Research to Develop A Community Needs Index

US Department of Housing and Urban Development
Office of Policy Development and Research

Research to Develop A Community Needs Index

Prepared for

U.S. Department of Housing and Urban Development
Office of Policy Development and Research

Prepared by

Econometrica, Inc.
Bethesda, MD

Frederick J. Eggers, Ph.D.

June 2007

Acknowledgements

Econometrica, Inc. conducted this research under contract to the U.S. Department of Housing and Urban Development (HUD). Fred Eggers was the Principal Investigator; Alex Thackeray and Fouad Moumen compiled and analyzed the data; and Larry Campbell edited the report.

The Econometrica Team benefited from the assistance provided by many persons. James Broughman, George Galster, Garth Taylor, and Christopher Walker served as consultants to the project and contributed many helpful ideas and thoughtful criticisms. Kurt Usowski, Craig Davis, and Ian Keith at HUD provided data and suggestions on how to combine data from different sources. Harold Bunce, John Carruthers, Stanley Gimont, Michael Hollar, Derek Hyra, and Kevin Neary of HUD contributed useful comments on the first two drafts of the report; the final report is much better because of their insights. The Team also appreciates the thoughts and opinions provided by the participants at the Orientation Meeting and at the Expert Panel Meeting.

Special thanks are due to two people at HUD who made extraordinary contributions to the success of this research. Marina Myhre served as the Government Technical Representative. Her guidance, comments, and attentive management were crucial to the success of the research. Todd Richardson shared his knowledge and experience generously with the Team and also furnished the 2000 census data used in the analysis. The U.S. Postal Service vacancy series used as a proxy for abandonment were created by Todd Richardson.

FOREWORD

In order to understand the most efficient and fair way to allocate Community Development Block Grant funds, HUD staff since 1976 have worked on developing measures of community needs. This study, *Research to Develop a Community Needs Index*, marks a further advance by developing an index that not only shows current needs but also can be used to demonstrate changing community conditions.

The study draws on a number of public databases, including the American Community Survey (ACS). It tests the feasibility of relying on the ACS for annual information about community needs, and it devises a method to compare those needs over time. Specifically this study used 2005 ACS data and other readily-available sources in order to create an index of community needs. It then applied that index to measure changes in community needs since 2000.

This study also develops and implements an innovative index of real fiscal capacity, which measures the extent to which communities are capable of dealing with their problems without federal assistance. To construct this index, the study compares the ability of cities to raise revenue from various sources. The “real fiscal capacity” index ranks 234 cities on the real resources that they could have used in order to solve their community needs in 2005.

The study finds that it is possible to combine a “needs” index and a “fiscal capacity” index for the purpose of measuring relative need for CDBG and other federal support. This study was limited to exploratory and methodological issues.

Darlene F. Williams
Assistant Secretary for Policy
Development and Research

Contents

Contents
(continued)

Contents
(continued)

Tables

Tables
(continued)

Appendix A

Appendix B

Appendix C

This page left blank intentionally.

Executive Summary

The U.S. Department of Housing and Urban Development (HUD) funded this research for the purpose of developing an index of community needs. Such an index would take information from various public databases on different types of community problems and produce an overall assessment of the "neediness" of a community. As far back as 1976, HUD devoted its own staff resources to studying community needs and devising ways to synthesize various types of needs into an overall index of needs. HUD's efforts have been sporadic because the primary source of data on community needs has been the decennial censuses, and thus new information on needs has been available only at 10-year intervals. Now, the American Community Survey (ACS) will provide every year the information that previously was available only from the decennial censuses. The annual availability of information through the ACS makes a community needs index much more valuable for HUD.

From HUD's perspective, this research would provide the foundation for its future analysis of community needs by:

- Testing the feasibility of relying on the ACS for annual information about community needs.

- Devising a methodology to compare conditions in communities over time.

In the early stages of the research, HUD expanded the goals to include developing an index of fiscal capacity and investigating an alternative methodology for constructing an index.

Identifying and Measuring Community Needs

The first step in the research was to define the range of problems to be grouped together as "community needs" and to identify "indicators" for each of the problems. In this research, "community" means city and "needs" means the problems, experienced by cities, that are relevant to HUD's urban mission. The "indicators" are quantitative measures available on a consistent basis for all or most of the cities studied.

HUD views its mission as including the support of community development. In its Strategic Plan, HUD declares its concern about a wide variety of problems related to strengthening communities; included among HUD's concerns are housing conditions, physical conditions, the quality of life, and economic opportunities. With this in mind, the research team formulated a preliminary list of indicators that covered a broad array of community ills. In selecting the indicators, the team reviewed measures used in previous studies and data available from a variety of databases that contain information at the city level or that could be manipulated to produce city-level measures. In a November 21, 2006, meeting involving the authors, HUD experts, consultants with previous experience in comparing conditions at the local level, representatives from the U.S. Government Accountability Office, and representatives from the District of Columbia government, the strengths and weaknesses of a variety of indicators were discussed and, in additional consultation with HUD, a final list of 26 indicators was selected.

Eight indicators identify population groups that may have needs for city services beyond those of the typical citizen. These include:

1. Poverty population.
2. Children living in poverty.
3. Persons over age 74 living in poverty.
4. Low-income population (excludes poverty population).
5. Single-parent families.
6. Adults without a high school diploma.
7. Working-age persons without a college degree.
8. Recent immigrants.

Four indicators identify problems with housing, housing markets, or housing finance. These include:

9. Lack of affordable rental housing.
10. Overcrowded housing.
11. Older rental housing occupied by poor persons.
12. Mortgage-loan denial rate.

Three indicators identify the extent to which cities have seriously troubled neighborhoods. These include:

13. Population living in high-poverty census tracts.
14. Population living in moderate-poverty census tracts.
15. Abandoned buildings.

Four indicators identify social and economic problems at the city level. These include:

16. Rate of violent crimes.
17. Rate of nonviolent crimes.
18. School-age population living in poverty.
19. Unemployment rate.

Four indicators identify conditions that might complicate a city's efforts to deal with its problems. These include:

20. Linguistic isolation.
21. City-metropolitan differences in minority population.
22. City-metropolitan differences in poverty rate.
23. City-metropolitan differences in median family income.

Three indicators identify detrimental long-term trends. These include:

24. Excess infrastructure/loss of households.
25. Change in employment base.
26. Change in concentration of low-income families.

Table 1 in Chapter 2 defines each of these indicators more precisely and explains why each was included. All the indicators are defined in percentage or ratio terms so that their magnitude does not depend on city size. Also, all indicators are defined so that the more serious the condition, the larger the value of the indicator.

Input from HUD and outside experts was used to choose the indicators. The list includes several innovative indicators. The abandoned building indicator was developed by HUD staff using a combination of census data and vacancy rates compiled by the United States Postal Service (USPS). The lack of affordable rental housing indicator (#9) uses a technique similar to that used by HUD to identify difficult development areas for the low-income housing tax credit program. The mortgage denial rate is used for the first time in this study. Variants of the city-metropolitan difference variables (#21 to #23) have been used in previous studies, but this research uses a simplified definition that makes it easier to calculate these indicators. All three long-trend indicators (#24 to #26) are new formulations for this research.[1]

The indicators require data from the ACS, the decennial censuses, the economic censuses, USPS vacancy surveys, Home Mortgage Disclosure Act records, the FBI Uniform Crime Report, and the Bureau of Labor Statistics Local Area Unemployment Statistics. The 2005 ACS reported information on 473 cities (not including Puerto Rico) with populations of 65,000 or more. The research attempted to calculate the 26 indicators for each city. Information needed for individual indicators was missing for a number of cities. The most serious missing data problem involved the crime data, which were not available for 107 cities.

Finding Common Patterns among the Needs Indicators

The next step in the analysis was to determine the extent to which the needs indicators can be distilled into a small (more manageable) number of underlying common “themes” or components. The report uses factor analysis to search for common themes and to produce a simpler way to observe how needs vary across communities. Previous HUD research used factor analysis for this purpose.

[1] A 27th indicator based on Housing Mortgage Discrimination Act data was identified—poor housing appreciation in high-poverty neighborhoods—but it could not be implemented within the scope of the project.

The research applied standard factor analysis techniques to the 26 indicators and identified three dimensions of community needs. These include:

- Needs associated with poverty and structural problems (Factor 1).
- Needs associated with immigration and lack of affordable housing (Factor 2).
- Needs arising from limited economic prospects (Factor 3).

The robustness of the factor analysis was tested in several ways. First, factor analysis was applied to the same indicators using 2000 data. The 2000 and 2005 analyses identified factors that were nearly identical; this result confirmed that factors developed using 2005 data could be applied to 2000 data on needs indicators. Second, the sample of cities was split into those with populations of 200,000 or more and those with populations of less than 200,000. Factor analysis applied separately to the two samples produced results that were similar enough to suggest that the same pattern of needs apply across different size classes of cities. Third, a different measure for violent crimes—one based on occurrences rather than arrests—was substituted for the measure used in the initial analysis. The results of the factor analysis did not seem to vary significantly when the alternative measure was used. Fourth, the needs indicators were examined to see where problems with missing data caused a large number of cities to drop out of the analysis. Based on this examination, the two crime indicators were dropped. When factor analysis was applied to the smaller set of needs indicators, the same factors were found as were found with the full set of indicators. Eliminating the two crime variables increased the number of cities examined from 292 to 370.

The factor analysis based on 24 needs indicators is the one used for all the analyses in the remainder of the report. Factor scores were computed for each city on each factor by multiplying a set of standardized scoring coefficients derived from the factor analysis by the standardized value of the needs indicators for the city and summing the products. A standardized value for a needs indicator is obtained by subtracting a mean value from the value of the indicator for that city and dividing the difference by a standard deviation.

The explicit goal of this project was to develop a single-valued index of community needs. The report compared six alternative single-valued indices constructed by using various linear combinations of the scores on the three factors. The report was unable to find any statistical, programmatic, or logical reasons that made a *compelling* case for choosing one index over any of the others. Statistically, an equal weight index—an index formed by giving each of the three factors a weight of 1/3—produces results that are very similar to the results from the other indices that vary the weights given to the factors. For this reason, the report uses the equal weight index in all the analyses involving a single-valued index.

High correlation across all cities does not mean that the ranking of some cities is not substantially different depending upon the index used. If HUD were to use one of these indices to allocate funds to cities, the choice of index would be of great concern to individual cities. But, if HUD is interested primarily in analyzing the variation in needs across cities and over time, then the results from the equal weight index will be similar to those from any index that applies reasonable weights to the factor scores.

Comparing Community Needs across Time

This research developed a methodology for applying factor analysis to data on needs at two points in time and successfully implemented the methodology. There are two keys to carrying out intertemporal comparisons correctly.

- First, the dimensions of need identified in the base year must still be relevant in the comparison year.
    - The comparison of factor analyses using 2000 and 2005 data confirmed that the same factors applied in 2000 and 2005.
- Second, needs must be measured relative to conditions in the year in which the factor analysis is performed—that is, the means and standard deviations from the year used to derive the standardized scoring coefficients must be used to standardize the needs indicators in both years.
    - Since the report uses 2005 data to identify the factors, the report uses the means and standard deviations calculated on data for the 24 needs indicators in 2005 to standardize the values of the needs indicators in both 2000 and 2005.

Using this technique, the report compares conditions in cities in 2000 with conditions in 2005 using each of the factors and the equal weight index. The scores are positively related to needs—that is, for each factor and for the equal weight index, an increase in the score means that a city is worse off in 2005 than in 2000.

Between 2000 and 2005, cities—on average—became worse off with respect to poverty and structural problems as well as immigration and housing affordability problems, but improved with respect to the limited economic prospects factor.

- Regional differences appeared on the individual factors, such as:
    - The Northeast had the highest average scores on the poverty and structural problems factor in both 2000 and 2005 and the largest increase in average scores between the two years. The West had the lowest average scores on this factor in both years and the smallest increase between the two years.
    - For the immigration and housing affordability factor, the average scores of cities in the Northeast and West were higher than the national average

in both 2000 and 2005. Cities in the Northeast had the highest average change between 2000 and 2005.

  - Cities in the Northeast had the lowest scores on the limited economic prospects factor in 2000 and showed the greatest improvement between 2000 and 2005.

- Differences by class size of cities were less common. For example:

  - There appeared to be a systematic relationship between the scores on the poverty and structural problems factor and city size. The average score declined by size class in both 2000 and 2005. The change in scores was approximately the same for all the size classes, except for cities with populations between 500,000 and one million, which had a slightly higher increase in average scores.

  - With the exception of cities with over one million residents, there appeared to be little relationship between population size and the prevalence of problems related to immigration and housing affordability. The largest cities had an average score of 0.70 or more in both 2000 and 2005; the national average was 0.00 in 2005.

- There were also some interesting patterns in the lists of cities with the biggest increases in scores (becoming worse off) and the lists of cities with the biggest decreases in scores (becoming better off).

  - Some of the worse off cities on the poverty and structural problems factor experienced big increases on this factor between 2000 and 2005; the cities were Camden, Detroit, Cleveland, Rochester, Reading, and Syracuse.

  - Compared with other states, California had the most cities—95—among the 370 scored. Still, California cities appeared in higher than expected proportions on the list of the 40 biggest losers and gainers. One would expect, proportionally, 10 cities from California on each list. Instead:

    - Twenty-four of the 40 cities with the biggest improvements on the poverty and structural problems factor were California cities.
    - Fifteen of the 40 cities with the worse changes on the immigration and housing affordability factor were California cities.
    - The five cities with the largest improvements on the immigration and housing affordability factor, and 18 of the top 40, were California cities.

The equal weight index showed that, on average, community needs decreased slightly between 2000 and 2005. According to the index, conditions were stable or got better in 202 of 370 cities. However, the report notes that the observed improvement appears to be related strongly to the substantial increase in the proportion of adults with a high school diploma between 2000 and 2005, a fact that was questioned when the report reviewed data on each of the indicators.

Measuring Fiscal Capacity

The federal government, in general, and HUD in particular, are interested in developing an index of community needs because they want to know the extent to which communities require federal assistance. But a needs index answers only one-half of this question; the federal government also needs to know the extent to which communities are capable of dealing with their problems without federal assistance.

The report develops and implements an index of real fiscal capacity. To construct the index, the report compares cities on their ability to raise revenue from various sources, including assistance from state governments. Then, the report translates the potential revenue into real terms by dividing total potential revenue by the average annual wage for government employees calculated at the metropolitan-area level. Using real capacity adjusts for differences across cities in the costs of responding to community needs. The real fiscal capacity index ranks 266 cities on the real resources that they can potentially use to solve community needs in 2005.

The report also develops a technique for combining the equal weight index of community needs with the index of real fiscal capacity to obtain an adjusted needs index that looks at both needs and capacity. The report calculates adjusted needs index scores for 234 cities in 2005.

The most important findings from the research on fiscal capacity are:

- It is possible to construct an index of real fiscal capacity, which is a very important advancement in analyzing the need for federal assistance.

- The index of real fiscal capacity is sensitive to both income and wage rates. Places with high income or lower government wages are more likely to have high real fiscal capacity. High-income places can generally afford more government services because they can raise more tax revenue; places with low government wages can generally afford more government services because every tax dollar goes further in providing services.

- The index is negatively correlated with the equal weight index of community needs. Cities with high community needs are more likely to have low real fiscal capacity.

- It is possible to combine a needs index and a fiscal capacity index. The adjusted needs index developed in this chapter produced different rankings from the equal weight index of community needs. But, in general, the change in rankings was not great, probably because of the negative correlation between the two component indices.

Implications for Future Analysis

One objective of this research was to test whether the ACS data would support the same type of analysis that HUD had conducted using long-form data. The answer to this question is “yes.” In the future, HUD can depend on the ACS to monitor conditions in cities and counties. The report successfully uses ACS data to construct useful measures of community needs using factor analysis. Of the 24 needs indicators used in the final factor analysis, 16 used ACS data, one used ACS data combined with long-form data, and four used long-form data. All five indicators that used either long-form data or a combination of ACS and long-form data should be available in the future from the ACS.

The following are some issues and open questions that HUD will have to keep in mind in future work using the ACS.

- The reporting rules used in the ACS are similar to those used for the long form of the decennial census. But, because the ACS sample size is smaller, the rules can result in more frequent suppression of data.

- The Census Bureau has established, as a general policy, releasing for the ACS all tabulations prepared for the 2000 long-form data. However, some special tabulations of long-form data have not yet been released. HUD should probably contact the Census Bureau to make sure that these tabulations are not forgotten.

- The ACS has not released data on persons in group quarters yet. So, there has been no experience with the usefulness of the tabulations or the reliability of the data.

- The Census Bureau will make revisions to the ACS questionnaire, and revisions always create the possibility of discontinuities in the data.

An explicit goal of this project was to develop a single-valued index of community needs. The research achieved this objective, but the outcome was only a qualified success. The report was unable to find any statistical, programmatic, or logical reasons that make a *compelling* case for choosing one index over any of the others. At HUD’s request, the report examined the use of regression analysis to provide definitive guidance in weighting the factors or the needs indicators. However, the prominent role of housing affordability in Factor 2 and in two or three of the needs indicators undermined attempts to apply the regression results directly. The regression approach did provide some insights on deriving weights, but the report could not explore the full implication of these insights.

HUD indicated early on in the project that it was interested in the lessons from this research that could be applied to measuring needs at the tract level. The Administration has proposed creating a special fund within the CDBG program to award communities for making progress in reducing neighborhood distress. Such a proposal would require a community needs measure at the neighborhood level. Since ACS data will be available at the census-tract level beginning in 2010, it was hoped that the experience gained here in constructing a city-level index using ACS data would be useful to HUD in developing a neighborhood-level index.

This research laid the ground work for a measure of progress at the census-tract level in three important ways: the identification of needs indicators, the successful application of factor analysis to the needs indicators, and the development of a methodology for making intertemporal comparisons of needs. Despite these useful insights, HUD will need to do a lot of conceptual and empirical work to develop a technique capable of measuring progress at the local level. The obstacles include:

- Several of the needs indicators used at the city level would not be applicable at the tract level because of the absence of data at the tract level or because the concepts behind the indicators are more applicable at the city level than at the tract level.

- Because of the substantial change in the number and type of indicators, a new factor analysis would have to be performed at the tract level. This factor analysis is likely to identify different dimensions of need than the three identified at the city level in this report.

- The ACS has lower sampling rates than the long-form survey in the decennial censuses. This raises concerns about data suppression at the tract level and about measurement errors.

- On the conceptual side, a clear distinction needs to be made between measuring a change in needs and measuring how local government actions have reduced community needs. Conceptually, one would like to control for outside influences so that cities would not benefit from favorable external conditions or suffer from unfavorable external conditions. In this respect, measuring needs is simpler than measuring progress.

- At the tract level, gentrification can give the appearance of progress in reducing needs, but progress is not really achieved because many people with needs are forced to relocate with their needs still unmet.

Recommendations for Future Work

The most important area for future work is to expand and improve upon the list of needs indicators. This report uses a well-conceived, broad-based, and carefully defined set of needs indicators that provide the basis for a useful factor analysis. However, the greatest payoff for understanding community needs is likely to come from improving these indicators and filling in some missing gaps. Future work should concentrate on getting good measures of education and health needs and, most important, on getting better measures of the impact of long-term economic forces on cities.

1. Introduction

1.1. HUD's Mission and an Index of Community Needs

The U.S. Department of Housing and Urban Development (HUD) funded the research reported in this document for the purpose of developing an index of community needs. Such an index would take data from various sources on different types of community problems and produce an overall assessment of the "neediness" of a community.

Consistent with the "Urban Development" portion of its name, HUD views its mission as including the support of community development. In its latest Strategic Plan, HUD identifies the following five objectives under the goal of strengthening communities:[2]

- Assist disaster recovery in the Gulf Coast region.
- Enhance sustainability of communities by expanding economic opportunities.
- Foster a suitable living environment in communities by improving physical conditions and quality of life.
- End chronic homelessness and move homeless families and individuals to permanent housing.
- Address housing conditions that threaten health.

These objectives, particularly the last four, indicate HUD's concern with a wide variety of problems that confront local governments. An accurate and reliable index of community needs would help HUD carry out its responsibilities in several ways. These include:

- An index would enable HUD to rank communities by the extent of their needs.
- Such a ranking would help HUD develop equitable formulas for distributing funds to communities.
- An index would also enable HUD to track whether a community's needs are improving or getting worse over time.
- Information on the components that enter into the calculation of an index score would help HUD diagnose the type of problems facing communities in general and individual communities.

[2] *HUD Strategic Plan FY 2006 – FY 2011*, U.S. Department of Housing and Urban Development, March 31, 2006.

- Construction of an index would help HUD understand how the various kinds of community problems relate to one another and the extent to which they represent the same or different types of need.

As far back as 1976, HUD devoted its own staff resources to studying community needs and devising ways to synthesize various types of needs into an overall index of needs. HUD's efforts have been sporadic because the primary source of data on community needs has been the decennial censuses, and thus new information on needs has been available only at 10-year intervals. Now the American Community Survey (ACS) will provide every year the information that previously was available only from the decennial censuses.[3] The annual availability of information through the ACS makes a community needs index much more valuable for HUD. For this reason, HUD contracted with Econometrica, Inc. to build upon HUD's previous research to develop a community needs index that could be implemented with ACS and other contemporary data to provide yearly information on community needs.

1.2. Policy Context

In February 2005, HUD issued a report (Richardson 2005) that measured community needs and analyzed how well the current Community Development Block Grant (CDBG) formula distributes funds with respect to community needs. This report also presented alternative formulas that would distribute CDBG funds more equitably with respect to community needs. This was the sixth in a series of reports on the CDBG formula, but it was the first report that HUD prepared without being requested to do so by Congress. The Administration subsequently proposed changes in the CDBG allocation mechanism.

In April 2005, the U.S. Government Accountability Office (GAO) presented to Congress the results of its study of the CDBG formula and testified that the allocation mechanism could be improved. In June 2006, GAO officials testified on the Administration's proposal and explained how GAO planned to respond to a request from Congress to assess the CDBG formula. The GAO created an expert panel using its National Academy of Sciences connection. The panel was asked to examine:

- HUD's construction of a needs index as a criterion for measuring community needs, including HUD's factor analysis and the specific indicators of need included in its index.

[3] The ACS revolutionizes the way the federal government collects demographic data. The ACS collects virtually the same information annually that the long form of the decennial census collected at 10-year intervals, but the ACS has a lower sampling rate than the long form. In 2006, the Census Bureau released data from the 2005 ACS for most places with populations of 65,000 or more and, thereafter, plans to release ACS data every year for those places. Beginning in 2008, it will release 3-year moving average data for all places with populations of 20,000 or more. Thereafter, it plans to release 3-year moving average data every year for these places. Beginning in 2010, it will release 5-year moving average data for all places, including census tracts and block groups, and, thereafter, plans to release 5-year moving average data every year for all places.

- The development of an evaluation criterion for GAO to use that accounts for the potential mismatch between a jurisdiction's community needs and its economic and fiscal capacity to meet that need.

As of the date of this report, GAO has not completed work on its study.

A community needs index based on ACS data would be valuable in assessing proposed changes to the CDBG formula arising from the Administration or GAO.

The Administration's proposal also contained a provision that would create a special fund within the CDBG program to award communities for making progress in reducing neighborhood distress. Such a proposal would require a community-needs measure at the neighborhood level. Since ACS data will be available at the census-tract level beginning in 2010, the experience gained here in constructing a city-level index using ACS data should be useful to HUD in developing a neighborhood-level index.

1.3. History of Research into Community Needs

Between 1976 and 2005, HUD personnel conducted five studies of community needs:

- 1976: *An Evaluation of the Community Development Block Grant Formula,* prepared by Harold L. Bunce.

- 1979: *City Need and Community Development Funding,* prepared by Harold L. Bunce and Robert L. Goldberg.

- 1983: *Effects of the 1980 Census on Community Development Funding,* prepared by Harold L. Bunce, Sue G. Neal, and John L. Gardner.

- 1995: *Effect of the 1990 Census on CDBG Program Funding*, prepared by Kevin Neary and Todd Richardson.

- 2005: *CDBG Formula Targeting to Community Needs*, prepared by Todd Richardson.

These five studies had three common characteristics: First, each study focused on whether the formula used to distribute CDBG funds was doing so effectively and equitably. Second, each study gathered data from a variety of sources on conditions in communities receiving CDBG funding. Variables were selected to measure problems that communities are allowed to use CDBG funds to treat. Third, each study used factor analysis to search out underlying patterns among the need variables and to simplify the data for calculating an index.

1.4. Project Goals

The primary goal of the project is to use 2005 ACS data and other data to create an index of community needs that has the following properties:

- HUD can use the index to evaluate the needs of cities with populations of 65,000 or more as of 2005.
- In 2007 and every year thereafter, when the Census Bureau releases new ACS data, HUD can enter the new data into the index and update its assessment of city needs.
- HUD can rely on the index to track changes in the needs of individual cities over time.
- The index, with minor modifications as may be required, can be used to evaluate the needs of smaller cities and urban counties when more detailed ACS data become available in 2008.

Using an index to compare needs at two different points in time extends previous work with community needs indices and requires a revised methodology. Each new wave of ACS data will provide new information on individual community needs and the opportunity to construct a new community needs index. Since each index creates its own frame of reference, a single frame of reference has to be selected and criteria developed to ensure the validity of the chosen frame.

HUD intended Econometrica, Inc. to build the index using the factor analysis approach employed in HUD's previous work on need indices. However, the project has some secondary research goals, which are to:

- Examine whether previous approaches should be modified to take into account community boundary changes and cost-of-living differences across communities.
- Explore an alternative approach for creating a needs index based on hedonic-like regression models.
- Explore the development of an index of the capacity of communities to deal with problems.

As noted in Section 1.2, the Administration has proposed a special fund within the CDBG program to award communities for making progress in reducing neighborhood distress. HUD hopes to use the lessons from this project to provide insights into developing a means to measure progress at the neighborhood level. In the concluding chapter, the report discusses how the experience from this research at the city level could be applied in creating an index of neighborhood distress at the census tract level.

1.5. Overview of Methodology and Organization of the Report

The process of developing a community needs index involves a number of steps, each of which has its own conceptual issues that must be resolved. The principal steps that an analyst must undertake are:

A. The analyst must establish what concepts should be included in the notion of "community needs." For the purpose of this research, "community" means city or county. The residents of cities and counties experience a wide range of problems. The first step in developing a community needs index is to identify the subset of these problems that cities and counties have the responsibility of alleviating and that are consistent with the "urban development" mission of HUD.

B. The analyst must create valid measures of these concepts. For each concept in Step A, the analyst must find data that adequately represent the problem, that are reliable, and that are available for all the communities being studied. Care must be taken to avoid conceptual errors such as measuring the consequences of not dealing with problems instead of measuring the problems themselves.

C. The ability of a city or county to deal with community needs depends upon the resources available to the city or county, that is, on its fiscal capacity, and on conditions, such as long-run economic decline or racial segregation, that may make problems more difficult to resolve. The analyst must be able to identify complicating conditions, determine how to measure them, and figure out how to relate them to direct measures of needs. In addition, the analyst must determine whether it is feasible to measure a community's capacity to meet its needs and, if so, how to relate capacity to needs.

D. The outcome of Steps A, B, and C should be a set of variables that measures needs and complicating conditions for the universe of communities being studied. Next, the analyst must determine the extent to which these measures can be distilled into a small (more manageable) number of underlying common "themes" or components. The report uses factor analysis to search for common themes and to produce a simpler way to observe how needs vary across communities.

E. Next, the analyst must decide how the various components of need should be weighted in the creation of a summary index of need. One can look to previous research, relevant legislative guidance, "common-sense rules of thumb," or other methods to combine the output from Step D into a single index.

F. Finally, the analyst must figure out how to use the components of need developed in Step D or the single index developed in Step E to measure needs at a different point in time.

This report discusses how each of these steps was accomplished and what was learned in resolving the issues involved in each step. The report provides a list of needs indicators that are generally available for all cities with populations of 65,000 or more and that will be available in the future for smaller cities and for counties. From the needs indicators, a set of three factors that summarizes the types of needs associated with the needs indicators was found, and the report used alternative ways to combine the factors into a single index. The report applies the factors and a single-valued index based on the factors to explore relative need among 370 cities in 2005 and to monitor changes in need from 2000 to 2005.

This report contains the following six chapters:

1. *Introduction.*

2. *Indicators of Community Needs* – Chapter 2 identifies cities as the entities being studied and defines the range of conditions to be considered as "needs" at the city level. It deals with all of the issues involved in Steps A and B and the issues in Step C associated with conditions that make it more difficult for cities to deal with problems. After examining data on various measures of need, we selected 26 needs indicators to be used in the factor analysis.

3. *Factor Analysis, Dimensions of Need, and a Community Needs Index* – Chapter 3 applies factor analysis to the data on needs indicators and identifies three common themes (factors) that encompass the conditions measured by the needs indicators. The chapter combines these three factors into a single index using four alternative sets of weights for the factors and compares the alternatives indices. Finally, the chapter develops the methodology to apply the factor analysis developed using 2005 data to measure city needs in 2000. The chapter deals with the issues involved in Steps D, E, and F. As such, it lays out the methodology used in this study and proposed to be used with future rounds of ACS data.

4. *Community Needs in 2000 and 2005* – Chapter 4 applies the results from Chapter 3 to examine how cities differ in needs in 2005 and how city needs changed from 2000 to 2005.

5. *Measuring Fiscal Capacity* – Chapter 5 develops a methodology for measuring fiscal capacity, implements the methodology for 292 cities in 2005, and explores how one could combine a measure of fiscal capacity with a community needs index to obtain a complete picture of the relative dependence of cities on federal aid. This chapter deals with the issues involved in Step C associated with fiscal capacity.

6. *Implications* – Chapter 6 summarizes the lessons learned in Chapters 2 through 5 and applies them to the three main objectives of this study: developing techniques for measuring community needs that can be used with future rounds of ACS data, developing techniques for tracking changes in needs for individual communities, and exploring ways to measure progress in resolving needs at the neighborhood level.

Chapter 4 contains the most important empirical results—a comparison of needs in 370 cities in 2000 and 2005. Chapter 5 presents the empirical findings related to fiscal capacity and the joint consideration of community needs and fiscal capacity.

This project involved a substantial amount of methodological work, both in conceptualizing and implementing the analysis. Chapter 2 contains the conceptual work related to the selection of needs indicators. Chapter 3 presents the methodology involved in the factor analysis and in applying factor analysis in multiple time periods. Chapter 5 describes the rationale and processes involved in constructing an index of real fiscal capacity and in combining the index of community needs and the index of real fiscal capacity. Appendix B describes the methodology behind the hedonic-type analysis and contains the results of that work.

