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Identifying Robust, Parsimonious Neighborhood Indicators

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ABSTRACT

Identifying Robust, Parsimonious Neighborhood Indicators

Identifying a few indicators that summarily tracked key dimensions of neighborhoods would be invaluable for neighborhood monitoring and measuring impacts of interventions. Our goal is to search empirically for such robust, parsimonious indicators. In five cities we analyze the interrelationships among a broad set of census tract indicators related to: mortgage market activity; home prices; jobs and firms; demographic, socio-economic, and housing stock characteristics; crime; and public assistance and health. Through factor analysis we identify four to six neighborhood dimensions among these indicators that are common across cities. Using regression we identify a parsimonious number of indicators that are inexpensive, annually updated, and available for all U.S. communities, yet robustly capture significant variation in these neighborhood dimensions. Home Mortgage Disclosure Act (HMDA) data on mortgage approval rates, loan amounts, and loan applications, and Dunn and Bradstreet data on businesses comprise such a set for four of the dimensions.

This paper is motivated by the following musings of a hypothetical planner:

> *If only I could find a way to monitor reliably, frequently, and inexpensively what was transpiring in my community's neighborhoods! If such a neighborhood indicator capacity were available, I could get early warnings about emergent concerns and could marshal my community's programmatic resources pro-actively, instead of merely reacting once problems have become severe. Or, more optimistically, I could see where the market was heating up. I could even use such neighborhood indicators to measure the performance of various planning interventions I might concoct. But, what indicator gives me an accurate, annually updated barometer of a wide range of neighborhood demographic, social, economic and housing characteristics? Can I afford to collect the data to operationalize such a robust indicator?*

Acknowledging the validity and importance of these musings, we aim in this paper to provide the answers. Accordingly, our approach will be unabashedly practical and empirical, not theoretical.

Development of quantitative social indicators has been the subject of serious scholarly study for over thirty years (e.g., Campbell and Converse, 1972; Rossi, 1972). The geographic unit of analysis for indicators has typically been nations, metropolitan areas, or cities. Until recently, virtually all indicator analyses at the neighborhood scale depended upon census data collected only every ten years. This limited their usefulness to community leaders, local planners and policy makers, who typically seek more up-to-date information that can portray richer dynamic processes than decennial snapshots (Ferriss, 1988; Sawicki and Flynn, 1996).

The advent of user-friendly Geographic Information System (GIS) technology has opened numerous opportunities for the construction of neighborhood indicators (Sawicki and Flynn, 1996). These are built through the geo-coding and subsequent geographic aggregation of information about individual people, properties, businesses, events and transactions that may be recorded in a variety of local administrative, federal, or proprietary databases. Moreover, inasmuch as most of these databases are updated annually, they offer great potential for more "real-time" monitoring of or even predicting neighborhood changes (Auclair and Karl, 2002; Taylor, 2002). However, annually updated, multi-faceted neighborhood indicator databases are simply beyond the financial or technical capacities of the vast majority of American communities.

Yet, even where such sophisticated databases are available a final practical problem remains. There are so many potential indicators, which are the robust measures that can capture the most dimensions of neighborhood demographic, social, economic, and housing trends?

Thus, the uncomfortable situation regarding neighborhood indicators currently confronting planners, community leaders, local policy makers, and scholars of neighborhood can be summarized as follows. For the purposes of monitoring neighborhood changes and measuring impacts of various public and private community development initiatives, there is a critical need for a few, powerful indicators that can be obtained frequently and for reasonable cost. Census data are detailed and inexpensive to acquire, but rapidly become dated. Purposive community surveys and local administrative databases also can provide a wide range of annually updated information, but typically at prohibitive cost. Proprietary databases may have up-to-date information, but it is often limited in scope and moderately expensive. Whatever the source, databases may be capable of supporting so many indicators that one loses sight of the most important, or the welter of indicators provides a muddled portrait. One way out of this thorny situation would be to discover a handful of neighborhood indicators that have all three desiderata: annually updated, inexpensive to acquire, and summarize the information embodied in a much larger set of indicators.

This paper reports on our successful search for such a parsimonious set of robust neighborhood indicators. We analyze statistically the interrelationships among a wide set of indicators from a variety of sources to determine whether a few, easily operationalized, commonly available, cost-effective indicators track significant variations in demographic, social, economic, and housing characteristics of neighborhoods. We conduct this exercise in five cities as a test for generality of both common dimensions of neighborhood and the power of our candidates for robust indicators.

Our paper proceeds as follows. We first identify five cities for which the richest available set of neighborhood (census tract) data can be assembled related to: mortgage market activity, home sales prices, jobs and firms, census-type demographic socio-economic, and housing stock characteristics, and unique local administrative records on crime, public assistance and health statistics.[1] Second, we develop a wide range of neighborhood indicators from all these data sources. Third, we conduct exploratory factor analyses on the five city databases to ascertain whether a smaller number of distinct dimensions of neighborhood conditions can be identified. Fourth, we ascertain through regression and correlation analyses the degree to which a more limited set of indicators that are inexpensive, available and annually updated in all cities captures significant variation in the aforementioned factors; this will be the parsimonious, robust indicator set sought. We find that Home Mortgage Disclosure Act (HMDA) data on mortgage approval rates, loan amounts, and loan applications, and Dunn and Bradstreet data on businesses comprise the parsimonious, robust indicator set for four of the broader neighborhood factors. Finally, we note caveats about these indicators and draw conclusions and implications for planning practice.

Data Sources for Neighborhood Indicators Related to Demographic, Social, Economic and Housing Conditions[2]

To develop indicators for what is happening to neighborhood demographic, social, economic, and housing conditions, local planners and policy-makers have access to three potential sources of extant data, each of which offers various strengths and weaknesses.[3] First, Census data are available for all cites at essentially no cost, but (unless the American Community Survey becomes a reality later in this decade) are available only every ten years, and even then with a substantial lag before public release. Second, cities typically collect annually updated administrative data on health statistics, crime, and real property characteristics, but it takes considerable effort, expertise, and expense to assemble data from different departments' databases into a common platform and aggregate them to the census tract level. These barriers are significant enough that few cities have developed a useable neighborhood database from their administrative data (Sawicki and Flynn, 1996). Third, annually updated data related to home mortgage lending, home sales, and employment and businesses are provided by federal agencies or private vendors for most if not all cities, although in the case of vendor-supplied data some costs are involved in acquisition and aggregating information to the neighborhood level.

We believe that this third category, what we henceforth will call "generic data" because they are universally available at modest cost, offers the greatest potential for developing a robust, parsimonious set of neighborhood indicators. We investigated census tract indicators for the 1993-1999 period derived from three generic data sources: mortgage lenders' information reported by the Federal Financial Institutions Examination Council under the auspices of HMDA, property assessors' data for single-family home sales prices purchased from the vendor DataQuick, Inc., and employment and firm data purchased from the vendor Dunn and Bradstreet.

