliable neighborhood-level population, income, and poverty data were available only from the decennial census.[5]

Crime rates may also be useful measures of neighborhood quality. For instance, Deller and Ottem (2001) used county crime rates as neighborhood quality controls in hedonic property value regressions.

Crime rate data are also available at lower levels of aggregation for some localities. Cahill (2006) reported crime rates (averaged over 1998 through 2002) for census tracts and block groups for three U.S. cities (Nashville, Tucson, and Portland).[6] An increasing number of areas, such as Seattle, are making neighborhood crime data available through their crime mapping programs.[7]

Neighborhood quality should also be positively related to educational achievement. Sedgley, Williams, and Derrick (2008) found that eighth-grade test scores and SAT scores have significant positive effects on housing prices. They found no consistent effect for third-grade scores, however.

Survey measures are available that measure residents' subjective perceptions of their neighborhoods. Buron and Patrabansh (2008) provided evidence that subjective perceptions of neighborhood quality may not correlate highly with objective measures, such as poverty rates.

A related literature studied the differences in perceived neighborhood quality in the same localities due to differences in characteristics such as race, ethnicity, gender, and income (St. John and Clark, 1984). Differences may be especially apparent regarding neighborhood crime (Austin, Furr, and Spine, 2002). For instance, females may manifest more sensitivity toward violent crime.

Many researchers have measured perceived neighborhood quality with AHS data (Chapman and Lombard, 2006; Dilulio, 1994; Newman and Schnare, 1993). For instance, Hipp (2007) studied the relationship between AHS household crime perceptions and county crime rates. He found household perceptions of crime were more strongly related to violent crime than property crime.

[5] Designed to replace the decennial census long form, the American Community Survey will soon provide tract-level estimates (averaged over multiple years).

[6] See Cahill (2006) for data and information.

[7] http://spotcrime.com/wa/seattle.

Other studies have measured neighborhood quality with CSS data. Buron and Patrabansh (2008) studied the relationship between CSS household neighborhood quality responses and census data and, as indicated previously, they found little correspondence. This lack of correspondence calls into question the use of social indicators, such as poverty rates, as measures of neighborhood quality.

Buron and Patrabansh's findings, however, may be affected by their use of household-level data. This study found that resident perceptions aggregated to the tract level have fairly strong correlation with poverty and income.

Gray, Haley, and Mast (2009) reported wide variation in CSS neighborhood ratings across demographic groups. Mast (2009b), using CSS data, estimated that West Virginia crime perceptions relate more strongly with property crime than violent crime.

Comparing Estimates From Independent Surveys

Numerous studies have compared and contrasted estimates from independent surveys. For example, Bishaw and Stern (2006) examined differences in poverty estimates based on the Census Bureau's American Community Survey (ACS) and Current Population Survey (CPS).

A few studies have compared CSS and AHS estimates. Buron, Kaul, and Patterson (2003) matched 2001 CSS households with a sample of unassisted AHS households. Although they reported lower housing quality for HCVP households relative to similar unassisted families, they cautioned that their results may be driven by methodology and questionnaire differences.

Mast (2009a) studied crime perception questions on both the CSS and 2001 AHS. The wording of the crime question differs on the two surveys. The AHS asks residents if "a neighborhood crime problem" exists, and the CSS asks if crime or drugs "is a big problem in (the) neighborhood." Response options also differ. Despite these discrepancies, Mast (2009a) recoded responses into binary indicators with similar means. Of AHS HCVP households, 31.5 percent were estimated to have a crime problem compared with 33.8 percent of CSS households.

Two of the most similar questions on each survey ask AHS and CSS respondents to rank their home and neighborhood on a scale of 1 to 10. Mast (2009b) compared both rankings on the CSS with those for HCVP households in the 2001 AHS. For both homes and neighborhoods, CSS rankings are just slightly higher than AHS estimates for HCVP homes.

Mast (2009a) suggested that, because AHS and CSS crime estimates are similar, they are well suited for Bayesian methods. Because the CSS sample size is much larger than the AHS, I employed a Bayesian Hierarchical Model. AHS national estimates are used as priors, along with CSS county data, to estimate Bayesian posterior county estimates. Compared with estimates solely based on CSS data, the Bayesian estimates have lower variance and correlate more highly with county violent and property crime rates. Consistent with Hipp (2007), the relationship is strongest with violent crime.

Data Description

This section reports 2002 AHS and CSS summary statistics on three measures of neighborhood quality: neighborhood ratings, home ratings, and crime perceptions.

Both surveys ask respondents to rate the neighborhoods and homes on an ordinal scale of 1 to 10. Because the response categories are numerical, we could compute mean ratings. We would be making an assumption, however, that a rating of 6 is exactly twice as good as a rating of 3. For subjective ordinal data, it is therefore customary to compute only order statistics, such as the median or other percentiles.

Exhibit 1 reports percentiles (10th, 25th, median, 75th, and 90th) for neighborhood and home ratings. AHS data are reported for all occupied rental units and HCVP households. The CSS ratings are based on responses for HCVP households in the 13 AHS metropolitan areas between 2000 and 2002.[8] Survey responses for AHS renters are weighted to be representative of all renters in the 13 metropolitan areas; AHS HCVP and CSS responses are weighted to be representative of all voucher households in the 13 metropolitan areas.[9]

Neighborhood ratings correspond highly with home ratings. Neighborhood ratings in the 25th percentile are 6 for all three samples (AHS renters, AHS HCVP, and CSS). Home ratings in the 25th percentile are 6 for AHS renters, 7 for AHS HCVP households, and 6 for CSS families. All median ratings are 8. Neighborhood ratings in the 75th percentile are 9 for both AHS samples and 10 for the CSS. Home ratings in the 75th percentile are 9 for both AHS samples and 10 for the CSS.

Exhibit 1

Neighborhood and Home Rating Percentiles

Weighted Percentile	Neighborhoods			Homes		
	AHS–All Renters	AHS–HCVP Households	CSS	AHS–All Renters	AHS–HCVP Households	CSS
10th percentile	5	5	4	5	5	4
25th percentile	6	6	6	6	7	6
Median	8	8	8	8	8	8
75th percentile	9	9	9	9	10	10
90th percentile	10	10	10	10	10	10

AHS = American Housing Survey. CSS = Customer Satisfaction Survey. HCVP = Housing Choice Voucher Program.