Appendix A contains supplemental tables. Appendix C compares the 2000 factor analysis performed by Richardson in his 2005 study with a 2000 factor analysis using the needs indicators developed in this study.

This page left blank intentionally.

2. Indicators of Community Needs

HUD designed this study to test the use of ACS data to measure a variety of community needs and track changes in needs over time. This focus shaped the choice of data, time period, and type of communities used in the analysis. The first section of this chapter discusses these choices. The second section describes the range of problems and conditions considered as community needs, proposes a set of needs indicators, and explains why certain variables were not included as needs indicators. The third section examines data on the proposed indicators to test whether they are reliable measures of need prior to the factor analysis in Chapter 3. The fourth section contains our assessment of the accuracy and comprehensiveness of the needs indictors.

2.1. Data Issues in Building an Index of Community Needs

This section discusses the issues involved in gathering data for an index of community needs.

2.1.1. Type and Size of Community

In this report, community will mean a city with a population in 2005 of 65,000 or more. The recent availability of ACS data motivated this research and, as of now, the Census Bureau has released ACS data only for states and for cities and counties with populations of 65,000 or more. Data on places with populations of 20,000 or more will become available in 2008.

Counties are not included in the analysis for two reasons: non-urban counties probably have a different mix of problems, and including them with cities and urban counties could produce misleading results. Second, in the community development area, HUD usually deals with units of governments, which means that it may work with both a county and with cities within that county. This creates data difficulties because, depending upon the issue, HUD may want data at the county level that relate to community needs for both the overall county and individual cities within the county. In awarding CDBG funds to an urban county, HUD considers only the portion of the county outside of cities that receives CDBG funds directly from HUD. Conceptually, it would be possible to construct ACS estimates for these pieces of counties, but the current 65,000-minimum-population rule and confidentiality constraints that limit reporting in individual tables would eliminate numerous urban counties from the analysis. For these reasons, HUD excluded counties from the analysis.

The Census Bureau lists 499 places for which it has released ACS data, including 7 in Puerto Rico. We dropped the seven places in Puerto Rico because of problems with particular variables. For five cities (Indianapolis, Louisville, Nashville, Augusta, and

Athens), the information is reported for "balance" of the jurisdiction. Based on correspondence with the Census Bureau, these data cover the consolidated city and county, but omit incorporated places within the consolidated city/county. It is possible that the city/county government is responsible for community needs in the omitted incorporated areas, but there is nothing in the ACS data to confirm or deny responsibility. These five places are included in the analysis. Twenty-seven of the 499 places are "census designated places" (CDPs). Of these, one (Honolulu) is a CDBG central city, and six are CDBG noncentral city entitlement cities. We kept these seven places.[4]

New Orleans and other Gulf Coast cities present special problems. Two-thirds of the ACS data for these areas were collected prior to Hurricane Katrina and one-third afterwards, although response rates were probably low. If the primary purpose of this study were to rank cities by need, we might have eliminated many of the Gulf Coast cities because their needs today are probably much different from their needs measured by the 2005 data.[5] But, as noted previously, this study concentrates mainly on developing techniques for measuring need. The ACS data provide a reasonable good measure of conditions in these places prior to Katrina and, therefore, we included them as part of the universe of places used to test the techniques.

After these adjustments, the analysis begins with 472 cities; the actual number included in any analysis depends upon how many cities have data for all the measures used in that analysis. Of the 472 cities, 235 are principal cities, and 137 are suburban cities.

2.1.2. Sources of Data Used to Measure City Needs

The types of analyses that are used to construct a community needs index require that the data be defined and collected consistently across cities. This means that we must rely on national databases and ignore valuable local data sources.[6] The databases used are:

- The 2005 American Community Survey.
- The 2000 decennial census.
- The 1997 and 2002 Economic Censuses.
- United States Postal Service (USPS) vacancy data for 2006.
- 2005 Home Mortgage Disclosure Act data.
- FBI Uniform Crime Report data for 2000 and 2004.

[4] Initially we also retained an eighth CDP—Arlington, VA—which is a CDBG urban county. However, Arlington dropped out of the analysis at an early stage because of missing information for some variables.
[5] The Census Bureau published a report using ACS data to compared conditions in Gulf Coast states prior to and after Katrina. The report provides data at the state level, distinguishing between the set of counties designated as disaster areas and the balance of the state. See http://www.census.gov/acs/www/Products/Profiles/gulf_coast/index.htm.
[6] Examples of relevant local records are city records that bear on neighborhood conditions, such as building code violations or abandoned cars, and county records that bear on real estate conditions, such as property transactions, property valuations, housing court, and evictions. Unfortunately, the methods for collecting and storing these sources of information are not standardized.

- Bureau of Labor Statistics Local Area Unemployment Statistics for 2000 and 2005.

Information from other sources—principally, the 2002 Census of Local Governments and the 2001 Residential Finance Survey—was used to adjust data from the ACS and the Economic Censuses to create measures of fiscal capacity.

2.1.3. Time Consistence of Needs Indicators

To encompass as wide a range of city problems as feasible, we combined ACS data with data from other nationally available sources. In almost every instance, we used the version of those data collected in 2005 or as close to 2005 as possible. The most recently released FBI uniform crime data were compiled in 2004. The most recent Economic Census covered calendar year 2002. HUD used USPS data (2006) to construct an estimate of abandoned structures. Because of the extensive work involved in calculating this estimate, HUD used the most recent data (2006) and decided not to construct a separate 2005 estimate for this study.

In some cases, the Census Bureau has not yet produced tables for the ACS that it published for the 2000 decennial census; in other cases, comparable ACS tables are published, but the tables were empty for a number of our 472 cities because of small sample sizes. Tables reporting tenure, age of structure, and poverty status jointly are examples of the first situation, and the table on overcrowded housing is an example of the second situation. In these situations, we used data from the 2000 census. We also used 2000 census data for those indicators of need that require information at the census-tract level.

The ACS will be adding tables in upcoming years, and census-tract data will be available in 2010.

2.2. Selection of Needs Indicators

2.2.1. How the Needs Indicators Were Selected

Econometrica team members met with HUD to discuss the research at an Orientation Meeting on October 12, 2006. One of the issues on the agenda was the range of city problems to be considered in gathering data for the needs index. As noted in Chapter 1, the previous HUD studies had focused on needs that are eligible for assistance under the Community Development Block Grant program. The question posed to HUD was whether to focus strictly on problems that can be treated using CDBG funds or to take a wider perspective on community needs. The goals of the CDBG program are broad, and very few things are excluded de facto as eligible activities. So, using CDBG eligibility as the criterion would not significantly limit the types of needs included in the analysis.

Nevertheless, the participants in the Orientation Meeting agreed that the study should adopt a broad definition of community needs—that is, a definition that included needs beyond those typically eligible for unrestricted funding under the CDBG program. The participants reasoned that HUD's mission extends to most problem areas that affect cities and other communities.

Given this direction, we investigated a wide range of data sources and developed a list of potential variables for discussion at an expert panel meeting on November 21, 2006. The list drew upon the variables used in the previous HUD studies and ideas developed by GAO for its ongoing study.

The participants in the November expert panel meeting stressed certain principles in selecting variables, including:

- Variables should clearly relate to city-level needs.
- Proxies should be avoided in deference to direct measures of need.
- Failure of a city to respond to a problem should not be considered a need.
- Variables should be defined to avoid spurious needs, such as the low income of college students who receive support from their families.

Using these principles, the panel rejected a number of variables on the list and suggested some additions to the list. In some cases, the panel suggested we investigate alternative measures of particular needs and make the final selection after reviewing the data. A revised list of variables was submitted on December 4, 2006, and work was begun on collecting data to implement the variables. Discussion continued via e-mail on how to construct useful measures from the data collected under the Home Mortgage Disclosure Act (HMDA).

2.2.2. Needs Indicators

Table 1 identifies the 27 needs indicators that HUD and Econometrica jointly selected. The list includes variables related to population subgroups with special needs, housing needs, social needs, neighborhood needs, economic needs, conditions that make it more difficult for cities to respond to various needs, and indicators of unfavorable long-run trends. These needs indicators deal with the broad range of problems covered by the five objectives relating to supporting community development in HUD's strategic plan. Table 1 classifies each indicator with respect to the category of problem that it measures. However, many of the indicators relate to more than one type of problem.

Table 1. Needs Indicators for Developing an Index of Community Needs

Variable (Short-name Used in Tables)	Comments	Definition
Populations with Needs: The first eight indicators identify subgroups in the populations that may have specialized needs that require the attention and resources of city governments.		
POOR PERSONS (POORPERS)	Poverty in cities has always been a central concern to HUD. The CDBG program requires that cities use 70 percent of program funds to benefit low and moderate income persons. In line with previous research, we eliminate poor college students on the grounds that most receive support from their parents that is not included in income.	Ratio of persons age 3 and over not enrolled in college who live in households with below poverty incomes to all persons age 3 and over who live in households.
POOR CHILDREN (POORCHILD)	Children living in poor households require different and perhaps more city-supplied services than poor working age adults.	Percent of persons under 18 (children) in the household population living in households with below poverty incomes
POOR ELDERLY (POOROVER74)	The elderly require different services and perhaps more city-supplied services than poor working age adults. We chose "over 74" rather than "over 64" for two reasons: (1) with long life spans, "over 74" seems to be a better identifier of "the elderly" who are likely to have special needs, and (2) it is less correlated with overall poor population (POORPERS) and therefore more likely to identify different types of needs.	Percent of persons over 74 living in households with below poverty incomes
LOW INCOME HOUSEHOLDS (LWINCHHDS)	This variable was added to pick up low-income households whose incomes exceed the poverty level. The CDBG emphasis on low and moderate income persons argues for including more than just the poverty level population.	Percent of persons living in households with incomes greater than the poverty level and less than 50 percent of area median income. Note the decennial census does not contain the table needed to calculate this variable, thus the 2005 ACS data are use for both 2000 and 2005.
SINGLE-PARENT FAMILIES WITH CHILDREN (SGLPRNTFAM)	Single-parent households frequently require city-supplied services and unsupervised children in some of these households may create neighborhood problems. We chose "single-parent" over "female-headed" because the needs associated with these families are not limited to "female-headed" families. Previous studies had used female-headed families.	Percent of families that are single parent-headed with own children under 18.
UNEDUCATED POPULATION (UNEDUCADULTS)	Adults without a high school diploma generally have lower skills than other workers and may require some support and training during periods of unemployment and may not have adequate preparation for post-employment living support.	Percent of household population over 18 without a high school diploma.
UNDEREDUCATED WORKING AGE POPULATION (UNDEREDWORKAGE)	These workers are more vulnerable to being unemployed and have greater difficulty finding new jobs.	Percent of household population over 24 and less than 65 without a college degree.
RECENT IMMIGRANT POPULATION (RCNTIMMIG)	Language problems and cultural differences create adjustment problems for many members of this group.	Percent of household population that is foreign born and entered the United States within the last 15 years.

Table 1. Needs Indicators for Developing an Index of Community Needs (continued)

Variable (Short-name Used in Tables)	Comments	Definition
Housing Needs: The next five indicators identify problems with housing, housing markets, or housing finance that require city attention or resources or reduce the attractiveness of a city.		
LACK OF AFFORDABLE RENTAL HOUSING (LACKAFFDRENTALS)	There is no good measure of affordability problems in rental housing. HUD has successfully used a close variant of this measure to identify cities where housing costs relative to income justify additional assistance under the Low Income Housing Tax Credit.	Ratio of median gross rent (city) to median family income (city).
OVERCROWDED HOUSING (OVERCROWD2000)	A comprehensive study by the British Government has found potential links between overcrowded housing and health and development problems.	Percent of households living in units where the number of person per room is 1.01 or greater. Note this variable is available only for 2000 and the 2000 values are used for both 2000 and 2005.
POOR QUALITY HOUSING (PR70RENTPOV)	Previous studies have used the percent of housing built prior to 1940 as both an indicator of deteriorated housing and older infrastructure. This variable has been criticized for being an inaccurate indicator of either housing or infrastructure deterioration. Richardson (2005) found that the percent of the housing stock that (1) was built prior to 1970, (2) was rental, and (3) was occupied by a household with below poverty income was a better indicator of poor quality housing. We use the Richardson (2005) indicator. We have a separate indicator of infrastructure problems.	Percent of occupied housing units built prior to 1970 and occupied by a poor renter household. Note this variable is available only for 2000 and the 2000 values are used for both 2000 and 2005.
DENIAL RATE FOR MORTGAGE APPLICATIONS (DENIAL)	This variable identifies cities where lenders are restricting credit because of poor appreciation prospects or some combination of inadequate income or credit problems on the part of potential buyers.	Percent of loan applications denied.
POOR HOUSING APPRECIATION IN HIGH POVERTY NEIGHBORHOODS (POORAPPRECHIGH-POVNGHS)	HUD and panel members wanted a variable that could discriminate between poor neighborhoods and poor neighborhoods with poor appreciation potential.	Percent change between 2000 and 2005 in average mortgage amount on loans in high poverty neighborhoods. (As explained in the text, this variable was not calculated.)
Neighborhood Needs: The next three indicators identify the extent to which cities may have seriously troubled neighborhoods.		
HIGH POVERTY NEIGHBORHOODS (PCTPOPHIGH-POVNGHS	Previous research has found that social problems are markedly greater in neighborhoods with a high percentage of poor persons. The research typically uses 40 percent as the crucial percentage.	Percent of city population living in census tracts with poverty rates of 40 percent or higher. Note this variable is available only for 2000 and the 2000 values are used for both 2000 and 2005.
MODERATE POVERTY NEIGHBORHOODS (PCTPOPMOD-POVNGHS)	Since there is a relationship between concentrated poverty and neighborhood problems, we included this variable to identify neighborhoods – other than the highest poverty neighborhoods – where the poverty concentration may be a problem.	Percent of city population living in census tracts with poverty rates greater than or equal to 20 percent but less than 40 percent. Note this variable is available only for 2000 and the 2000 values are used for both 2000 and 2005.

Table 1. Needs Indicators for Developing an Index of Community Needs (continued)

Variable (Short-name Used in Tables)	Comments	Definition
ABANDONMENT (PCTVACMOD-POVCITY)	Abandoned buildings are a blighting influence and could affect community health. HUD has always wanted a reliable measure of abandoned building but data on abandonment are neither universally nor consistently collected at the city level. To solve this problem, HUD analysts have collected data on vacant housing units from the USPS and have counted the number of such structures in moderate to high poverty neighborhood under the presumption that vacant units in such neighborhood have a high probability of being or becoming abandoned.	Ratio of vacant housing units (from 2006 USPS surveys) in tracts with 20 percent or more poor (identified from 2000 census) to total housing units in city (from 2005 ACS). Note only one version of this variable is available and is used for both 2000 and 2005.
City-Wide Social or Economic Problems: The next four indicators identify social or economic problems at the city level.		
PART 1 CRIME (PT1CRIME)	Part 1 crimes include violent crimes and serious nonviolent crimes. Crimes of this nature are a social problem in themselves and have a blighting influence on neighborhoods.	Number of part 1 crimes per 100,000 population. Based on 2004 FBI data on arrests for murder, rape, burglary, motor vehicle theft, arson, and other part 1 crimes - see http://www.fbi.gov/ucr/cius_04/appendices/appendix_02.html for definitions of Part 1 and Part 2 crimes.
PART 2 CRIME (PT2CRIME)	Part 2 crimes include offenses that are less serious but that nevertheless reduce the quality of life of city residents.	Number of part 2 crimes per 100,000 population. Based on 2004 FBI data on arrests for forgery, fraud, simple assault, prostitution, drug offenses, drunkenness, disorderly conduct, and other part 2 crimes - see http://www.fbi.gov/ucr/cius_04/appendices/appendix_02.html for definitions of Part 1 and Part 2 crimes.
POOR SCHOOL AGED POPULATION (SCHPOPPOOR)	This variable was included as a measure of the problems faced by a city in carrying out its responsibility to provide quality education to its youth.	Percent of the school aged population (between 5 and 17) living in households with below poverty income.
UNEMPLOYMENT RATE (UNEMPCEN)	We chose the unemployment rate measured by the ACS and the decennial census over a Bureau of Labor Statistics variable for two reasons: (1) its is calculated from sample data not estimated by a model and (2) its less precise definition of labor force may be successful at capturing disguised unemployment, that is, the unemployment of persons who have left the labor force because of discouragement.	Percent of household population over 16 that is unemployed and looking for work (in labor force). This variable is calculated from the 2000 decennial census or the ACS.
Conditions that Complicate Dealing with Other Problems: The next four variables were added to identify conditions that might make it more difficult for cities to deal with the needs of people, housing, neighborhoods, or general social or economic problems.		
LINGUISTICALLY ISOLATION (LINGISOL)	This variable identifies language difficulties that may complicate a city's efforts to provide services and may generate the need for additional services.	Percent of households in which all adults (high school age and older) have some limitation in communicating in English. (A household is classified as "linguistically isolated" if no household members age 14 years and over spoke only English, and no household members age 14 years and over who spoke a language other than English spoke English "Very well.")

Table 1. Needs Indicators for Developing an Index of Community Needs (continued)

Variable (Short-name Used in Tables)	Comments	Definition
MEASURE OF RACIAL DISSIMILARITY (MINCON)	Cities in highly segregated metropolitan areas may experience additional difficulties in providing ordinary services and will have to deal with segregation and its consequences. The CDBG program has as an objective promoting an increase in the diversity of neighborhoods.	Ratio of minority population rate in city to minority population rate in metropolitan area
INDEX OF ECONOMIC DISSIMILARITY (POVCON)	Cities in areas where the poverty population is concentrated may experience additional difficulties in providing ordinary services and will have to deal with poverty concentration and its consequences. The CDBG program has as an objective reducing the isolation of income groups.	Poverty rate in city divided by poverty rate in metropolitan area
LOCAL FISCAL DISPARITY (MEDINCCBS2CITY)	Disparity in incomes between central cities and suburbs make it difficult for central cities to meet their needs and can create disparity problems that affect the entire local economy.	Median family income of metro area relative to median family income of jurisdiction
Long-run Decline: The final three indicators identify cities that are suffering from long-run decline.		
EXCESS INFRASTRUCTURE (EXCSINFRA)	The panel initially focused on this variable as a good indicator of the extent to which a city may be faced with maintaining more infrastructure than it needs. The indicator also identifies declining cities.	Ratio of maximum population measured in households (without reference to boundary changes) at 1970, 1980, 1990, and 2000 to current population
CHANGE IN EMPLOYMENT BASE (CHNGEMPLOYBASE)	This variable focuses on the recent performance of the city economy. It compares growth in the labor force to growth in actual jobs within the city.	The ratio of two ratios: the first ratio is labor force in 2005 to labor force in 2000 from BLS; the second ratio is jobs in the city from the 2002 economic census to jobs in the city from the 1997 economic census.
CHANGE IN THE CONCENTRATION OF LOW INCOME FAMILIES (CHGLOWINCCON)	This variable measures how well incomes in the city are keeping pace with incomes throughout the country with special attention to a city's relative share of low income families.	Calculate the proportion of families in a city that have incomes in the bottom quintile for all families in the country and then take the ratio of this proportion in 2005 (or 2000) and divides by the proportion in 1970 (based on 1969 income).

We defined each indicator in percentage or per capita terms or as a ratio, so that the value of the indicator would depend only on conditions in a city and not on city size. We also defined each indicator in such a way that an increase in the value of the indicator means that conditions measured by that indicator have worsened. Consistent definition of the indicators will make it easier to interpret the factor analysis in Chapter 3.

The poverty variable (POORPERS) is based on an estimate from the ACS, using a national poverty-level income, of the number of poor persons.[7] It is reasonable to expect that the consequences of poverty are greater in high-cost areas than in low-cost areas. Because the count is based on data available only to the Census Bureau, there is no easy way to adjust these data for cost-of-living differences.

UNEDUCADULTS and UNDEREDWORKAGE were developed based on similar but slightly different concerns, and therefore are defined using different age qualifications. UNEDUCATDULTS refers to all persons over age 18, whereas UNDEREDWORKAGE refers to the 18-65 years-old population. In both cases, lack of education was considered to place persons at greater risk of unemployment, and therefore the focus on working age is appropriate for both variables. In addition, persons without a high school education may not have had the earning capacity during their working years to adequately prepare themselves for retirement. Therefore, UNEDUCADULTS also focuses on persons over age 65. This different focus creates some problems in Appendix B, but the rationale seems reasonable.

The recent immigrant population variable (RCNTIMMIG) counts all persons who were foreign born and immigrated to the United States during the previous 15 years, including both citizens and non-citizens. According to the Census Bureau:[8]

> The American Community Survey questionnaires do not ask about immigration status. The population surveyed includes all people who indicated that the United States was their usual place of residence on the survey date. The foreign-born population includes naturalized U.S. citizens, Lawful Permanent Residents (immigrants), temporary migrants (e.g., foreign students), humanitarian migrants (e.g., refugees), and unauthorized migrants (people illegally present in the United States).

Legal and illegal immigrant households can present similar problems for local governments, most notably, language difficulties in the workplace, language difficulties in schools, and the need for medical services. To the extent that the Census Bureau is successful in including illegal immigrants in the ACS, they should be counted in this indicator.

HMDA data were used to construct the DENIAL RATE FOR MORTGAGE APPLICATIONS indicator.

[7] There are separate poverty levels for Alaska and Hawaii.

[8] *American Community Survey, Puerto Rico Community Survey, 2005 Subject Definitions,* page 31, http://www.census.gov/acs/www/UseData/Def.htm.

We also planned to use HMDA data to identify low-income neighborhoods with stagnant or declining housing markets. This is the POOR HOUSING APPRECIATION IN HIGH POVERTY NEIGHBORHOODS indicator listed in Table 1. The construction of this indicator proved to be too complicated for the limited scope of this project, and therefore this indicator is not used in the subsequent analysis.[9]

2.2.3. Other Indicators Considered But Not Used

We considered a large number of potential indicators and excluded many for various reasons. The following two exclusions deserve additional discussion:

- *Persons with a Disability Limiting Employment*: We had originally planned to use this variable. We dropped it because changes in the skip pattern used to ask this question appear to have produced a substantial downward shift in the percentage between 2000 and 2005.

- *Decline of the Middle Class*: We constructed an indicator that focused on the proportion of families in a city that are middle-income families. We defined middle income as having an income higher than the incomes of the poorest 20 percent of American families but lower than the richest 20 percent of American families. We took the ratio of this proportion in 2005 (or 2000) to the ratio in 1970 to determine whether the city was gaining or losing middle-class families. We decided not to use this variable because a city can have a lower proportion of middle-class families as a result of growing poorer or growing richer. Among the 100 cities that had the largest decline in middle-income families between 1970 and 2005, 34 also had a decline in the proportion of poor families. In these 34 cities, only the proportion of rich families was growing. We used CHANGE IN THE CONCENTRATION OF LOW-INCOME FAMILIES as an indicator of long-term trends instead of the decline in the middle-class indicator.

2.3. Review of Indicators Prior to Index Building

2.3.1. Correlations Among the Needs Indicators

After gathering data on the needs indicators for both 2000 and 2005, we examined the distribution of each variable and its correlation with the other variables to determine

[9] Construction of the variable would require HMDA data from two different years. The main problem is that the 2000 HMDA data do not contain a variable to identify mobile homes. In constructing the DENIAL variable, we eliminated investor loans and mobile-home loans because of concern that their inclusion would affect the results. We had the same concern about the PRICE APPRECIATION indicator. To eliminate mobile homes would require matching the HMDA data to a list prepared by HUD analysts of lenders who specialize in mobile-home lending.

whether the indicator is performing as anticipated and to uncover any problems with the indicator. It was this analysis that led to the elimination of the employment disability and decline of the middle-class indicators discussed above.

The first test in the correlation analysis was to determine if any of the needs indicators is highly correlated with population. As noted, we defined the indicators so that their values should be independent of city size and, therefore, we expected to find low correlations between population and the various needs indicators. None of the 26 variables had a correlation with population greater in absolute value than 0.20.

Next, we examined the correlations among the needs indicators. This analysis provides some prior indication of how the factor analysis will sort the indicators and can identify problem with the indicators as implemented. Table A.1 in Appendix A reports these correlations. The most interesting findings from the correlation analysis were:

- POORPERS has correlations of 0.60 or higher with 15 other indicators. These include all but two of the variables that use income or poverty in their definitions, but also include SGLPRNTFAM, DENIAL, UNEMPCEN, MINCON, UNEDUCADULTS, and EMPLOYDISB.

- UNEMPCEN seems to correlate with the same variables with which POORPERS correlates, but at lower rates.

- OVERCROWD_2000, the crime variables, and RCNTIMMIG have low correlations with POORPERS.

- RCNTIMMIG has correlations of 0.60 or higher only with LINGISOL and OVERCROWD_2000.

- POOROVER74 is weakly related to all the other variables.

- The crime indicators (PT1CRIME and PT2CRIME) correlate most highly with each other, but the correlation is only 0.53. These crime indicators correlate weakly with all the other variables.

The low correlation of the crime variables with each other is puzzling and, as we shall see in Chapter 3, these variables do not perform well in the factor analysis. We discuss these indicators more in Section 2.3.3.

MEDINCCBS2CITY, POVCON, and MINCON are indicators that measure conditions recognized in previous studies as either problems in themselves or as factors that complicate the solution of other problems. While the concepts behind POVCON and MINCON are not new, the definitions of these indicators are new. Richardson (2005) used a dissimilarity index to measure the extent of racial segregation. We considered using dissimilarity indices to measure both racial and income segregation, but were persuaded in the November 21 meeting that the definitions in Table 1 were simpler to implement and provided much the same information. The correlation analysis reveals no problems with these variables as defined.

- MEDINCCBS2CITY correlates highly with the other variables we used to characterize city/suburb differences: POVCON (0.86) and MINCON (0.73). It also correlates highly with the poverty variables.

Six of the needs indicators in Table 1 were defined for the first time in this study; these are: LACKAFFDRENTALS, DENIAL, PCTVACMODPOVCITY, EXCSINFRA, CHNGEMPLOYBASE, and CHGLOWINCCON.

- LACKAFFDRENTALS correlates most highly with UNEDUCADULTS (0.66), a somewhat surprising result. It has only modest to low correlations with the other housing variables: OVERCROWD_2000 (0.58), PR70RENTPOV (0.49), DENIAL (0.28), and PCTVACMODPOVTOCITY (0.15). LACKAFFDRENTALS appears to pick up different types of housing problems than the other housing indicators.

- DENIAL correlates most highly with PCTVACMODPOVTOCITY (0.76) and has correlations above 0.60 with some of the indicators of population groups with special needs and with UNEMPCEN, MINCON, and MEDINCCBS2CITY.

- PCTVACMODPOVTOCITY correlates most highly with DENIAL (0.76) and has correlations of greater that 0.60 with seven other indicators, including poor persons, poor children, poor school-aged children, excess infrastructure, poor quality rental housing, and minority concentration.

- EXCSINFRA correlates most highly with PCTVACMODPOVTOCITY (0.64) and has correlations over 0.50 only with DENIAL and PR70RENTPOV. DENIAL appears to be picking up some "older city" problems.

- CHNGEMPLOYBASE does not correlate highly with any of the other variables; its highest correlations are with the education variables, UNDEREDWORKAGE (0.18) and UNEDUCADULTS (0.13). The correlation results for CHNGEMPLOYBASE are not disturbing. It is intended to identify a type of need different from that of the other indicators and some association with education limitations should be expected.

- CHGLOWINCCON has modest correlations with three variables and low correlations with the remaining variables; its highest correlations are with MEDINCCBS2CITY (0.47), DENIAL (0.44), and LWINCHHDS (0.42).

2.3.2. Analysis of Means

After the correlation analysis, we compared the means of the indicators in 2000 and 2005 for two reasons: to identify data errors and to obtain a sense of how conditions changed between 2000 and 2005. Table 2 reports these comparisons.

Table 2. Comparison of Means for the Needs Indicators

Variable	2005 Mean	2000 Mean	Absolute Difference	Percent Difference
POORPERS	0.140	0.125	0.0148	11.8%
POORCHILD	0.207	0.181	0.0265	14.7%
POOROVER74	0.109	0.108	0.0002	0.2%
SGLPRNTFAM	0.181	0.160	0.0201	12.5%
UNEDUCADULTS	0.169	0.204	-0.0350	-17.2%
UNDEREDWORKAGE	0.691	0.715	-0.0239	-3.3%
RCNTIMMIG	0.099	0.091	0.0081	8.9%
LACKAFFDRENTALS	0.180	0.159	0.0208	13.1%
SCHPOPPOOR	0.198	0.175	0.0233	13.3%
UNEMPCEN	0.076	0.066	0.0096	14.5%
LINGISOL	0.071	0.060	0.0109	18.0%
MINCON	1.281	1.255	0.0267	2.1%
POVCON	1.196	1.139	0.0573	5.0%
MEDINCCBS2CITY	1.125	1.081	0.0436	4.0%
EXCSINFRA	1.025	1.015	0.0105	1.0%
CHGLOWINCCON	1.245	1.310	0.0650	5.2%
PT1CRIME	957.036	1004.970	-47.9337	-4.8%
PT2CRIME	4133.420	4311.420	-178.0000	-4.1%
LWINCHHDS	0.299	0.299	Same data	Same data
OVERCROWD_2000	0.083	0.083	Same data	Same data
PR70RENTPOV	0.052	0.052	Same data	Same data
PCTVACMODPOVCITY	0.010	0.010	Same data	Same data
DENIAL	0.220	0.220	Same data	Same data
PCTPOPHIGHPOVNGHS	0.026	0.026	Same data	Same data
PCTPOPMODPOVNGHS	0.175	0.175	Same data	Same data
CHNGEMPLBASE	0.836	0.836	Same data	Same data

For the last eight indicators in Table 2, we were unable to calculate values for both 2000 and 2005, and therefore used the same values of these variables for each city in both years. We had data only for 2000 for OVERCROWD_2000, PR70RENTPOV, PCTPOPHIGHPOVNGHS, and PCTPOPMODPOVNGHS. We had data only for 2005 for LWINCHHDS, PCTVACMODPOVCITY, DENIAL, and CHNGEMPLBASE. Therefore, Table 2 does not calculate the absolute or percent differences for the means of these eight indicators.