To ascertain how neighborhood indicators developed from these generic data sources relate to those developed from the other two data sources, we analyzed five municipalities we knew to have an exceptionally rich array of administrative data assembled into a census tract database with annual observations 1993-1999. These cities were: Boston (MA), Cleveland (OH), Indianapolis (IN), Oakland (CA), and Providence (RI). These five administrative databases for tracts were assembled as part of the Urban Institute's National Neighborhood Indicators Partnership[4]. We attached 1990 census data and 1993-1994 and 1998-1999 generic data to these administrative databases to create our analysis dataset. The goal is to ascertain how well indicators based on generic data available for virtually all U.S. communities serve as proxies for richer collections of indicators that are infrequently measured, if at all.

Methodological Overview

After assembling the data from census, administrative, and generic sources, our analysis proceeded as follows. We first developed a broad set of neighborhood indicators. Next, we conducted exploratory factor analyses for each of our five cities, using first 1993-94 data and then 1998-99 data, to see whether the data suggested the existence of common dimensions of neighborhood that were stable across cities and time. As explained below, we identified five or six such dimensions, depending on the city. Finally, we identified with regression analysis a subset of indicators based on generic data that were highly correlated with one or more of these dimensions, but not with each other. These constitute what we call "robust, parsimonious indicators," inasmuch as they succeed in capturing much of importance transpiring in neighborhoods while using only a few variables that can be readily obtained in all communities. Each of these steps, and the results they produced, are explained in detail following.

Operationalizing Neighborhood Indicators

Our approach to selecting geographic, social, economic, and housing indicators for analysis was largely opportunistic and exhaustive. That is, we drew upon every publicly available database in our five cities providing census tract information, then specified from each as many indicators as possible that we thought plausibly could measure some aspect of aforementioned neighborhood conditions of potential importance.

From administrative databases available in Boston, Cleveland, Indianapolis, Oakland, and Providence we operationalized indicators like welfare usage rates, percentages of births to unmarried women, percentages of babies born of low weight, percentages of structures that are single-family homes, percentages of parcels that are tax delinquent, percentages of parcels that have non-residential uses, and (except in Indianapolis and Providence) property and violent crime rates. Most of the five administrative databases used contained similar information, although there were some inconsistencies. The list of indicators developed from administrative data and the cities for which they were available are presented in the middle panel of Table 1.

We also extracted a wide range of 26 indicators from 1990 census tract data, STF-4.[5] Even though annual updates of such indicators were not available during the 1990s, we nevertheless think it important to see how these indicators correlate with those from other data sources. The census-based indicators we employed are presented in the first panel of Table 1. They include such things as: female household headship and marriage rates, racial, immigration, and age characteristics, incomes and unemployment, education and occupational status, and housing stock ages, vacancy rates, values, and structure types.

Finally, we developed nine indicators from our three generic sources. From the Dunn and Bradstreet data, we operationalized indicators for the number of firms, number of jobs, and total dollar volume of sales annually in the census tract. We operationalized the median value of single-family home sales in the tract (averaged over two years), using DataQuick data.[6] From HMDA data, we operationalized the two-year annual average indicators: number of home purchase mortgage application records (LARS), approval rate of such applications, median value of approved home purchase loans, and the percentages of all mortgage applications intended for home purchase and for home improvements.[7] See the third panel of Table 1.

[Table 1 about here]

In total we specified between 37 and 49 indicators of neighborhood quality of life, depending on the idiosyncrasies of each city's administrative data. All five cities employed the full complement of 26 census indicators and nine generic indicators. We recognize that these indicators do not provide measures of all neighborhood aspects of potential interest. Nevertheless, we are unapologetic in suggesting that the 63 – 75 indicators we analyze collectively measure a great deal that traditionally has been of central concern to many parties observing neighborhoods.

Identifying Dimensions of Neighborhood

We analyzed the aforementioned set of indicators for each of our five cities with an exploratory factor analysis (principal components analysis using varimax rotation), a longstanding procedure in this field (e.g., Ross, Bluestone and Hines, 1979; Wong, 2002).[8] For each site we replicated the analysis with both 1994 and 1999 indicators developed from administrative and generic databases; indicators based on 1990 census data were employed in both cases.

There was remarkable cross-sectional and inter-temporal comparability in results, especially considering the wide range of city location, age, demographic composition, and economic base. In four of our five cities, five or six common clusters of indicators emerged; in one city, four emerged.[9] Cumulatively, these factors explained approximately two-thirds of the total variance, differing modestly by up to five percentage points depending on city and date. Table 2 shows the details for each of our five cities.

[Table 2 about here]

The most heavily weighted indicators in each factor provide a heuristic suggestion of a label signifying a dimension of neighborhood. We label these six factors descriptively, not normatively: *Social Disadvantage, Housing Type and Tenure, Prestige, Business and Employment, Crime*, and *Housing Vacancy*. This listing corresponds to the general rank ordering of factors by explanatory power evinced in most cities (see Table 2).

The first factor, Social Disadvantage, heavily weights indicators like female headship rates, teen birthrates, welfare usage, and percentages of black and (negatively) white populations. The second factor, Housing Type and Tenure, consists predominantly of the percentages of structures that are single-family homes and that are owner-occupied. The third factor, Prestige, loads heavily on percentages with college degrees and those in managerial, professional, or technical occupations, and median home values. The fourth factor, Business and Employment, is heavily comprised of the number of businesses and number of jobs, and less so on the volume of sales. The fifth factor, Crime, involves typically both property and violent crime rates, though such data are only available for three of our five cities. The last factor, Housing Vacancy, loads heavily on residential vacancy rates in all cities, though in several it also involves the percentage of units lacking some minimal plumbing. For each city, there is remarkable stability in the indicators' factor loadings between the two years.

We believe that there is a good deal of commonality in the factors across the cities. Business and Employment and Housing Type and Tenure are distinct dimensions in all five cities. Similarly, Crime emerges as a separate factor in all three cities for which crime data were available. In Oakland, the variables that elsewhere formed a distinct Prestige factor here loaded on to the Social Disadvantage Factor instead. In Providence, Housing Vacancy merged with Housing Type and Tenure. As explained below, these slight differences in factors in Oakland and Providence proved unimportant because the same robust indicators predicted them across all five cities, whether they were separated into distinct factors or not.

Appendix Tables A.1-A.6 present all the indicators that have a factor loading (i.e., are correlated with the factor) of .50 or more, for each of the six factors and each of our five cities. In each table the indicators are grouped according to the database of origin: administrative first, then census, finally generic.

Robust, Parsimonious Indicators from Generic Data Sources

Tests for Robustness

Having identified several dimensions of neighborhood consistent across five cities, our next task is to ascertain the degree to which any individual indicators based on commonly available, generic sources serve as strong proxies for these dimensions.

For this part of our investigation we regressed each factor produced for a particular city and period on each of the generic-based indicators individually. The resultant r-squared values provide an easily interpretable measure of how well each indicator explains the cross-census tract variation in the factors. Averages of r-squares across the cities and years are presented in Table 3; detailed results by factor, city, and year, are presented in Appendix Table A.7.