For neighborhood ratings, N equals 16,458 for AHS renters, 503 for AHS-HCVP households, and 26,822 for the CSS. For home ratings, N equals 16,510 for AHS renters, 503 for AHS-HCVP households, and 26,987 for the CSS.

Source: Author's calculation using 2002 AHS and CSS data

[8] CSS data were matched to the AHS by county for counties in the 13 metropolitan areas according to the Office of Management and Budget June 1999 definitions. For information on metropolitan area definitions, see http://www.census.gov/population/www/metroareas/metrodef.html.

[9] The metropolitan AHS is stratified by metropolitan area, with weights summing to total households. The CSS is stratified by public housing agency (PHA) and year, with weights summing to HCVP households in all sampled PHAs in a given year. Only a tiny fraction of PHAs was excluded. For more information on the survey designs for the AHS, see http://www.huduser.org/datasets/ahs.html and, for the CSS, see Mast (2009b) and Gray, Haley, and Mast (2009).

We can compute binary indicators of high neighborhood and home ratings for which mean analysis is appropriate. For this study I treated ratings of at least 8 as high ratings. The threshold is admittedly arbitrary.

Exhibit 2 reports mean percentages of households with high neighborhood and high home ratings. More than one-half of the households in each sample rated their neighborhood 8 or above. Of AHS renters, 55.6 percent have high neighborhood ratings, as do 54.4 percent of AHS HCVP households and 52.8 percent of CSS households.

On average, voucher families tend to rate their homes better than renters in general. Of AHS HCVP families, 64.4 percent rate their homes 8 or above, as do 59.6 percent of CSS households; the corresponding mean for all AHS renters is 54.7 percent.

The wording of the crime question differs on the two surveys. The AHS asks households if their "neighborhood has a neighborhood crime problem." Response categories include "No," "Don't Know," and "Yes." The CSS asks if crime or drugs "is a big problem in (the) neighborhood." Response categories include "No Problem," "Don't Know," "Some Problem," and "Big Problem."

To facilitate comparison of crime variables from both surveys, I recoded responses as binary indicators of low crime. For the AHS, "Yes" responses were set to zero, and "No" and "Don't know" responses were treated as ones. For the CSS, "some problem" and "big problem" responses were set to zero, and "no problem" and "don't know" responses were set to one. Nonresponses for both surveys were set to missing.

Mean indicators of low-crime perceptions are reported in exhibit 2. Compared with all renters, voucher households rate their neighborhoods as less safe. Of all the renters surveyed, 77.0 percent do not perceive a major crime problem in their area. The corresponding means are 67.7 percent for AHS voucher households and 66.5 percent of CSS households.

Exhibit 2

Mean Indicators of High Neighborhood Quality

Variable	AHS–All Renters		AHS–HCVP Households		CSS–HCVP Households	
	Responses	Weighted Mean	Responses	Weighted Mean	Responses	Weighted Mean
High neighborhood rating	16,458	0.556	503	0.544	26,822	0.528
High home rating	16,510	0.547	503	0.644	26,987	0.596
Low-crime indicator	16,777	0.770	509	0.677	27,376	0.664

AHS = American Housing Survey. CSS = Customer Satisfaction Survey. HCVP = Housing Choice Voucher Program.
High home and neighborhood ratings are ≥8 on a scale of 1 to 10.
Source: Author's calculation using 2002 AHS and CSS data

Exhibits 3, 4, and 5 report summary statistics by metropolitan area for high neighborhood ratings, high home ratings, and low-crime indicators, respectively. According to the AHS, Phoenix has the lowest fraction of high neighborhood rating for all renters (0.517) and HCVP households (0.322). The Kansas City metropolitan area has the best neighborhood ratings, according to all AHS renters (0.595), and the worst neighborhoods according to CSS households. One possible explanation for differing opinions between all renters and voucher households is clustering of affordable rental

Exhibit 3

Mean Indicators of High Neighborhood Ratings, by Metropolitan Area

Metropolitan Area	AHS–All Renters		AHS–HCVP Households		CSS–HCVP Households	
	Responses	Weighted Mean	Responses	Weighted Mean	Responses	Weighted Mean
Santa Ana-Anaheim-Irvine, CA Division	1,513	0.562	44	0.563	1,624	0.610
Buffalo-Cheektowaga-Tonawanda, NY	1,022	0.535	57	0.485	1,734	0.546
Charlotte-Gastonia-Concord, NC-SC	1,014	0.579	18	0.600	2,237	0.538
Columbus, OH	1,230	0.541	55	0.464	1,651	0.453
Dallas-Plano-Irving, TX Division	1,437	0.560	41	0.616	3,677	0.494
Fort Worth-Arlington, TX Division	1,203	0.526	40	0.523	1,584	0.498
Kansas City, MO-KS	1,058	0.595	43	0.488	2,938	0.442
Miami-Fort Lauderdale-Miami Beach, FL	1,218	0.574	27	0.590	2,807	0.591
Milwaukee-Waukesha-West Allis, WI	1,388	0.581	30	0.566	1,681	0.451
Phoenix-Mesa-Scottsdale, AZ	1,200	0.517	30	0.322	2,375	0.499
Portland-Vancouver-Beaverton, OR-WA	1,271	0.525	32	0.433	1,609	0.534
Riverside-San Bernardino-Ontario, CA	1,386	0.553	28	0.563	1,344	0.514
San Diego-Carlsbad-San Marcos, CA	1,518	0.570	58	0.677	1,561	0.568

AHS = American Housing Survey. CSS = Customer Satisfaction Survey. HCVP = Housing Choice Voucher Program.
High neighborhood ratings are ≥8 on a scale of 1 to 10.
Source: Author's calculations using CSS and 2002 AHS data

units meeting HUD housing quality guidelines in particular neighborhoods. According to voucher households participating in the CSS, Santa Ana has the best neighborhoods.