Only two of the changes in means are surprising. The 17-percent decline in uneducated adults seems remarkably large for social statistics that frequently change at glacial rates. However, the national data show a 25-percent decline in this ratio. The Census Bureau report comparing the 2000 decennial census with the ACS-type C2SS collected in 2000 reveals no substantial differences between the two surveys on educational attainment. The ACS Subject Definition document mentions changes in the questions prior to 1999, but no changes that would have affected the 2000 comparisons. The 18-percent increase in linguistic isolation also seems large. The base is small, and the national change was a 16-percent increase.

Except for the crime and education indicators, all the needs indicators have higher mean values in 2005. This suggests that conditions in cities, on average, worsened over the period from 2000 to 2005.

2.3.3. Analysis of the Crime Variables

The results involving the crime variables were puzzling. The 2004 versions of PT1CRIME and PT2CRIME had only a 0.53 correlation with each other and had low correlations with all the other variables. Both indicators had low loading on all the factors and, as noted in Chapter 3, the test of sampling adequacy indicated that PT1CRIME was not a good candidate for factor analysis. All the previous studies used some indicator of crimes, and our panel of experts concurred in the inclusion of the two crime measures among the needs indicators. So, at HUD's request, we investigated why the crime indicators did not perform better.

First, we examined the correlations between our crime variables in 2000 and 2004. It turns out that PT1CRIME as measured in 2000 had a correlation of only 0.20 with PT1CRIME measured in 2004, and PT2CRIME as measured in 2000 had a correlation of only 0.27 with PT2CRIME measured in 2004. These low correlations heighten our concern about the crime data.

The FBI distinguishes between Part 1 crimes and Part 2 crimes in its Uniform Crime Report data. In the Part 1 crime data, the FBI reports separately on: criminal homicide, forcible rape, robbery, aggravated assault, burglary, larceny-theft, motor vehicle theft, and arson. Normally, the FBI data on Part 1 crimes include both known offenses and those cleared by arrests, but the data we received contained only arrest records. In retrospect, we are not sure why the Department of Justice gave us only arrest data for Part 1 crimes. The Uniform Crime Report data on Part 2 crimes are based solely on arrest data; perhaps the DOJ data staff provided the Part 1 and Part 2 data on a matching basis—that is, using information from arrests only.

From the FBI Web site, we downloaded data on Part 1 crimes for 2005; these data include both arrests and known occurrences.[10] The correlation between these data, which the FBI Web site label "violent crime," and our PTICRIME variable (based on 2004 data) was 0.20. It appears that either there are substantial differences between the arrest data

[10]http://www.fbi.gov/ucr/05cius/data/table_08.html.

and the combination of arrests and known offenses, or there are problems with our arrest data. (We checked the programs used to read the data carefully.)

The correlations between VIOLCRIME and the other needs indicators are also reported in Table A.1 in Appendix A. VIOLCRIME has correlations between 0.5 and 0.6 with DENIAL, PCTVACMODPOVCITY, POORCHILD, POORPERS, SCHPOPPOOR, and SGLPRNTFAM; all the other correlations are less than 0.5. While VIOLENT crime has stronger associations with other needs indicators than PT1CRIME, its correlations with the other indicators are modest to low.

2.4. Assessment of Needs Indicators

Table 1 includes eight indicators that are designed to identify population groups that may have needs for city services beyond those of the typical citizen. The variables measure separately the poor and low-income persons, poor children, the elderly poor, single-parent households, persons with limited education, and immigrants. The ACS provides detailed information on important subgroups, and it should be possible to implement all eight indicators in future years for cities of all sizes and counties, including HUD-defined urban counties.

Table 1 lists five indicators of problems with housing, but we were only able to implement four of the indicators. Of these four, two used 2000 census data. ACS data were used only for LACKAFFDRENTALS. In the future, however, HUD should be able to use ACS data to estimate the overcrowded housing variable and the poor quality rental housing variable as well as this variable for cities of all sizes and for counties. Also in the future, HUD will be able to estimate the DENIAL indicator using HMDA data and perhaps will be able to use these data to create a useful indicator that identifies high-poverty neighborhoods with poor appreciation of owner-occupied housing. At this time, the housing indicators are limited in scope, but some of these limitations appear to be temporary.

Table 1 contains three indicators of the extent of neighborhood problems. All three variables are based on tract-level data from the 2000 decennial census. But beginning in 2010, HUD should be able to employ ACS tract-level data in these indicators. The primary indicator is proportion of the population living in high-poverty tracts, defined as tracts with a poverty rate of 40 percent or more. The urban literature has highlighted these neighborhoods as having problems related to the concentration of poverty. The abandonment variable was developed by HUD in an attempt to identify problems associated with abandoned buildings. The distribution and correlation analyses suggest that the abandoned building indicator is working reasonably well.

Table 1 contains only four indicators of city-wide social or economic problems. As noted above and discussed further in Chapter 3, the crime variables seem to be surprisingly unrelated to other indicators of need. We were unable to find any city-level data on health needs, and we were able to find only one measure to associate with problems in education. For our education indicator, we chose percentage of the school-age population that is poor, because it appears to represent the problem facing a city in providing quality education. There were three reasons for the lack of more measures related to education: inconsistent definition of measures across schools and school districts, difficulty converting the education data provided by the federal government for schools and school districts into city-level measures, and concern that some of the measures represented failures on the part of cities to meet their education responsibilities rather than difficulties of the education challenges presented to cities. With respect to the third reason, test scores are an example of a measure that could indicate either poor performance or difficult-to-educate populations.

Table 1 contains measures of four conditions—LINGISOL, MEDINCCBS2CITY, POVCON, and MINCON—that we believe complicate the ability of cities to deal with their problems. All four indicators can be easily calculated using ACS data and should be available in the future for all cities and for all counties.

Table 1 contains three indicators of unfavorable long-run trends that affect cities. EXCSINFRA both measures a condition that is a problem in its own right—having to maintain more infrastructure per household than the typical city—and identifies cities in long-run decline—that is, cities that are losing households. CHGLOWINCCON identifies cities that are losing their middle- and upper-income households. Both indicators represent important dimensions of long-run change at the city level. A third dimension is economic vitality. The indicator chosen to represent this dimension is limited in three ways: the indicator changes only every 5 years; its calculation requires the integration of data from two different sources; and the confidentiality rules applied to the Economic Census data introduce noise into the calculation.

At this stage, we believe that we have very good indicators of the needs associated with certain demographic groups, fairly good indicators of housing problems, good indicators of neighborhood-level problems, only marginally adequate measures of city-wide social and economic problems, good measures of complicating conditions, and adequate measures of two out of three of the key long-term trends. As more ACS data become available, the problems with the housing indicators should be eliminated, and all of the indicators should be available for all cities, for counties, and for HUD-defined urban counties.

Future work to improve indicators of community needs should focus on:

- Getting good measures of education and health needs.
- Testing other formulations of the national crime data to find a more robust crime indicator.
- Getting a better measure of the impact of long-term economic forces on cities.

3. Factor Analysis, Dimensions of Need, and a Community Needs Index

In developing an index of community needs, analysts face two problems. These can be succinctly, and fairly accurately, described as “too much data” and “not enough data.”[11]

The ACS and other national data sets provide a wealth of information on persons and housing, the local economy, and some social problems such as crime. Using these sources, we constructed 26 indicators of need. We could have included many more, such as per capita income, persons with disabilities, and retail and wholesale jobs.[12] The previous chapter described how we worked with HUD and other experts to narrow down the list of potential indicators. Now having selected indicators, we need to figure out how to make sense of so much information. How does a one-percentage-point higher unemployment rate compare in neediness to a three-percentage-point higher poverty rate or 15 more serious crimes per 100,000 population? Does the overcrowded housing indicator simply indicate low income or high housing prices and therefore duplicate the poverty or lack of affordable housing indicators, or does it represent a different type of problem? Questions like these need to be answered in order to create a mathematical formula that translates the needs indicators into a single number.

On the other hand, despite all the data available from the Census Bureau and other sources, our information on community needs is incomplete. While we have multiple indicators of needs related to specific demographic groups and to housing, we have limited information in other areas. As Section 2.4 points out, we have only one indicator of education problems and no indicators of health problems. We also have only one indicator of long-term economic trends, and it has limitations. The available economic data are limited by the timeliness of the every 5-year economic census and, even more so, by the confidentiality requirements that result in suppressed data for many useful variables—for example, the total number of jobs in a city. It would be comforting to know that the some of other 24 indictors were providing reasonable proxies for the type of problems measured by our lone education and economic indicators.

Previous research has turned to factor analysis to solve the problems discussed in the two preceding paragraphs—that is, to aggregate multiple measures into simpler indicators of need and to identify distinct dimensions of need that hopefully span the full range of problems that affect cities. This chapter carries out factor analysis using the indicators

[11] The advent of the ACS eliminated a third problem that seriously limited previous efforts to measure community needs: the absence of timely data.

[12] We did not use per capita income because we consider it a measure of capacity, and this analysis considers need and capacity separately. We did not use persons with disabilities because the consensus at the November 21 meeting was that employment disabilities, and not disabilities in general, is the more relevant needs indicator. As mentioned in Chapter 2, the persons with employment disabilities indicator was dropped because of suspected data problems. We did not use retail and wholesale jobs because that data series provides an incomplete picture of economic activity, and the data needed to properly balance the picture do not exist.

developed in Chapter 2; it explains factor analysis and explains how we use the results of factor analysis to create a single-valued community needs index and to track conditions in cities over time. Chapter 4 uses the results of our factor analysis to compare the needs of different cities and to see how the needs of individual cities changed from 2000 to 2005.

The discussion in this chapter is organized as follows:

- Section 3.1 provides a simple explanation of factor analysis.

- Section 3.2 uses factor analysis to reduce the needs indicators developed in Chapter 2 to three independent dimensions of need—based, for the most part, on 2005 data. The long discussion in Section 3.2 is divided into six subsections:

    - Section 3.2.1 lists the expectations we carried into the factor analysis; these expectations guided the choices we made during factor analysis.

    - Section 3.2.2 reports the results using all 26 needs indicators. The footnotes in this Section give technical details on how we did the factor analysis.

    - Section 3.2.3 discusses tests that we ran to determine whether the factor analysis would support the uses to which we plan to put it.

    - Section 3.2.4 considers the possibility of dropping some needs indicators to increase the number of cities for which we can report results.

    - Section 3.2.5 carries out a second factor analysis using fewer needs indicators. The factors developed in this section are used in Section 3.4 to construct a single-valued community needs index and in Chapter 4 to compare conditions in different cities in 2000 and 2005. Table 3 presents the factor loading for these factors.

    - Section 3.2.6 explains how we calculated factor scores for each city.

- Section 3.3 explains the problems involved in using factor analysis to compare needs across time and describe the methodology we used to make comparisons between needs in 2000 and 2005.

- Section 3.4 explains the problems involved in combining the separate dimensions of need that are the product of factor analysis into a single-valued index of community needs. We consider six alternative ways to combine the dimensions and compare results from the alternative indices.

- Section 3.5 provides a brief summary of the chapter.

3.1. A Brief Introduction to Factor Analysis

Factor analysis is a statistical technique that examines multifaceted data to find simpler, underlying patterns. Researchers apply factor analysis to data sets that have three characteristics: (1) there are a sizable number of units being observed (472 cities in our case); (2) there are a variety of pieces of information (variables) on each unit (26 needs indicators in our case); and (3) there are reasons to believe that there are certain natural groupings among the variables that reflect common contributory sources.[13] The third characteristic is the defining characteristic of factor analysis. The first two characteristics provide the data structure needed for the analysis, while the third characteristic motivates the analysis. The goal of factor analysis is to uncover patterns in the data that can be characterized in a useful fashion.

Factor analysis achieves "data reduction"—that is, it replaces a large number of variables with a smaller number that approximates the range of joint variation found in the data set with the larger number of variables. There are other statistical techniques that result in data reduction, most notably, principal components analysis. We could have applied principal components analysis to our database of 26 indicators for 472 cities. The results would have looked similar to those from factor analysis. The output from both factor analysis and principal components analysis would be three or four new variables that represent the range of variation found in the data set with 26 indicators. But the techniques used to obtain the smaller set of variables are different; the statistical properties of the new variables are different; and the interpretation of the new variables is different.[14] The fundamental difference between the two techniques is the difference in interpretation. Factor analysis posits the existence of unobservable "causes" that produce the correlations among the original variables; principal components analysis does not look for underlying causes. Because of this different orientation, the two techniques use different statistical algorithms. The principal components algorithm attempts to explain as much of the variance in the original data as possible, while the factor analysis algorithm attempts to explain the correlation among the variables in the original data.

The output of factor analysis is in the format of the table that follows this paragraph. The factor loadings are numbers between 1 and -1 that relate each unobserved factor to the observed variables. For reading the rows, the larger the factor loading, the more important a factor is in determining the value of that variable. For reading the columns, the larger the factor loading, the stronger the association is between that factor and those variables. Understanding what variables are associated with a factor helps the analyst

---

[13] In factor analysis, the assumption is that every variable V_i is a result of factors that act on two or more of the variables and other unique circumstances that act on that variable only. Statistically, this assumption translates into the following equation: $V_i = \Sigma\alpha_j F_j + U_i$, where U_i are influences unique to that variable and F_j are the common factors. Factor analysis assumes that there are common underlying forces that are providing joint causation, but it cannot prove their existence or identify what they are.

[14] See Jae-On Kim and Charles W. Mueller, *FACTOR ANALYSIS Statistical Methods and Practical Issue*, Series: Quantitative Applications in the Social Sciences, Number 14, Sage Publications, 1978, pp. 14-23, for a discussion of the similarities and differences between factor analysis and principal components analysis.

understand the nature of the unobserved factor. In the work described in this chapter, we will pay particular attention to the factor loadings.

	Factor 1	Factor 2	Factor 3	Factor 4
Variable 1	Factor loading	Factor loading	Factor loading	Factor loading
Variable 2	Factor loading	Factor loading	Factor loading	Factor loading
Variable 3	Factor loading	Factor loading	Factor loading	Factor loading
Variable 4	Factor loading	Factor loading	Factor loading	Factor loading
Variable 5	Factor loading	Factor loading	Factor loading	Factor loading
Variable 6	Factor loading	Factor loading	Factor loading	Factor loading
Variable 7	Factor loading	Factor loading	Factor loading	Factor loading
Variable 8	Factor loading	Factor loading	Factor loading	Factor loading

Unlike most statistical techniques, factor analysis does not produce definitive results in the following three senses:

- The mathematical formulas involved in factor analysis will always produce a table like the one above, whether or not there are unobserved causes at work in determining the value of the variables. Although there is a test to determine whether data are suitable for factor analysis, there is no test to prove the existence of a factor.

- The mathematic formulas involved in factor analysis will identify many possible "factors" that may or may not be real. Although there are techniques for deciding on how many of the possible factors to use, the choice always involves some judgment.

- The factor loadings are not unique. After determining how many factors to select, one can apply certain statistical techniques and produce different tables of the type above from the same data. Each of the tables identifies the same number of factors, and those factors explain the same amount of variation in the data. The tables differ in factor loading, and therefore offer different perspectives on the possible underlying factors. Choosing which of the possible tables to use also requires some judgment.

Using factor analysis, we will find three factors that appear to underlie the 26 needs indicators. We interpret these factors as measuring more fundamental "dimensions of need" than the 26 individual needs indicators—that is, we view the "factors" or "dimensions" as logical aggregations of needs that have similar origins or that occur together. Using the needs indicators, factor analysis provides a technique to generate a "score" for each city on each factor. We will build a needs index around these three factor scores. This last step also requires judgment since nothing in the factor analysis process tells us how much importance to give to each factor.

3.2. Application of Factor Analysis to Needs Indicators

3.2.1 Anticipated Results from Factor Analysis

The need to exercise judgment at various stages in performing factor analysis makes it essential to have a clear sense before beginning the analysis of what to expect to find in the way of factors. For this reason, HUD and Econometrica team members discussed their expectations regarding the factors that would be revealed. Based on previous experiences with factor analysis and an understanding of the forces affecting cities, HUD and Econometrica anticipated finding up to four factors and expected those factors to be related to poverty, immigration, economic decline, and city/suburb disparities.

Every previous study that has used factor analysis to identify dimensions of community needs has found a "poverty" factor, and "poverty" has always been the first factor—that is, the factor that accounts for most of the variation among the chosen needs indicators. One reason for the primacy of the poverty factor is that the national data sources, particularly the decennial census (and now the ACS), contain an abundance of data that relate to various forms or manifestations of poverty. Among our 26 needs indicators, we have an indicator of overall poverty, poor elderly persons, poor children, and poor school-age children. Our measures also include single-parent families—a group that generally has lower income—and households with incomes higher than the poverty level but lower than 50 percent of metropolitan-area median income. In addition, we measure the percent of the population living in neighborhoods with poverty levels of 40 percent or more, and the percent living in neighborhoods with poverty levels between 20 and 40 percent. In choosing these needs indicators, we were careful to avoid needless duplication. For example, we measured poverty among the elderly, poverty among children, and poverty among school-age children in addition to overall poverty, because we thought each of these groups required somewhat different responses from local government. Also, previous research has found that social problems are greater where poverty is concentrated, particularly in neighborhoods where the poverty rate is 40 percent or more. We did not include female-headed households along with single-parent households.

Immigration, economic decline, and city/suburb disparities can be thought of as conditions that generate problems. "Poverty" can be thought of both as a condition that generates problems and as a problem in itself that results from other underlying causes. Poverty could result from a variety of causes: lack of human capital (that is, poor education); market imperfections, such as discrimination or a spatial mismatch between jobs and housing; or general economic decline. In evaluating the findings from factor analysis, we will look at "poverty" in both ways.

3.2.2. Initial Results from Factor Analysis

Using 2005 data on the 26 needs indicators for the 472 cities, we performed a standard factor analysis using the factor analysis feature of the statistical program known as SAS™. We were not able to calculate values for all 26 needs indicators for every city. Missing crime data was the primary reason for dropping cities. In other cases, the missing data resulted from suppression of data by the Census Bureau—either to protect the confidentiality of respondents or because the sample sizes were too small to justify reporting the results. Because of missing data, only 292 cities were used in the initial factor analysis.

The procedures in SAS™ first examine the data to determine whether there are sufficient relationships among the indicators to justify factor analysis. The 2005 data seem to be well-suited to factor analysis. The SAS™-provided measure of sampling adequacy was strong for all the variables except CHNGEMPLBASE and PT1CRIME. [15] Only the PT1CRIME measure was considered unacceptable and then only marginally so; the implication is that PT1CRIME is not determined by any of the factors that appear to be related to the other indicators. The overall measure of sample adequacy was considered strong.

Any factor analysis program, such as SAS™, reports factors in the order in which they help explain the variation in the data.[16] In deciding how many of the reported factors to use, we considered two rules. The first rule selects factors until the group selected account for all of the variation. This approach led to the selection of seven factors. Examination of the factor loading indicated that after the first three or four factors, the remaining factors had no useful interpretation. Therefore, we used a second rule that indicated that only three factors should be considered.[17] The three factors selected appeared to be readily interpretable. The first factor appeared to be associated with poverty, central city/suburb disparities, and long-run decline; the second factor appeared to be associated with immigration and housing affordability; and the third factor appeared to be associated with more immediate limited economic prospects. The factor loading for these factors is reported in Table A.2 in Appendix A.[18]

Next, we used a feature available in all factor analysis programs and "rotated" the factors. Rotation is a process that finds alternative factor loadings that are equivalent to the initial

[15] This is known as the Kaiser test. The Kaiser measure was strong (0.78 or better) for all the variables except CHNGEMPLBASE (0.60) and PT1CRIME (0.49). The overall Kaiser measure was 0.91, which is considered strong.

[16] We used the "principal factor" approach to extract factors.

[17] The second rule is known as the Eigenvalue rule. An Eigenvalue is computed for each factor, and only factors with an Eigenvalue greater than one are chosen. In simplest terms, an Eigenvalue greater than 1 means that a factor explains more than the average amount of variation explained by all the factors.

[18] These initial loadings are called the "unrotated" loadings because the next step in the factor analysis process is to "rotate" the factors to produce alternative loadings that may be more easily interpreted.

loading but may be more easily interpreted.[19] We chose to obtain "orthogonal" factors, that is, factors that are uncorrelated with each other.[20] Having factors that are statistically uncorrelated with each other is useful in developing an index, because it enables us to consider the components of the index as independent contributors to overall need.[21] Table A.3 in Appendix A reports the factor loading for these orthogonal factors.

Despite the small differences between the rotated and unrotated factors, the rotated factors provide a somewhat clearer interpretation, such as:

- Factor 1 could be interpreted as a "poverty" factor, but it can also be interpreted as a "city/suburb disparities combined with long-term decline" factor.

- Factor 2 is a combined "immigration and housing affordability" factor.

- Factor 3 is a "weak economy" factor because of the importance of the two education indicators, viewed in a human capital context, and the change in employment base indicator.

Statistically, there is no reason to favor rotated factors over unrotated factors or the interpretation attributed to one set of factors over another. Both sets of factors explain the same amount of variation in the data; both satisfy the test for sample adequacy and the same criterion for selecting factors. Fortunately, the interpretations of the unrotated and rotated factors are sufficiently close that use of the rotated factors raises no concerns.

3.2.3. Testing the Robustness of the Factor Analysis

Before proceeding further with the analysis, we carried out three important tests. First, we repeated the factor analysis using 2000 data. A prime objective of the research, as specified by HUD, is to develop an index that can be used to track conditions in cities over time. To do this, we need to be confident that the factors that appear to explain the 2005 data are also capable of explaining the 2000 data. To test this, we compared the factor loadings from factor analysis on the 2000 data with the factor loading from factor analysis on 2005 data. Table A.4 in Appendix A reports the results of this analysis.[22]

[19] The factor loading are equivalent in the sense that they explain the same amount of variation in the data and represent the same hypothetical factors. The mathematical techniques used in factor analysis involve the solution to a matrix algebra problem that has no unique solution; the unrotated and rotated factor loading are alternative solutions.

[20] We employed the Varimax rotation, which maximizes the variance of the squared factor loading for each factor.

[21] While the orthogonal factors are derived in such a way that the unobserved factors are uncorrelated, the factor scores will not be uncorrelated.

[22] Because of missing information or other difficulties, some of the needs indicators have the same values in the 2000 data as in the 2005 data. These are: CHNGEMPLBASE, DENIAL, OVERCROWD, LWINCHHDS, PCTPOPHIGHPOVNGHS, PCTPOPMODPOVNGHS, PCTVACMODPOVCITY, and PR70RENTPOV.

The factor patterns in Table A.4 are close, but not identical, to those in Tables A.2 and A.3. In 2000 data, PR1CRIME (arrests related to more serious crimes) loads most heavily on Factor 1, and UNEDUCADULTS (adults without a high school diploma) loads most heavily on rotated Factor 2 instead of Factor 3. When we look at the entire pattern of factor loadings, only the PT1CRIME loadings are noticeably different. In our opinion, the patterns of factor loadings are close enough to justify applying the 2005 factor scoring coefficients to 2000 data. Section 3.3 explains how one should perform a similar test if, for example, one were to use the 2005 factor analysis to compare conditions in 2005 and 2010.

The second test examined whether the same factors explain conditions in large cities and small cities. Splitting the sample of cities roughly in half, we ran the factor analysis separately for cities with 200,000 or more residents and cities with less than 200,000 residents. Table A.5 in Appendix A reports the results for the rotated factors.

The main difference between factor analysis applied to large and small cities is that the rule used to select factors for the large cities calls for using four factors. The new fourth factor is most strongly associated with declining household population as measured by EXCSINFRA, but EXCSINFRA still loads strongly on Factor 1. There are three other noteworthy changes from the analysis involving all cities, including:

- The change in employment base indicator (CHNGEMPLBASE) is more strongly associated with Factor 2 for large cities than Factor 3.

- The lack of affordable rental indicator (LACKAFFDRENTALS) is more strongly associated with Factor 1 than Factor 2 for the large cities.

- The uneducated adults indicator (UNEDUCADULTS) is more strongly associated with Factor 2 than Factor 3 for large cities.

Despite these differences, we believe that it is appropriate to apply factor analysis to the combined database that includes both large and small cities. The fourth factor adds little to the analysis and the other differences are minor.[23] Therefore, with only minor reservations, we proceed with the factor analysis.

As noted in Section 2.3.3, we have some concerns about the quality of the crime data. For this reason, we replaced PT1CRIME with VIOLCRIME and carried out the factor analysis again. Table A.5 in Appendix A reports the results. Previously, PT1CRIME had very low loading on all three factors; now VIOLCRIME has a loading of 0.56 on Factor 1. Despite the higher loading, VIOLCRIME is only the 16th most important of the 26 needs indicators for this factor.[24] A comparison of Table A.6 with Table A.5 shows that

---

[23] The test of sampling adequacy suggests that CHNGEMPLBASE is not an appropriate variable for inclusion in either the large city or small city analysis.

[24] In Richardson's 2000 analysis, the comparable crime variable had higher factor loadings but was not among the most important variables in defining either the unrotated or rotated factors. See Todd Richardson (2007), "Analyzing a Community Development Needs Index," in *Cityscape*.

replacing PT1CRIME with VIOLCRIME had virtually no effect on the interpretation of the three factors.

3.2.4. Culling the Needs Indicators

After the initial results, we explored alternative ways to structure the factor analysis. In particular, we considered dropping variables that had a large number of missing values in order to increase the number of cities in the analysis. The crime indicators (PT1CRIME and PT2CRIME) were missing for 107 cities.[25] The next four indicators in terms of missing values were: (1) change in the low-income concentration (CHGLOWINCCON), with 42 missing values; (2) the relative concentration of minorities in the central city (MINCON), with 36 missing values; (3) the proportion of immigrants who entered the United States in the last 15 years (RCNTIMMIG), with 25 missing values; and (4) change in the employment base over a recent 5-year period (CHNGEMPLBASE), with 17 missing values.

We decided to eliminate the crime indicators because they had low loadings on all the factors; the test of sampling adequacy indicated that, at least, PT1CRIME was not a good candidate for factor analysis; and the analysis in Section 2.3.3 suggests that there may be some problems with PT1CRIME. We decided to keep the remaining variables because all four were important to the interpretation of the factors on which they loaded. In addition, MINCON and RCNTIMMG had high factor loadings on their respective factors. Eliminating the crime indicators increased the number of cities in the factor analysis from 292 to 370, with a total population of 83,246,832 in 2005.

3.2.5. Derivation of the Final Factors Used in this Report

We reran the factor analysis for those 370 cities using 24 needs indicators. Again, the rule we used in the initial analysis and our judgment led us to select three factors. Table 3 contains the factor loadings for those three factors based on an orthogonal rotation. To make it easier to interpret each factor, we ranked the indicators by their loadings on each factor. The final factors (below) are easy to interpret:

- Factor 1: Three of the four indicators that identify various types of poverty loaded heavily on Factor 1. These are the overall proportion of poor persons (POORPERS), the proportion of children living in households with poverty incomes (POORCHILD), and the proportion of school-age children living in households with poverty incomes (SCHPOPPOOR). The proportion of persons over 74 living in poverty (POOROVER74) had a modest loading of Factor 1, but this indicator loaded more heavily on this factor than either of the other factors. The indicators that related neighborhood poverty also load heavily on Factor 1.

[25] Early in the project, HUD had suggested experimenting with excluding some indicators to determine whether their exclusion made any difference to the analysis.

The three measures of city/suburb disparity load heavily on Factor 1; these are POVCON, MEDINCCBS2CITY, and MINCON. Finally, although the two indicators of long-term trends, EXCSINFRA and CHGLOWINCCON, have modest loadings on Factor 1, it is the factor on which they load most heavily.

- Factor 2: The proportion of households that are linguistically isolated (LINGISOL) and the proportion of the population who are recent immigrants to the United States (RCNTIMMIG) load heavily on Factor 2. Overcrowded housing (OVERCROWD2000) and the lack of affordable rental housing also load heavily on Factor 2. The proportion of adults without a high school diploma (UNEDUCADULTS) loads heavily on Factor 2.

- Factor 3: Only the proportion of adults between 25 and 65 years of age without a college degree (UNDEREDWORKAGE) and the proportion of adults without a high school diploma (UNEDUCADULTS) load heavily on Factor 3, although UNEDUCADULTS loads slightly more heavily on Factor 2. The change in the employment base over a recent 5-year period (CHNGEMPLBASE) has its highest loading on this factor. The proportion of mortgage applications that are denied (DENIAL) also has a modest loading on this factor.

Table 3. Rotated Factor Loadings for Final Factor Analysis, Each Factor Sorted by Loadings

	Factor 1: Poverty and Structural Problems		Factor 2: Immigration and Housing Affordability		Factor 3: Limited Economic Prospects
POORPERS	0.92728	LINGISOL	0.91800	UNDEREDWORKAGE	0.78216
POORCHILD	0.91442	RCNTIMMIG	0.85752	UNEDUCADULTS	0.54446
POVCON	0.89969	OVERCROWD2000	0.82505	DENIAL	0.43440
SCHPOPPOOR	0.89838	LACKAFFDRENTALS	0.64700	UNEMPCEN	0.28849
PR70RENTPOV	0.87989	UNEDUCADULTS	0.59240	OVERCROWD2000	0.25630
SGLPRNTFAM	0.85591	LWINCHHDS	0.32419	PCTPOPMODPOVNGHS	0.24034
MEDINCCBS2CITY	0.85455	MEDINCCBS2CITY	0.29163	CHNGEMPLBASE	0.23059
LWINCHHDS	0.85063	PCTPOPMODPOVNGHS	0.27201	CHGLOWINCCON	0.20700
MINCON	0.78498	UNDEREDWORKAGE	0.20307	POORPERS	0.18606
PCTVACMODPOVCITY	0.77777	POOROVER74	0.20099	SGLPRNTFAM	0.17529
PCTPOPMODPOVNGHS	0.77370	CHGLOWINCCON	0.18643	LACKAFFDRENTALS	0.15992
DENIAL	0.73175	PR70RENTPOV	0.14105	PCTVACMODPOVCITY	0.15615
PCTPOPHIGHPOVNGHS	0.68063	POORPERS	0.12609	POORCHILD	0.13772
UNEMPCEN	0.63363	POVCON	0.10734	SCHPOPPOOR	0.11026
EXCSINFRA	0.58278	SCHPOPPOOR	0.09173	LINGISOL	0.09723
UNEDUCADULTS	0.47999	POORCHILD	0.06533	MEDINCCBS2CITY	0.09539
POOROVER74	0.45757	UNEMPCEN	0.06183	PCTPOPHIGHPOVNGHS	0.05213
LACKAFFDRENTALS	0.44787	CHNGEMPLBASE	0.02851	POOROVER74	0.03401
CHGLOWINCCON	0.36726	PCTPOPHIGHPOVNGHS	0.02778	EXCSINFRA	0.01141
UNDEREDWORKAGE	0.35296	SGLPRNTFAM	0.01532	MINCON	-0.00458
LINGISOL	0.04718	MINCON	0.00792	LWINCHHDS	-0.00897
OVERCROWD2000	-0.01856	EXCSINFRA	-0.10178	PR70RENTPOV	-0.14311
RCNTIMMIG	-0.11242	DENIAL	-0.15728	RCNTIMMIG	-0.15913
CHNGEMPLBASE	-0.16812	PCTVACMODPOVCITY	-0.28525	POVCON	-0.16557

Based on these loadings, we ascribe these interpretations to the three factors:

- Factor 1 is the poverty-structural problems factor.
- Factor 2 is the immigration-housing factor.
- Factor 3 is the limited economic prospects factor. The low education of the work force, combined with recent declines in jobs relative to the labor force, result in this label. We think the modest loading of DENIAL and the unemployment rate (UNEMPCEN) are consistent with this interpretation.