[Table 3 about here]

Examination of the results in Tables 3 and A.7 yields several key findings.

HMDA-Based Indicators. Several HMDA-based indicators prove to be especially strong, consistent predictors of the Social Disadvantage and Prestige factors 1 and 3, but some are also predictive of the Housing Type and Tenure factor 2 and the Crime factor 5. In particular:

- the mortgage approval rate seems most robust, being predictive of the Social Disadvantage and Prestige factors at r-squared values of .38 and .45, respectively, on average (see Table 3)
- the mortgage approval rate is reasonably predictive of the Crime factor 5 as well (average r-squared of .22), though this is somewhat misleading because the average is strongly influenced by the results from only one city, as explained below
- the median dollar amount of mortgages issued proves to be a strong predictor of the Prestige factor 3 (average r-squared of .74) and Social Disadvantage factor 1 (average r-square of .28)

- the number of home purchase loan application records (LARs) is the only generic-based indicator that is even modestly predictive of Housing Type and Tenure (average r-squared of .27)
- the share of mortgages intended for home purchase or the share for home improvements are modestly predictive of the Social Disadvantage and Prestige factors (average R-squared values of .22 and .28, respectively), but in both cases the explanatory power is less than that provided by the mortgage approval rate indicator

Thus, for four of the dimensions of neighborhood there is consistent and often remarkably strong predictive power of HMDA-based indicators, especially mortgage approval rates. Arguably, this is the most surprising and practically important finding here.

DataQuick-Based Indicators. Median sales price (value) of single-family homes proves to be a good predictor of the Social Disadvantage and Prestige factors 1 and 3. The average r-squares are .25 and .72 respectively (see Table 3). As amplified below, it performs virtually identically (though with slightly less explanatory power) in this and other regards to the median mortgage amount indicator.

Dunn and Bradstreet-Based Indicators. Business or jobs (and, to a much lesser extent, sales volume) are extremely predictive of the Business and Jobs factor 4, with r-squares typically exceeding .95. This is not surprising, given that these two indicators are typically the only two heavily loaded constituents of the factor. However, it is noteworthy that no other generic indicator apart from those based on Dunn and Bradstreet explain more than 15 percent of its variance, and typically much less than 10 percent. Mortgage market and housing market activity clearly do not vary across census tract space in a common pattern with business activity.

Unfortunately, none of the indicators based on commonly available HMDA, DataQuick, or Dunn and Bradstreet data proved powerful predictors of the two factors with the least amount of explained variance of the six factors that met our criteria for inclusion: Crime and Housing Vacancy. The average r-squares do not exceed .22 (see Table 3). Only in Boston is there an exception, with the mortgage approval rate explaining between 45 and 56 percent of the variance in Crime, and the home purchase mortgage percentage explaining between 33 and 47 percent. In Cleveland and Oakland, no generic indicator explains more than 18 percent of the Crime factor. Similarly, the Housing Vacancy factor is typically not well explained by any generic-based indicators. Inasmuch as the average r-squares do not exceed .12 (see Table 3). The one possible exception is Indianapolis in 1994, where several generic indicators explain between a fourth and a third of its variation. Otherwise, no other r-squared value exceeds .21 in any one of our five cities and typically they are in the single digits. Thus, it appears from this set of three cities with available data that proxies from HMDA, DataQuick, and Dunn and Bradstreet provide relatively weak substitutes for more direct measures of crime and housing vacancy rates.

To summarize, our work suggests that five indicators based on generic data sources offer extremely robust proxies for the Social Disadvantage, Prestige, and Business and Employment factors of neighborhood: home purchase mortgage approval rate, median amount of home purchase loan originated, median sales price of homes, and numbers of businesses and jobs. A sixth, the number of home purchase loan applications, offers a modestly robust proxy for the Housing Type and Tenure factor.

Tests for Parsimony

Next we consider parsimony: whether a smaller subset of the robust indicators above might suffice to provide roughly the same explanatory power. A straightforward way of identifying indicators providing redundant information is to correlate them with all others, using all census tracts with available information from our entire sample of five cities. This is shown for the generic-based indicators in Table 4.

[Table 4 about here]

Table 4 reveals that two pairs of indicators based on generic data sources are clearly redundant: (1) median loan amount – median home sales price, and (2) number of businesses – number of jobs. Both indicators in each pair are highly correlated in identical fashion in both years, .95 for the former and .86 for the latter. As noted above, however, median home sales prices and number of jobs provide slightly less explanatory power for our neighborhood dimensions than their correlated counterpart, so they will not be maintained in the parsimonious set.

By contrast, the three robust HMDA-based indicators, mortgage approval rate, number of loan applications, and median loan amount originated, and the robust Dunn and Bradstreet-based indicator, number of businesses, do not prove, in our opinion, to be sufficiently inter-correlated to render any one redundant. Pearsonian correlations ranged from .09 to .34 in 1994 and .20 to .47 in 1999; see Table 4. These four indicators, then, become our recommendations for the robust, parsimonious set.

Practical Implications, Conclusions and Caveats

Key Findings

In this research we have sought what might be seen as the “holy grail” of neighborhood indicators: a small set of measures that capture multiple dimensions of neighborhood conditions of importance, are updated annually, and are readily available at minimal cost and technical expertise. Our research has uncovered four indicators that we believe meet these criteria; the first three are based on HMDA data, the fourth on Dunn and Bradstreet data:

- Approval rate of home purchase mortgage loan applications (two-year average)
- Number of home purchase mortgage loan applications (two-year annual average)
- Median dollar amount of home purchase mortgage loans originated over two years
- Number of businesses

The mortgage approval rates and loan amounts offer extremely robust proxies for the Social Disadvantage and Prestige factors of neighborhood that we identified; the Dunn and Bradstreet data do the same for the neighborhood Business and Employment factor. Mortgage loan applications and approval rates evince somewhat lower, but nontrivial predictive power for the Housing Type and Tenure and Crime factors, respectively. An ancillary finding of importance is the remarkable correlation across time and cities of median home purchase mortgage amounts (from HMDA data) and median sales prices of single-family homes (from DataQuick data), both based on two years’ worth of data.

Implications for Planners

In practical terms, based on our results we recommend the following guidelines for those who wish to monitor neighborhood demographic, social, economic and housing changes in a summary fashion:

- Track home mortgage approval rates as a proxy for changing Social Disadvantage, especially changes in female headship rates, racial composition and unemployment rates
- Track median amount of home purchase loans originated as a proxy for Prestige, especially housing values, managerial/professional households, and college-educated households
- Track the number of mortgage loan applications as a proxy for Housing Type and Tenure, especially single-family home and owner-occupancy rates
- Track the number of businesses as a measure not only of businesses but also employment and sales

But what about costs? The good news is that operationalizing the recommended robust indicators for any particular city uses readily available data that do not require inordinate resource outlays to prepare and manipulate. For HMDA data, costs are currently $50 to purchase one year of data for the entire nation and the associated extraction software. The amount of time required to extract information for a particular city and render it usable depends upon desired thoroughness, but we estimate that investing 15 days of skilled staff time is sufficient for eliminating any serious problems. The Dun & Bradstreet national data package currently costs $300 per quarter of information (or $900 per year). We estimate that approximately 10 days of staff time is required to extract the data and convert it from zip codes to census tracts.