Two of the three survey estimates rank Santa Ana as the safest metropolitan area. Of Santa Ana AHS renters, 84.3 percent report no major crime problem, as do 86.5 percent of AHS HCVP households and 80.6 percent of CSS respondents. Columbus is the least safe metropolitan area according to two of three survey measures. Of the AHS renters surveyed, 68.6 percent report no major crime problems in the Columbus area, compared with 53.0 percent of AHS HCVP households and 54.0 percent of CSS households. According to AHS voucher respondents, the Phoenix area has the greatest perceived crime problem, but the difference might merely reflect small sample size.

Exhibit 6 summarizes absolute values of percentage differences between the metropolitan-level AHS and CSS means reported in exhibits 3, 4, and 5. For each indicator of neighborhood quality, two differences are summarized—one between AHS renter means and CSS means and the other between AHS HCVP means and CSS means.

Exhibit 4

Mean Indicators of High Home Ratings, by Metropolitan Area

Metropolitan Area	AHS–All Renters		AHS–HCVP Households		CSS–HCVP Households	
	Responses	Weighted Mean	Responses	Weighted Mean	Responses	Weighted Mean
Santa Ana-Anaheim-Irvine, CA Division	1,517	0.531	44	0.666	1,641	0.701
Buffalo-Cheektowaga-Tonawanda, NY	1,026	0.563	57	0.674	1,741	0.608
Charlotte-Gastonia-Concord, NC-SC	1,016	0.550	18	0.718	2,242	0.583
Columbus, OH	1,235	0.511	55	0.576	1,660	0.526
Dallas-Plano-Irving, TX Division	1,445	0.558	41	0.741	3,690	0.539
Fort Worth-Arlington, TX Division	1,203	0.509	40	0.640	1,593	0.564
Kansas City, MO-KS	1,060	0.589	43	0.580	2,956	0.522
Miami-Fort Lauderdale-Miami Beach, FL	1,218	0.546	27	0.670	2,830	0.659
Milwaukee-Waukesha-West Allis, WI	1,393	0.589	30	0.678	1,691	0.543
Phoenix-Mesa-Scottsdale, AZ	1,205	0.549	30	0.702	2,390	0.547
Portland-Vancouver-Beaverton, OR-WA	1,279	0.512	32	0.648	1,630	0.624
Riverside-San Bernardino-Ontario, CA	1,392	0.554	28	0.423	1,356	0.587
San Diego-Carlsbad-San Marcos, CA	1,521	0.549	58	0.639	1,567	0.634

AHS = American Housing Survey. CSS = Customer Satisfaction Survey. HCVP = Housing Choice Voucher Program.
High home ratings are ≥8 on a scale of 1 to 10.
Source: Author's calculations using CSS and 2002 AHS data

Differences in mean neighborhood indicators based on AHS renters range from 0.4 percent in Phoenix to 29.5 percent in Kansas City, with a median of 7.2 percent in Riverside. Neighborhood indicator differences based on the AHS HCVP sample are slightly larger on average. The mean difference based on AHS renters is 9.5 percent, versus 14.1 percent for the AHS HCVP sample. Differences based on the AHS voucher sample vary from 0.2 percent in Miami to 43.2 percent in Phoenix, with a median difference of 10.9 percent in Charlotte.

Differences in home indicators by metropolitan area are quite similar in magnitude to differences in neighborhood indicators. The mean difference in home indicator means is 10.5 percent based on AHS renters and 14.3 percent based on AHS vouchers. Because the larger differences with the AHS vouchers are almost certainly a consequence of the small sample sizes, I consistently use the overall AHS renter population as the reference point for the remainder of the article.

When independent surveys estimate the same variable, Bayesian methods can produce a more reliable estimate using information from both surveys. The next section demonstrates how a Bayesian Hierarchical Model can produce more robust tract-level estimates using metropolitan AHS data and tract CSS data.

Exhibit 5

Mean Indicators of Low-Crime Perceptions, by Metropolitan Area

Metropolitan Area	AHS–All Renters		AHS–HCVP Households		CSS–HCVP Households	
	Responses	Weighted Mean	Responses	Weighted Mean	Responses	Weighted Mean
Santa Ana-Anaheim-Irvine, CA Division	1,530	0.843	44	0.865	1,668	0.806
Buffalo-Cheektowaga-Tonawanda, NY	1,074	0.783	60	0.745	1,756	0.636
Charlotte-Gastonia-Concord, NC-SC	1,028	0.806	19	0.659	2,264	0.634
Columbus, OH	1,243	0.686	56	0.530	1,692	0.540
Dallas-Plano-Irving, TX Division	1,461	0.725	42	0.668	3,746	0.629
Fort Worth-Arlington, TX Division	1,220	0.788	40	0.727	1,627	0.638
Kansas City, MO-KS	1,089	0.803	43	0.649	2,981	0.598
Miami-Fort Lauderdale-Miami Beach, FL	1,238	0.860	27	0.847	2,876	0.729
Milwaukee-Waukesha-West Allis, WI	1,418	0.725	30	0.600	1,713	0.591
Phoenix-Mesa-Scottsdale, AZ	1,215	0.706	30	0.518	2,418	0.572
Portland-Vancouver-Beaverton, OR-WA	1,300	0.707	32	0.561	1,642	0.703
Riverside-San Bernardino-Ontario, CA	1,399	0.771	28	0.679	1,379	0.684
San Diego-Carlsbad-San Marcos, CA	1,562	0.763	58	0.645	1,614	0.689

AHS = American Housing Survey. CSS = Customer Satisfaction Survey. HCVP = Housing Choice Voucher Program.

Source: Author's calculations using CSS and 2002 AHS data

Exhibit 6

Absolute Percentage Differences Between AHS and CSS Metropolitan Means

Absolute Percentage Difference	High Neighborhood Rating Indicator		High Home Rating Indicator		Low-Crime Indicator	
	AHS Renters vs. CSS (%)	AHS HCVP vs. CSS (%)	AHS Renters vs. CSS (%)	AHS HCVP vs. CSS (%)	AHS Renters vs. CSS (%)	AHS HCVP vs. CSS (%)
Minimum difference	0.393	0.186	0.482	0.804	0.528	0.667
Median difference	7.216	10.890	8.010	10.457	20.449	7.025
Mean difference	9.497	14.064	10.523	14.287	16.758	8.622
Maximum difference	29.515	43.146	27.590	32.500	29.237	22.588

AHS = American Housing Survey. CSS = Customer Satisfaction Survey. HCVP = Housing Choice Voucher Program.