Factor 3 is the least well-defined factor. Lack of clear definition probably results from the paucity of good information on economic trends in cities that was discussed in the conclusion to Chapter 2.

Chapter 4 compares cities based on these three factors and on an index derived from these factors in Section 3.5.

3.2.6. Calculating Factor Scores

Having identified three common dimensions of need among cities with populations of 65,000 or more, the next step is to calculate a score for each city on each factor so that we can compare the need level in different cities on each dimension. A factor-loading table, such as Table 3, provides information on the relationship between the unobserved factors and the observed needs indicators. This information is useful in characterizing the unobserved factors, but it cannot be used to estimate the factors. In general, factors are *not* linear combinations of the variables used to identify them.[26]

Techniques have been developed to use the observed variables to create linear approximations of the unobserved factors. These techniques first transform the observed variables into standardized form and then use one of several methods to create a set of "standardized scoring coefficients."[27] The standardized variables are multiplied by the standardized scoring coefficient to provide a linear approximation of each factor and, using this approximation, to create a score for each city on each factor. To derive the standardized scoring coefficients, we used a technique that employs a regression method to minimize the squared deviation between the "estimated" factors and the unobserved factors. Table A.7 in Appendix A presents the standardized scoring coefficients.

Because the scores are linear combinations of standardized indicators, the expected value of the score for each scored factor is zero. Because we have defined each indicator such that higher values indicate worse conditions on that indicator, score values greater than zero indicate higher-than-average problems. The unobserved factors are uncorrelated

[26] This is another example of how factor analysis differs from principal components analysis. By definition, principal components are linear combinations of the variables that they represent.
[27] A standardized value is calculated by the formula: (value – mean value)/standard deviation.

with each other, but because the standardized scoring coefficients only create linear approximations of the unobserved factors, the set of factor scores have non-zero correlations. Table 4 shows that the three sets of factor scores are almost uncorrelated—an indication that the scores measure distinctly different conditions.

Table 4. Correlations among Factor Scores[28]

Correlations	Factor 1	Factor 2	Factor 3
Factor 1	1.000	0.012	0.003
Factor 2		1.000	0.016
Factor 3			1.000

3.3. Comparing Needs at Different Times

Typically analysts use factor analysis to compare conditions in different cities at a given point in time—for example, to compare the community needs of Denver and Wichita in 2005. But, often analysts want to know whether conditions in a given city have improved or worsened between two points in time. For example, does Denver have more community needs in 2005 than it had in 2000? Factor analysis can also be used for this purpose, but analysts need to take some conceptual issues into account.

A factor score is calculated as the weighted sum of the number of standard deviations above (+) or below (-) the mean for each need indicator. The weights are the factor scoring coefficients calculated as part of the factor analysis. With each new wave of ACS data, there will be new means and standard deviations for the needs indicators and, if the factor analysis is repeated, new factor scoring coefficients. Potentially a new factor analysis could even reveal new factors or major changes in factor definitions. With so many possible changes in the inputs used to compare conditions between the two time periods, it is important to define a process that yields a result that has a clear interpretation.

The approach we proposed and used has the following steps:

1. Choose a base year. We used 2005 as the base year because the project focused on using the 2005 ACS data. The comparison year is 2000.

2. Derive factors in the base year and save the standardized scoring coefficients to use as weights in both the base year and the comparison year. Table A.7 contains the standardized scoring coefficients.

3. Do a new factor analysis with each new comparison year. Use this to determine whether conditions have changed so much as to make the use of the base-year factor analysis no longer legitimate. Section 3.2.4 reports the comparison we made between the 2000 and 2005 factor analyses. If the base-year factors appear

[28] Because we have adhered strictly to the protocols involved in factor analysis, we treat the factor scores as cardinal measurements and therefore use Pearson correlation coefficients.

to be the same as the factors in the comparison year, proceed to the following steps.

4. Translate the needs indicators into standardized form in both the base year and the comparison year *using the means and standard deviations calculated in the base year*. This step is crucial because the standardized scoring coefficients derived from the base year are designed to produce factor scores using standardized needs indicators, defined by the means and standard deviations of the base year. In this way, conditions on each need indicator are measured by the distance from the mean of that indicator in the base year using the base-year standard deviation as the unit of measure. Therefore, conditions on each need indicator are measured consistently in both years.

5. Compute the weighted sum of the standardized needs indicators in both the base year and the comparison year. Subtract the base-year score from the comparison-year score. A positive difference indicates that community needs on that factor increased between the base year and the comparison year; a negative difference indicates that community needs on that factor decreased between the base year and the comparison year.

6. For each factor, compute the mean factor score for all cities in the base year and in the comparison year. Subtract the mean factor score in the base year from the mean factor score in the comparison year. This difference indicates whether community needs as measured by that factor have improved or worsened on average. This comparison is not weighted by the size of the cities.

There are two important points that need to be made about Steps 5 and 6:

- While Steps 5 and 6 are described in terms of a single factor, the same procedure could be applied to a single-value needs index that is calculated as a linear combination of the factors. Instead of using the standardized scoring coefficients for a single factor as the weights in Step 5, one would use a linear combination of the standardized scoring coefficients as weights. The same linear combination would be applied to the standardized scoring coefficients as the one applied to the factor scores in computing the single-valued index.

- In both Steps 5 and 6, we use the differences between the scores rather the ratio of the scores. Because the scores can be both positive and negative, the ratio of the scores will not produce a consistent ranking. [29]

Chapter 4 presents the results of Steps 1 through 6.

Steps 1 through 6 should produce reasonable results for comparisons between points in time that are close together. Over longer time periods, it is possible that factor analysis

[29] Section 5.4.2 discusses this issue in more detail with respect to combining a measure of fiscal capacity with a single-valued needs index.

will not produce a similar set of factors using the base-year and comparison-year data on the needs indicators. Using the experience with price indices as a guide, we suggest the following approach to handling this problem:

- If the comparison-year factor structure is no longer consistent with the base-year structure, then use the comparison-year factor structure as a new baseline. This is analogous to using a new basket of goods and services for a price index. One could continue to report the old index along with the new index. This approach used the method applied to price indices until the introduction of chain-linked indicators.

We considered whether it would be possible to create the equivalent of a chain-linked indicator to handle this situation. Chain-linked indices have two key characteristics: they allow the weights to evolve over time, and applying the technique year-by-year over a period of years produces the same result as applying it to the beginning and end years of the period. To achieve these two characteristics, chain-link indicators use geometric means instead of arithmetic means. Unfortunately, factor scoring is based on arithmetic averaging instead of geometric averaging. Therefore, we cannot construct a chain-link index to compare needs over time.

3.4. Creating a Single-Valued Index of Community Needs

3.4.1. Alternative Indices

The explicit goal of this project is to produce an index of community needs—a formula that will assign one number to each city to indicate its relative need. The needs index will be a function of the three factor scores; but because the factor scores are linear combinations of the needs indicators, it will also be a function of the 24 needs indicators.

Section 3.1 noted that factor analysis provides no information that can be used to choose weights to combine the factors into a single-valued index. In this section, we construct six alternative indices; some are based on external rationales while others are created to test how sensitive the index results are to the choice of weights. Table 5 defines the alternative indices and the reasons we constructed them.

Table 5. Alternative Single-Valued Community Needs Indices

Index	Index Name	Factor 1 (Poverty and Structural Problems) Weight	Factor 2 (Immigration and Housing Affordability) Weight	Factor 3 (Limited Economic Prospects) Weight	Rationale for Index
1	Equal weight	1/3	1/3	1/3	This index treats all three factors the same. It is the standard to which we compared the other indices.
2	Triple weight to poverty and structural problems	0.60	0.20	0.20	Legislation provides virtually no guidance in choosing weights. However, the CDBG statute does give precedence to "the development of viable urban communities, by providing decent housing and suitable living environment and expanding economic opportunities, *principally for persons of low and moderate income* [emphasis added]." Therefore, we provide a triple weight to the factor that relates to poverty. We decided on triple weights so that Indices 2 and 3 would parallel Index 4.
3	Triple weight to immigration and housing affordability factor	0.20	0.60	0.20	Indices 2 and 4 provide extra weights to Factors 1 and 3 respectively. We added this index to see what happens when we add extra weight to Factor 2 alone.
4	Triple weight to limited economic prospects factor or hedonic weights	0.20	0.20	0.60	The hedonic analysis in Section B.3 in Appendix B indicates that Factor 3 should receive three times the weight of Factor 1. It provides no information on how to weight Factor 2; we gave Factor 2 the same weight as Factor 1.
5	Richardson weights	0.80	0.15	0.05	Richardson chose these weights for his unrotated factors. Our rotated factors do not match well with either Richardson's unrotated or rotated factors but they are more similar to his unrotated factors.
6	Partial hedonic weights	0.60	0.28	0.12	Using the hedonic analysis in Appendix B, we chose these weights to obtain the closest match between the weighted sum of the scoring coefficients for eight needs indicators to beta coefficients for those variables in the hedonic-type equation. See Section B.4 for an explanation of how we derived these weights.

The equal weight index (Number 1) is the standard to which we compare the other indices; it treats all the factors equally. We have some rationale for Indices 2, 4, 5, and 6. Index 2 puts a triple weight on the poverty and structural problems factor because the CDBG legislation emphasizes assistance to low- and moderate-income person indices. Index 5 uses the same weights that Richardson employed when he constructed an index based on 2000 census data. Richardson used four unrotated factors, which he identified with poverty, immigration, high poverty concentration, and income growth. He gave these factors weights of 0.80, 0.15, 0.05, and 0.00 respectively. Our Factors 1 and 2 correspond roughly to Richardson's first two factors; there appears to be little overlap between our Factor 3 and Richardson's third factor. We based Index 5 on the Richardson weights. The hedonic analysis reported in Appendix B provides some guidance on weighting the factors. A regression involving the factor scores suggests that Factor 3 should be receive three times the weight of Factor 1 but provides no guidance on what weight should be given to Factor 2. We incorporated this information into the weights for Index 4. A separate regression involving the 24 needs indicators provided useful information on how eight of the indicators affect property values. We incorporated this information into the weights for Index 6. Index 3 was added to test the sensitivity of the results to added weight to Factor 2.

3.4.2. Comparisons of Scores on Alternative Indices

Table A.8 in Appendix A contains the scores on all six indices for the 370 cities for which we computed factor scores. Table 6 presents some key statistics on the indices. Indices 2, 5, and 6 have larger ranges than the other three indices because these indices give a heavy weight to the poverty and structural problems factor and because the scores for that factor have a larger range than the scores for the other two factors.[30] The equal weight index has the smallest standard deviation while the Richardson index has the largest.

Table 6. Basic Statistics on the Alternative Indices

	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Mean	**-0.01**	**-0.01**	**-0.01**	**-0.02**	**-0.01**	**-0.01**
Variance	0.28	0.38	0.36	0.36	0.57	0.39
Std Dev	0.53	0.61	0.60	0.60	0.76	0.62
Max	2.03	3.02	2.45	1.62	3.82	3.11
Min	-1.21	-1.26	-0.96	-1.91	-1.34	-1.21
Range	3.25	4.29	3.41	3.53	5.17	4.32

[30] The ranges for the three factor scores are: 6.0, 5.0, and 5.2.

Table 7 presents the correlations between population and the six indices and the correlations among the indices. This table shows that all the indices except the hedonic index (Index 4) have some correlation with population. Larger cities appear to have more need; this effect is small in all cases. The needs indicators were defined in per capita or percentage terms so that they would be independent of city size, and Table A.1 in Appendix A shows that correlations between population and the needs indicators were very low, ranging from -0.06 to 0.17. So the small positive correlations between five of the index scores and population suggest that larger cities have somewhat greater community needs.[31]

Table 7. Correlations Among the Alternative Indices

	Population	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Population	1.000	0.122	0.152	0.140	0.026	0.163	0.172
Index 1	0.122	1.000	0.874	0.875	0.872	0.719	0.863
Index 2	0.152	0.874	1.000	0.644	0.641	0.964	0.987
Index 3	0.140	0.875	0.644	1.000	0.649	0.492	0.704
Index 4	0.026	0.872	0.641	0.649	1.000	0.420	0.565
Index 5	0.163	0.719	0.964	0.492	0.420	1.000	0.964
Index 6	0.172	0.863	0.987	0.704	0.565	0.964	1.000

The correlations between the equal weight index (Index 1) and all the other indices are strong.[32] The Richardson index (Index 5) has the lowest correlation with the equal weight index (0.719); the other four indices have correlations of approximately 0.87. This suggests that an equal weight index is a reasonable approximation to a wide range of weighted indices.

Weighting does affect the scoring. While the equal weight index correlates well with the other indices, the correlations among the weighted indices vary more. We focus on Indices 2, 3, and 4 because they represent, respectively, emphasizing Factors 1, 2, or 3 heavily. Correlations among these indices are in the range of 0.60 to 0.65. The Richardson index weighs Factor 1 very highly and gives small weight to the other two factors. It correlates highly with Indices 2 and 6, which also weigh Factor 1 highly but has correlations in the 0.40 to 0.50 range with Indices 3 and 4.

Table 8 compares the scores on the equal weight index (Index 1) to the score from Indices 2, 3, and 4, which successively give triple weight to Factors 1, 2, and 3. Scores on Index 1 varied from a high of 2.03 to a low of -1.21, a range of 3.25 points. The

[31] The correlations between population and the factor scores were: 0.148 for Factor 1, 0.127 for Factor 2, and -0.065 for Factor 3.
[32] The Spearman rank-order correlations among the six indices are very close to the Pearson correlations reported in Table 7 and display the same pattern.

scores for all the cities on Indices 2, 3, and 4 are within 1.00 points of their scores on Index 1; the scores for over 90 percent of the cities are within 0.50 points of their scores on Index 1; and the scores for over 60 percent of the cities are within 0.25 points of their scores on Index 1. Camden had the largest difference in scores between Indices 1 and 2; it scored 0.99 points higher on Index 2. Despite this large difference in scores, Camden was the city with the highest score on both Index 1 and Index 2. Miami had the largest difference in scores between Indices 1 and 3; it scored 0.87 points higher on Index 3. Miami was ranked as the 56th most needy city on Index 1 and was ranked as the 16th most needy city on Index 3. Cambridge, MA had the largest difference in scores between Indices 1 and 4; it scored 0.96 points lower on Index 4. Cambridge was ranked as the 357th most needy city on Index 1 and was ranked as the 368th most needy city on Index 4.

Table 8. Comparison of Scores between Index 1 and Indices 2, 3, and 4 for 370 Cities

Absolute Difference between Score on Index 1 and Score on --	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Triple Weigh to Limited Economic Prospects
Mean	0.23	0.23	0.23
Std Dev	0.18	0.18	0.18
Max	0.99	0.87	0.96
Number of Cities whose Score on Index 1 is	**Index 2**	**Index 3**	**Index 4**
Within 1.00	370	370	370
Within 0.50	339	338	340
Within 0.25	234	223	230

The data in Tables 6, 7, and 8 indicate that, from a statistical perspective, an equal weight index provides scores and rankings similar to those provided by indices that weigh the factor scores unevenly. The numeric and rank-order correlations between Index 1 and Indices 2, 3, and 4 are all above 0.85. Using Indices 2, 3, or 4, rather than Index 1, would affect the scores of 60 percent of the cities by less than 0.25 points. For this reason, we will use the equal weight index as our single-valued index in comparing conditions across cities and between 2000 and 2005 in Chapter 4.

Statistical closeness does not mean that the ranking of some cities are not substantially different depending upon the index used. Washington, DC had the biggest change in ranking between Index 1 and Index 2; it is ranked 243rd on Index 1 and 80th on Index 2. Sunnyvale, CA had the biggest change in ranking between Index 1 and Index 3; it is ranked 284th on Index 1 and 98th on Index 3. Providence had the biggest change in ranking between Index 1 and Index 4; it is ranked 48th on Index 1 and 256th on Index 4. If HUD were to use one of these indices to allocate funds to cities, the choice of index would be of great concern to individual cities. But, if HUD is interested primarily in analyzing the variation in needs across cities and over time, then the results from the equal weight index will be similar to those from any index that applies reasonable weights to the factor scores.

3.4.3. Transformation of the Factor Score Functions into Functions of Needs Indicators

Because the factor scores are linear combinations of the needs indicators, the choice of index determines which needs indicators will have the greatest impact on the index score.[33] Interpreting the indices in terms of the needs indicators helps identify the cities that might do best or worst on a particular Index.

Table 9 uses the standardized scoring coefficients in Table A.7 to transform Indices 1 through 4 from weighted sums of factor scores into weighted sums of the 24 needs indicators. The entries in Table 9 tell how much increase in the relevant index score would result from a one standard deviation increase in need on a given need indicator. SCHPOPPOOR, LWINCHHDS, MEDINCCBS2CITY, MINCON, and EXCSINFRA are needs indicators that contribute to high scores on Index 2. As expected, RCNTIMMG, LINGSOL, OVERCROWD_2000, and LACKAFFRDRENTALS contribute to high scores on Index 3. DENIAL, CHNGEMPLBASE, UNDEREDWORKAGE, UNEDUCADULTS, and UNEMPCEN contribute to high scores on Index 4.

[33] Increases in some needs indicators—for example, POOROVER74—would decrease the index score for that city. The factor loading and the standardized scoring coefficients take into account correlations among the needs indicators, and thus some of the loading and some of the scoring coefficients are negative.

Table 9. Transformation of Factor-Scoring Coefficients into Scoring Coefficients for Needs Indices

Need Indicator	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Triple Weight to Limited Economic Prospects
POORPERS	0.1413	0.1596	0.0881	0.1761
POORCHILD	0.0253	0.0505	-0.0378	0.0633
SCHPOPPOOR	0.0070	0.0525	0.0392	-0.0707
POOROVER74	-0.0061	-0.0008	-0.0040	-0.0135
LWINCHHDS	0.0078	0.0160	0.0442	-0.0367
SGLPRNTFAM	0.0170	0.0342	0.0016	0.0152
PCTPOPHIGHPOVNGHS	-0.0126	-0.0019	-0.0116	-0.0244
PCTPOPMODPOVNGHS	0.0249	0.0185	0.0331	0.0232
PCTVACMODPOVCITY	-0.0006	0.0365	-0.0530	0.0148
MEDINCCBS2CITY	0.0970	0.1397	0.0988	0.0525
MINCON	0.0038	0.0193	-0.0077	-0.0003
POVCON	-0.1085	-0.0261	-0.0628	-0.2367
EXCSINFRA	0.0082	0.0247	-0.0040	0.0039
CHGLOWINCCON	0.0134	-0.0010	0.0056	0.0357
RCNTIMMIG	0.0178	0.0076	0.1093	-0.0637
LINGISOL	0.0868	0.0396	0.1966	0.0241
OVERCROWD_2000	0.0659	0.0325	0.1052	0.0601
LACKAFFDRENTALS	0.0290	0.0107	0.0630	0.0132
PR70RENTPOV	-0.0288	0.0432	-0.0136	-0.1160
DENIAL	0.0516	0.0530	-0.0116	0.1134
CHNGEMPLBASE	0.0159	0.0066	0.0114	0.0297
UNDEREDWORKAGE	0.1037	0.0395	0.0424	0.2292
UNEDUCADULTS	0.1688	0.0849	0.1533	0.2682
UNEMPCEN	0.0129	0.0156	-0.0038	0.0270

3.5. Summary of Factor Analysis

This chapter applied standard factor techniques to a set of 26 needs indicators developed in Chapter 2. The majority of these needs indicators use data from the 2005 American Community Survey. The factor analysis identified three dimensions that represent community needs in 2005 for the 292 cities for which we have data.

We tested the factor analysis results in three ways. First, we compared the factor analysis using 2005 data for most needs indicators to factor analysis using 2000 data for most needs indicators. The two analyses identified factors that were nearly identical. This process gives us confidence that we could apply factors developed using 2005 data to 2000 data on needs indicators. Second, we split the sample of cities into those with populations of 200,000 or more and those with populations of less than 200,000. Factor analysis applied separately to the two samples produced results that were very similar. These results gave us some confidence that community needs are similar in larger and smaller cities. Finally, we substituted a different measure for violent crimes than the measure used in the initial analysis (PT1CRIME). The results of the factor analysis did not seem to vary significantly when the alternative measure of violent crimes was used. This relieved some concerns we had about the original measure of violent crimes.

Next, we examined the needs indicators to see where problems with missing data caused a large number of cities to drop out of the analysis. Based on this examination, we eliminated PT1CRIME and PT2CRIME from the set of indicators and reran the factor analysis. When applied to the smaller set of needs indicators, factor analysis identified the same factors found with the full set of indicators. Eliminating these two variables increased the number of cities included from 292 to 370. This factor analysis is the one that we use for the remainder of the analysis in the report. We interpret the factors to represent the needs associated with:

- Poverty and structural problems,
- Immigration and lack of affordability housing, and
- Limited economic prospects.

The first two factors are well-defined; the third factor is weakly defined. We ascribed the weak definition of the limited economic prospects factor to the lack of multifaceted data on economic conditions and trends in cities.

In Section 3.3, we discussed technical issues in applying factors developed at one point to data on the same needs indicators at a different point in time. This provided the conceptual background for the comparisons in Chapter 4.

Finally, we examined six alternative single-valued needs indicators based on linear combinations of scores from the three factors. Examining the correlations among the indices and other statistics, we concluded that an equal weight index would provide adequate information on the variation in community needs across cities and across time. We use the equal weight index in Chapters 4 and 5.

4. Community Needs in 2000 and 2005

While this research project has multiple objectives, the two principal goals are to test the feasibility of using ACS data to measure community needs and to test the feasibility of measuring changes in community needs over time. Chapter 2 identified 26 indicators of problems at the city level, most of which either use ACS data or will be capable of using ACS data once the ACS begins to release 5-year moving average data for census tracts. Chapter 3 performed factor analysis using 24 of the 26 indicators and identified three factors that track different dimensions of community needs. Chapter 3 also examined several single-valued indices based on the three factors and explained how to apply factor analysis in different years.

This chapter compares conditions in 370 cities in 2000 and 2005 using each of the three factors and also using the equal weight index developed in Chapter 3. The chapter examines changes in each factor between 2000 and 2005 to obtain a fuller picture of how conditions in individual cities are changing. The equal weight index provides a convenient summary of these changes. As noted in Chapter 3, the results from the equal weight index are similar in scope and general details to that from other indices that weigh the factors unequally. While unequal weighting can markedly change the scoring of individual cities, the overall patterns are more stable.

The reader should keep in mind the following facts about how the analysis in this chapter was carried out: (1) 2005 data were used to identify the factors and to develop standardized scoring coefficients; (2) the standardized scoring coefficients were applied to standardized data on 24 indicators in 2000 and 2005; and (3) standardization of the indicators was achieved in both 2000 and 2005 by taking the value of the indicator in the relevant year and subtracting the mean value of the indicator in 2005 and dividing the difference by the standard deviation of the indicator in 2005. Table A.9 in Appendix A presents the results of these calculations for 2000 and 2005 for the three factors and for the equal weight index for all 370 cities.

Section 4.1 looks at the how conditions changed on average for the 370 cities between 2000 and 2005. Sections 4.2, 4.3, and 4.4 examine changes across individual cities for each of the three factors. Section 4.5 uses the equal weight index to compare changes in overall community needs. Section 4.6 contains a summary of findings.

4.1. Changes in Community Needs for Cities with Populations of 65,000 or More

Table 10 computes the average score on each factor in 2000 and 2005 and the average score on the equal weight index in both years. On each factor and on the index, an increase in the scores (a positive change) indicates an increase in community needs while a decrease in scores (a negative change) indicates a decrease in community needs.

Before looking at the numbers in Table 10, it is important to call attention to two previous results. Table 9 indicated that, of the 24 needs indicators, UNEDUCADULTS has the largest impact on the equal weight index. (Table A.7 in Appendix A indicates that UNEDUCADULTS also has a strong impact on the scoring for Factor 3.) Table 2 noted that the mean of the unstandardized data for UNEDUCADULTS declined by 17 percent between 2000 and 2005. The discussion of Table 2 expressed surprise at the size of this decline, but examination of Census Bureau reports comparing the decennial census with the ACS failed to find any indication of problems with this variable. In addition, the observed decline for the cities studied closely paralleled the decline in the data for the entire United States. Because we found no evidence of problems with this variable, we included it among the needs indicators.

Table 10. Average Factor Scores and Average Equal Weight Index Scores in 2000 and 2005

	Factor 1 (Poverty and Structural Problems)	Factor 2 (Immigration and Housing Affordability)	Factor 3 (Limited Economic Prospects)	Equal Weight Index
Mean - 2005	-0.006	0.004	-0.034	-0.012
Mean - 2000	-0.154	-0.067	0.192	-0.010
Change	0.149	0.070	-0.226	-0.002
Ratio of change to standard deviation in 2005	16.1%	7.8%	-25.4%	-0.5%
Number of cities worse off	283	231	44	168
Number of cities no worse off	87	139	326	202

Table 10 shows that, on average, community needs—as measured by the equal weight index—decreased slightly between 2000 and 2005. This decline was due solely to improvement in the needs represented by Factor 3, the limited economic prospects factor. As discussed above, the improvement in Factor 3 and the equal weight index can be attributed to the substantial reduction in the percentage of adults without a high school diploma (UNEDUCADULTS) between 2000 and 2005.

Table 10 also shows that community needs related to poverty and structural problems (Factor 1) and immigration and housing affordability (Factor 2) worsened between 2000 and 2005. Conditions worsened most with respect to poverty and structural problems. The average city experienced a move of 1/6 of a standard deviation up in the score on this factor whereas the average city experienced a move of only 1/12 of a standard deviation up in the score on the immigration and housing affordability factor. Consistent with the relative size of the average changes, the number of cities that were worse off (had higher scores) in 2005 was larger for Factor 1 than Factor 2.

Correlation analysis found little evidence of a relationship between changes in the score on one factor and changes in the scores on either of the other two factors between 2000 and 2005. Changes in the score of Factor 1 have a correlation of 0.18 with changes in the scores of Factor 2. The other two pairings have negative correlations of -0.01 and -0.06.[34] In addition, there was no relationship between population and changes in the scores on any of the factors or on the score for the equal weight index.

4.2. Comparison of Scores in 2000 and 2005 on Factor 1

The Factor 1 scores rank cities on community needs related to poverty and structural problems. Between 2000 and 2005, 283 of the 370 cities became worse off on this dimension of need. Table 11 shows how the scores on this factor varied by region and by size class of cities.

Table 11. Changes in Factor 1 Scores between 2000 and 2005, by Region and Population

Region	Number of Cities	2000 Factor 1	2005 Factor 1	Difference
South	110	-0.11	0.03	0.14
West	150	-0.48	-0.40	0.08
Midwest	69	-0.06	0.18	0.24
Northeast	41	0.77	1.05	0.28
Population				
1,000,000+	9	0.46	0.59	0.13
500,000-999,999	21	0.33	0.53	0.20
300,000-499,999	23	0.30	0.44	0.14
200,000-299,999	37	0.07	0.23	0.16
100,000-199,999	124	-0.22	-0.08	0.15
under 100,000	156	-0.32	-0.18	0.14
All cities	370	-0.15	-0.01	0.15

The Northeast has the highest average scores on the poverty and structural problems factor in both 2000 and 2005 and the largest increase in average scores between the two years. The West region has the lowest average scores on this factor in both years and the smallest increase between the two years. Using 2005 as the standard, only the average scores in the Northeast were above the average for 2005 in 2000; by 2005, all regions except the West had above-average scores.

There appears to be a systematic relationship between the scores on the poverty and structural problems factor and city size. The average score declined by size class in both 2000 and 2005. The change in scores is approximately the same for all the size classes—except for cities with populations between 500,000 and a million, which have a slight higher increase in average scores.

[34] As expected, scores of a factor in 2000 are highly correlated (approximately 0.97) with scores on the same factor in 2005.

Table 12 lists the 40 cities that had the largest increase in need on this factor between 2000 and 2005. The list contains cities that already had serious problems related to this factor in 2000—such as Camden, Detroit, Cleveland, Rochester, Reading, and Syracuse—and cities that were relatively well off on Factor 1 in 2000—such as Redwood, CA; West Covina, CA; Hillsboro, OR; Garland, TX; Upland, CA; and Cedar Rapids. The latter cities moved up sharply in the ranking on Factor 1. The Northeast region is heavily represented among those cities with the largest increases in Factor 1 scores. Of the 41 Northeast cities, 14 are on the list of 40 cities with the largest increase in Factor 1 needs between 2000 and 2005.