Our exploration has been aimed at uncovering what indicator works, not *why* it works. Nevertheless, it is worth speculating as to the potential bases of the power of the robust indicators we've identified. The number of businesses proved robust tautologically, as no variables unrelated to firms, jobs, or sales loaded heavily on the underlying factor. The efficacy of number of home purchase mortgage applications in explaining variations in Housing Type and Tenure can be easily understood by reference to the fact that this factor was closely correlated with the percentages of single-family homes and owner-occupant households in the census tract. Inasmuch as it is collinear with median home sales prices, the median amount of mortgages originated can be thought of as the market capitalization of a host of localized externalities (Palmquist, 1992). Such externalities have shown in previous hedonic index studies of property values to be correlated with many Social Disadvantage and Prestige constituent variables (Grieson and White, 1989).

The approval rate for home purchase mortgages is perhaps the least-expected robust indicator. The results here are consistent with the hypothesis that loan officers and/or home appraisers have accurate, comprehensive knowledge about a variety of neighborhood conditions that may affect prospective collateral value of the loan. Indeed, Pearsonian correlations between 1994 mortgage approval rates and 1990 census tract percentages: (1) unemployed, with college degrees and in managerial/professional occupations exceeded .52 in absolute value; and (2) high school dropouts, female-headed households with children, units with no vehicle available, and owner-occupied units exceeded .30 in absolute value.

Caveats

Several limitations of our investigation must be noted. Although we analyzed 63 – 75 neighborhood indicators (depending on the availability of administrative data in our five cities), our selections were clearly not exhaustive. There are certainly other objective domains of neighborhood that are of importance, such as social interaction patterns among neighbors (Galster, 1987), cohesion and collective efficacy (Cook, Shagle, and Degirmencioglu, 1997; Sampson, Raudenbush and Earls, 1997; Coulton, Korbin and Su, 1999), and health and environmental quality (Campbell and Converse, 1972; Rossi and Gilmartin, 1980).[10] Moreover, there are significant subjective domains of neighborhood, such as residential expectations and evaluations (Lansing, Marans, and Zehner, 1970; Campbell and Converse, 1972; Andrews and Withey, 1974; Marans and Rodgers, 1975; Ross, Bluestone and Hines, 1979; Ahlbrandt and Cunningham, 1979; Rossi and Gilmartin, 1980; Galster, 1987; Diener and Suh, 1997).[11] These objective and subjective domains of neighborhood were not investigated here because we could not find census tract-level data in a variety of cities to support their operationalization. Future research could productively ascertain the degree to which domains of indicators beyond the scope of this study are correlated with the parsimonious, robust indicators we identified.

Finally, a practical limitation of the robust, parsimonious set of indicators we identified must be acknowledged. HMDA data will only be available for census tracts in which mortgage activity undertaken by HMDA-reporting institutions occurs. This means, in practice, that neighborhoods that are: (1) primarily renter-occupied, (2) have low-levels of turnover of owner-occupied homes, and/or (3) have sales heavily financed by sellers or land contracts may not have sufficient observations of HMDA data to generate reliable indicators. Unfortunately, it is often these sorts of neighborhoods where the need for such indicators is greatest. In our study we compensated for paucity of observations by calculating two-year averages. We recommend that at least two-year moving averages be used when HMDA-based indicators are employed operationally (as per Milczarski, 2002).

Finally, mention should be made of political considerations. Our identification of a parsimonious set of robust indicators does not, of course, imply its automatic acceptance and normal use in the monitoring, planning and program evaluation operations of a local government. Clearly, those who wish to translate the value of our findings from potential into practice must pay attention to the political process and bureaucratic context in which indicators may be adopted (Innes, 1990, Rossi and Gilmartin, 1980; Sawicki and Flynn, 1996). We do not underestimate the challenges here.

Despite these limitations, we believe that our work has revealed something of eminent practical benefit to planners, local policymakers, community leaders, and social scientists alike. A few powerful, yet simple, neighborhood indicators are available at little cost virtually “off the shelf,” that can be used to monitor a broad set of neighborhood changes on almost a real-time basis and potentially assess a wide range of impacts of various public and private neighborhood interventions.

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Authors' Biographical Briefs

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Chris Hayes is a Research Associate at the Urban Institute. He served as project manager for the recently completed, HUD-funded project to assess the impact of CDBG resources at the neighborhood level, from which this paper was extracted. Mr. Hayes also was the data collection manager for the evaluation of the Lila Wallace-Reader's Digest Fund's Urban Parks Initiative, a four-year study of park user perceptions and behavior patterns in selected urban parks.

Jennifer Johnson, formerly a Research Associate at the Urban Institute, has over ten years of experience in affordable housing and housing finance research, with a focus on the Low Income Housing Tax Credit Program, the spatial effect of housing programs on neighborhoods, and how changing demographics will impact housing markets in the future. Ms. Johnson has a Masters of Arts from the University of Chicago's Irving B. Harris School of Public Policy.

Notes

1. We recognize that census tract may sometimes correspond poorly to what residents perceive as their neighborhood. Yet, it is the standard unit of geography with which cross-sectionally comparable neighborhood analyses are conventionally conducted.

2. We recognize that there are other aspects of neighborhood besides demographic, social, economic, and housing that may be of interest. Nevertheless, we believe that these form the core of any neighborhood monitoring system.

3. For purposes of this discussion, we do not consider neighborhood information gathered from purposive surveys, such as in Sampson, Raudenbush and Earls (1997) and Coulton, Korbin and Su (1999).

4. NNIP is a collaborative of organizations in over a dozen cities across the U.S. that, since the mid-1990s, has collected administrative data for their host cities and created comparable, annually updated indicators at the census tract level. The Urban Institute provides coordination, technical assistance, and dissemination services for the NNIP. For details, see Sawicki and Flynn (1996).

5. Census tract data for 2000 were not available at the time of this study.

6. We employed a two-year period to reduce the variability associated with small sample sizes of home sales and mortgages in many census tracts. Recent explorations by Milczarski, (2002) also indicate that the annual volatility in HMDA-based indicators reduces their usefulness.

7. In preliminary trials we experimented with the proportion of mortgages purchased by the secondary market, but this never was correlated with any quality of life indicators.

8. Inasmuch as we wished to explore data to determine the factors that account for the covariation among the aforementioned neighborhood indicators, not test hypotheses, we employed exploratory, not confirmatory, factor analysis (Stapleton, 1997).

9. Each factor had Eigen values greater than unity and explained three percent or more of the variance in the dataset. Because data limitations meant that we could not analyze

identical sets of indicators across all five cites, we eschewed employing confirmatory factor analysis to formally test the similarity of factors across sites (Stapleton, 1997).