Source: Author's calculations using CSS and 2002 AHS data

Data Analysis

This section analyzes neighborhood, home, and crime measures from the CSS and 2002 AHS. My goal was to produce Bayesian tract estimates of neighborhood quality based on both surveys. Although conventional Bayesian updating would require AHS and CSS tract-level estimates, the AHS sample is not large enough to produce reliable tract estimates. Therefore, I chose a Bayesian Hierarchical Model using AHS metropolitan estimates and CSS tract estimates.

AHS responses are aggregated at the metropolitan level for 13 metropolitan areas, and 26,264 CSS responses are aggregated into 3,749 census tracts in the AHS metropolitan areas.[10]

Neighborhood Indicators

Although the neighborhood and home ratings are ordinal, such data do not easily lend themselves to Bayesian methods.[11] For my analysis, I used the binary indicators of high neighborhood ratings (X_1), high home ratings (X_2), and low-crime perceptions (X_3) discussed previously.

Only a small percent of the CSS census tract samples meet the usual normality criteria for any of the indicators.[12] Therefore, I assumed X_1-X_3 follow a Binomial (n,p_i) distribution, for i = 1 to 3. n represents the number of weighted responses, which is the same for all indicators in a given census tract. I computed weighted responses by multiplying the original survey weight by responses divided by the sum of the original weights.[13]

Using weighted counts based on original sampling weights summing to total HCVP households would treat estimated counts as known values. This would grossly understate variance by ignoring sampling variability. To reduce bias, I used weighted counts with adjusted weights summing to responses. Compared with estimates based on the original sampling weights, this reweighting produces estimates with the same weighted means and a more realistic variance.

p_i represents the probability that indicator X_i equals 1. Although each indicator has a separate distribution for each tract, for simplicity I did not use tract subscripts.

p_i follows a Beta (α_i,β_i) probability distribution, where α_i equals the weighted count of high-quality indicators. β_i equals the weighted count of low-quality indicators, which equals $n - \alpha_i$. The Beta probability distribution has a mean $\alpha/(\alpha + \beta)$ and standard deviation equal to the square root

[10] I excluded 2,397 CSS responses when either (1) the address could not be accurately geocoded at the tract level or (2) no valid response existed for the home rating, neighborhood rating, or crime question.

[11] Limited combinations of distributions exist for data and parameters, referred to as conjugate pairs, with analytic solutions for Bayesian posterior distributions. Although a conjugate model for multinomial categorical data exists, it does not account for ordering of the categories. Therefore, I employed a binomial-beta conjugate model, where the household neighborhood indicators are binomial and the probability of a high rating follows a beta distribution. For a Bayesian analysis of AHS and CSS data with a normal-normal conjugate model, see Mast (2009a).

[12] I considered a CSS tract sample proportion to be normally distributed if weighted responses were at least 30 and each binary category had at least 5 weighted responses.

[13] Let Wi be the original survey weight with n responses summing to population, and let Wi* be the adjusted weight summing to responses: $Wi^* = nWi/\sum Wi$.

of $\alpha\beta/[(\alpha + \beta)^2(\alpha + \beta + 1)]$. For example, if n = 45 and we have 30 high-quality responses, the estimated probability that a random tenant would give the neighborhood a high rating would be 0.667, with a standard deviation of 0.005.

Exhibit 7 reports descriptive statistics for the 3,749 CSS tract distributions of X_1-X_3. The first variable listed is X_1, the indicator for high neighborhood ratings. Weighted responses for X_1 vary from 0.096 to 173.486, with a median of 3.984 and a mean of 7.043. α_1, the count of high neighborhood ratings, ranges from 0 to 171.083. The median number of high neighborhood ratings equals 2.088, and the mean is 3.720. p_1, the mean probability of a high neighborhood rating, varies across census tracts from 0 to 1. 543 tracts have $p_1 = 0$ (no high neighborhood ratings), and 1,122 have $p_1 = 1$ (all high ratings); these tracts have 0 standard deviation. The median probability of a high neighborhood rating is 0.619, and the mean is 0.593.

CSS respondents rate their homes slightly higher on average than their neighborhoods. X_2 is the indicator of high home ratings, and the p_2 is the mean probability of a high home rating. The median value of p_2 is 0.680, and the mean is 0.638.

Most CSS households do not report major crime problems in their neighborhoods. X_3 indicates low-crime perceptions, and p_3 is the mean probability of a low-crime perception. p_3 has a median of 0.816 and a mean of 0.713.

Exhibit 7

CSS Census Tract Summary Statistics

	X_1 (High Neighborhood Rating)			
	Minimum	**Median**	**Mean**	**Maximum**
Weighted responses	0.096	3.984	7.043	173.486
Count of high ratings (α)	0.000	2.088	3.720	171.083
Count of low ratings (β)	0.000	1.305	3.323	170.264
Mean probability of a high rating (p)	0.000	0.619	0.593	1.000
Standard deviation of p	0.000	0.087	0.093	0.443
	X_2 (High Home Rating)			
	Minimum	**Median**	**Mean**	**Maximum**
Weighted responses	0.096	3.984	7.043	173.486
Count of high ratings (α)	0.000	2.281	4.202	171.901
Count of low ratings (β)	0.000	1.133	2.841	46.045
Mean probability of a high rating (p)	0.000	0.680	0.638	1.000
Standard deviation of p	0.000	0.091	0.094	0.443
	X_3 (Low-Crime Perception)			
	Minimum	**Median**	**Mean**	**Maximum**
Weighted responses	0.096	3.984	7.043	173.486
Count of high ratings (α)	0.000	2.550	4.657	169.881
Count of low ratings (β)	0.000	0.662	2.386	45.114
Mean probability of a high rating (p)	0.000	0.816	0.713	1.000
Standard deviation of p	0.000	0.056	0.081	0.457

CSS = Customer Satisfaction Survey.