Table 12. Forty Cities with the Largest Increases in Factor 1 Scores, 2000-2005

	City	State	2005 Population	2000 Factor 1	2005 Factor 1	Difference	2000 Rank	2005 Rank
1	Lawrence city	Massachusetts	82,191	1.88	2.89	1.01	12	5
2	Hillsboro city	Oregon	82,732	-0.74	0.19	0.94	276	120
3	Camden city	New Jersey	73,305	3.62	4.51	0.89	1	1
4	Reading city	Pennsylvania	81,302	2.04	2.89	0.85	8	6
5	Passaic city	New Jersey	68,422	0.93	1.76	0.83	32	20
6	Scranton city	Pennsylvania	67,314	0.28	1.07	0.80	91	42
7	Redwood City city	California	81,195	-1.00	-0.25	0.74	312	204
8	Gainesville city	Florida	100,879	0.24	0.93	0.69	97	52
9	West Covina city	California	116,371	-0.97	-0.33	0.64	309	223
10	Baton Rouge city	Louisiana	205,442	0.79	1.44	0.64	45	27
11	Dayton city	Ohio	132,679	1.92	2.56	0.64	11	9
12	Springfield city	Massachusetts	146,948	1.32	1.96	0.64	22	18
13	Birmingham city	Alabama	222,154	1.82	2.46	0.64	14	11
14	Hammond city	Indiana	72,507	0.35	0.97	0.62	84	50
15	Cleveland city	Ohio	414,534	2.52	3.14	0.62	4	2
16	Somerville city	Massachusetts	74,869	-0.12	0.48	0.60	152	85
17	Cedar Rapids city	Iowa	119,670	-0.62	-0.04	0.58	255	171
18	Nampa city	Idaho	67,112	-0.27	0.31	0.58	180	111
19	Allentown city	Pennsylvania	105,231	0.89	1.46	0.57	38	26
20	Albany city	New York	78,402	1.53	2.10	0.57	18	13
21	Detroit city	Michigan	836,056	2.59	3.13	0.54	3	3
22	Gresham city	Oregon	95,334	-0.43	0.11	0.54	222	138
23	Syracuse city	New York	132,495	2.02	2.55	0.53	10	10
24	Pueblo city	Colorado	101,302	0.35	0.86	0.51	82	57
25	Avondale city	Arizona	61,666	-0.42	0.08	0.50	219	144
26	Bryan city	Texas	56,277	0.09	0.59	0.50	119	75
27	Lansing city	Michigan	119,675	0.57	1.06	0.49	67	43
28	Rochester city	New York	189,312	2.42	2.90	0.48	6	4
29	Vancouver city	Washington	155,488	-0.31	0.17	0.47	190	126
30	Garland city	Texas	235,750	-0.73	-0.27	0.46	273	210
31	Lowell city	Massachusetts	96,876	0.65	1.10	0.44	56	38
32	South Bend city	Indiana	97,070	0.65	1.08	0.44	57	41
33	Milwaukee city	Wisconsin	556,948	1.29	1.72	0.43	24	22
34	Lynn city	Massachusetts	83,419	0.66	1.09	0.43	54	39
35	Pawtucket city	Rhode Island	72,896	0.50	0.92	0.42	72	53
36	Toledo city	Ohio	285,937	0.72	1.14	0.42	47	34
37	High Point city	N Carolina	101,852	-0.15	0.26	0.42	163	112
38	Upland city	California	74,420	-0.70	-0.29	0.41	265	214
39	Rockford city	Illinois	139,173	0.26	0.67	0.41	92	71
40	Tyler city	Texas	87,687	0.09	0.50	0.40	117	82

Table 13 lists the 40 cities that experienced the greatest improvement on the poverty and structural problems factor between 2000 and 2005.

Table 13. Forty Cities with the Largest Decreases in Factor 1 Scores, 2000-2005

	City	State	2005 Population	2000 Factor 1	2005 Factor 1	Difference	2000 Rank	2005 Rank
1	Miami city	Florida	361,701	0.84	0.10	-0.73	42	140
2	Glendale city	California	194,620	-0.38	-0.88	-0.50	209	306
3	Turlock city	California	74,883	-0.38	-0.84	-0.46	210	298
4	Rialto city	California	93,284	-0.26	-0.67	-0.41	178	277
5	Pomona city	California	161,257	0.16	-0.24	-0.40	111	203
6	Oceanside city	California	162,259	-0.58	-0.98	-0.40	247	320
7	Wilmington city	N Carolina	91,207	0.30	-0.05	-0.35	88	173
8	Alexandria city	Virginia	133,479	-0.51	-0.85	-0.34	232	303
9	Redding city	California	89,362	-0.19	-0.51	-0.32	170	255
10	Westminster city	California	97,946	-0.77	-1.08	-0.31	281	338
11	Santa Monica city	California	82,777	-0.74	-1.00	-0.27	274	324
12	Hemet city	California	77,076	0.01	-0.26	-0.27	131	206
13	Pompano Beach	Florida	94,892	-0.02	-0.28	-0.26	135	213
14	Bethlehem city	Pennsylvania	68,144	0.20	-0.04	-0.24	100	167
15	Richmond city	Virginia	180,757	1.22	0.98	-0.24	26	48
16	Long Beach city	California	463,956	0.62	0.38	-0.24	62	104
17	San Marcos city	California	77,445	-0.71	-0.94	-0.23	270	314
18	Escondido city	California	133,017	-0.46	-0.69	-0.22	226	280
19	Columbia city	S Carolina	88,450	0.93	0.72	-0.21	34	67
20	Deltona city	Florida	85,979	-0.86	-1.04	-0.18	298	330
21	Newark city	New Jersey	254,217	2.21	2.02	-0.18	7	16
22	Peoria city	Illinois	102,136	0.86	0.68	-0.18	41	70
23	Fullerton city	California	142,064	-0.84	-1.00	-0.16	292	323
24	Quincy city	Massachusetts	84,080	-0.69	-0.85	-0.16	262	302
25	Stockton city	California	278,515	0.52	0.38	-0.14	69	102
26	Orange city	California	137,994	-1.00	-1.14	-0.14	315	350
27	Inglewood city	California	120,204	0.63	0.48	-0.14	60	84
28	Suffolk city	Virginia	77,922	-0.26	-0.39	-0.13	179	235
29	Chino city	California	69,732	-1.16	-1.29	-0.13	338	364
30	McKinney city	Texas	92,337	-0.95	-1.07	-0.13	307	334
31	Merced city	California	65,391	0.68	0.55	-0.12	52	77
32	El Cajon city	California	92,507	0.06	-0.06	-0.12	123	177
33	North Las Vegas	Nevada	165,061	-0.35	-0.47	-0.12	201	247
34	Melbourne city	Florida	76,373	-0.45	-0.58	-0.12	225	267
35	Riverside city	California	294,059	-0.37	-0.49	-0.12	204	253
36	Buena Park city	California	76,062	-0.82	-0.94	-0.12	289	315
37	Simi Valley city	California	116,722	-1.18	-1.30	-0.12	340	365
38	Berkeley city	California	90,432	0.19	0.08	-0.11	104	145
39	Clearwater city	Florida	108,382	-0.35	-0.46	-0.10	202	245
40	Modesto city	California	202,971	-0.29	-0.39	-0.10	188	234

Twenty-four of the 40 cities are in California; 11 others are in the South region. Only Long Beach and Miami have populations over 300,000. Interesting cases include Newark, which moved from 7th highest score in 2000 to the 16th highest score in 2005, and Richmond, which moved from the 26th highest score to the 48th highest.

4.3 Comparison of Scores in 2000 and 2005 on Factor 2

The Factor 2 scores rank cities on community needs related to immigration and the housing affordability. Between 2000 and 2005, 231 of the 370 cities became worse off on this dimension of need. Table 14 shows how the scores on this factor varied by region and by size class of cities.

Table 14. Changes in Factor 2 Scores between 2000 and 2005, by Region and Population

Region	Number of Cities	2000 Factor 2	2005 Factor 2	Difference
South	110	-0.40	-0.33	0.07
West	150	0.34	0.41	0.06
Midwest	69	-0.63	-0.59	0.04
Northeast	41	0.28	0.41	0.14
Population				
1,000,000+	9	0.70	0.76	0.06
500,000-999,999	21	-0.14	-0.10	0.04
300,000-499,999	23	0.21	0.23	0.02
200,000-299,999	37	-0.27	-0.16	0.11
100,000-199,999	124	-0.12	-0.05	0.07
under 100,000	156	-0.05	0.02	0.08
All cities	370	-0.07	0.00	0.07

Cities in the Northeast experienced the greatest worsening of conditions on this factor, an increase of 0.14 standard deviations, which was twice the national average. With the exception of cities with over a million residents, there appears to be little relationship between population size and the prevalence of problems related to immigration and housing affordability. The largest cities had an average score of 0.70 or more in both 2000 and 2005.

Table 15 lists the 40 cities that had the greatest increase in the score on Factor 2. California, Texas, and Florida account for 26 of the 40 cities. None of the cities on this list had populations above 300,000. Only Salinas, CA and Lawrence, MA had been ranked in the top 20 in 2000, and only five of these cities had been ranked in the top 50 in 2000. Mesquite, TX and Cape Coral, FL had the biggest increase in rank on this factor. Mesquite moved from 248th to 153rd while Cape Coral moved from 244th to 179th.

Table 15. Forty Cities with the Largest Increases in Factor 2 Scores, 2000-2005

	City	State	2005 Population	2000 Factor 2	2005 Factor 2	Difference	2000 Rank	2005 Rank
1	Deerfield Beach	Florida	71,599	0.27	1.11	0.84	102	47
2	Mesquite city	Texas	126,895	-0.58	0.02	0.61	248	153
3	Camden city	New Jersey	73,305	0.77	1.36	0.59	61	29
4	Union City	California	65,239	1.16	1.74	0.58	32	20
5	San Bernardino	California	204,552	1.00	1.56	0.55	41	24
6	Trenton city	New Jersey	77,471	0.15	0.69	0.54	115	72
7	Redwood City	California	81,195	0.82	1.34	0.52	56	30
8	Aurora city	Illinois	170,490	0.46	0.96	0.49	83	58
9	Reading city	Pennsylvania	81,302	0.12	0.62	0.49	119	83
10	Hemet city	California	77,076	0.11	0.60	0.49	122	85
11	Lowell city	Massachusetts	96,876	0.64	1.10	0.46	67	49
12	Rialto city	California	93,284	0.65	1.11	0.46	66	48
13	Garland city	Texas	235,750	0.26	0.72	0.46	104	68
14	Palmdale city	California	145,800	0.22	0.66	0.44	108	77
15	Gresham city	Oregon	95,334	-0.09	0.35	0.44	151	105
16	Salinas city	California	156,950	2.14	2.56	0.43	10	4
17	Cape Coral city	Florida	134,388	-0.58	-0.16	0.42	244	179
18	Fremont city	California	210,387	0.86	1.26	0.40	54	34
19	Hollywood city	Florida	138,412	0.29	0.68	0.39	99	73
20	Turlock city	California	74,883	0.32	0.71	0.39	95	69
21	Newark city	New Jersey	254,217	1.27	1.65	0.38	29	22
22	Tracy city	California	82,218	-0.20	0.18	0.38	172	126
23	Pompano Beach	Florida	94,892	0.18	0.54	0.36	110	88
24	Lawrence city	Massachusetts	82,191	2.05	2.41	0.35	13	7
25	Worcester city	Massachusetts	154,398	0.12	0.47	0.35	120	95
26	Antioch city	California	103,339	-0.28	0.07	0.35	183	145
27	Pasadena city	Texas	150,180	0.70	1.05	0.34	63	52
28	Fairfield city	California	102,642	-0.13	0.21	0.34	154	122
29	Hesperia city	California	79,714	-0.19	0.15	0.34	170	131
30	Kent city	Washington	84,979	0.09	0.43	0.34	124	98
31	Victorville city	California	93,042	-0.04	0.29	0.32	142	115
32	Salem city	Oregon	142,006	-0.32	0.00	0.32	187	157
33	Palm Bay city	Florida	90,102	-0.56	-0.25	0.31	239	191
34	Bloomington city	Indiana	55,406	-0.47	-0.16	0.31	213	178
35	Wyoming city	Michigan	68,960	-0.52	-0.21	0.31	226	187
36	Irving city	Texas	212,262	0.85	1.16	0.31	55	40
37	Costa Mesa city	California	105,333	0.88	1.19	0.31	51	38
38	Scranton city	Pennsylvania	67,314	-0.95	-0.65	0.30	337	274
39	Lewisville city	Texas	81,484	-0.37	-0.08	0.29	199	166
40	Bryan city	Texas	56,277	-0.02	0.27	0.29	138	117

Table 16 lists the 40 cities that had the largest decrease in scores for the immigration and housing affordability factor.

Table 16. Forty Cities with the Largest Decreases in Factor 2 Scores, 2000-2005

	City	State	2005 Population	2000 Factor 2	2005 Factor 2	Difference	2000 Rank	2005 Rank
1	Pasadena city	California	129,400	0.92	0.34	-0.58	47	107
2	Santa Barbara city	California	90,708	0.63	0.14	-0.49	69	134
3	San Marcos city	California	77,445	0.79	0.33	-0.47	57	110
4	Baldwin Park city	California	84,812	2.82	2.36	-0.46	4	8
5	Santa Ana city	California	302,302	3.81	3.39	-0.42	1	3
6	Fort Lauderdale	Florida	141,307	0.14	-0.26	-0.40	116	196
7	Elizabeth city	New Jersey	121,137	2.32	1.93	-0.39	6	16
8	Alhambra city	California	76,309	2.50	2.15	-0.35	5	12
9	McKinney city	Texas	92,337	-0.27	-0.60	-0.33	182	260
10	Hayward city	California	135,474	1.31	1.00	-0.30	28	57
11	Killeen city	Texas	98,434	-0.65	-0.91	-0.27	271	332
12	Mountain View	California	69,427	1.11	0.87	-0.24	39	61
13	Alameda city	California	77,058	0.31	0.11	-0.20	96	139
14	San Jose city	California	887,330	1.31	1.12	-0.19	27	45
15	Southfield city	Michigan	75,053	-0.67	-0.87	-0.19	276	321
16	New Bedford city	Massachusetts	84,898	0.30	0.10	-0.19	98	140
17	Chico city	California	71,298	-0.36	-0.55	-0.19	195	249
18	Waukesha city	Wisconsin	62,690	-0.72	-0.91	-0.19	291	330
19	Glendale city	California	194,620	2.29	2.11	-0.18	8	13
20	Evanston city	Illinois	62,258	-0.47	-0.65	-0.18	215	275
21	Westminster city	Colorado	99,305	-0.54	-0.72	-0.18	234	290
22	Upland city	California	74,420	-0.11	-0.29	-0.17	153	199
23	Chattanooga city	Tennessee	139,158	-1.07	-1.24	-0.17	353	365
24	San Francisco city	California	719,077	1.12	0.95	-0.17	37	59
25	Carson city	California	92,156	0.66	0.49	-0.17	64	93
26	Suffolk city	Virginia	77,922	-0.84	-1.00	-0.17	320	344
27	North Las Vegas	Nevada	165,061	0.99	0.82	-0.16	42	63
28	Simi Valley city	California	116,722	-0.38	-0.54	-0.16	201	245
29	Sioux City city	Iowa	78,395	-0.58	-0.74	-0.16	245	298
30	Lorain city	Ohio	65,476	-0.76	-0.91	-0.15	305	331
31	Roanoke city	Virginia	90,074	-0.91	-1.06	-0.15	331	347
32	Pawtucket city	Rhode Island	72,896	0.49	0.34	-0.14	79	108
33	Westland city	Michigan	80,284	-0.68	-0.82	-0.14	277	315
34	Peoria city	Illinois	102,136	-1.21	-1.35	-0.14	364	369
35	Honolulu CDP	Hawaii	362,252	0.71	0.57	-0.14	62	87
36	Round Rock city	Texas	81,639	-0.51	-0.65	-0.14	225	273
37	Newton city	Massachusetts	82,383	-0.43	-0.57	-0.14	208	254
38	Los Angeles city	California	3,731,437	2.01	1.88	-0.14	14	18
39	Fargo city	North Dakota	88,809	-0.79	-0.92	-0.13	309	333
40	Buena Park city	California	76,062	1.16	1.03	-0.13	33	55

The five cities with the largest decreases, and 18 of the top 40, are in California; the California cities include three very large cities—Los Angeles, San Jose, and San Francisco. Five of the 10 cities with the highest scores on this factor in 2000 were among the 40 cities with the largest decreases. Fort Lauderdale had the greatest change in rank, moving from 116th in 2000 to 196th in 2005.

4.4. Comparison of Scores in 2000 and 2005 on Factor 3

The Factor 3 scores rank cities on community needs related to limited economic prospects. Between 2000 and 2005, the average score on Factor 3 declined, indicating that conditions improved on average for cities on this dimension of need. Table 17 shows how the changes in scores for this factor varied by region and size class of cities.

Table 17. Changes in Factor 3 Scores between 2000 and 2005, by Region and Population

Region	Number of Cities	2000 Factor 3	2005 Factor 3	Difference
South	110	0.29	0.08	-0.21
West	150	0.26	0.02	-0.24
Midwest	69	0.05	-0.10	-0.14
Northeast	41	-0.07	-0.44	-0.36
Population				
1,000,000+	9	0.21	-0.08	-0.29
500,000-999,999	21	-0.16	-0.40	-0.24
300,000-499,999	23	0.09	-0.12	-0.21
200,000-299,999	37	0.22	0.03	-0.19
100,000-199,999	124	0.28	0.07	-0.21
under 100,000	156	0.17	-0.07	-0.24
All cities	370	0.19	-0.03	-0.23

On average, cities in every region and in every size class improved on this factor between 2000 and 2005. Cities in the Northeast had the lowest scores on this factor in 2000 and showed the greatest improvement between 2000 and 2005. There does not appear to be any consistent relationship between city size and either the Factor 3 scores or the changes in the Factor 3 scores.

Table 18 lists the 40 cities that had the largest increase in community needs on the limited economic prospects factor between 2000 and 2005. Only 44 of the 370 cities became worse off on this factor. For 24 of these cities, the increases in Factor 3 scores were negligible, 0.10 standard deviations or less. Carrollton, TX; Gastonia, NC; and Cedar Rapids, IA had the largest increases. These increases combined with the general pattern of decreases created some large changes in the rankings on Factor 3. Carrollton moved from 214th to 125th; Gastonia moved from 70th to 27th; and Cedar Rapids moved from 268th to 194th.

Table 18. Forty Cities with the Largest Increases in Factor 3 Scores, 2000-2005

	City	State	2005 Population	2000 Factor 3	2005 Factor 3	Difference	2000 Rank	2005 Rank
1	Carrollton city	Texas	122,699	0.12	0.42	0.30	214	125
2	Gastonia city	N Carolina	72,183	0.91	1.14	0.23	70	27
3	Cedar Rapids city	Iowa	119,670	-0.23	-0.01	0.22	268	194
4	Lawton city	Oklahoma	79,486	0.96	1.15	0.19	63	26
5	Southfield city	Michigan	75,053	0.43	0.62	0.19	162	91
6	Westminster city	California	97,946	0.71	0.88	0.17	114	48
7	Irving city	Texas	212,262	0.35	0.51	0.16	175	107
8	Arlington city	Texas	348,965	0.48	0.63	0.16	152	85
9	Mesquite city	Texas	126,895	1.47	1.62	0.15	19	5
10	Topeka city	Kansas	117,326	0.31	0.45	0.14	184	122
11	Sioux City	Iowa	78,395	0.77	0.90	0.13	101	44
12	Glendale city	California	194,620	-0.62	-0.49	0.13	312	266
13	Bloomington city	Indiana	55,406	-2.34	-2.21	0.13	366	364
14	Champaign city	Illinois	65,600	-1.62	-1.51	0.11	355	348
15	High Point city	N Carolina	101,852	0.65	0.76	0.11	122	66
16	Lorain city	Ohio	65,476	1.42	1.53	0.11	21	8
17	Cary town	N Carolina	107,446	-1.26	-1.16	0.10	344	331
18	Fayetteville city	N Carolina	128,777	0.72	0.82	0.10	111	56
19	Lakewood city	Colorado	142,434	0.05	0.14	0.09	234	173
20	Turlock city	California	74,883	1.04	1.14	0.09	50	28
21	Midland city	Texas	100,799	1.02	1.11	0.09	54	31
22	Dayton city	Ohio	132,679	0.55	0.64	0.08	141	84
23	Orlando city	Florida	221,299	-0.21	-0.13	0.07	264	220
24	Killeen city	Texas	98,434	0.62	0.69	0.07	130	76
25	Chico city	California	71,298	-0.93	-0.87	0.06	334	312
26	Gresham city	Oregon	95,334	0.45	0.50	0.05	157	110
27	Plano city	Texas	251,648	-0.72	-0.68	0.05	324	291
28	Berkeley city	California	90,432	-3.26	-3.22	0.04	370	369
29	Tempe city	Arizona	166,171	-0.64	-0.61	0.04	316	278
30	Wichita city	Kansas	354,582	0.36	0.39	0.03	174	134
31	Garland city	Texas	235,750	1.14	1.17	0.03	41	23
32	Toledo city	Ohio	285,937	1.00	1.03	0.03	57	34
33	Hemet city	California	77,076	1.34	1.37	0.03	24	13
34	Madison city	Wisconsin	203,704	-2.04	-2.02	0.02	365	362
35	Pontiac city	Michigan	59,472	1.13	1.16	0.02	42	24
36	Lubbock city	Texas	199,789	0.68	0.70	0.02	115	74
37	Aurora city	Colorado	291,317	0.37	0.40	0.02	170	133
38	Spokane city	Washington	192,777	-0.11	-0.09	0.02	254	209
39	Clearwater city	Florida	108,382	0.14	0.16	0.02	208	170
40	Cleveland city	Ohio	414,534	0.72	0.73	0.01	110	70

Table 19 lists the 40 cities that showed the greatest improvement on the limited economic prospects factor.

Table 19. Forty Cities with the Largest Decreases in Factor 3 Scores, 2000-2005

	City	State	2005 Population	2000 Factor 3	2005 Factor 3	Difference	2000 Rank	2005 Rank
1	Deerfield Beach	Florida	71,599	0.67	-0.27	-0.94	116	245
2	Davie town	Florida	88,683	0.56	-0.20	-0.76	137	228
3	Indio city	California	65,091	1.65	0.89	-0.76	12	46
4	Tustin city	California	79,811	0.31	-0.40	-0.71	185	260
5	Newark city	New Jersey	254,217	0.44	-0.24	-0.67	160	236
6	Hawthorne city	California	100,754	1.41	0.74	-0.67	22	68
7	Upland city	California	74,420	0.40	-0.27	-0.67	164	241
8	Allentown city	Pennsylvania	105,231	0.21	-0.44	-0.65	197	262
9	Worcester city	Massachusetts	154,398	-0.50	-1.14	-0.64	300	330
10	Lawrence city	Massachusetts	82,191	-0.24	-0.88	-0.64	272	314
11	Miami Beach city	Florida	84,086	-0.07	-0.70	-0.63	248	296
12	Jersey City	New Jersey	246,335	-0.49	-1.11	-0.62	298	327
13	Baltimore city	Maryland	608,481	0.20	-0.41	-0.62	200	261
14	Alhambra city	California	76,309	-0.03	-0.64	-0.61	243	284
15	Cambridge city	Massachusetts	81,260	-2.67	-3.28	-0.60	367	370
16	Cranston city	Rhode Island	77,025	0.75	0.17	-0.57	105	169
17	Miramar city	Florida	115,444	0.66	0.09	-0.57	118	182
18	Birmingham city	Alabama	222,154	0.82	0.26	-0.56	90	155
19	Fayetteville city	Arkansas	58,839	-0.89	-1.44	-0.55	329	342
20	Napa city	California	73,085	0.21	-0.33	-0.55	196	254
21	Pittsburgh city	Pennsylvania	284,366	-0.22	-0.76	-0.54	265	305
22	Carson city	California	92,156	1.56	1.02	-0.54	15	35
23	Washington city	District of Columbia	515,118	-1.74	-2.28	-0.54	359	366
24	Santa Maria city	California	88,817	1.19	0.65	-0.54	35	83
25	Camden city	New Jersey	73,305	0.77	0.23	-0.54	100	159
26	Hollywood city	Florida	138,412	0.46	-0.07	-0.53	153	202
27	Santa Fe city	New Mexico	66,453	-0.22	-0.75	-0.53	267	301
28	Fall River city	Massachusetts	97,612	1.10	0.58	-0.52	44	97
29	Suffolk city	Virginia	77,922	0.96	0.45	-0.51	62	121
30	Pleasanton city	California	67,018	-0.68	-1.19	-0.50	321	332
31	Lowell city	Massachusetts	96,876	-0.33	-0.83	-0.50	280	310
32	Portsmouth city	Virginia	95,183	0.80	0.30	-0.50	92	149
33	Bellingham city	Washington	69,057	-0.94	-1.44	-0.49	335	341
34	Livermore city	California	87,054	-0.09	-0.58	-0.49	252	275
35	Paterson city	New Jersey	148,353	0.61	0.13	-0.48	131	177
36	Baldwin Park city	California	84,812	1.99	1.50	-0.48	3	9
37	New York City	New York	7,956,113	-0.60	-1.08	-0.48	310	326
38	Savannah city	Georgia	117,478	0.49	0.01	-0.48	149	190
39	Lafayette city	Louisiana	108,175	0.39	-0.08	-0.47	167	207
40	Clovis city	California	80,529	0.85	0.38	-0.47	82	135

Deerfield Beach, FL—the city that experienced the greatest worsening of Factor 2—showed the greatest improvement on Factor 3. New York, Washington, Pittsburgh, Newark, Jersey City, and Birmingham were among the cities with the largest decreases in Factor 3 scores. There were 13 Northeastern cities on the list, nine more than would have been expected by chance.

4.5. Comparison of Scores in 2000 and 2005 on the Equal Weight Index

Table 20 shows how the changes in scores for the equal weight index varied by region and size class of cities. According to the equal weight index, conditions improved in the West, were stable in the South, and worsened in the Midwest and Northeast. Overall conditions were generally stable; if the differences in the last column were carried to three decimal places as was done in Table 10, the difference for all cities would be -.002, a very small improvement at the national level. There was no consistent pattern in the changes by city size. According to the equal weight index, conditions were stable or got better in 202 cities.

Table 20. Changes in Equal Weight Index Scores between 2000 and 2005, by Region and Population

Region	Number of Cities	2000 Equal Weight Index	2005 Equal Weight Index	Difference
South	110	-0.08	-0.07	0.00
West	150	0.04	0.01	-0.03
Midwest	69	-0.21	-0.17	0.05
Northeast	41	0.33	0.34	0.02
Population				
1,000,000+	9	0.46	0.42	-0.03
500,000-999,999	21	0.01	0.01	0.00
300,000-499,999	23	0.20	0.18	-0.02
200,000-299,999	37	0.01	0.03	0.02
100,000-199,999	124	-0.02	-0.02	0.00
under 100,000	156	-0.07	-0.07	-0.01
All cities	370	-0.01	-0.01	0.00

Table 21 lists the 40 cities that experienced the biggest worsening of conditions between 2000 and 2005. Nineteen of the 40 are cities in the Northeast and Midwest; the proportionate share of the 40 from these two regions would be 11. Dallas is the only city with 500,000 or more population. Camden, Passaic, and Lawrence, MA had high scores in 2000 and experienced big increases between 2000 and 2005. We were able to score 11 cities in North Carolina; four of them made the list of worst change in overall condition.

Table 21. Forty Cities with the Largest Increases in Equal Weight Index Scores, 2000-2005

	City	State	2005 Population	2000 EW Index	2005 EW Index	Difference	2000 Rank	2005 Rank
1	Reading city	Pennsylvania	81,302	0.93	1.34	0.40	17	6
2	Gresham city	Oregon	95,334	-0.02	0.32	0.34	169	89
3	Garland city	Texas	235,750	0.22	0.54	0.31	107	51
4	Camden city	New Jersey	73,305	1.72	2.03	0.31	2	1
5	Redwood City city	California	81,195	-0.18	0.12	0.30	228	141
6	Mesquite city	Texas	126,895	-0.02	0.28	0.29	167	101
7	Springfield city	Massachusetts	146,948	0.52	0.81	0.29	50	27
8	Dayton city	Ohio	132,679	0.35	0.64	0.28	83	38
9	Union City city	California	65,239	0.03	0.29	0.26	153	96
10	Hillsboro city	Oregon	82,732	-0.17	0.09	0.26	226	147
11	Lawrence city	Massachusetts	82,191	1.23	1.47	0.24	10	5
12	Bloomington city	Indiana	55,406	-0.90	-0.66	0.24	361	334
13	Passaic city	New Jersey	68,422	1.49	1.71	0.23	5	2
14	Cedar Rapids city	Iowa	119,670	-0.60	-0.37	0.23	332	276
15	Scranton city	Pennsylvania	67,314	-0.02	0.21	0.23	168	119
16	Hammond city	Indiana	72,507	0.36	0.57	0.21	79	47
17	Gainesville city	Florida	100,879	-0.41	-0.20	0.21	288	231
18	Palmdale city	California	145,800	0.44	0.64	0.21	61	36
19	Irving city	Texas	212,262	0.21	0.42	0.21	109	65
20	Trenton city	New Jersey	77,471	0.86	1.07	0.21	22	14
21	Bryan city	Texas	56,277	0.34	0.54	0.20	85	50
22	Cleveland city	Ohio	414,534	0.75	0.96	0.20	30	18
23	Baton Rouge city	Louisiana	205,442	0.10	0.30	0.20	135	94
24	Dallas city	Texas	1,144,946	0.60	0.80	0.20	46	28
25	Carrollton city	Texas	122,699	-0.33	-0.14	0.20	273	213
26	Aurora city	Colorado	291,317	-0.04	0.16	0.19	175	131
27	Wyoming city	Michigan	68,960	-0.09	0.10	0.19	195	142
28	West Covina city	California	116,371	0.16	0.35	0.18	118	82
29	Greensboro city	N Carolina	208,552	-0.25	-0.08	0.18	257	192
30	Gastonia city	N Carolina	72,183	0.23	0.40	0.17	106	72
31	Aurora city	Illinois	170,490	0.07	0.24	0.17	141	110
32	Arlington city	Texas	348,965	-0.11	0.06	0.17	203	153
33	Rochester city	New York	189,312	0.60	0.77	0.17	45	29
34	Champaign city	Illinois	65,600	-0.76	-0.59	0.17	347	324
35	High Point city	N Carolina	101,852	-0.01	0.16	0.16	164	130
36	Kansas City city	Kansas	142,341	0.41	0.57	0.16	68	45
37	Lawton city	Oklahoma	79,486	0.02	0.18	0.16	156	122
38	Winston-Salem	N Carolina	183,467	-0.09	0.07	0.16	199	152
39	Somerville city	Massachusetts	74,869	-0.28	-0.13	0.16	264	208
40	Brooklyn Park	Minnesota	66,408	-0.38	-0.22	0.15	281	241

Table 22 lists the 40 cities that experienced the greatest improvement in community needs between 2000 and 2005 as measured by the equal weight index.