10. However, there is reason to believe that, when our indicators are collapsed into factors, they will be correlated with several sociological attributes of the neighborhood. Several studies have identified strong connections between tract-level indicators of disadvantage, such as poverty, unemployment, and female headship rates, and: perceived neighborhood quality (Coulton, Korbin, and Su, 1999); patterns of informal social control (Elliott et al.,1996; Sampson, Morenoff and Earls, 1999); assessments of social disorder (Kohen, Brooks-Gunn, Leventhal, and Hertzman, 2000; Coulton, Korbin, and Su, 1999); collective efficacy (Sampson, Raudenbush, and Earls, 1997); and perceptions of neighborhood violence and youth delinquency (Sampson, Raudenbush, and Earls,1997; Sampson, 1997). Measures of neighborhood stability (typically related to home ownership rates) have proven predictive of: collective efficacy (Sampson, Raudenbush, and Earls, 1997); perceptions of neighborhood violence and youth delinquency (Sampson, Raudenbush, and Earls, 1997; Sampson, 1997); and "intergenerational closure" (degree to which adults and children in community are linked) and "reciprocated exchange" (intensity of inter-family and –adult interaction with respect to child rearing) (Sampson, Morenoff and Earls, 1999). Neighborhood indicators associated with affluence and prestige, like percentages who are college-educated and in profession/managerial/technical occupations are predictive of "intergenerational closure" and "reciprocated exchange" (Sampson, Morenoff and Earls, 1999). Perhaps most telling is the work of Cook, Shagle, and Degirmencioglu (1997), who measured at the tract level a comprehensive array of subjective scales related to "social process," ranging from social control and cohesion, to neighborhood resources, satisfaction, and participation rates. These scales were then analyzed in light of ten census tract demographic variables. They found [pp. 109-110] that they were able to use tract demographic variables to predict "very high percentages of the neighborhood-level variation in social process." Correlations among the neighborhood social process variables and the tract demographics averaged .37. The combination of percentage white (or black), median income, and percentage

in professional-technical occupations alone produced a multiple R of .77 when predicting variation in a global neighborhood social process measure. Their principal components analysis resulted in one dominant factor, wherein virtually all the social process and tract demographic variables loaded heavily. They conclude that they "do not find clear demarcation into process and demographic factors" [p. 113].

11. We note, however, the strong interrelationships between objective measures such as ours and conventionally employed subjective evaluations of quality of life (Galster and Hesser, 1981, Cummins, 2000).

Table 1
Neighborhood Quality of Life Indicators Analyzed

Census Data Indicators	*Adminstrative Data Indicators*	*Generic Data Indicators*
% Female-Head Households w/Kids*	Welfare Usage Rate (C, P)	HMDA-Based:
% High School Dropouts 16-19 yrs.*	Food Stamp Usage Rate (O, P)	
% Population Age 0-9 yrs.*	Violent Crime Rate (B, C, O)	Mortgage Approval %**
% Population Age 10-19 yrs.*	Property Crime Rate (B, C, O)	Median Loan Amount**
Median Household Income*	% Parcels Non-Residential (B, C)	# Loan Applications**
Med. Value Owner-Occ. Homes*	% Res. Parcels Single-Family (B, C)	Home Improvement as % Orig.**
% No Vehicle Available*	% Parcels Tax-Delinquent (C)	Home Purchase as % Orig.**
% Persons Below Poverty Line*	% Commercial Parcels Vacant (C)	
% Population Black*	% Residential Parcels Vacant (C)	Dunn-Bradstreet-Based:
% Population White*	% Birth Mothers w/ < HS Diploma (C)	
% Population Hispanic*	% Birth Mothers w/ No Prenatal Care (C, O, P)	Total # Businesses
% Population Other*	% Birth Mothers Not Married (C)	Total # Jobs
% Unemployed, Labor Force aged 16+*	% Females Age 10-14 Giving Birth (C)	Total $ Sales
% w/ College Degree, age 25+*	% Females Age 15-19 Giving Birth (C, I, O)	
% w/ No HS Diploma, age 25+*	% Births w/ Low Weight (C, I, O, P)	Data Quick-Based:
% Manage./Prof./Tech. Occ.*	% Births to Black Mothers (O)	
% Females age 15+ Married*	% Births to White Mothers (O)	Median Home Sales Price**
% Persons Foreign-Born*	% Births to Asian Mothers (O)	
% Persons Institutionalized*	% Births to Hispanic Mothers (O)	
% Housing Units Built Since 1970*	% Births to Teen Mothers (O)	
% Housing Units Built pre-1940*	% Births to Mothers age 15-17 (P)	
% Housing Units Owner-Occupied*		
% Housing Units Lacking Plumbing*		
% Aged 5+ In Same Unit 5+ Years*		
% Units in Single-Family Structures*		
% Housing Units Vacant*		

* 1990 Census data
** Two-year averages, 1993-94 or 1998-99 for generic indicators
Parenthetical terms after adminstrative data indicators show cities for which indicator is available:
B = Boston; C = Cleveland; I = Indianapolis; O = Oakland; P = Providence

Table 2
Overview of Common Factors Extracted from Principal Components Analysis

	1994-1999 Ranges of Proportion of Variance Explained, by City				
Factor:	Boston	Cleveland	Indianapolis	Oakland	Providence
1. Social Disadvantage		.13 - .36	.12 - .13	.37 - .39**	.07 - .14***
2. Housing Type & Tenure	.17 - .29	.12 - .33	.07 - .09	.13 - .15	.12 - .15
3. Prestige	.20 - .31	.08	.41 - .42	**	.34 - .41
4. Business & Employment	.06	.04 - .05	.05 - .06	.05 - .06	.05 - .08
5. Crime	.03 - .08*	.03 - .05	N/A	.04	N/A
6. Housing Vacancy	.04 - .05	.03 - .04	.05	.03 - .04	****

* separate factors for violent and property crimes; proportion shown is sum of both
** includes dimensions of prestige in social disadvantage factor
*** social disadvantage split into two factors; proportion shown is sum of both
**** includes housing vacancy in housing type and tenure factor
Blank=no factor of this type produced
N/A - Not Applicable because crime data not available for analysis
Note: only one parameter reported means no difference in 1994 & 1999 values

Table 3
Proportion of Variance in Factor Explained by Various Generic indicators

Averages across five cities and both 1994, 1999

	Factor # :					
Indicators	1	2	3	4	5	6
Mtg. Approval Rate	0.38	0.08	0.45	0.06	0.22	0.12
# LARs	0.07	0.27	0.12	0.04	0.08	0.07
Med. Loan Amt.	0.28	0.09	0.74	0.07	0.15	0.10
Home Purch. % Orig.	0.22	0.06	0.08	0.03	0.04	0.07
Home Imp. % Orig.	0.19	0.03	0.28	0.05	0.17	0.07
Median Home Price	0.25	0.11	0.72	0.04	0.13	0.06
# Businesses	0.03	0.03	0.10	0.95	0.04	0.03
# Jobs	0.03	0.02	0.07	0.94	0.03	0.03
$ Sales	0.02	0.05	0.09	0.42	0.03	0.03