N = 3,749 tracts.

Source: Author's calculations using CSS data

Bayesian Estimates

The Bayesian posterior distribution of p_i for each tract follows a Beta (α_i*,β_i*) distribution where α_i* = $\alpha_{i,prior}$ + α_i, and β_i* = $\beta i_{,prior}$ + β_i. $\alpha_{i,prior}$ is our prior best guess for the number of high ratings, with no knowledge of the CSS data. $\beta_{i,prior}$ is our prior guess for the number low ratings. α_i is the CSS weighted count of high ratings, and β_i is the CSS weighted count of low ratings.

Reliable tract-level information from the AHS is not available. Therefore, I employed a Bayesian Hierarchical Model adopted from Gelman et al. (2004).[14] For each metropolitan area, I used a common prior distribution for all tracts in that metropolitan area based on the AHS data. As noted previously, I used data for all AHS renters.[15]

α_{prior} is set to the AHS weighted mean probability of a high rating multiplied by 4, and β_{prior} is set to 4- α_{prior}. This results in a prior Beta distribution with the same weighted mean as the AHS metropolitan distribution but a smaller sample size of 4 and a larger standard deviation.

Using the AHS number of weighted responses for the prior sample size would result in posterior distributions dominated by the AHS for most tracts. For a tract with the median CSS weighted responses close to 4, my choice of 4 for the prior sample size results in a posterior distribution where the AHS and CSS have approximately equal influence.

For example, consider X_2 (high home rating). Exhibit 8 depicts the prior, CSS, and Bayesian posterior probability density functions for X_2 in one tract (045031100) in one randomly selected metropolitan area (Columbus). The tract was chosen because CSS weighted responses of 3.803 are close to 4 (the median for all metropolitan areas). The AHS-based metropolitan prior distribution has 2.045 high ratings, 1.955 low ratings, and a mean probability of a high rating equal to (2.045/4) or 0.511. The prior standard deviation is 0.224. The CSS tract distribution is highly skewed toward favorable ratings, with 3.370 weighted high ratings, 0.433 weighted low ratings, and a mean probability of (3.370/3.803) or 0.866. The CSS tract standard deviation is 0.145.

The Bayesian posterior distribution is distributed Beta (α*,β*) with α* = 2.045 + 3.370 = 5.415, and β* = 1.955+ 0.433 = 2.388. The posterior mean probability equals 5.415/(5.415 + 2.338) or 0.694. Because the prior and CSS distribution have about the same sample size, the posterior mean is approximately a simple average of the prior and CSS means. The posterior standard deviation is 0.155.

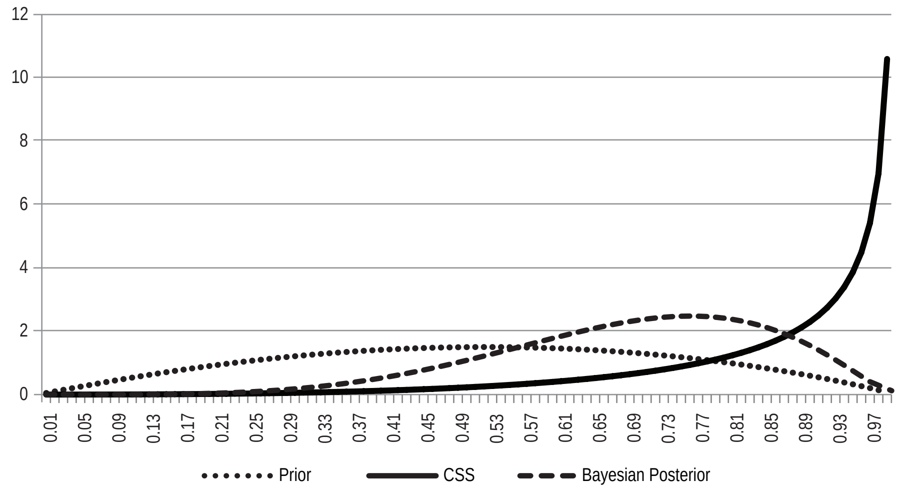
When CSS weighted responses increase, the CSS data have greater influence on the posterior distribution. Exhibit 9 depicts the X_2 prior, CSS, and posterior probability density functions for Columbus area tract 041011520. The tract was chosen because it has 8.972 weighted CSS responses, which is close to 9 (the 75th percentile for all metropolitan areas). The metropolitan-level prior distribution, described previously, has a mean of 0.511. The CSS tract distribution has a mean of 0.329 and

[14] For an accessible introduction to Bayesian Hierarchical Models, see http://volgenau.gmu.edu/~klaskey/SYST664/Bayes_Unit5.pdf.

[15] I also produced Bayesian posterior estimates using metropolitan priors based on the AHS HCVP sample. These estimates had lower correlation with auxiliary variables compared with estimates with priors based on all renters (results available upon request).

Exhibit 8

X_2 Prior, CSS, and Bayesian Posterior Probability Density Functions—Columbus Tract 045031100



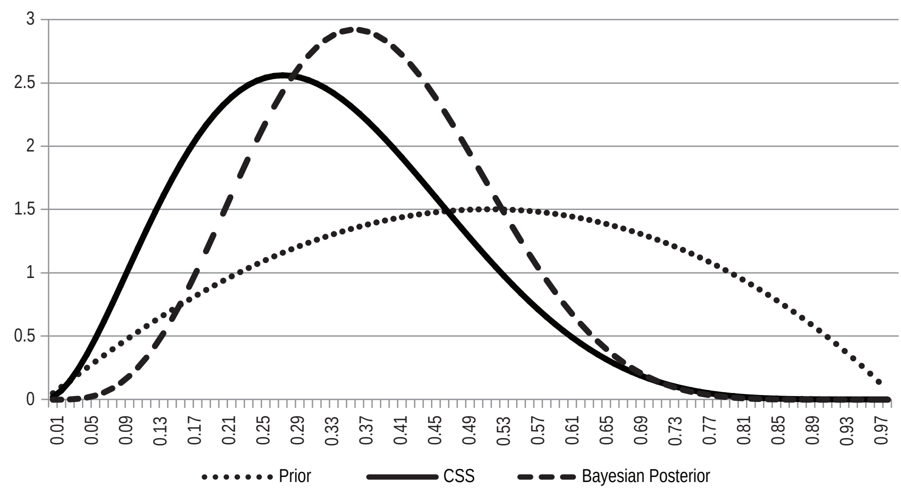
CSS = Customer Satisfaction Survey.