Table 22. Forty Cities with the Largest Decreases in Equal Weight Index Scores, 2000-2005

	City	State	2005 Population	2000 EW Index	2005 EW Index	Difference	2000 Rank	2005 Rank
1	Pasadena city	California	129,400	0.07	-0.28	-0.34	143	254
2	San Marcos city	California	77,445	0.24	-0.09	-0.33	103	197
3	Alhambra city	California	76,309	0.68	0.37	-0.31	38	78
4	McKinney city	Texas	92,337	-0.38	-0.67	-0.29	282	336
5	Suffolk city	Virginia	77,922	-0.05	-0.32	-0.27	183	265
6	North Las Vegas	Nevada	165,061	0.66	0.41	-0.25	40	68
7	Santa Ana city	California	302,302	1.83	1.59	-0.24	1	3
8	Oceanside city	California	162,259	0.06	-0.18	-0.24	149	225
9	Peoria city	Illinois	102,136	-0.20	-0.43	-0.23	236	290
10	New York city	New York	7,956,113	0.55	0.33	-0.22	48	87
11	Fort Lauderdale	Florida	141,307	0.13	-0.09	-0.22	125	196
12	Miami city	Florida	361,701	0.61	0.39	-0.22	44	74
13	Redding city	California	89,362	-0.09	-0.31	-0.22	197	264
14	Santa Barbara city	California	90,708	-0.17	-0.37	-0.20	225	274
15	Baldwin Park city	California	84,812	1.52	1.32	-0.20	4	8
16	Miramar city	Florida	115,444	0.04	-0.16	-0.20	151	215
17	Wilmington city	N Carolina	91,207	-0.27	-0.47	-0.20	263	302
18	Buena Park city	California	76,062	0.40	0.21	-0.19	70	118
19	Hawthorne city	California	100,754	1.16	0.97	-0.19	12	16
20	Columbia city	S Carolina	88,450	-0.12	-0.31	-0.19	209	263
21	Los Angeles city	California	3,731,437	0.87	0.69	-0.19	20	33
22	Glendale city	California	194,620	0.43	0.25	-0.18	63	109
23	Tustin city	California	79,811	0.06	-0.13	-0.18	150	209
24	Indio city	California	65,091	1.26	1.09	-0.18	7	13
25	Miami Beach city	Florida	84,086	1.65	1.47	-0.18	3	4
26	Santa Monica city	California	82,777	-0.74	-0.91	-0.18	344	362
27	Long Beach city	California	463,956	0.62	0.45	-0.17	43	62
28	Pomona city	California	161,257	1.26	1.09	-0.17	8	12
29	Alexandria city	Virginia	133,479	-0.54	-0.72	-0.17	321	342
30	Burbank city	California	100,053	-0.08	-0.25	-0.17	192	245
31	Asheville city	N Carolina	74,889	-0.32	-0.49	-0.17	270	305
32	Stockton city	California	278,515	0.78	0.61	-0.17	28	42
33	Fayetteville city	Arkansas	58,839	-0.54	-0.71	-0.17	320	341
34	Roanoke city	Virginia	90,074	0.12	-0.05	-0.16	129	183
35	Carson city	California	92,156	0.42	0.26	-0.16	67	106
36	Des Moines city	Iowa	196,917	-0.14	-0.30	-0.16	220	260
37	Cambridge city	Massachusetts	81,260	-0.72	-0.88	-0.16	341	357
38	Newark city	New Jersey	254,217	1.30	1.15	-0.16	6	10
39	Fullerton city	California	142,064	0.00	-0.16	-0.16	162	218
40	Evanston city	Illinois	62,258	-0.94	-1.10	-0.16	364	368

The two largest cities, New York and Los Angeles, were among the biggest improvers. Consistent with the improvement in the West region, 21 of the 40 are California cities—11 more than would have been expected by chance. Among the biggest improvers were cities that, in 2000, had been ranked number 1 in community needs (Santa Ana); number 3 (Miami Beach); number 4 (Baldwin Park, CA); number 6 (Newark); number 7 (Indio, CA); and number 8 (Pomona, CA).

4.6. Summary

Factor analysis has allowed us to represent 24 needs indicators by three dimension of need: poverty and structural problems, immigration and housing affordability, and limited economic prospects. This chapter successfully applied factor analysis to compare conditions in 370 cities in 2000 and 2005 on each of the dimensions of needs and an equal weight index of community needs.

While the equal weight index offers a reliable summary statistic on community needs, the analysis in this chapter shows that considering the individual factors separately paints a fuller picture of what is happening in American cities. The factor-by-factor analysis revealed the following:

- Between 2000 and 2005, cities on average became worse off with respect to poverty and structural problems and with respect to immigration and housing affordability problems but became better off with respect to the limited economics prospects factor.

- Regional differences appeared on the individual factors.

    - The Northeast has the highest average scores on the poverty and structural problems factor in both 2000 and 2005 and the largest increase in average scores between the two years. The West region has the lowest average scores on this factor in both years and the smallest increase between the two years.

    - For the immigration and housing affordability factor, the average scores of cities in the Northeast and West were higher than the national average in both 2000 and 2005. Cities in the Northeast had the highest average change between 2000 and 2005.

    - Cities in the Northeast had the lowest scores on the limited economic prospects factor in 2000 and showed the greatest improvement between 2000 and 2005.

- Differences by class size of cities were less common.

    - There appears to be a systematic relationship between the scores on the poverty and structural problems factor and city size. The average score declines by size class in both 2000 and 2005. The change in scores is approximately the same for all the size classes, except for cities with populations between 500,000 and one million, which have a slight higher increase in average scores.

    - With the exception of cities with over a million residents, there appears to be little relationship between population size and the prevalence of problems related to immigration and housing affordability. The largest cities had an average score of 0.70 or more in both 2000 and 2005; the national average was 0.00 in 2005.

- There were also some interesting patterns in the lists of cities with the biggest increase in scores (becoming worse off) and the lists of cities with the biggest decreases in scores (becoming better off).

    - Some of the worse off cities on the poverty and structural problems factor experienced big increases on this factor between 2000 and 2005; the cities were Camden, Detroit, Cleveland, Rochester, Reading, and Syracuse.

    - Compared with the other states, California has the most cities—95—among the 370 scored. Still, California cities appeared in higher than expected proportions on the lists of the 40 biggest losers and gainers. One would expect, proportionally, 10 cities from California on each list, yet:

        - Twenty-four of the 40 cities with the biggest improvements on the poverty and structural problems factor were California cities.
        - Fifteen of the 40 cities with the worse changes on the immigration and housing affordability factor were California cities.
        - The five cities with the largest improvements on the immigration and housing affordability factor, and 18 of the top 40 were California cities.

The equal weight index showed that, on average, community needs decreased slightly between 2000 and 2005. According to the index, conditions were stable or got better in 202 cities. However, the chapter notes that the observed improvement appears to be related strongly to the substantial increase in the proportion of adults with a high school diploma between 2000 and 2005, a fact that was questioned in Section 2.3.2.

This page left blank intentionally.

5. Measuring Fiscal Capacity

The federal government, in general, and HUD in particular, are interested in developing an index of community needs because they want to know the extent to which communities require federal assistance. But a needs index answers only one-half of this question; the federal government also needs to know the extent to which communities are capable of dealing with their problems without federal assistance.

At the Orientation Meeting for this project on October 12, 2006, the question was raised as to whether the project should attempt to construct a measure of fiscal capacity so that needs and capacity could be looked at jointly. Opinions differed. Those opposed to looking at capacity argued that needs are independent of the capacity of the local government to address those needs. In general, those present seemed to favor developing a parallel measure of capacity, because federal aid must take both needs and capacity into account. For this reason, we attempted to create a measure of capacity and to combine the needs and capacity measures to achieve an integrated view of local conditions.[35]

This chapter explores the issues involved in estimating capacity, develops a methodology to measure capacity, implements the methodology, and then explores how to combine a measure of need with a measure of capacity. The capacity measure developed is a significant advancement in assessing need at the city level. It allows one to look at cities from two different perspectives—needs and capacity. While the work on combining the needs and capacity measures is only exploratory, the results are reasonable and provide the first comprehensive assessment of the relative need for federal assistance.

Section 5.1 describes the methodology we used to construct a measure of fiscal capacity. Section 5.2 lists the variables we used to compute fiscal capacity and how we calculated the weights applied to those variables. Section 5.3 reports the results of implementing the measure of fiscal capacity. Section 5.4 explores how to combine a measure of fiscal capacity with an index of community needs. Section 5.5 reports the results from combining the equal weight index developed in Chapter 3 with the fiscal capacity measure developed in this chapter. Section 5.6 provides a brief summary.

5.1. General Approach

We interpret capacity as "access to resources." This approach equates capacity with the ability to raise money through taxation—that is, we are concerned with the fiscal capacity of cities. We measure fiscal capacity, independent of competence. If a city has an ineffective government but the same access to resources as another city with an effective government, then, in our opinion, the two cities should be considered to have equal capacity. We take this perspective based on the premise that achieving effective

[35] The GAO has indicated that it intends to look at capacity in its study of community needs and the CDBG formula.

government at the local level is the responsibility of citizens at the local level and not the responsibility of the federal government.

A similar logic guides us to focus on the ability to raise money for community needs rather than actual performance in raising money or using funds for community needs. How much to tax and how to spend tax revenue are matters of choice. A measure of fiscal capacity should be independent of choice. This orientation affects how we measure fiscal capacity and the data sources we use.

The Census of Governments collects extensive information on expenditures by class and on tax revenue by source, for units of government ranging from states to special districts. Unfortunately, we cannot use this information directly, because those data record the choices made by cities rather than the capacity of cities. Cities may differ in terms of what they spend on parks and recreation or how much they collect from property taxes, either because they differ in the capacity to raise revenue and address local needs or because they choose to tax and spend differently. For this reason, we chose to estimate what cities could raise through taxes, rather than what they do raise.

This approach requires us to estimate various tax bases separately, such as income, sales, and property values, and to find a way to aggregate these bases. Income is a flow, while property values are a stock, and for this reason they are taxed differently. Adding personal income to the value of all property would not be a useful measure of fiscal capacity. The methodological problem is to find a set of weights to combine different tax bases; the weights should be chosen so as to represent the potential to raise taxes from each of the bases. We selected average tax rates as weights because they represent actual experience in translating taxable potential into tax revenue.[36]

The choice of average tax rates raises two questions. First, the use of average rates may bias the measure toward current practice instead of what could be achieved if cities taxed to maximum capacity. The goal is not to create a measure of maximum potential tax revenue; instead the goal is create a measure that treats each city fairly in portraying its fiscal capacity. Actual practice seems to be the best way to achieve this fairness.

Second, since state laws prohibit some cities from taxing certain bases, is it fair to use average rates when the actual tax rate applicable in a particular city may be zero? We do not consider this a major limitation. First, states could eliminate any restrictions on what can be taxed. The rationale behind creating a capacity measure is that the federal government should not respond to a problem if the local government has the capacity to solve the problem. Failure of a state to provide jurisdictions with the tools needed to deal with their problems should not be a reason for federal support. Second, if a jurisdiction cannot tax one source, it can increase the rate at which it taxes other sources. The real

[36] Table 23 shows how we computed the average tax rates and applied them to estimates of income, value, or sales as appropriate. In general, we used information from the 2002 Census of Government on revenue raised by various taxes as the numerator for the average tax rates, and estimates of the taxable source in 2002 from other data sets. For property taxes, we used information in the 2001 Residential Finance Survey to estimate the average tax rate.

limit on the ability to raise taxes is the willingness of voting taxpayers to be taxed. The willingness or ability of taxpayers to bear taxes should depend more on how much is raised than on how the taxes are collected.

A final concern is the difference in the cost of providing services across cities. Cities with the same taxing capacity may not be able to provide the same level of services because it costs more in one city to provide services than it does in the other city. We solve this problem by dividing the dollar measure of capacity by the average wage of all government employees in the core-based statistical area in which the city is located.

5.2. Variables Used to Measure Fiscal Capacity

Table 23 explains how we constructed the dollar measure of capacity.

- Variables 2 through 6 are our estimates of the various tax bases potentially available to cities, each weighted by an estimate of the applicable average tax rate.

- Variable 1 sums variables 2 through 6 and puts the combined taxing capacity on a per capita basis; it is our estimate of the capacity that cities have available from their own resources.

- Variable 7 is our estimate of what cities can expect in funding from states.

- Variable 8 is our estimate of fiscal capacity in dollar terms. It sums the capacity available to cities from their own resources (variable 1) and the capacity available to them from their respective states (variable 7).

- Variable 9 is per capita income. We compare our estimate with an estimate based strictly on per capita income.

- Variable 10 is our government wage variable.[37]

- Variable 11 is our estimate of real capacity; it is variable 8 divided by variable 10.

A HUD reviewer pointed out that the use of local government wages as a cost-of-services deflator may create a bias, because cities differ in how they contract out services. If one city contracts out services that employ low-wage workers, its wage rate may be higher than an identical city that provides those services directly. We acknowledge that this is a potential bias, but we believe it is minimized by our use of local wage data at the level of

[37] A HUD reviewer suggested using the federal locality pay tables instead of the BLS data on government wages. We think that it would be complicated trying to adjust the federal tables for the local mix of white collar and blue collar workers. The BLS data cover all local employees.

Core-Based Statistical Areas (CBSA).[38] Contracting patterns will vary across the CBSA, and there should be some averaging-out of practices. Another HUD reviewer noted that we use 2005 population to transform our estimates of capacity into per capita estimates while some of our data are from 2002. Measures 2, 3, 4, and 7 use 2005 data; measures 5 and 6 use 2002 data.[39] We think 2005 population is probably the best choice for this mix.

[38] CBSAs are defined by OMB using criteria that make CBSAs coterminous with local labor markets, and therefore all governments in a CBSA should face the same wage scale.

[39] The weights we apply to measures 2, 3, 4, and 7 are based on data from 2001 and 2002, but the numbers that vary across cities are from 2005.

Table 23. Variables Used to Measure Fiscal Capacity

	Variable	Short-Name	Definition
1	LOCAL FISCAL CAPACITY	LOCFISCAP	Sum variables 2 through 6 and divide the sum by city population
2	INCOME TAX CAPACITY	INCTAXCAP	Aggregate household income multiplied by the ratio of local income taxes from 2002 Census of Governments to national household income from 2002 ($17,185,681,000/$6,142,192,043,242 = 0.003)
3	RESIDENTIAL PROPERTY TAX CAPACITY (owner-occupied)	OWNPROPTAXCAP	Aggregate property value multiplied by ratio of real estates paid to owner-occupied housing value from 2001 Residential Finance Survey (RFS) (0.01).
4	RESIDENTIAL PROPERTY TAX CAPACITY (rental)	RENTPROPTAXCAP	Aggregate contract rent multiplied by ratio of net operating income to rent income from 2001 RFS divided by national cap rate (from Goodman[40]) multiplied by ratio of real estates paid to rental housing value from 2001 Residential Finance Survey. We do this estimate separate for central cities and non-central cities because found that cap rates vary between central cities and suburbs. For central cities: (Estimate aggregate contract rent)*95*0.01 For non-central cities: (Estimate aggregate contract rent)*125*0.01
5	SALES TAX CAPACITY	SALESTAXCAP	Retail sales in 2002 from the Economic Census multiplied by ratio of local revenue from the sum of the general sale taxes and selective sales taxes in all localities from the 2002 Census of Governments to total retail sales in 2002 from Census of Economic Census ($61,761,893,000/$3,056,421,997,000 = 0.02)
6	BUSINESS TAX CAPACITY (includes payroll taxes, business property taxes, and corporate income taxes)	BUSTAXCAP	Aggregate payrolls for the 12 sectors for which the 2002 Economic Census provides place data times 0.05. 0.05 was derived by estimating commercial real estate taxes, local corporate taxes, and proportion of local income taxes attributed to non-residents working in city; summing these items; and taking the ratio of this sum to the US total of payrolls from the 12 sectors.
7	STATE CAPACITY TO ASSIST JURISDICTION	STATECAP	Aggregate state income times (the ratio of state aid to local governments to total state revenue from all sources) times (the ratio of total state revenue from all sources to aggregate state income) times (the ratio of city population to the sum of the populations of all cities in our list in that state) divided by (city population). (Aggregate state income times 0.007 divided by the sum of the populations of all cities in our list in that state.) Note that this provides a per capita amount conceptually available to all cities.
8	TOTAL FISCAL CAPACITY	TOTFISCAP	Sum of variables 1 and 7
9	PER CAPITA INCOME	PERCAPINC	City per capita income
10	AVERAGE GOVERNMENT WAGES	CBSAGOVWAGE	The average wage rate of local government employees measured at the CBSA level using 2004 Bureau of Labor Statistics data.
11	REAL FISCAL CAPACITY	REALFISCAP	Variable 8 divided by variable 10.

[40] *Issues in Housing Finance: An Analysis of Data from the 2001 Residential Finance Survey*, Chapter 11: Estimating Capitalization Rates for Multifamily Rental Properties with the 2001 Residential Finance Survey, a report submitted by Econometrica, Inc. to HUD, October 30, 2006.

We can estimate state funding for all our cities and have data on wages for all but five cities. We were able to estimate variables 2 through 6 for 266 of the 473 cities, and therefore could estimate real fiscal capacity only for these 266 cities. The next section contains our findings. First, however, we note that the correlation of per capita income with the revenue that a city itself can raise (variable 1) is 0.78. If one wanted to create estimates of real fiscal capacity for other cities, one could do so by using per capita income and other relevant variables to model variable 1.

Second, we also note that adjusting capacity for the cost of providing services eliminates the need to adjust needs for differences in costs of living across jurisdictions. This does not apply to the counts of poor persons, but does apply to dealing with the needs of citizens, including poor persons.

5.3. Variations in Fiscal Capacity

Deflating total fiscal capacity by average local government wages translates a dollar measure of capacity into a measure of the fraction of a year that a city could apply to a local government worker's time on a per capita basis to the needs of its citizens. Across the 266 cities for which we have data, this measure ranges between 0.026 in Laredo, TX to 0.136 in Charleston, SC. The mean is 0.059 with a standard deviation of 0.018, and the median is 0.057. This measure implies that, on average, cities should be able to devote the equivalent of 6 percent of a year's work from the typical city employee to solving the needs of a specific citizen. We say "equivalent," because a city will devote some of its revenue to purchases of goods and services other than labor, for example, interest on bonds, rent on buildings, and supplies. Since our estimate sums several different sources of tax revenue, it probably overestimates the amount available on average since most cities do not use all the sources. This is not a problem because the index does not try to measure absolute capacity—only relative capacity.

To provide some impression of how the fiscal capacity measure performs, we produced three tables. Table 24 lists the 25 cities with the highest fiscal capacity scores based on the sum of real own resources and state resources per capita; Table 25 lists the 25 cities with the lowest fiscal capacity scores, and Table 26 shows how this measure varies across the 25 largest cities for which we have sufficient data to estimate capacity.[41]

Tables 24 and 25 show how the presence or absence of resources (income and wealth) and the costs of providing services interact to determine rank on this measure. Table 24 contains both cities with high per capita income and cities with low government wages. Eight of the 25 cities in Table 24 (Santa Monica, Scottsdale, Cambridge, Bellevue, Santa Barbara, Santa Fe, Atlanta, and Boulder) are among the 25 with the highest per capita income among the 266 cities for which we have data. At the same time, four of the 25 (Fort Smith, Boise, Salt Lake City, and North Charleston) are among the 25 with the

[41] Since we have data on both needs and real capacity for only 266 cities, many of the cities discussed in Chapter 4 do not appear in this analysis. This includes some cities with very high need scores such as Camden and Trenton.

lowest annual wages for government employees based on data at the metropolitan-area level.

Table 25 contains both cities with low per capita income and cities with high government wages. Nine of the 25 cities in Table 25 (Brownsville, Laredo, Hialeah, Gary, San Bernardino, Pomona, Inglewood, and Flint) are among the 25 with the lowest per capita income among the 266 cities for which we have data. At the same time, two of the 25 (Mount Vernon and Yonkers) are among the 25 with the highest annual wages for government employees based on data at the metropolitan-area level. Brownsville is an interesting case; it has the lowest per capita income of any of the 25 cities and the eighteenth lowest annual government wages. Despite low government wages, Brownsville ranks as the city with the third lowest real fiscal capacity.

Table 24. Twenty-five Cities with Greatest Real Fiscal Capacity

	City	State	Population	Real Own + State Resources Per Cap
1	Charleston city	South Carolina	109,151	0.136
2	North Charleston city	South Carolina	70,001	0.121
3	Cambridge city	Massachusetts	81,260	0.116
4	Bloomington city	Minnesota	80,055	0.106
5	Boulder city	Colorado	83,432	0.105
6	Santa Monica city	California	82,777	0.104
7	Atlanta city	Georgia	394,929	0.101
8	Bellevue city	Washington	114,748	0.100
9	Nashua city	New Hampshire	84,632	0.099
10	Fort Smith city	Arkansas	81,054	0.096
11	Little Rock city	Arkansas	176,924	0.095
12	Asheville city	North Carolina	74,889	0.092
13	Billings city	Montana	92,844	0.092
14	Fargo city	North Dakota	88,809	0.090
15	Salt Lake City	Utah	182,670	0.089
16	West Palm Beach city	Florida	86,804	0.089
17	Fort Lauderdale city	Florida	141,307	0.088
18	Scottsdale city	Arizona	215,933	0.087
19	St. Cloud city	Minnesota	59,624	0.086
20	Santa Barbara city	California	90,708	0.085
21	Santa Fe city	New Mexico	66,453	0.085
22	Norwalk city	Connecticut	86,354	0.085
23	Boston city	Massachusetts	520,702	0.085
24	Boise City	Idaho	191,667	0.085
25	Manchester city	New Hampshire	109,308	0.085

Table 25. Twenty-five Cities with the Least Real Fiscal Capacity

	City	State	Population	Real Own + State Resources Per Cap
1	Laredo city	Texas	207,787	0.026
2	Inglewood city	California	120,204	0.028
3	Brownsville city	Texas	171,528	0.028
4	Pomona city	California	161,257	0.030
5	Pasadena city	Texas	150,180	0.032
6	Mount Vernon city	New York	65,354	0.032
7	Garland city	Texas	235,750	0.032
8	San Bernardino city	California	204,552	0.033
9	Gary city	Indiana	97,057	0.033
10	Hemet city	California	77,076	0.033
11	El Paso city	Texas	583,419	0.034
12	Detroit city	Michigan	836,056	0.034
13	Garden Grove city	California	192,345	0.034
14	Glendale city	Arizona	229,913	0.035
15	Mesquite city	Texas	126,895	0.035
16	Kansas City	Kansas	142,341	0.035
17	Hialeah city	Florida	213,791	0.035
18	Stockton city	California	278,515	0.036
19	Flint city	Michigan	111,948	0.036
20	Peoria city	Arizona	141,941	0.036
21	Fresno city	California	477,251	0.037
22	Long Beach city	California	463,956	0.037
23	Mesa city	Arizona	442,445	0.037
24	Yonkers city	New York	193,327	0.037
25	Arlington city	Texas	348,965	0.037

Table 26. Real Fiscal Capacity for 25 Largest Cities with Data

	City	State	Population	Real Own + State Resources Per Cap
1	New York city	New York	7,956,113	0.041
2	Los Angeles city	California	3,731,437	0.043
3	Chicago city	Illinois	2,701,926	0.049
4	Houston city	Texas	1,941,430	0.053
5	Philadelphia city	Pennsylvania	1,406,415	0.047
6	Phoenix city	Arizona	1,377,980	0.043
7	San Diego city	California	1,208,331	0.065
8	San Antonio city	Texas	1,202,223	0.038
9	Dallas city	Texas	1,144,946	0.056
10	San Jose city	California	887,330	0.051
11	Detroit city	Michigan	836,056	0.034
12	Jacksonville city	Florida	768,537	0.050
13	Indianapolis (balance)	Indiana	765,310	0.064
14	San Francisco city	California	719,077	0.064
15	Columbus city	Ohio	693,983	0.057
16	Austin city	Texas	678,457	0.059
17	Memphis city	Tennessee	642,251	0.049
18	Baltimore city	Maryland	608,481	0.066
19	Fort Worth city	Texas	604,538	0.041
20	Charlotte city	North Carolina	601,598	0.066
21	El Paso city	Texas	583,419	0.034
22	Milwaukee city	Wisconsin	556,948	0.048
23	Denver city	Colorado	545,198	0.066
24	Las Vegas city	Nevada	538,653	0.040
25	Seattle city	Washington	536,946	0.082

In the 25 largest cities, local governments can devote between 0.03 to 0.08 percent of a city government employee's time to the needs of each resident. The largest cities tend to have lower fiscal capacity, 17 of the 25 largest have a fiscal capacity score below the average of 0.059.

5.4. Combining Need and Fiscal Capacity

5.4.1. Background

The primary reason for developing a measure of real fiscal capacity was to complete the picture of city need for federal community development assistance. It was felt that the need for federal help depends both on community needs and the resources available at the community level to deal with those needs. However, an important question remains: How does one combine information on community needs and real fiscal capacity to obtain an accurate assessment of need? Our aims in this section are modest. We discuss some ideas we have about combining the needs and real fiscal capacity measures and explore one simple way to combine them.

We experiment with combining our estimate of city needs from Chapter 3 with the estimate of the capacity of cities to deal with their needs from this chapter. There are 234 cities for which we have both an equal weight index score and an estimate of real fiscal capacity.

5.4.2. Simple Options for Combining the Measures

In Chapter 4, we looked at city needs in two different ways: we looked at conditions measure by each of the three factors from the factor analysis in Chapter 3, and then we combined the factor scores into a single-valued index of need using several different weighing options. At this stage, we have to choose a single-valued needs index because it would be meaningless to combine the real fiscal capacity measure with the individual factors ("meaningless" in the sense that we would still be missing parts of the puzzle—namely, needs measured by the omitted factors). For the purposes of this work, we will use the equal weight index because it is the simplest. Any of the other options could have been combined with the real fiscal capacity measure in the manner described below.

Our first thoughts involved taking a ratio of needs to capacity as measured by the two indices. The attraction of this approach was the possibility of making statements—such as a city's needs exceed its capacity by 10 percent. However, the ratio approach, and all approaches involving a multiplicative joining of the indices, falters because the two measures have both positive and negative values. There is no way to combine series with positive and negative values in a multiplicative way and obtain consistent results.

We define a positive needs score as meaning a city has above-average community needs and a positive capacity score as meaning a city has above-average real fiscal capacity. Negative scores mean being below average on both of the component indices. Using these conventions, the following table shows how the various possibilities combine to produce either positive or negative ratios.

Sign of the ratio of indices	Above average needs	Below average needs
Above average fiscal capacity	Positive	Negative
Below average fiscal capacity	Negative	Positive

In this table, the best possible situation (having below-average needs and above-average capacity) has the same sign as the worst possible situation (having above-average needs and below-average capacity). This result is not desirable.

One could try to avoid this problem by redefining the real fiscal capacity index so that having above-average capacity results in a negative score and having below-average capacity results in a positive score. If one does this, then the previous table becomes:

Sign of the ratio of indices	Above average needs	Below average needs
Above average fiscal capacity	Negative	Positive
Below average fiscal capacity	Positive	Negative

Now the best possible situation and the worst possible situation both produce positive ratios. Again, this is not a desirable result.

The next simplest approach was an additive approach. We standardized both the scores from the equal weight index and our estimates of real fiscal capacity. After standardization, a need score of +1.00 indicates that the needs of a city are one standard deviation above the needs of the average city, while a real fiscal capacity score of +1.00 means that a city's capacity to meet the needs of its citizens is one standard deviation above the average city. We subtract the standardized capacity score from the standard needs score, so that a city with needs of +1.00 and capacity of +1.00 would have a combined score of 0.00. Both the needs score and the capacity score refer to 2005.

The following table characterizes the results of combining the indices using this approach.

Sign from the subtraction of indices	Above average needs	Below average needs
Above average fiscal capacity	Uncertain	Negative
Below average fiscal capacity	Positive	Uncertain

Now the best possible situation (below-average needs and above-average capacity) has a negative sign, while the worst possible situation (above-average needs and below-average capacity) has a positive sign. The signs of the other two alternatives depend on the magnitude of the indices involved in the subtraction. If needs are above average by more than capacity is above average, the score will be positive. If needs are below average by less than fiscal capacity is below average, the score will also be positive. While the technique of subtracting the real fiscal capacity index from the community needs index is simple, it does produce a consistent ranking of cities.[42]

The scores produced by subtracting the index of real fiscal capacity from the index of community needs only rank cities by relative need; they do not indicate whether an individual city needs federal assistance and, if so, how much. Consider the situation of a city with a community needs score of 1.00 and a real fiscal capacity score of 1.00; the combined index produces a score of 0.00. This score tells us nothing about the absolute need for federal assistance; it does tell us only that the city needs assistance more than cities with negative scores and less than cities with positive scores.

[42] This approach assumes an implicit equivalence between the standard deviations of needs and real capacity; in other words, it assumes that being one standard deviation away from the average has the same implications for the two indices. A city with average needs but real capacity one standard deviation below average will have a score of 1.00; a city with average needs one standard deviation above average but with average real capacity will also have a score of 1.00. This approach presumes that these two scores indicate the same level of need from the federal government.

By standardizing the two components before combining them, we produce an index where 0.00 is the average value. Does a city where needs and capacity balance need assistance? On average, are cities able to deal with their problems or on average do they need assistance? None of the analysis in this chapter or anywhere in this report is capable of answering these questions.   This is perhaps the fundamental issue of fiscal federalism.

5.5. An Index of Needs Adjusted for Capacity

Combining the two indices produces an index of community needs adjusted for real fiscal capacity. As explained in Section 5.4.2, we calculate it, first, by standardizing both the equal weight index of community needs and the index of real fiscal capacity across the 234 cities for which we have data and then by subtracting the index of real fiscal capacity from the equal weight index of community needs.   For simplicity, we call the resulting index, the adjusted needs index. Table A.10 in Appendix A reports the score on the adjusted needs index for all 234 cities.

The adjusted needs index has a mean of 0.00 and a standard deviation of 1.76.   Positive values indicate adjusted needs higher than average, and negative values indicate adjusted needs lower than average. Adjusted needs ranges from 4.29 (Santa Ana, TX) to -5.28 (Charleston, SC). The range is large (9.57), and the standard deviation is large relative to the standard deviations of the component indices because there is moderately strong negative correlation between community needs and fiscal capacity. The correlation between the two component indices is -0.55. In general, the greater the needs of a city, the less real fiscal capacity the city has. This is an important finding.

From the 234 cities for which we have data on both needs and capacity with the highest index of community needs, Table 27 takes the 50 cities with the highest scores on the equal weight index of community needs and shows how taking fiscal capacity into account would affect their ranking. Because of the negative correlation between the two component indices, adjusting needs for capacity does not produce large changes in the rankings of these cities. Only nine of the cities ranked among the top 50 on community needs have a rank lower than 50 on the combined index; these are Dayton (25 to 52), Birmingham (34 to 98), Lynn (36 to 53), Irving (43 to 115), Waco (44 to 69), Jersey City (45 to 57), Miami Beach (46 to 81), Memphis (48 to 62), and Escondido (50 to 65).