Factor Codes: 1 = social disadvantages; 2 = housing types and tenure;
3 = prestige; 4 = business & employment; 5 = crime; 6 = housing vacancy

Table 4
Correlation Among Selected Generic Data Indicators

All Sample Cities, 1994 and 1999

1994 Generic Indicator	1	2	3	4	5	6	7	N
1. Mtg. Approval Rate	1.00							3300
2. # LARs	0.34	1.00						3333
3. Median Loan Amt.	0.09	0.34	1.00					3333
4. Home Purch. % Orig.	0.38	0.05	-0.21	1.00				3301
5. Median Home Price	-0.01	0.39	0.95	-0.31	1.00			1992
6. # Businesses	0.12	0.21	0.25	0.12	0.23	1.00		3173
7. # Jobs	0.12	0.12	0.16	0.13	0.11	0.86	1.00	3174
1999 Generic Indicator								
1. Mtg. Approval Rate	1.00							3320
2. # LARs	0.27	1.00						3352
3. Median Loan Amt.	0.47	0.20	1.00					3352
4. Home Purch. % Orig.	0.31	0.08	0.04	1.00				3323
5. Median Home Price	0.44	0.24	0.95	0.16	1.00			2354
6. # Businesses	0.21	0.24	0.23	0.30	0.26	1.00		3191
7. # Jobs	0.20	0.14	0.15	0.25	0.14	0.86	1.00	3194

N = # observations of census tracts with valid data for given indicator in all sample cities

Table A.1
Principal Components of Social Disadvantage Factor # 1
Factor Loadings, by City and Year

	Boston			Cleveland	
Indicator	1994	1999	Indicator	1994	1999
	[No factor for social disadvantage]		Welfare Usage Rate	.54	
			% Births Unmarried Females	.70	.68
			% Parcels Tax Delinquent	.87	.86
			% Female-Headed Households*	.83	.81
			% Female 15+ Married*	-.70	-.67
			% Pop. Foreign Born*	-.51	-.61
			% Pop. Black*	.92	.93
			% Pop. White*	-.95	-.95
			% Pop. Age 10-19*	.51	
			% Unemployed*	.58	
			Mortgage Approval**	-.72	-.53
			Med. Loan Amount**	-.63	
			Home Purchase % Orig.**	-.70	-.59
			Home Improve % Orig.**	.84	
Sample N	133	126	Sample N	143	170

Note: Only loading > I .50 I shown
Note: ' = separate social disadvantage factor

* 1990 Census data
** Two-year averages, 1993-94 or 1998-99 for generic indicators
[Sample N may vary between years due to data availability]

Table A.1 Cont.

	Indianapolis			Oakland	
Indicator	1994	1999	Indicator	1994	1999
Welfare Usage Rate	N/A	.72	Welfare Usage Rate	.84	.87
Food Stamp Usage Rate	N/A	.66	% Births Black Mothers	.62	.63
			% Births White Mothers	-.87	.90
			% Births Teen Mothers	.65	.56
			Food Stamp Usage Rate	.83	.86
% Female-Headed Households*	.80	.85	% Female-Headed Households*	.69	.68
% Females 15+ Married*	-.66	-.70	% HS Dropouts 16-19 yrs.*	.53	
% No Vehicle Available*	.58	.61	% Pop. Age 0-9 yrs.*	.76	.68
% Below Poverty Line*	.58	.64	% Pop. Age 10-19 yrs.*	.79	.75
% Pop. Black*	.96	.93	Median Income*	-.69	-.71
% Pop. White*	-.96	-.94	Med. Value Owner-Occ.*	-.69	-.71
% Unemployed*	.58	.60	% No Vehicle Available*	.57	.60
			% Below Poverty Line*	.69	.67
			% Pop. Black*	.80	.82
			% Pop. White*	-.95	-.96
			% Unemployed*	.78	.78
			% w/ College Degree*	-.93	.94
			% w/ No HS Diploma*	.81	.83
			% Manage./Prof./Tech. Occ.*	-.90	-.92
Mortgage Approval**	-.59		Mortgage Approval %**	-.70	-.77
Home Purchase % Orig.**	-.57		Median Loan Amount**	-.75	-.75
Home Improve % Orig.**	.53		Median Home Sales Price**	-.78	-.78
			Home Improve % Orig.**		-.57
Sample N	165	167	Sample N	87	87

Note: Only loading > I .50 I shown
Note: ' = separate social disadvantage factor

* 1990 Census data
** Two-year averages, 1993-94 or 1998-99 for generic indicators

Table A.1 Cont.

	Providence	
Indicator	1994	1999
Welfare Usage Rate'	.81	.82
Food Stamp Case Load'	.79	.83
% Births Low Weight		.63
% Birth Mothers 15-17 yrs.		.81
% HS Dropouts 16-19 yrs.*		.76
% Pop. Institutionalized*		.85
% Units Built Since 1970*		.75
% Units Built Pre - 1940*		-.67
% No Vehicle Available*		.67
# LARs'		.57
Sample N	35	37

Note: Only loading > I .50 I shown
Note: ' = separate social disadvantage factor

* 1990 Census data
** Two-year averages, 1993-94 or 1998-99 for generic indicators

Table A.2
Principal Components of Housing Type and Tenure Factor # 2
Factor Loadings, by City and Year

	Boston			Cleveland			Indianapolis	
Indicator	1994	1999	Indicator	1994	1999	Indicator	1994	1999
% Structures Single-Family	.90	.90	Med. Assessed Value	.62	.68			
			% Nonresidential Parcels	-.51	-.51			
			% Structures Single-Famliy	.88	.88			
% Females 15+ Married*	.68	.70	% Females 15+ Married*	.52	.56	% Owner-Occ. Dwellings*	.89	.88
Med. Income*	.58	.59	Med. Value Owner-Occ.*	.50	.57	% Living Same Unit 5+ Yrs.*	.77	.80
% No Vehicle Available*	-.78	-.79	Med. Income*	.69	.73	% Structures Single-Family*	.93	.93
% Owner-Occ. Dwellings*	.89	.90	% No Vehicle Available*	-.64	-.69			
% Below Poverty Line*	-.53	-.53	%Owner-Occ. Dwellings*	.92	.93			
% Living Same Unit 5+ Yrs.*	.61	.62	% Below Poverty Line*	-.51	-.60			
% Structure Single-Famliy*	.94	.94	% Living Same Unit 5+ Yrs.*	.52				
			% Structures Single-Family	.93	.93			
			% Units Lacking Complete Plumbing*		-.51			
			% Units Vacant*		.53			
Home Purchase % Orig.**		-.51						
Sample N	133	126	Sample N	143	170	Sample N	165	167

* 1990 Census data
** Two-year averages, 1993-94 or 1998-99 for generic indicators
[Sample N may vary between years due to data availability]

Table A.2 cont.