X_2 is an indicator for a high home rating. The Columbus metropolitan area was randomly chosen. The tract was chosen with CSS weighted responses closest to the median = 4.

Source: Author's calculations using CSS and 2002 American Housing Survey data

Exhibit 9

X_2 Prior, CSS, and Bayesian Posterior Probability Density Functions—Columbus Tract 041011520



CSS = Customer Satisfaction Survey.

X_2 is an indicator for a high home rating. The Columbus metropolitan area was randomly chosen. The tract was chosen with CSS weighted responses closest to the 75th percentile = 9.

Source: Author's calculations using CSS and 2002 American Housing Survey data a standard deviation of 0.149. The posterior distribution has a mean probability of a high rating equal to 0.385. The CSS sample size is about 2.25 times that of the prior sample size of 4, thus the CSS has about 2.25 times the influence on the posterior distribution.

Exhibit 10 reports summary statistics for the Bayesian posterior means and standard deviations. Exhibit 11 depicts a histogram of CSS and Bayesian means for X_1 (high neighborhood rating). The mean of the 3,749 Bayesian mean estimates for X_1 is 0.558, which is lower than the CSS mean of 0.593 reported in exhibit 7. Compared with CSS estimates, the Bayesian estimates are much more normally distributed, with fewer tracts with very low or high means. The CSS estimates for X_1 have 543 tract distributions with mean = 0 and 1,122 with mean = 1; these degenerate distributions have 0 standard deviation. The Bayesian mean estimates, however, range from 0.031 to 0.985. Although the CSS standard deviations range from 0 to 0.443, the Bayesian standard deviations range from 0.009 to 0.221.

Exhibit 10

Summary Statistics for Bayesian Posterior Distributions

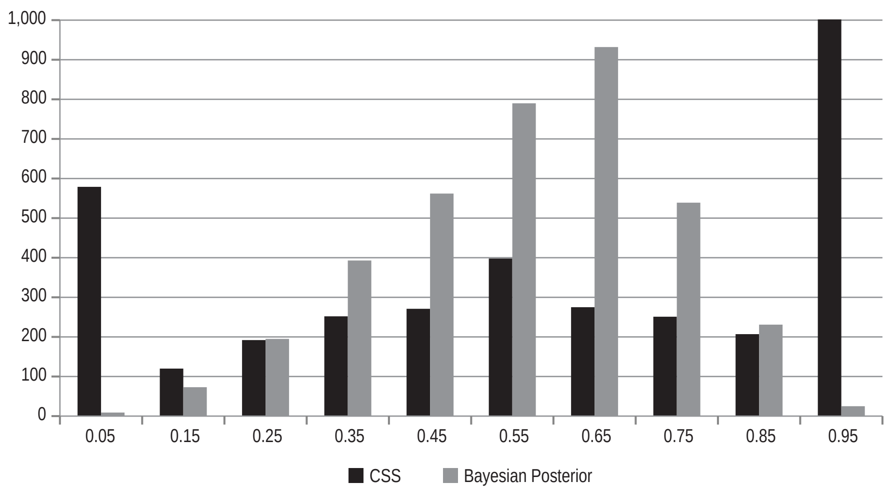
	X_1 (High Neighborhood Rating)		X_2 (High Home Rating)		X_3 (Low-Crime Perception)	
	Mean	**Std**	**Mean**	**Std**	**Mean**	**Std**
Minimum	0.031	0.009	0.080	0.008	0.088	0.009
Median	0.577	0.156	0.598	0.156	0.764	0.133
Mean	0.558	0.152	0.581	0.152	0.726	0.132
Maximum	0.985	0.221	0.989	0.221	0.985	0.208

N = 3,749 tracts.

Source: Author's calculations using Customer Satisfaction Survey and 2002 American Housing Survey data

Exhibit 11

Histogram of CSS and Bayesian Mean Estimated Probabilities for X_1



CSS = Customer Satisfaction Survey.

N = 3,749 tracts. X_1 is an indicator for a high neighborhood rating.

Source: Author's calculations using Customer Satisfaction Survey and 2002 American Housing Survey data

Data Validation

This section compares the CSS and Bayesian estimates with other tract-level measures of neighborhood quality. These variables include median household income, percent of families living below the poverty line, and an indicator for 671 tracts qualifying for LIHTC.[16] Exhibit 12 reports summary statistics for these measures.

Exhibit 13 reports Pearson correlation coefficients for the previously mentioned auxiliary variables with the CSS and Bayesian estimated mean probabilities for X_1-X_3. All coefficients are significant at the 0.0001 level with the expected signs. Median income is positively related with neighborhood quality, although the poverty rate and the LIHTC indicator correlate negatively.

For each neighborhood indicator, the CSS and Bayesian correlations with the auxiliary variables are very close. Of course, the Bayesian distributions are a weighted average of the prior and CSS distributions. As such, the CSS and Bayesian estimates are highly correlated. The Pearson correlation coefficient between the CSS and Bayesian means for X_1 (high neighborhood rating) is 0.866. The Bayesian model is not intended to drastically change most of the CSS estimates; its purpose is to reduce outliers and make estimation possible for tracts with few CSS responses. Differences may be more apparent for tracts with larger differences between the CSS and Bayesian estimates.

Exhibit 12

Summary Statistics for Auxiliary Neighborhood Quality Measures

Variable	Minimum	Median	Mean	Std
Median income*	7483.000	38946.000	40470.806	14473.096
Poverty rate*	0.280	12.140	15.029	10.814
LIHTC indicator**	0.000	0.000	0.179	0.383

LIHTC = low-income housing tax credit. N = 3,749 tracts.