Table 27. Impact of Combining Needs and Fiscal Capacity for 50 Cities with the Highest Community Needs

Equal Weight Index Rank	City	State	Population	Equal Weight Index	Real Fiscal Capacity	Adjusted Needs Index	Adjusted Needs Index Rank
1	Passaic city	New Jersey	68,422	3.28	-0.959	4.24	2
2	Santa Ana city	California	302,302	3.04	-1.245	4.29	1
3	Miami city	Florida	361,701	2.82	-0.116	2.93	13
4	Lawrence city	Massachusetts	82,191	2.81	-1.011	3.82	3
5	Reading city	Pennsylvania	81,302	2.55	-0.277	2.83	15
6	Salinas city	California	156,950	2.52	-1.239	3.76	4
7	Paterson city	New Jersey	148,353	2.29	-0.984	3.28	10
8	Newark city	New Jersey	254,217	2.18	-0.704	2.89	14
9	San Bernardino	California	204,552	2.12	-1.531	3.65	6
10	Pomona city	California	161,257	2.07	-1.692	3.76	5
11	Detroit city	Michigan	836,056	1.89	-1.460	3.34	9
12	Elizabeth city	New Jersey	121,137	1.84	-0.726	2.56	16
13	Cleveland city	Ohio	414,534	1.81	-0.394	2.21	24
14	Inglewood city	California	120,204	1.81	-1.809	3.62	7
15	Oxnard city	California	178,871	1.81	-1.127	2.93	12
16	Pasadena city	Texas	150,180	1.79	-1.564	3.36	8
17	Garden Grove	California	192,345	1.58	-1.437	3.01	11
18	Ontario city	California	156,679	1.55	-0.729	2.28	21
19	Houston city	Texas	1,941,430	1.54	-0.365	1.91	29
20	Springfield city	Massachusetts	146,948	1.52	-0.407	1.93	28
21	Dallas city	Texas	1,144,946	1.51	-0.237	1.74	35
22	Rochester city	New York	189,312	1.46	-0.278	1.74	37
23	Yakima city	Washington	79,517	1.37	-0.317	1.69	40
24	Los Angeles city	California	3,731,437	1.29	-0.961	2.25	22
25	Dayton city	Ohio	132,679	1.20	-0.240	1.44	52
26	Anaheim city	California	329,483	1.17	-0.930	2.10	26
27	Stockton city	California	278,515	1.13	-1.342	2.48	19
28	New Bedford	Massachusetts	84,898	1.12	-0.782	1.90	30
29	Kansas City	Kansas	142,341	1.07	-1.383	2.45	20
30	Hemet city	California	77,076	1.06	-1.488	2.55	17
31	Providence city	Rhode Island	160,264	1.04	-0.831	1.87	32
32	Buffalo city	New York	256,492	1.03	-1.178	2.21	23
33	Garland city	Texas	235,750	1.00	-1.548	2.55	18
34	Birmingham city	Alabama	222,154	1.00	0.706	0.29	98
35	Fall River city	Massachusetts	97,612	0.95	-0.783	1.74	36
36	Lynn city	Massachusetts	83,419	0.90	-0.512	1.41	53
37	Pawtucket city	Rhode Island	72,896	0.86	-1.119	1.98	27
38	Milwaukee city	Wisconsin	556,948	0.86	-0.637	1.49	50
39	Lowell city	Massachusetts	96,876	0.85	-0.699	1.54	47
40	Philadelphia city	Pennsylvania	1,406,415	0.83	-0.744	1.58	44
41	Long Beach city	California	463,956	0.83	-1.294	2.12	25
42	Syracuse city	New York	132,495	0.82	-0.563	1.39	55

Table 27. Impact of Combining Needs and Fiscal Capacity for 50 Cities with the Highest Community Needs (continued)

Equal Weight Index Rank	City	State	Population	Equal Weight Index	Real Fiscal Capacity	Adjusted Needs Index	Adjusted Needs Index Rank
43	Irving city	Texas	212,262	0.77	0.871	-0.10	115
44	Waco city	Texas	107,146	0.75	-0.405	1.15	69
45	Jersey City	New Jersey	246,335	0.74	-0.625	1.36	57
46	Miami Beach	Florida	84,086	0.72	0.108	0.61	81
47	Oakland city	California	373,910	0.72	-0.990	1.71	39
48	Memphis city	Tennessee	642,251	0.71	-0.583	1.29	62
49	Fort Worth city	Texas	604,538	0.68	-1.048	1.73	38
50	Escondido city	California	133,017	0.67	-0.567	1.24	65

Looking at all 266 cities, some of the changes in ranking are substantial. West Palm Beach is ranked 65th on the equal weight index but 182nd on the adjusted needs index; Atlanta is ranked 95th on the equal weight index but 211th on the adjusted needs index. Other cities benefit substantially by the adjustment for fiscal needs. Peoria is ranked 190th on the equal weight index but 89th on the adjusted needs index; Henderson, NV is ranked 208th on the equal weight index but 108th on the adjusted needs index.

5.6. Summary

This chapter explains why it is important to construct an index of fiscal capacity, develops a methodology to construct such an index, finds data to implement the index, and suggests a reasonable approach for combining information on community needs and real fiscal capacity to obtain an index of community needs adjusted for real fiscal capacity.

The most important findings from the chapter are:

- It is possible to construct an index of real fiscal capacity.
- The index used is sensitive to both income and wage rates. Places with high income or lower government wages are more likely to have high scores on the index—that is, to have better-than-average fiscal capacity.
- The index is negatively correlated with the equal weight index of community needs. Cities with high community needs are more likely to have low real fiscal capacity.
- It is possible to combine a needs index and a fiscal capacity. The adjusted needs index developed in this chapter produced different rankings than the equal weight index of community needs. But, in general, the change in rankings was not great, probably because of the negative correlation between the two component indices.

6. Implications

This chapter discusses the implications of this research for future analysis in areas of operational interest to HUD. The topics covered in successive sections are:

1. Feasibility of using ACS data to monitor community needs at the city and county levels.

2. Feasibility of constructing a single-valued index of community needs.

3. Feasibility of comparing community needs at different points in time.

4. Feasibility of extending the factor analysis developed in this report to different geographies when the ACS releases data for smaller places.

5. Feasibility of constructing a measure of neighborhood improvement to implement the Administration proposal to reward communities for successful community developments efforts.

6. Feasibility of measuring fiscal capacity.

7. The relevance of boundary changes and cost-of-living differences to an analysis of community needs.

The last section identifies areas where more work needs to be done to improve HUD's ability to monitor community needs.

6.1. ACS Data and Community Needs

In previous studies, researchers at HUD used data from the long form of the decennial census and other sources to identify and measure community needs. The Census Bureau has replaced the long form with the American Community Survey, a monthly survey of 250,000 households that reports data using 5-year moving averages for all levels of geography, using 3-year moving averages for places with 20,000 or more persons, and using annual data for places with 65,000 or more persons. One objective of this research was to test whether the ACS data would support the same type of analysis that HUD had conducted using long-form data.

The answer to this question is "yes." In the future, HUD can depend on the ACS to monitor conditions in cities and counties. The report successfully uses ACS data to construct useful measures of community needs using factor analysis. Of the 24 needs indicators used in the final factor analysis, 16 used ACS data, one (POORPERS) used ACS data combined with long-form data, and four used long-form data. All five indicators that either used long-form data or a combination of ACS and long-form data should be available in the future from the ACS.

The study did not use as a needs indicator the proportion of persons with a disability that limits employment. This variable is reported by both the ACS and the long form, but a change in the way the Census Bureau collects this information created an artificial shift in the published results. HUD should be able to use this variable as a need indicator in future analyses.

There are some issues and open questions that HUD will have to keep in mind in future work using the ACS:

- The reporting rules used in the ACS are similar to those used for the long form of the decennial census; but because the ACS sample size is smaller, the rules can result in more frequent suppression of data. Data on overcrowded housing was missing for so many places in the 2005 ACS data that we substituted 2000 long-form data for this need indicator. We also had to drop 36 cities from the analysis because the ACS suppressed data on the number of minorities in the cities. HUD should be able to work around suppression of data at the city or county level by using 3-year or 5-year moving average data. There will be no solution to suppression of data at the tract level.

- As a general policy, the Census Bureau plans to release for the ACS all tables released for the 2000 long-form data. However, some special tabulations that were made public for long-form data have not yet been released for ACS data. The ones relevant to community needs analysis involve the intersection of information on poverty level, age of housing, and tenure. HUD should probably contact the Census Bureau to make sure that these tabulations are not forgotten.

- The ACS has not released data on persons in group quarters yet, so we have no experience with the usefulness of the tabulations or the reliability of the data.

- The Census Bureau will make revisions to the ACS questionnaire. Revisions always create the possibility of discontinuities in the data, such as the one that occurred with the disability questions. Users will have to be aware of possible problems.[43]

[43] The Census Bureau plans to restrict revisions to the ACS questionnaire to once every decade. All changes will be incorporated into the surveys beginning in the year ending in an "8," e.g., 2008. Using this procedure, the first 5-year moving average using the new questionnaire for all 5 years will be centered on a year ending in "0," e.g., 2010. This procedure ensures that the data centered on a decennial census year will all use the same questionnaire.

6.2. A Single-Valued Index of Community Needs

The explicit goal of this project was to develop a single-valued index of community needs. The research achieved this objective, but the outcome was only a qualified success. Nevertheless, the research resulted in two important insights: first, that an equal-weighted index correlates highly with most reasonable alternatives, and second, that changes in individual factor scores provide more useful information than do changes in an index, for understanding how conditions in individual cities have changed. The research also explored a new methodology that may prove useful in related future work and incorporated fiscal capacity into the analysis.

Using data from the ACS and other sources, this report carried out a factor analysis that identified three dimensions of community needs: needs associated with poverty and structural problems, needs associated with immigration and lack of affordable housing, and needs arising from limited economic prospects. The report used these factors in an equal weight index that ranked cities on community needs.

The equal weight index was one of six indices that the report considered. The report was unable to find any statistical, programmatic, or logical reasons that make a *compelling* case for choosing one index over any of the others. We had hoped that the hedonic analysis would provide definitive guidance in weighting the factors or even the needs indicators. However, the prominent role of housing affordability in Factor 2 and in two or three of the needs indicators undermined attempts to apply the hedonic results directly. Index 4, which provides a triple weight to the limited economic prospects factor, is derived from the hedonic analysis. Index 6 applies information from the hedonic analysis to derive weights. This approach is interesting, but we did not have the opportunity to examine its strengths and weaknesses. We consider the equal weight index to be only a qualified success because of our inability to justify the choice of weights.

The efforts to develop a single-valued index did lead to two useful insights. First, comparing the six indices indicated that the rankings of cities across the other five indices were highly correlated with the ranking on the equal weight index. Statistically, the equal weight index produces results that are very similar to the other indices. Statistical closeness does not mean that the ranking of some cities are not substantially different depending upon the index used. If HUD were to use one of these indices to allocate funds to cities, the choice of index would be of great concern to individual cities. But, if HUD is interested primarily in analyzing the variation in needs across cities and over time, then the results from the equal weight index will be similar to those from any index that applies reasonable weights to the factor scores.

Second, the analysis revealed that a single-valued index provides simplicity at the cost of concealing interesting information. If HUD is interested in how community needs vary across cities and over time, it should look at variation and changes in both the individual factors and a single-valued index.

The most important contribution of the research to the development of an index of community needs was the development of an index of real fiscal capacity and the development of a technique to combine an index of community needs with an index of fiscal capacity. From the perspective of the federal government, needs cannot be considered without reference to capacity.   We discuss further the implications of the work on fiscal capacity in Section 6.6.

6.3. Intertemporal Comparisons of Needs

This research developed a methodology for applying factor analysis to data on needs at two points in time and successfully implemented the methodology. The methodology allows HUD to compare factor scores from two different years to measure how conditions have changed in individual cities. Because the factor scores are computed from sample data, they are subject to sample variation and thus some care must be taken in interpreting the results.   But the sample variation problem is no more serious than comparison involving sample data.

There are two keys to carrying out intertemporal comparisons correctly. First, one must be sure that the dimensions of need identified in the base year are still relevant in the comparison year. Second, one must measure needs relative to conditions in the year in which the factor analysis is performed—that is, one must use the means and standard deviations from that year to standardize the needs indicators in both years.

After reviewing the first draft of this report, HUD asked us to comment on whether we thought the factors identified in this report would be capable of comparing conditions in individual cities in 2005 and 2010. As noted above, one must always check to see if the dimensions of need are the same in both the base year and comparison year. To do this, one applies factor analysis to the needs indicators in both the base year and the comparison and compares the results.   The factor analysis and the needs indicators should pass the Kaiser test for factor suitability in both years, and the test used to choose the number of factors should result in the same number of factors in both years. In addition, the factor loading should be similar in both years. To our knowledge, there is no statistical test to determine whether the loadings are similar, so this will be a judgment call.

There are three reasons why HUD may not be able to apply the factor analysis developed for 2005 in this report to data from 2010. First, the underlying relationship between the needs indicators may change between 2005 and 2010. In our opinion, a change in the underlying relationships in only 5 years would be unusual but this is an empirical question. If there is a change in the underlying relationships, then the only solution is to recognize the break in pattern and try to interpret how needs have changed by comparing the results from using factors derived from both years. In other words, one would develop a set of factors using data from 2005 on needs indicators, apply the standardized scoring coefficients to standardized data from 2005 and 2010, and record how conditions changed. Then, one would repeat the steps using factors based on data from 2010. For each city, one would compare the answers from the two sets of factor analyses and try to obtain a reasonable estimate of how conditions have changed in that city.

In our view, the other two reasons for a break in factor patterns are more likely. First, as the ACS releases data on smaller cities, HUD will be applying the factor analysis to more cities and to urban counties. The addition of more observations may result in a change in factor pattern. Second, we believe that HUD should attempt to expand the needs indicators to provide more information on economic conditions and to cover needs related to education and public health. The addition of new indicators could also result in a change in factor pattern. In both cases, there is a simple solution. One would apply the factor pattern based on more observation or more needs indicators and derived in 2010 to both 2005 and 2010.

6.4. Factor Analysis Involving Different Geographies

In 2008, the Census Bureau will release ACS data based on 3-year moving averages for counties and places with populations of 20,000 or more. The 2008 release will cover data collected in 2005, 2006, and 2007. The availability of new data raises three issues with respect to the factor analysis developed in this research:

- Will HUD be able to use the ACS data to construct urban counties and will the addition of urban counties change the factor pattern?
- Will the addition of cities with populations between 20,000 and 65,000 change the factor pattern?
- Should non-urban counties be included in the same factor analysis as cities and urban counties?

A related issue is whether to use 3-year moving average data for all places, even those where annual data are available.

The answers to all of these questions are inherently empirical. Researchers will have to wait for the 2008 ACS data and see how they change the analysis. The work in this project is most relevant to the issue of whether the factor patterns will change with the additions of observations on cities with populations between 20,000 and 65,000.

Section 3.2.3 discusses the results we obtained when we split the sample into cities with 200,000 or more residents and cities with less than 200,000 residents and ran factor analysis on the two groups separately. (Table A.5 in Appendix A reports the results for the rotated factors.) The most important difference between the two factor analyses involved the Eigenvalue test that we used to determine the number of factors. The test identified four factors for the cities with 200,000 or more residents and only three factors for cities with less than 200,000 residents. There were some other noteworthy differences that are discussed in Section 3.2.3. Despite these differences, we applied factor analysis to the combined database that includes both large and small cities. In our opinion, the fourth factor added little to the analysis, and the other differences were minor.

Our greatest concern about combining large and small cities is that the test we applied in Section 3.2.3 uses a boundary point, a population of 200,000, which does not adequately distinguish large cities from small cities. The problem is that there are too few “large” cities to run a separate factor analysis with a boundary point much higher than 200,000. This problem will not lessen when the Census Bureau releases data on smaller cities. It may be that adding more cities to the under-200,000 group will result in a sharper difference in factor patterns between the two groups. However, we do not think this is the likely outcome. The factor pattern for the under-200,000 group is very close to the factor pattern for the entire group of cities. This leads us to believe that adding smaller cities will not greatly change the factor pattern.

With respect to the other questions, we offer our opinions below, with the proviso that we think reliable answers are empirical and must await the 2008 data.

- With respect to the urban counties issues, we believe that the 3-year moving average data will allow HUD to construct reliable needs indicators for urban counties and that adding urban counties to the factor analysis will not change factor pattern greatly. (In this discussion, we use the HUD definition of urban counties.)

- With respect to non-urban counties, we believe that factor analysis applied separately to non-urban counties and to cities and urban counties combined would result in different factor patterns. At a minimum, combining the two groups would require eliminating important needs indicators, including MEDINCCBS2CITY, POVCON, and MINCON, because they are defined in the context of metropolitan areas. These needs indicators figured heavily in the interpretation of Factor 1.

- With respect to using 3-year moving average data or annual data, we favor consistency—that is, using the data defined for the same period for all places. At the city and urban county level, we think 3-year average data are current enough to represent present needs. One possible problem is that the Census Bureau may not release some 3-year average data for smaller cities, just as it has not released annual data on minority populations and overcrowded housing for some cities with populations greater than 65,000. In this case, we favor using 5-year average data for the missing variables and relying on 3-year average data for most of the needs indicators.

6.5. Measuring Progress at the Tract Level

HUD indicated early in the project that it was interested in the lessons that could be drawn from this research that are applicable to measuring needs at the tract level. The

Administration has proposed creating a special fund within the CDBG program to award communities for making progress in reducing neighborhood distress. Such a proposal would require a community-needs measure at the neighborhood level. Since ACS data will be available at the census-tract level beginning in 2010, it was hoped that the experience gained here in constructing a city-level index using ACS data would be useful to HUD in developing a neighborhood-level index.

In trying to apply our experience to this issue, we first considered the applicability at the tract level of the 27 needs indicators in Table 1. We think 7 or 8 of the 27 would not be applicable at the tract level. The two crime variables are not available because the FBI does not collect crime data at the tract level. The three long-run decline variables, EXCSINFRA, CHNGEMPLOYBASE, and CHGLOWINCCON, are relevant only in the city context. Finally, there are three variables linked to poverty rate of the tract; these are PCTPOPHIGHPOVNGHS, PCTPOPMODPOVNGHS, and PCTVACMODPOVCITY. The first two of these variables could not be integrated into a tract-level factor analysis because they become binary variables (100 percent or 0 percent) at the tract level. Conceptually, one could incorporate PCTVACMODPOVCITY into a tract-level factor analysis because this variable takes on more than two values. The other 19 needs indicators could be computed at the tract level using 5-year moving average data from the ACS.[44]

Because of the substantial change in the number and type of indicators, a new factor analysis would have to be performed at the tract level. This factor analysis is likely to identify different dimensions of need than the three identified at the city level in this report. Finding appropriate weights for the factors will continue to be a problem if a single-value index of community needs is required.

There are important data and conceptual considerations in measuring progress at the tract level. First, the ACS has a lower sampling rate over 5 years than the long-form survey in the decennial censuses. For this reason, the Census Bureau is more likely to suppress data used for some of the needs indicators at the tract level. Second, measurement error will be relatively high so that year-to-year changes on individual indicators may not reflect actual changes. The use of moving averages will dampen the effect of an unusual sample in any one year, but the dampened effect will persist for 5 years. Third, the use of 5-year moving average data probably determines the time frame to be used to measure progress. One is likely to want to compare conditions at 5-year intervals so that none of the samples overlap in the before and after comparison.

On the conceptual side, a clear distinction needs to be made, if one plans to reward cities for alleviating needs, between measuring a change in needs and measuring how local government actions have reduced community needs. Even at the city level, needs can change independent of the efforts of the city to lessen needs. In the context of the factor analysis used in this report, a strong national economy can lower the values of important

[44] The three dissimilarity indicators—MEDINCCBS2CITY, POVCON, and MINCON—could be computed at the tract level but may have a different meaning at the tract level. We included these variables as indicators of complicating conditions at the city level.

needs indicators, such as the unemployment rate, the overall poverty rate, the proportion of poor children and school-age children, and even the disparity in incomes between cities and metropolitan areas. The same consequences of a strong national economy apply to measured needs at the tract level. Conceptually, one would like to control for outside influences so that cities would not benefit from favorable external conditions or suffer from unfavorable external conditions. One possible way of doing this would be to measure progress against some national average.

At the tract level, lower values for the needs indicators may or may not correspond to what HUD would consider improved conditions. Consider two different scenarios that result in a lower poverty rate for a single tract. In the first scenario, the city provides training to low-skilled workers, provides day care for working families, and encourages small business startups in the tract. These changes result in lower unemployment and higher incomes. In the second scenario, the city undertakes rigorous code enforcement resulting in demolition of low-rent structures, increases police protection, and improves neighborhood schools. These changes result in gentrification and, therefore, a lower poverty rate for the tract. The values of many of the needs indicators that can be computed at the tract level are sensitive to movement of households into and out of a tract.[45] The ACS tables on migration offer limited help in controlling for the impact of gentrification. The ACS provides tables on age, race, household type, education attainment, individual income, and poverty status separately for persons who lived in the same house one year ago and persons who moved into the house within the past year.

All of these considerations suggest that, despite some useful insights gained from factor analysis at the city level, HUD will need to do a lot of conceptual and empirical work to develop a measure capable of implementing the Administration's proposal.

6.6. Measuring Fiscal Capacity

The report developed and implemented a measure of real fiscal capacity. This is a substantial advance in understanding the relative need for federal assistance among cities. In our opinion, capacity should be considered along with needs in determining how much federal assistance cities should receive.

With respect to the measure of real fiscal capacity, more work needs to be done in two areas.

First, because of data limitations, we were able to estimate relative real fiscal capacity for only 266 of our 473 cities. The data failure that had the largest impact on the analysis was the absence of data from the 2002 Economic Census for a large number of cities. We used the economic census data to estimate sales tax capacity and business tax

[45] As noted earlier in the discussion of this topic, 19 of the 27 need indicators can be computed at the tract level. Fifteen of these depend on the characteristics of persons residing in the tract, and therefore are affected by movement of households into and out of the tract. Examples of these are: POORPERS, POORCHILD, LWINCHHDS, SGLPRNTFAM, RCNTIMMIG, and UNEDUCADULTS.

capacity. There are three possible strategies for increasing the number of cities for which real fiscal capacity can be computed. First, HUD could work with the Census Bureau to obtain data on more places from the economic census. Perhaps, HUD could construct the index at the Census Bureau using data not released to the public. Second, HUD could try to find alternative ways to estimate sales tax capacity and business tax capacity. Third, HUD could use the data from the 266 cities to develop a model of real fiscal capacity applicable to all cities.

We think the modeling approach is imminently doable. The correlation between per capita income and fiscal capacity was 0.78, indicating the per capita income explains half of the variation in fiscal capacity. The addition of other variables such as region, city size, principal city/suburb status, and proportion of working-age population should produce a model that fits the data well.

Second, more thought needs to be given to how to combine an index of real fiscal capacity with an index of community needs. The approach we developed provides a consistent linking of the two indices and works reasonably well. Its main weakness is the assumption that the extent to which a city is below average on real fiscal capacity (measured in standard deviations) indicates the same level of need for federal assistance as an equal distance above average on community needs.

6.7. Changing City Boundaries and Cost-of-Living Differences

In the Statement of Work, HUD asked us to consider the implications for an index of community needs of changing city boundaries and cost-of-living differences between cities.

After selecting the 27 needs indicators in Table 1, we considered whether changes in city boundaries could affect the relevance or interpretation of any of the indicators. This question is particularly relevant to this research because an explicit goal was to measure, city-by-city, changes in community needs between 2000 and 2005. The indicators are defined so that they record conditions in a city using the boundaries in effect on the date the data were collected. Some indicators, such as the change in the concentration of low income families (CHGLOWINCCON), compare conditions at two points in time—for example, 1970 and 2005. These multiyear indicators are defined using the city boundaries in effect at each point in time.

If a principal city annexed a high-income suburb in 2003, our changing-boundaries definition would result in the city having a lower measured poverty rate in 2005 than in 2000 even if it had the same number of poor persons in both years. In the case of the poverty rate variable (POORPERS), this result is completely consistent with the role of that need indicator in the analysis. We looked at each of the needs indicators in this way; in every case, we concluded that any change in city boundary between 2000 and 2005 should be incorporated into the measurement of that indicator.

This conclusion applies to the three multiyear variables—EXCSINFRA, CHNGEMPLOYBASE, and CHGLOWINCCON—as well. However, we acknowledge that boundary changes could confound EXCSINFRA, but we believe that this possibility is remote. EXCSINFRA, as calculated in 2005, compares the maximum number of households recorded in 1970, 1980, 1990, 2000, and 2005 to the number of households in the city in 2005. If a city is steadily growing, then the maximum number of households would have occurred in 2005 and EXCSINFRA = 1. If a city is declining, then the maximum number of households would have occurred earlier than 2005 and EXCSINFRA > 1. The possibility exists that the original part of a city declined between 1970 and 2005, but the city annexed surrounding areas so that the number of households stayed constant or increased. In such a case, EXCSINFRA = 1, but the city would have excess infrastructure in the original part. We think that this possibility is remote and that, if a case like this did exist, holding original boundaries constant could produce an undesirable result as well.[46]

Cost-of-living differences enter into the analysis of community needs in two ways. First, the poverty rate (POORPERS) and related variables are based on counts of persons living in households with incomes below poverty-level incomes. The assumption is that these persons have needs that cities have to provide for either because they have insufficient incomes or because they have other characteristics, such as an elderly age, that combines with insufficient income to create needs. Insufficient income is a function of both income level and the cost of necessities. Being below the national poverty level in Wichita poses fewer problems for a family than being below the national poverty level in San Francisco because of the cost of housing and other necessities.[47] Need indicators based on cost-adjusted poverty levels would be desirable.[48]

Cost-of-living differences also enter the analysis in terms of the cost of responding to needs. A poor elderly person may need services such as meals on wheels, adult day care, and visiting nurse care. The costs of providing such services will differ across cities. We believe that the real fiscal capacity index adjusts for these differences directly and, therefore, no corresponding adjustments need to be made in the needs indicators used in constructing measures of community needs.

6.8. Areas for Future Work

In our opinion, the most important area for future work is to expand and improve upon the list of needs indicators. We believe that the 27 variables in Table 1 are a well-conceived, broad-based, and carefully defined set of needs indicators. We believe these

[46] For example, if the original part of the city was small in population relative to its size in 2005, then the decline in households measured using constant boundaries would be out of proportion to the problem.
[47] The Census Bureau bases its poverty counts in the 48 contiguous states on the same income levels by household size; it uses higher income levels in Alaska and Hawaii.
[48] The Government Accountability Office (GAO) has asked the Census Bureau to produce counts of poor persons using a poverty level adjusted for cost-of-living differences. The GAO used HUD fair market rents to adjust the poverty level. HUD should experiment with the special counts prepared for GAO.

indicators provided the basis for a useful factor analysis, and we would recommend the inclusion of all of these indicators in future work. However, we think the greatest payoff for understanding community needs is to improve these indicators and fill in some missing gaps. Here are our suggestions:

- Carry out further analysis of the crime variables to determine whether there were any data errors, on our part or the part of the FBI, which caused the low correlations between the part 1 arrest data and the violent crime statistics. Since these data have many missing observations, the gains from solving this mystery may be limited. Future work may avoid crime statistics to keep from losing cities because of missing data.

- Test whether there are any significant changes in the factor analysis results if one substitutes for POORPERS the counts that the Census Bureau is preparing for GAO using fair market rent (FMR) data to adjust for cost-of-living differences.

- Test whether the employment disability counts can be used in the future.

- Test whether the "poor housing appreciation in high poverty neighborhood" indicator based on HMDA data provides useful information. We agreed that this was a reasonable variable in concept but were not able to compute it within the resources available.

- Explore with the Census Bureau the possibility of obtaining better information from the economic censuses to gauge the change in economic conditions in cities. In our opinion, this may be the single most important improvement to the set of needs indicators. It may be necessary to conduct some of the analysis at the Census Bureau to take advantage of data not released to the public. However, it is possible that HUD could obtain public release of useful data. For example, the Census Bureau does not release the count of total jobs in a city. HUD may need to know only the change in the number of total jobs. The Census Bureau may be willing to release the change in jobs but not the total number of jobs.

- Investigate whether there are other useful measures of long-term trends that could be constructed.

- Investigate whether HUD could work with the Department of Education to construct useful measures of education needs defined at the city level, such as the number of children who are not fluent in English.

- Investigate whether HUD could compile from HHS useful information at the city level on public health needs and conditions such as infant mortality rates.

While we believe better data would produce the best payoff for measuring community needs, we also recommend some future conceptual work in the following areas:

- Further testing of the regression approach.

- Further analysis of the relationship between the regression approach and factor analysis. We believe that looking at the relationship between principal components analysis and the regression approach may be a useful way to proceed in this area.

- Development of a model to estimate real fiscal capacity for the cities for which the needed data are not available.

- Further consideration of how to combine a measure of real fiscal capacity with a measure of community needs.