	Oakland			Providence	
Indicator	1994	1999	Indicator	1994	1999
% Females 15+ Married*	.72	.71	% Females 15+ Married*	.72	.67
Med. Value Owner-Occ.*	.66	.64	Median Income*	.72	.68
% No Vehicle Available*	-.57	-.51	% No Vehicle Available*	-.63	-.59
% Owner-Occ. Dwellings*	.93	.91	% Units Owner-Occupied*	.91	.89
% Living Same Unit 5+ Yrs.*	.78	.75	% Structures Single-Famliy*	.84	.85
% Structures Single-Famliy	.94	.91	% Living Same Unit 5+ Yrs.*	.72	.58
Median Income*	.65	.62	% Units Lacking Plumbing*	-.58	
			% Below Poverty Line*	-.83	-.79
			% Units Vacant*	.55	
# LARs**	.56		# LARs**	.73	.57
Sample N	87	87	Sample N	35	37

* 1990 Census data
** Two-year averages, 1993-94 or 1998-99 for generic indicators

Table A.3
Principal Components of Prestige Factor # 3
Factor Loadings, by City and Year

	Boston			Cleveland	
Indicator	1994	1999	Indicator	1994	1999
% w/ College Degree*	.75	.72	% w/ College Degree*	.90	.90
Med. Value Homes*	.72	.66	Med. Value Homes*	.57	.54
Median Income*	.53	.59	% w/ No HS Diploma*	.60	.62
% w/ No HS Diploma*	-.59	-.56	% manage./Prof./Tech. Occup.*	.94	.93
% Manage./Prof./Tech. Occup.*	.80	.76			
Med. Mortgage Amount**	.87	.88	Med. Mortgage Amount**	.57	.64
Mortgage Approval Rate**		.60	Med. Home Sales Price**	.57	.55
Med. Home Sales Price**	.87	.91			
Sample N	133	126	Sample N	143	170

* 1990 Census data
** Two-year averages, 1993-94 or 1998-99 for generic indicators
[Sample N may vary between years due to data availability]

Table A.3 Cont.

Indicator	Indianapolis 1994	Indianapolis 1999	Indicator	Oakland 1994	Oakland 1999	Indicator	Providence 1994	Providence 1999
				[Prestige Factor included in Social Disadvantage Factor]		% Births w/ Prenatal Care	.51	.62
						% Births to Hispanic Mothers		-.61
% w/ College Degree*	.93	.88				% w/ College Degree*	.92	.94
Med. Value Homes*	.80	.80				Med. Value Homes*	.83	.82
Median Income*	.72	.73				Med. Income*	.63	.64
% w/ No HS Diploma*	-.78	-.76				% Pop. Under age 10	-.55	
% Below Poverty Line*	-.50					% w/ No HS Diploma*	-.81	-.82
% Manage./Prof./Tech. Occup.*	.92	.87				% Manage./Prof./Tech. Occup.*	.89	.91
% Unemployed*	-.51							
						Median Home Sales Price	.92	.93
						Median Mortgage Amount**	.92	.94
						Home Improve % Orig.**	-.66	-.52
						Mortgage Approval Rate**	.72	.78
Sample N	165	167	Sample N	87	87	Sample N	35	37

* 1990 Census data
** Two-year averages, 1993-94 or 1998-99 for generic indicators

Table A.4
Principal Components of Business & Employment Factor # 4
Factor Loadings, by City and Year

	Boston		Cleveland	
Indicator	1994	1999	1994	1999
# Businesses**	.94	.93	.94	.95
# Jobs**	.86	.87	.95	.87
$ Sales**		.55	.55	.31
Sample N	133	126	143	170

	Indianapolis	
Indicator	1994	1999
# Businesses**	.89	.87
# Jobs**	.93	.92
$ Sales**	.59	.50
Sample N	165	167

	Oakland		Providence	
Indicator	1994	1999	1994	1999
# Businesses**	.92	.97	.94	.94
# Jobs**	.98	.97	.98	.97
$ Sales**	.83	.57	.66	.77
Sample N	87	87	35	37

** Two-year averages, 1993-94 or 1998-99 for generic indicators
[Sample N may vary between years due to data availability]

Table A.5
Principal Components of Crime Factor # 5
Factor Loadings, by City and Year

	Boston	
Indicator	1994	1999
Violent Crime	.74	.68
% Female-Headed Households*	.54	
% Pop. Under Age 10*	.54	.52
% Pop. Black*	.95	.94
% Pop. White*	-.90	-.87
Mortgage Approval Rate**	-.54	-.64
Home Improve % Orig.**		.55
Sample N	133	126

	Cleveland	
Indicator	1994	1999
Property Crime Rate	.57	.53
Violent Crime Rate	.93	.92
% Parcels Non-Residential	.46	.58
Sample N	143	170

	Indianapolis	
Indicator	1994	1999
	N/A	N/A

	Oakland	
Indicator	1994	1999
Violent Crime Rate	N/A	.89
Property Crime Rate	N/A	.96
Sample N	87	87

	Providence	
Indicator	1994	1999
	N/A	N/A

* 1990 Census data
** Two-year averages, 1993-94 or 1998-99 for generic indicators

N/A = no crime data available
[Sample N may vary between years due to data availability]

Table A.6
Principal Components of Housing Vacancy Factor # 6
Factor Loadings, by City and Year

	Boston			Cleveland			Indianapolis	
Indicator	1994	1999	Indicator	1994	1999	Indicator	1994	1999
% Units Vacant*	.92	.93	% Units Vacant*	.83	.77	% Units Vacant*	.71	.76
% Units Lacking Plumbing*	.91	.91	% Units Lacking Plumbing*	.82	.77	% Units Lacking Plumbing*	.72	.75
Sample N	133	126	Sample N	143	170	Sample N	165	167

	Oakland			Providence	
Indicator	1994	1999	Indicator	1994	1999
% Units Vacant*	.67	.61	[Housing vacancy included in housing type and tenure factor]		
% Rental Units Vacant*	.69	.86			
% Units Lacking Plumbing*		.55			
Sample N	87	87			

* 1990 Census data
** Two-year averages, 1993-94 or 1998-99 for generic indicators
[Sample N may vary between years due to data availability]

Table A.7
Proportion of Variance in Factor Explained
by Various Generic Indicators, City, and Year

	City: Boston			Year: 1994		
	Factor #:					
Indicators	1	2	3	4	5	6
Mtg. Approval Rate	N/A	.03	.38	.11	.45	.05
# LARs	N/A	.20	.30	.05	.05	.08
Med. Loan Amt.	N/A	.01	.95	.11	.24	.01
Home Purch. % Orig.	N/A	.06	.00	.01	.00	.05
Home Imp. % Orig.	N/A	.01	.32	.11	.47	.03
Median Home Price	N/A	.05	.91	.09	.15	.00
# Businesses	N/A	.00	.11	.98	.08	.00
# Jobs	N/A	.02	.14	.89	.08	.01
$ Sales	N/A	.00	.25	.36	.04	.01
				Year: 1999		
Mtg. Approval Rate	N/A	.00	.49	.10	.56	.01
# LARs	N/A	.16	.16	.06	.01	.05
Med. Loan Amt.	N/A	.00	.92	.14	.16	.00
Home Purch. % Orig.	N/A	.26	.09	.06	.14	.02
Home Imp. % Orig.	N/A	.11	.29	.14	.33	.00
Median Home Price	N/A	.02	.96	.13	.15	.00
# Businesses	N/A	.00	.15	.98	.07	.04
# Jobs	N/A	.03	.14	.94	.07	.09
$ Sales	N/A	.01	.11	.49	.03	.06