*Sources: *U.S. Census Bureau 2000 Census; **http://www.huduser.org/datasets/lihtc.html*

Exhibit 13

Pearson Correlation Coefficients

Auxiliary Variable	X_1 (High Neighborhood Rating)		X_2 (High Home Rating)		X_3 (Low-Crime Perception)	
	CSS Mean	Bayesian Mean	CSS Mean	Bayesian Mean	CSS Mean	Bayesian Mean
Poverty rate	– 0.371	– 0.371	– 0.256	– 0.225	– 0.346	– 0.366
Median income	0.332	0.312	0.232	0.182	0.313	0.321
LIHTC indicator	– 0.263	– 0.270	– 0.169	– 0.162	– 0.238	– 0.260

CSS = Customer Satisfaction Survey. LIHTC = low-income housing tax credit.

N = 3,749 tracts. All correlation coefficients are significant at the .0001 level.

Source: Author's calculations using U.S. Census Bureau, HUD LIHTC, 2002 American Housing Survey, and CSS data

[16] LIHTC data indicators are for tracts qualifying in any year between 2000 and 2003. Original data were for qualifying tracts based on 1990 geography. For this study, I constructed qualifying tracts based on 2000 geography. For tracts that changed, I assumed a tract with 2000 geography qualified if it included any part of a tract qualified based on 1990 geography.

Exhibit 14 reports Pearson correlation coefficients for tracts with an absolute percentage difference between CSS and Bayesian estimates at or above the median difference. Median differences are 24.5 percent for X_1, 21.6 percent for X_2, and 14.4 percent for X_3. All of the correlations coefficients are significant at the 0.0001 level. For this subsample of tracts, 8 of the 9 Bayesian correlation coefficients are larger in absolute magnitude than their corresponding CSS coefficients.

Exhibit 15 reports Pearson correlation coefficients for tracts with an absolute percentage difference between CSS and Bayesian estimates at or above the 66th percentile; 66th-percentile differences are 55.3 percent for X_1, 52.4 percent for X_2, and 27.0 percent for X_3. All of the correlation coefficients are significant at the 0.0001 level. For this subsample of tracts, all Bayesian correlation coefficients are larger in absolute magnitude than their corresponding CSS coefficients. In addition, the differences between the CSS and Bayesian correlation coefficients are much larger for this subsample.

Exhibit 14

Pearson Correlation Coefficients, Subsample of Tracts With Differences Between CSS and Bayesian Estimates ≥ the Median

Auxiliary Variable	X_1 (High Neighborhood Rating)		X_2 (High Home Rating)		X_3 (Low-Crime Perception)	
	CSS Mean	Bayesian Mean	CSS Mean	Bayesian Mean	CSS Mean	Bayesian Mean
Poverty rate	– 0.430	– 0.463	– 0.301	– 0.309	– 0.407	– 0.460
Median income	0.379	0.397	0.252	0.246	0.381	0.417
LIHTC indicator	– 0.320	– 0.339	– 0.206	– 0.214	– 0.268	– 0.302

CSS = Customer Satisfaction Survey. LIHTC = low-income housing tax credit.

All correlation coefficients are significant at the 0.0001 level. N = 1,870 for X_1 and 1,874 for X_2 and X_3.

Source: Author's calculations using U.S. Census Bureau, HUD LIHTC, American Housing Survey 2002, and CSS data

Exhibit 15

Pearson Correlation Coefficients, Subsample of Tracts With Differences Between CSS and Bayesian Estimates ≥ the 66th Percentile

Auxiliary Variable	X_1 (High Neighborhood Rating)		X_2 (High Home Rating)		X_3 (Low-Crime Perception)	
	CSS Mean	Bayesian Mean	CSS Mean	Bayesian Mean	CSS Mean	Bayesian Mean
Poverty rate	– 0.422	– 0.492	– 0.348	– 0.402	– 0.382	– 0.468
Median income	0.398	0.448	0.308	0.343	0.408	0.468
LIHTC indicator	– 0.294	– 0.340	– 0.217	– 0.254	– 0.244	– 0.290

CSS = Customer Satisfaction Survey. LIHTC = low-income housing tax credit.

All correlation coefficients are significant at the 0.0001 level. N = 931 for X_1, and 938 for X_2 and X_3.

Source: Author's calculations using U.S. Census Bureau, HUD LIHTC, 2002 American Housing Survey, and CSS data

Conclusion

Although neighborhood quality is important for shaping public policy, it is also difficult to quantify. This study measured neighborhood quality using data from two sources: (1) the 2002 American Housing Survey and (2) HUD's Customer Satisfaction Survey of Section 8 Housing Choice Voucher Program households.

Although the AHS and CSS contain related questions, differences in survey methods and the questions' wording make direct comparison of the two surveys difficult. Bayesian methods are flexible enough, however, to use information from related questions from both surveys.

I examined survey responses in 13 metropolitan areas regarding neighborhood quality, home quality, and crime perceptions. Tract-level Bayesian estimates are computed using AHS metropolitan-level data and CSS census tract data.

Compared with estimates solely based on CSS data, the Bayesian estimates have fewer outliers. Bayesian analysis also allows for estimation for tracts with lower sample sizes than would be practical using only CSS data.

I compared the CSS and Bayesian estimates with other measures of neighborhood quality, such as poverty rates, median income, and indicators for tracts receiving low-income housing tax credits. The CSS and Bayesian indicators are highly correlated, and both the CSS and Bayesian correlate well with these auxiliary variables. For tracts with large differences between the CSS and Bayesian estimates, correlations are much stronger for the Bayesian estimates.

Future research could focus on testing the value of Bayesian neighborhood quality measures as left-hand-side and right-hand-side variables in any number of quantitative studies.

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References

Austin, D. Mark, L. Allen Furr, and Michael Spine. 2002. "The Effects of Neighborhood Conditions on Perceptions of Safety," *Journal of Criminal Justice* 30 (5): 417–427.

Bishaw, Alemayehu, and Sharon Stern. 2006. *Evaluation of Poverty Estimates: A Comparison of the American Community Survey and the Current Population Survey*. Washington, DC: U.S. Census Bureau.

Buron, Larry, Bulbul Kaul, and Rhiannon Patterson. 2003. *Quality of Housing Choice Voucher Housing.* Report prepared for the U.S. Department of Housing and Urban Development. Washington, DC: U.S. Department of Housing and Urban Development.

Buron, Larry, and Satyendra Patrabansh. 2008. "Are Census Variables Highly Correlated With Housing Choice Voucher Holders' Perception of the Quality of Their Neighborhoods?" *Cityscape: A Journal of Policy Development and Research* 10 (1): 157–183.

Cahill, Meagan Elizabeth. 2006 (August). *Geographies of Urban Crime in Nashville, Tennessee, Portland, Oregon, and Tucson, Arizona, 1998–2002*. Ann Arbor, MI: Inter-university Consortium for Political and Social Research. http://www.icpsr.umich.edu/cocoon/NACJD/STUDY/04547.xml (accessed October 2009).

Chapman, David W., and John R. Lombard. 2006. "Determinants of Neighborhood Satisfaction in Fee-Based Gated and Nongated Communities." *Urban Affairs Review* 41 (6): 769–799. http://www.sagepub.com/journalsProdDesc.nav?prodId=Journal200784 (accessed June 2010).

Deller, Steven C., and Thomas Ottem. 2001 (July). "Crime and the Quality of Life in Wisconsin Counties." *Agricultural and Applied Economics Staff Paper Series No. 442*. Madison, WI: University of Wisconsin-Madison, Department of Agricultural and Applied Economics. http://www.aae.wisc.edu/pubs/sps/pdf/stpap442.pdf (accessed July 2010).

Dilulio, John J., Jr. 1994. "The Question of Black Crime," *Public Interest* 117: 3–30.

Dubin, Robin A. 1992. "Spatial Autocorrelation and Neighborhood Quality," *Regional Science and Urban Economics* 22 (3): 433–452.

Gelman, Andrew, John B. Carlin, Hal S. Stern, and Donald B. Rubin. 2004. *Bayesian Data Analysis,* 2nd ed. London, United Kingdom: Chapman and Hall/CRC.

Gray, Robert W., Barbara A. Haley, and Brent D. Mast. 2009. Tell Us About Your Home: Three Years of Surveying Housing Quality and Satisfaction in the Section 8 Housing Choice Voucher Program. Unpublished paper. Washington, DC: U.S. Department of Housing and Urban Development, Office of Policy Development and Research.

Hipp, John. 2007 (March). Resident Perceptions of Crime: How Similar Are They to Official Crime Rates? Working paper. Washington, DC: U.S. Census Bureau, Center for Economic Studies. http://www.ces.census.gov/index.php/ces/cespapers?detail_key=101783 (accessed August 2010).

Lee, Peter M. 2004. *Bayesian Statistics: An Introduction,* 3rd ed. London, United Kingdom: Hodder Arnold.

Mast, Brent D. 2009a (August). "Bayesian Hierarchical Model Estimates of Local Crime Perceptions." *Program Monitoring and Research Division Working Paper Series*. Washington, DC: U.S. Department of Housing and Urban Development, Office of Policy Development and Research. http://www.huduser.org/publications/pmrd/pmrd_workpap1.html (accessed July 2010).

———. 2009b (July). "Measuring Housing Quality in the Housing Choice Voucher Program With Customer Satisfaction Survey Data," *Cityscape: A Journal of Policy Development and Research* 11 (2): 101–112. http://www.huduser.org/periodicals/cityscpe/vol11num2/index.html (accessed July 2010).

Newman, Sandra J., and Ann B. Schnare. 1993. "Last in Line: Housing Assistance for Households With Children," *Housing Policy Debate* 4 (3): 417–455.

Sedgley, Norman H., Nancy H. Williams, and Frederick W. Derrick. 2008 (June). "The Effect of Educational Test Scores on House Prices in a Model With Spatial Dependence," *Journal of Housing Economics* 17 (2): 191–200.

St. John, Craig, and Frieda Clark. 1984. "Racial Differences in Dimensions of Neighborhood Satisfaction," *Social Indicators Research* 15 (1): 43–60.

U.S. Department of Housing and Urban Development (HUD). 2008. *Housing Choice Voucher Program Guidebook*. Washington, DC: U.S. Department of Housing and Urban Development. http://www.hud.gov/offices/pih/programs/hcv/forms/guidebook.cfm (accessed September 2009).

Impact

A regulatory impact analysis must accompany every economically significant federal rule or regulation. The Office of Policy Development and Research performs this analysis for all U.S. Department of Housing and Urban Development rules. An impact analysis is a forecast of the annual benefits and costs accruing to all parties, including the taxpayers, from a given regulation. Modeling these benefits and costs involves use of past research findings, application of economic principles, empirical investigation, and professional judgment.

The Impacts of More Rigorous FHA Underwriting Guidelines

Alastair McFarlane
U.S. Department of Housing and Urban Development

Summary of Impact Analysis

The Federal Housing Administration's (FHA's) authorizing statute for insurance authorities, the National Housing Act, clearly states that the U.S. Department of Housing and Urban Development (HUD) will adjust program standards and practices to operate the Mutual Mortgage Insurance Fund (MMIF) on a self-sustaining basis. In the Notice "Federal Housing Administration Risk Management Initiatives: Reduction of Seller Concessions and New Loan-to-Value and Credit Score Requirements,"[1] FHA proposes to tighten portions of its underwriting guidelines that present an excessive level of risk to both homeowners and FHA. The benefit of the set of actions outlined in the Notice will reduce the net losses resulting from high rates of insurance claims on affected loans, and the cost of the action will be the value of the loan opportunity denied to the excluded borrowers. The total transfer to FHA would be $96 million, and the net cost of excluding borrowers could be as high as $85 million.

Need for Policy Change

FHA has resumed a countercyclical position, supporting private lending for homeownership when access to private sources of capital for credit enhancements is otherwise constrained by the recent financial crisis. This state of affairs is most evident in the rapid increase in the volume of FHA

[1] "Federal Housing Administration Risk Management Initiatives: Reduction of Seller Concessions and New Loan-to-Value and Credit Score Requirements," FR-5404-N-01. *Federal Register*, July 15, 2010. Available at http://federalregister.gov/a/2010-17326.