Factor Codes: 1 = social disadvantages; 2 = housing types and tenure;
3 = prestige; 4 = business & employment; 5 = crime; 6 = housing vacancy

N/A: No factor 1 produced by Boston Data

Table A.7 Cont.
Proportion of Variance in Factor Explained
by Various Generic Indicators, City, and Year

	City: Cleveland			Year: 1994		
	Factor #:					
Indicators	1	2	3	4	5	6
Mtg. Approval Rate	.42	.06	.13	.03	.02	.15
# LARs	.02	.09	.05	.02	.11	.08
Med. Loan Amt.	.25	.05	.35	.06	.06	.17
Home Purch. % Orig.	.39	.01	.00	.01	.00	.05
Home Imp. % Orig.	.59	.00	.12	.04	.02	.14
Median Home Price	.01	.08	.37	.03	.10	.17
# Businesses	.02	.03	.02	.94	.01	.02
# Jobs	.02	.02	.01	.93	.00	.02
$ Sales	.02	.01	.01	.36	.02	.01
				Year: 1999		
Mtg. Approval Rate	.35	.03	.17	.05	.00	.06
# LARs	.02	.26	.00	.01	.15	.12
Med. Loan Amt.	.08	.06	.42	.06	.12	.12
Home Purch. % Orig.	.42	.01	.08	.02	.05	.00
Home Imp. % Orig.	.04	.00	.02	.01	.00	.01
Median Home Price	.08	.07	.36	.05	.07	.11
# Businesses	.04	.06	.03	.98	.00	.04
# Jobs	.06	.05	.02	.86	.00	.03
$ Sales	.03	.00	.00	.18	.05	.01

Factor Codes: 1 = social disadvantages; 2 = housing types and tenure;
3 = prestige; 4 = business & employment; 5 = crime; 6 = housing vacancy

Table A.7 Cont.
Proportion of Variance in Factor Explained
by Various Generic Indicators, City, and Year

	City: Indianapolis			Year: 1994		
	Factor #:					
Indicators	1	2	3	4	5	6
Mtg. Approval Rate	.43	.00	.47	.07	N/A	.34
# LARs	.08	.10	.22	.12	N/A	.14
Med. Loan Amt.	.23	.01	.72	.14	N/A	.23
Home Purch. % Orig.	.40	.02	.07	.02	N/A	.26
Home Imp. % Orig.	.39	.02	.47	.12	N/A	.33
Median Home Price	N/A	N/A	N/A	N/A	N/A	N/A
# Businesses	.05	.02	.21	.90	N/A	.08
# Jobs	.05	.01	.13	.97	N/A	.05
$ Sales	.01	.00	.17	.48	N/A	.01
				Year: 1999		
Mtg. Approval Rate	.35	.00	.53	.17	N/A	.21
# LARs	.02	.14	.03	.04	N/A	.10
Med. Loan Amt.	.19	.02	.68	.15	N/A	.15
Home Purch. % Orig.	.35	.08	.28	.11	N/A	.10
Home Imp. % Orig.	.07	.01	.19	.05	N/A	.01
Median Home Price	N/A	N/A	N/A	N/A	N/A	N/A
# Businesses	.09	.01	.23	.89	N/A	.07
# Jobs	.08	.00	.10	.97	N/A	.03
$ Sales	.02	.01	.14	.42	N/A	.00

Factor Codes: 1 = social disadvantages; 2 = housing types and tenure;
3 = prestige; 4 = business & employment; 5 = crime; 6 = housing vacancy

N/A: Crime data and home sales data not available for Indianapolis

Table A.7 Cont.
Proportion of Variance in Factor Explained
by Various Generic Indicators, City, and Year

	City: Oakland			Year: 1994		
	Factor #:					
Indicators	1*	2	3*	4	5	6
Mtg. Approval Rate	.52	.11		.06	N/A	.08
# LARs	.10	.44		.00	N/A	.02
Med. Loan Amt.	.61	.21		.00	N/A	.11
Home Purch. % Orig.	.03	.03		.00	N/A	.00
Home Imp. % Orig.	.03	.00		.06	N/A	.00
Median Home Price	.64	.22		.00	N/A	.10
# Businesses	.02	.00		.90	N/A	.01
# Jobs	.00	.03		.98	N/A	.01
$ Sales	.01	.10		.66	N/A	.02
				Year: 1999		
Mtg. Approval Rate	.65	.04		.00	.09	.03
# LARs	.04	.36		.01	.07	.00
Med. Loan Amt.	.65	.23		.00	.18	.01
Home Purch. % Orig.	.12	.10		.00	.01	.06
Home Imp. % Orig.	.32	.04		.00	.01	.01
Median Home Price	.65	.23		.00	.18	.00
# Businesses	.03	.01		.96	.02	.00
# Jobs	.00	.01		.96	.00	.01
$ Sales	.01	.07		.38	.02	.08

Factor Codes: 1 = social disadvantages; 2 = housing types and tenure;
3 = prestige; 4 = business & employment; 5 = crime; 6 = housing vacancy

* Dimensions of prestige factors included in social disadvantages factor
N/A: Crime data not available in 1994

Table A.7 Cont.
Proportion of Variance in Factor Explained
by Various Generic Indicators, City, and Year

	City: Providence			Year: 1994		
	Factor #:					
Indicators	1	2	3	4	5*	6**
Mtg. Approval Rate	.16	.20	.65	.03		
# LARs	.13	.56	.18	.07		
Med. Loan Amt.	.19	.14	.95	.02		
Home Purch. % Orig.	.00	.05	.00	.03		
Home Imp. % Orig.	.10	.05	.53	.01		
Median Home Price	.11	.06	.88	.03		
# Businesses	.02	.12	.02	.97		
# Jobs	.05	.03	.00	.95		
$ Sales	.08	.10	.00	.33		
				Year: 1999		
Mtg. Approval Rate	.18	.29	.74	.00		
# LARs	.11	.40	.05	.01		
Med. Loan Amt.	.01	.13	.95	.00		
Home Purch. % Orig.	.03	.00	.14	.01		
Home Imp. % Orig.	.00	.05	.33	.00		
Median Home Price	.02	.13	.86	.02		
# Businesses	.00	.01	.02	.95		
# Jobs	.00	.00	.00	.96		
$ Sales	.00	.16	.00	.50		

Factor Codes: 1 = social disadvantages; 2 = housing types and tenure;
3 = prestige; 4 = business & employment; 5 = crime; 6 = housing vacancy

* No crime data available for Providence
** Housing vacancy factor included in housing type/tenure factor