Appendix A—Supplemental Tables

Table A.1. Correlation Matrix for Needs Indicators

	POP	CHGLOWINCCON	CHNGEMPLBASE	DENIAL	EXCSINFRA	LACKAFFDRENTALS	LINGISOL	LWINCHHDS	MEDINCCBS2CITY	MINCON	OVERCROWD_2000	PCTPOPHIGHPOVNGHS	PCTPOPMODPOVNGHS	PCTVACMODPOVCITY
POP	1.00	0.03	-0.06	0.07	0.03	0.08	0.11	0.12	0.10	0.06	0.10	0.17	0.14	0.06
CHGLOWINCCON	0.03	1.00	0.15	0.44	0.26	0.28	0.24	0.42	0.47	0.34	0.18	0.12	0.29	0.24
CHNGEMPLBASE	-0.06	0.15	1.00	0.08	-0.06	0.00	0.10	0.02	-0.01	-0.05	0.12	-0.01	0.04	0.01
DENIAL	0.07	0.44	0.08	1.00	0.52	0.28	-0.01	0.58	0.62	0.65	-0.03	0.51	0.60	0.76
EXCSINFRA	0.03	0.26	-0.06	0.52	1.00	0.21	-0.06	0.41	0.44	0.44	-0.07	0.33	0.38	0.64
LACKAFFDRENTALS	0.08	0.28	0.00	0.28	0.21	1.00	0.57	0.60	0.66	0.35	0.58	0.34	0.54	0.15
LINGISOL	0.11	0.24	0.10	-0.01	-0.06	0.57	1.00	0.32	0.30	0.09	0.77	0.10	0.34	-0.17
LWINCHHDS	0.12	0.42	0.02	0.58	0.41	0.60	0.32	1.00	0.90	0.70	0.29	0.51	0.74	0.52
MEDINCCBS2CITY	0.10	0.47	-0.01	0.62	0.44	0.66	0.30	0.90	1.00	0.73	0.23	0.46	0.71	0.52
MINCON	0.06	0.34	-0.05	0.65	0.44	0.35	0.09	0.70	0.73	1.00	0.00	0.45	0.57	0.61
OVERCROWD_2000	0.10	0.18	0.12	-0.03	-0.07	0.58	0.77	0.29	0.23	0.00	1.00	0.11	0.39	-0.15
PCTPOPHIGHPOVNGHS	0.17	0.12	-0.01	0.51	0.33	0.34	0.10	0.51	0.46	0.45	0.11	1.00	0.52	0.52
PCTPOPMODPOVNGHS	0.14	0.29	0.04	0.60	0.38	0.54	0.34	0.74	0.71	0.57	0.39	0.52	1.00	0.63
PCTVACMODPOVCITY	0.06	0.24	0.01	0.76	0.64	0.15	-0.17	0.52	0.52	0.61	-0.15	0.52	0.63	1.00
POORCHILD	0.12	0.36	0.05	0.71	0.39	0.45	0.14	0.80	0.72	0.68	0.14	0.62	0.79	0.69
POOROVER74	0.13	0.13	0.02	0.38	0.20	0.35	0.29	0.42	0.42	0.35	0.19	0.37	0.49	0.31
POORPERS	0.12	0.38	0.07	0.73	0.42	0.51	0.22	0.84	0.76	0.67	0.22	0.68	0.83	0.68
POVCON	0.11	0.34	-0.03	0.56	0.43	0.45	0.13	0.88	0.86	0.79	0.06	0.47	0.66	0.58
PR70RENTPOV	0.17	0.32	-0.05	0.59	0.51	0.49	0.20	0.82	0.80	0.71	0.16	0.57	0.77	0.63
VIOLCRIME	0.05	0.06	0.03	0.51	0.22	0.05	-0.16	0.42	0.36	0.39	-0.15	0.39	0.44	0.53
PT1CRIME	-0.02	-0.04	0.06	0.04	-0.03	-0.03	-0.08	0.03	0.05	0.06	-0.05	0.08	0.02	0.09
PT2CRIME	-0.03	-0.02	0.04	0.20	0.03	0.01	-0.12	0.12	0.20	0.20	-0.15	0.18	0.13	0.21
RCNTIMMIG	0.09	0.24	0.04	-0.17	-0.07	0.44	0.81	0.21	0.15	-0.02	0.60	-0.09	0.12	-0.27
SCHPOPPOOR	0.13	0.35	0.02	0.67	0.38	0.47	0.15	0.78	0.69	0.66	0.15	0.62	0.77	0.66
SGLPRNTFAM	0.07	0.35	0.01	0.68	0.44	0.47	0.02	0.74	0.76	0.69	0.05	0.55	0.69	0.64
UNDEREDWORKAGE	0.00	0.29	0.18	0.57	0.20	0.49	0.27	0.45	0.54	0.33	0.37	0.25	0.54	0.31
UNEDUCADULTS	0.10	0.35	0.13	0.48	0.20	0.66	0.65	0.65	0.64	0.41	0.69	0.39	0.71	0.28
UNEMPCEN	0.08	0.34	0.02	0.67	0.46	0.36	0.12	0.63	0.60	0.53	0.15	0.48	0.59	0.58

Table A.1. Correlation Matrix for Needs Indicators (continued)

	POORCHILD	POOROVER74	POORPERS	POVCON	PR70RENTPOV	VIOLCRIME	PT1CRIME	PT2CRIME	RCNTIMMIG	SCHPOPPOOR	SGLPRNTFAM	UNDEREDWOR KAGE	UNEDUCADUL TS	UNEMPCEN
POP	0.12	0.13	0.12	0.11	0.17	0.05	-0.02	-0.03	0.09	0.13	0.07	0.00	0.10	0.08
CHGLOWINCCON	0.36	0.13	0.38	0.34	0.32	0.06	-0.04	-0.02	0.24	0.35	0.35	0.29	0.35	0.34
CHNGEMPLBASE	0.05	0.02	0.07	-0.03	-0.05	0.03	0.06	0.04	0.04	0.02	0.01	0.18	0.13	0.02
DENIAL	0.71	0.38	0.73	0.56	0.59	0.51	0.04	0.20	-0.17	0.67	0.68	0.57	0.48	0.67
EXCSINFRA	0.39	0.20	0.42	0.43	0.51	0.22	-0.03	0.03	-0.07	0.38	0.44	0.20	0.20	0.46
LACKAFFDRENTALS	0.45	0.35	0.51	0.45	0.49	0.05	-0.03	0.01	0.44	0.47	0.47	0.49	0.66	0.36
LINGISOL	0.14	0.29	0.22	0.13	0.20	-0.16	-0.08	-0.12	0.81	0.15	0.02	0.27	0.65	0.12
LWINCHHDS	0.80	0.42	0.84	0.88	0.82	0.42	0.03	0.12	0.21	0.78	0.74	0.45	0.65	0.63
MEDINCCBS2CITY	0.72	0.42	0.76	0.86	0.80	0.36	0.05	0.20	0.15	0.69	0.76	0.54	0.64	0.60
MINCON	0.68	0.35	0.67	0.79	0.71	0.39	0.06	0.20	-0.02	0.66	0.69	0.33	0.41	0.53
OVERCROWD_2000	0.14	0.19	0.22	0.06	0.16	-0.15	-0.05	-0.15	0.60	0.15	0.05	0.37	0.69	0.15
PCTPOPHIGHPOVNGHS	0.62	0.37	0.68	0.47	0.57	0.39	0.08	0.18	-0.09	0.62	0.55	0.25	0.39	0.48
PCTPOPMODPOVNGHS	0.79	0.49	0.83	0.66	0.77	0.44	0.02	0.13	0.12	0.77	0.69	0.54	0.71	0.59
PCTVACMODPOVCITY	0.69	0.31	0.68	0.58	0.63	0.53	0.09	0.21	-0.27	0.66	0.64	0.31	0.28	0.58
POORCHILD	1.00	0.41	0.96	0.80	0.76	0.56	0.05	0.22	-0.05	0.98	0.79	0.49	0.57	0.65
POOROVER74	0.41	1.00	0.49	0.37	0.46	0.23	0.06	0.16	0.19	0.42	0.39	0.25	0.42	0.34
POORPERS	0.96	0.49	1.00	0.80	0.78	0.55	0.06	0.22	0.03	0.94	0.80	0.52	0.64	0.68
POVCON	0.80	0.37	0.80	1.00	0.82	0.47	0.07	0.23	0.04	0.77	0.74	0.32	0.45	0.55
PR70RENTPOV	0.76	0.46	0.78	0.82	1.00	0.40	0.03	0.17	0.06	0.73	0.73	0.30	0.51	0.59
VIOLCRIME	0.56	0.23	0.55	0.47	0.40	1.00	0.20	0.23	-0.24	0.53	0.50	0.27	0.19	0.40
PT1CRIME	0.05	0.06	0.06	0.07	0.03	0.20	1.00	0.53	-0.06	0.04	0.08	0.01	0.00	0.06
PT2CRIME	0.22	0.16	0.22	0.23	0.17	0.23	0.53	1.00	-0.19	0.19	0.27	0.09	0.04	0.17
RCNTIMMIG	-0.05	0.19	0.03	0.04	0.06	-0.24	-0.06	-0.19	1.00	-0.01	-0.12	-0.02	0.36	0.03
SCHPOPPOOR	0.98	0.42	0.94	0.77	0.73	0.53	0.04	0.19	-0.01	1.00	0.76	0.45	0.55	0.63
SGLPRNTFAM	0.79	0.39	0.80	0.74	0.73	0.50	0.08	0.27	-0.12	0.76	1.00	0.49	0.49	0.63
UNDEREDWORKAGE	0.49	0.25	0.52	0.32	0.30	0.27	0.01	0.09	-0.02	0.45	0.49	1.00	0.74	0.50
UNEDUCADULTS	0.57	0.42	0.64	0.45	0.51	0.19	0.00	0.04	0.36	0.55	0.49	0.74	1.00	0.51
UNEMPCEN	0.65	0.34	0.68	0.55	0.59	0.40	0.06	0.17	0.03	0.63	0.63	0.50	0.51	1.00

Table A.2. Initial Factor Analysis, 2005 Data: Factor Loading for Unrotated Factors

	Factor1	Factor2	Factor3
CHGLOWINCCON	0.42991	0.16552	0.07619
CHNGEMPLBASE	-0.10283	0.116	0.27252
DENIAL	0.7626	-0.23761	0.2932
EXCSINFRA	0.56431	-0.22377	-0.11208
LACKAFFDRENTALS	0.60586	0.55234	-0.07049
LINGISOL	0.21712	0.89532	-0.09646
LWINCHHDS	0.86956	0.11171	-0.25189
MEDINCCBS2CITY	0.90339	0.07241	-0.12628
MINCON	0.75356	-0.16559	-0.14176
OVERCROWD2000	0.17479	0.87566	0.05896
PCTPOPHIGHPOVNGHS	0.67931	-0.11091	-0.0474
PCTPOPMODPOVNGHS	0.84469	0.10956	0.08503
PCTVACMODPOVCITY	0.73709	-0.41366	0.05368
POORCHILD	0.91385	-0.1337	0.01959
POOROVER74	0.45471	0.0221	0.00709
POORPERS	0.94876	-0.07822	0.03881
POVCON	0.8429	-0.1709	-0.31292
PR70RENTPOV	0.8403	-0.11492	-0.28779
PT1CRIME	0.02003	-0.15022	0.09945
PT2CRIME	0.15692	-0.28168	0.11429
RCNTIMMIG	0.00871	0.82496	-0.32501
SCHPOPPOOR	0.89979	-0.11129	-0.00439
SGLPRNTFAM	0.85943	-0.1672	0.05814
UNDEREDWORKAGE	0.54942	0.27346	0.62907
UNEDUCADULTS	0.68537	0.57306	0.29624
UNEMPCEN	0.68953	-0.02331	0.1231

Table A.3. Initial Factor Analysis, 2005 Data: Factor Loading for Varimax Orthogonal Rotated Factors

	Factor1	Factor2	Factor3
CHGLOWINCCON	0.39005	0.15917	0.20137
CHNGEMPLBASE	-0.15496	0.00839	0.27243
DENIAL	0.73597	-0.26953	0.33119
EXCSINFRA	0.59824	-0.13193	-0.07606
LACKAFFDRENTALS	0.53521	0.58412	0.2224
LINGISOL	0.11422	0.88724	0.24041
LWINCHHDS	0.87577	0.25161	-0.04226
MEDINCCBS2CITY	0.89575	0.17422	0.06764
MINCON	0.78093	-0.05402	-0.0509
OVERCROWD2000	0.05267	0.81275	0.37078
PCTPOPHIGHPOVNGHS	0.68753	-0.04021	0.04124
PCTPOPMODPOVNGHS	0.8029	0.13272	0.26546
PCTVACMODPOVCITY	0.76776	-0.35445	0.04696
POORCHILD	0.91089	-0.06806	0.13793
POOROVER74	0.44246	0.05011	0.09498
POORPERS	0.93538	-0.02019	0.18005
POVCON	0.89404	0.00574	-0.19561
PR70RENTPOV	0.8808	0.04943	-0.15453
PT1CRIME	0.02421	-0.17337	0.04706
PT2CRIME	0.17296	-0.29207	0.04254
RCNTIMMIG	-0.04839	0.88482	-0.03193
SCHPOPPOOR	0.89774	-0.03985	0.12043
SGLPRNTFAM	0.85613	-0.11644	0.15311
UNDEREDWORKAGE	0.41377	0.07976	0.77123
UNEDUCADULTS	0.55759	0.48379	0.58389
UNEMPCEN	0.66185	-0.01566	0.22989

Table A.4. Factor Analysis Using 2000 Data: Unrotated and Rotated Factor Loading

	Unrotated Factors			Orthogonal Rotated Factors		
	Factor1	Factor2	Factor3	Factor1	Factor2	Factor3
CHGLOWINCCON_2000	0.49109	0.22375	0.1822	0.38067	0.3108	0.28796
CHNGEMPLBASE	-0.09228	0.08752	0.28443	-0.14108	-0.00066	0.27779
DENIAL	0.70361	-0.32571	0.23506	0.74345	-0.15634	0.28151
EXCSINFRA_2000	0.5542	-0.25625	-0.07394	0.61016	-0.0709	-0.03083
LACKAFFDRENTALS_2000	0.5449	0.62309	-0.12124	0.33975	0.76166	0.0655
LINGISOL_2000	0.28082	0.89816	-0.15684	0.00947	0.95329	0.03615
LWINCHHDS_2000	0.85302	0.07528	-0.23753	0.8088	0.35672	-0.09126
MEDINCCBS2CITY_2000	0.89187	0.05764	-0.17376	0.84491	0.33822	-0.02614
MINCON_2000	0.74313	-0.22709	-0.21605	0.79404	0.03778	-0.13627
OVERCROWD2000	0.2676	0.87692	0.09703	-0.02082	0.87873	0.27822
PCTPOPHIGHPOVNGHS_2000	0.68746	-0.21556	-0.03037	0.72008	-0.00419	0.0383
PCTPOPMODPOVNGHS_2000	0.88635	0.09892	0.13002	0.79826	0.31452	0.27599
PCTVACMODPOVCITY_2000	0.69735	-0.47671	0.07489	0.79845	-0.26775	0.0997
POORCHILD_2000	0.95021	-0.07487	0.06862	0.91725	0.18149	0.19727
POOROVER74_2000	0.71694	-0.09999	-0.08448	0.71821	0.12342	0.00887
POORPERS_2000	0.96514	0.02506	0.10894	0.89734	0.27141	0.25517
POVCON_2000	0.83176	-0.22906	-0.32327	0.88889	0.08221	-0.22784
PR70RENTPOV_2000	0.87912	-0.08413	-0.2715	0.88502	0.22114	-0.14654
PT1CRIME_2000	0.29437	-0.11921	0.03159	0.31223	-0.036	0.05548
PT2CRIME_2000	0.27073	-0.32528	-0.04544	0.35951	-0.22065	-0.05689
RCNTIMMIG_2000	0.05266	0.87531	-0.32979	-0.18353	0.90275	-0.17047
SCHPOPPOOR_2000	0.95062	-0.03845	0.05205	0.90821	0.21913	0.18714
SGLPRNTFAM_2000	0.90227	-0.23344	0.02561	0.92387	0.02783	0.1222
UNDEREDWORKAGE_2000	0.57969	0.24368	0.60105	0.41879	0.27028	0.71292
UNEDUCADULTS_2000	0.71862	0.55254	0.26904	0.48869	0.6657	0.46057
UNEMPCEN_2000	0.83467	0.06961	0.08606	0.76231	0.28137	0.22057

Table A.5. Factor Analysis Using 2005 Data, Rotated Factor Loadings for Large Cities and Small Cities

	Cities of 200,000 or More				Cities of Less Than 200,000		
Rotated	**Factor1**	**Factor2**	**Factor3**	**Factor4**	**Factor1**	**Factor2**	**Factor3**
CHGLOWINCCON	0.32092	0.22554	0.09338	0.10486	0.25905	0.21509	0.10375
CHNGEMPLBASE	-0.06154	0.13943	0.10658	-0.06794	-0.11825	0.00499	0.08009
DENIAL	0.60478	-0.2097	0.32227	0.2362	0.53746	-0.14706	0.38518
EXCSINFRA	0.5062	-0.10094	0.12355	0.70666	0.36096	-0.06999	0.04443
LACKAFFDRENTALS	0.60231	0.53932	0.35559	0.16933	0.37883	0.64542	0.29564
LINGISOL	-0.04102	0.96264	0.04793	-0.04789	0.0736	0.91129	0.06674
LWINCHHDS	0.87853	0.1837	0.03086	0.18513	0.82297	0.27014	0.08334
MEDINCCBS2CITY	0.83051	0.07524	0.16249	0.2488	0.73633	0.24373	0.21856
MINCON	0.62726	-0.15293	0.02349	0.46406	0.70944	0.02424	0.03982
OVERCROWD2000	0.02875	0.89844	0.23333	-0.05285	0.00614	0.8519	0.28414
PCTPOPHIGHPOVNGHS	0.77314	0.07007	0.18185	0.03701	0.57861	0.01207	0.13945
PCTPOPMODPOVNGHS	0.85335	0.22304	0.30456	0.1798	0.72246	0.22209	0.32766
PCTVACMODPOVCITY	0.68697	-0.3124	0.13567	0.42289	0.62676	-0.23827	0.14662
POORCHILD	0.9602	-0.05175	0.1048	-0.01914	0.93392	0.0226	0.22342
POOROVER74	0.56129	0.14416	0.08524	0.20817	0.31713	0.09699	0.03095
POORPERS	0.93887	0.04466	0.20104	0.09484	0.91952	0.07197	0.24322
POVCON	0.86501	-0.07434	-0.07634	0.19655	0.89469	0.02452	-0.05989
PR70RENTPOV	0.82284	0.05715	0.05072	0.37423	0.80899	0.08035	-0.03507
PT1CRIME	0.07619	-0.00352	0.00198	0.06547	-0.01406	-0.04468	-0.02989
PT2CRIME	0.05836	-0.2747	0.01233	0.00065	0.16651	-0.13149	0.03528
RCNTIMMIG	-0.16047	0.89867	-0.22456	-0.06925	-0.0769	0.87511	-0.2177
SCHPOPPOOR	0.96533	-0.03595	0.05385	-0.00219	0.90835	0.05846	0.20762
SGLPRNTFAM	0.82503	-0.13778	0.34831	0.14783	0.75812	-0.02687	0.29724
UNDEREDWORKAGE	0.28883	0.15058	0.85108	0.10433	0.30405	0.19232	0.7888
UNEDUCADULTS	0.45417	0.67608	0.51839	0.01181	0.442	0.5655	0.56173
UNEMPCEN	0.68525	-0.06257	0.21859	0.43727	0.46274	0.09936	0.34128

Table A.6. 2005 Factor Analysis Using VIOLCRIME Instead of PT1CRIME, VARIMAX Rotated Factors

	Factor1		Factor2		Factor3
POORPERS	0.94261	LINGISOL	0.91454	UNEMPCEN	0.19566
POORCHILD	0.91804	RCNTIMMIG	0.87042	UNEDUCADULTS	0.49499
SCHPOPPOOR	0.90272	OVERCROWD_2000	0.85383	UNDEREDWORKAGE	0.72952
MEDINCCBS2CITY	0.88857	LACKAFFDRENTALS	0.6461	SGLPRNTFAM	0.12659
POVCON	0.88566	UNEDUCADULTS	0.58219	SCHPOPPOOR	0.10997
PR70RENTPOV	0.87071	LWINCHHDS	0.28366	RCNTIMMIG	-0.13826
SGLPRNTFAM	0.86702	MEDINCCBS2CITY	0.23882	PT2CRIME	0.01392
LWINCHHDS	0.85881	CHGLOWINCCON	0.22623	PR70RENTPOV	-0.20693
PCTPOPMODPOVNGHS	0.80524	UNDEREDWORKAGE	0.20319	POVCON	-0.23032
PCTVACMODPOVCITY	0.78866	PCTPOPMODPOVNGHS	0.18899	POORPERS	0.1599
MINCON	0.7835	POOROVER74	0.07432	POOROVER74	0.07732
DENIAL	0.76327	PR70RENTPOV	0.07252	POORCHILD	0.13235
PCTPOPHIGHPOVNGHS	0.69193	UNEMPCEN	0.04013	PCTVACMODPOVCITY	0.05213
UNEMPCEN	0.6672	POORPERS	0.0348	PCTPOPMODPOVNGHS	0.23272
EXCSINFRA	0.59869	CHNGEMPLBASE	0.03249	PCTPOPHIGHPOVNGHS	0.02412
VIOLCRIME	0.55578	POVCON	0.01955	OVERCROWD_2000	0.27431
UNEDUCADULTS	0.54919	SCHPOPPOOR	0.0021	MINCON	-0.09542
LACKAFFDRENTALS	0.50896	PCTPOPHIGHPOVNGHS	-0.00745	MEDINCCBS2CITY	-0.01553
UNDEREDWORKAGE	0.43965	MINCON	-0.01292	LWINCHHDS	-0.10573
POOROVER74	0.4368	POORCHILD	-0.02401	LINGISOL	0.12639
CHGLOWINCCON	0.38837	SGLPRNTFAM	-0.05827	LACKAFFDRENTALS	0.11336
PT2CRIME	0.18253	EXCSINFRA	-0.08259	EXCSINFRA	-0.12857
LINGISOL	0.06766	DENIAL	-0.18631	DENIAL	0.31377
OVERCROWD_2000	0.0219	PT2CRIME	-0.23332	VIOLCRIME	0.13291
RCNTIMMIG	-0.09868	PCTVACMODPOVCITY	-0.31302	CHNGEMPLBASE	0.29818
CHNGEMPLBASE	-0.16497	VIOLCRIME	-0.35229	CHGLOWINCCON	0.14697

Table A.7. Standardized Scoring Coefficients, Based on 2005 Data Without Crime Variables

	Factor1	Factor2	Factor3
CHGLOWINCCON	-0.02266	-0.00619	0.06911
CHNGEMPLBASE	-0.00733	0.00465	0.05042
DENIAL	0.05521	-0.1065	0.2061
EXCSINFRA	0.04954	-0.02226	-0.00265
LACKAFFDRENTALS	-0.01665	0.11404	-0.01053
LINGISOL	-0.03114	0.36138	-0.06993
LWINCHHDS	0.02825	0.09883	-0.10354
MEDINCCBS2CITY	0.20368	0.10156	-0.01419
MINCON	0.04264	-0.02485	-0.00641
OVERCROWD_2000	-0.01755	0.16406	0.05127
PCTPOPHIGHPOVNGHS	0.01425	-0.01001	-0.042
PCTPOPMODPOVNGHS	0.00878	0.04533	0.02058
PCTVACMODPOVCITY	0.09204	-0.13162	0.03791
POORCHILD	0.0883	-0.1326	0.12027
POOROVER74	0.00719	-0.00089	-0.02458
POORPERS	0.18723	0.00824	0.2283
POVCON	0.09751	0.00589	-0.429
PR70RENTPOV	0.15118	0.00913	-0.24679
RCNTIMMIG	-0.00757	0.24664	-0.1858
SCHPOPPOOR	0.12067	0.08762	-0.1873
SGLPRNTFAM	0.06006	-0.02148	0.01251
UNDEREDWORKAGE	-0.05684	-0.04957	0.41739
UNEDUCADULTS	-0.04105	0.13016	0.41726
UNEMPCEN	0.01966	-0.02896	0.04813

Table A.8. Alternative Index Scores

City	State	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Birmingham city	Alabama	0.54	1.30	-0.12	0.43	1.81	1.19
Huntsville city	Alabama	-0.43	-0.28	-0.71	-0.30	-0.21	-0.36
Mobile city	Alabama	0.17	0.52	-0.35	0.36	0.68	0.37
Montgomery city	Alabama	-0.07	0.14	-0.54	0.21	0.20	-0.01
Anchorage municipality	Alaska	-0.47	-0.52	-0.57	-0.31	-0.60	-0.58
Avondale city	Arizona	0.42	0.28	0.52	0.44	0.19	0.30
Chandler city	Arizona	-0.46	-0.68	-0.39	-0.30	-0.85	-0.70
Glendale city	Arizona	0.05	-0.10	-0.03	0.28	-0.25	-0.16
Mesa city	Arizona	-0.03	-0.24	0.00	0.14	-0.42	-0.27
Peoria city	Arizona	-0.44	-0.73	-0.50	-0.10	-0.99	-0.81
Phoenix city	Arizona	0.33	0.19	0.48	0.34	0.09	0.21
Scottsdale city	Arizona	-0.85	-0.95	-0.81	-0.79	-1.03	-0.95
Tempe city	Arizona	-0.44	-0.54	-0.28	-0.51	-0.59	-0.50
Tucson city	Arizona	0.17	0.21	0.15	0.15	0.23	0.20
Yuma city	Arizona	0.28	0.02	0.11	0.70	-0.25	-0.10
Fayetteville city	Arkansas	-0.71	-0.43	-0.69	-1.00	-0.18	-0.37
Fort Smith city	Arkansas	0.13	0.18	-0.21	0.43	0.14	0.05
Little Rock city	Arkansas	-0.37	-0.16	-0.65	-0.31	-0.04	-0.23
Alameda city	California	-0.56	-0.53	-0.29	-0.85	-0.43	-0.41
Alhambra city	California	0.37	0.06	1.08	-0.03	-0.03	0.29
Anaheim city	California	0.62	0.11	1.02	0.74	-0.24	0.16
Antioch city	California	-0.03	-0.21	0.01	0.11	-0.36	-0.23
Bakersfield city	California	0.21	0.06	0.12	0.46	-0.10	-0.01
Baldwin Park city	California	1.32	0.82	1.73	1.39	0.50	0.89
Bellflower city	California	0.64	0.43	0.81	0.68	0.29	0.46
Berkeley city	California	-1.04	-0.59	-0.62	-1.91	-0.09	-0.33
Buena Park city	California	0.21	-0.25	0.54	0.35	-0.57	-0.21
Burbank city	California	-0.25	-0.49	0.03	-0.29	-0.62	-0.42

City	State	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Carlsbad city	California	-0.91	-1.07	-0.77	-0.89	-1.17	-1.04
Carson city	California	0.26	-0.14	0.35	0.56	-0.46	-0.18
Chico city	California	-0.35	-0.06	-0.43	-0.56	0.17	-0.04
Chino city	California	0.18	-0.41	0.20	0.75	-0.91	-0.52
Chula Vista city	California	0.17	-0.17	0.37	0.32	-0.42	-0.16
Clovis city	California	-0.28	-0.48	-0.34	-0.01	-0.68	-0.55
Concord city	California	-0.11	-0.32	0.18	-0.19	-0.44	-0.25
Corona city	California	-0.02	-0.45	0.06	0.33	-0.80	-0.50
Costa Mesa city	California	0.15	-0.17	0.56	0.05	-0.35	-0.07
Daly City	California	0.22	-0.14	0.84	-0.04	-0.29	0.04
El Cajon city	California	0.28	0.14	0.44	0.26	0.06	0.18
Escondido city	California	0.37	-0.05	0.68	0.47	-0.34	-0.01
Fairfield city	California	-0.11	-0.28	0.01	-0.08	-0.39	-0.26
Fontana city	California	0.62	0.13	0.82	0.91	-0.24	0.12
Fremont city	California	-0.34	-0.64	0.30	-0.68	-0.73	-0.44
Fresno city	California	0.63	0.58	0.66	0.65	0.54	0.58
Fullerton city	California	-0.16	-0.50	0.15	-0.14	-0.71	-0.44
Garden Grove city	California	0.83	0.23	1.52	0.75	-0.12	0.39
Glendale city	California	0.25	-0.20	0.99	-0.05	-0.41	0.00
Hawthorne city	California	0.97	0.78	1.26	0.88	0.68	0.86
Hayward city	California	0.26	0.02	0.56	0.19	-0.11	0.10
Hemet city	California	0.57	0.24	0.58	0.89	-0.05	0.18
Hesperia city	California	0.39	0.09	0.30	0.79	-0.20	-0.01
Huntington Beach city	California	-0.58	-0.81	-0.48	-0.46	-0.99	-0.82
Indio city	California	1.09	0.73	1.52	1.01	0.52	0.83
Inglewood city	California	0.96	0.77	1.17	0.94	0.65	0.81
Lakewood city	California	-0.27	-0.65	-0.18	0.02	-0.97	-0.69
Livermore city	California	-0.63	-0.80	-0.48	-0.61	-0.92	-0.78
Long Beach city	California	0.45	0.42	0.73	0.20	0.46	0.53

City	State	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Los Angeles city	California	0.69	0.56	1.16	0.33	0.57	0.73
Merced city	California	0.76	0.68	0.77	0.84	0.61	0.67
Mission Viejo city	California	-0.82	-1.10	-0.78	-0.58	-1.34	-1.15
Modesto city	California	0.15	-0.07	0.07	0.45	-0.28	-0.14
Mountain View city	California	-0.60	-0.72	-0.02	-1.08	-0.67	-0.50
Napa city	California	-0.14	-0.31	0.11	-0.22	-0.39	-0.24
Norwalk city	California	0.72	0.09	1.05	1.01	-0.37	0.10
Oakland city	California	0.39	0.59	0.73	-0.14	0.84	0.76
Oceanside city	California	-0.18	-0.50	0.02	-0.06	-0.73	-0.49
Ontario city	California	0.82	0.36	1.07	1.03	0.03	0.37
Orange city	California	-0.10	-0.52	0.09	0.14	-0.84	-0.53
Oxnard city	California	0.95	0.63	1.45	0.77	0.48	0.77
Palmdale city	California	0.64	0.35	0.65	0.93	0.10	0.29
Pasadena city	California	-0.28	-0.25	-0.03	-0.55	-0.16	-0.14
Pleasanton city	California	-0.93	-1.05	-0.72	-1.03	-1.09	-0.98
Pomona city	California	1.09	0.55	1.56	1.14	0.21	0.64
Redding city	California	-0.31	-0.39	-0.48	-0.06	-0.50	-0.47
Redlands city	California	-0.36	-0.42	-0.41	-0.26	-0.48	-0.45
Redwood City	California	0.12	-0.03	0.61	-0.22	-0.04	0.14
Rialto city	California	0.66	0.13	0.84	1.02	-0.29	0.09
Richmond city	California	0.34	0.36	0.56	0.09	0.43	0.45
Riverside city	California	0.23	-0.06	0.39	0.36	-0.27	-0.05
Roseville city	California	-0.58	-0.81	-0.53	-0.39	-0.99	-0.83
Sacramento city	California	0.26	0.37	0.36	0.06	0.48	0.43
Salinas city	California	1.32	0.78	1.82	1.37	0.42	0.87
San Bernardino city	California	1.11	1.18	1.29	0.87	1.29	1.27
San Buenaventura (Ventura) city	California	-0.44	-0.44	-0.38	-0.50	-0.43	-0.42
San Diego city	California	-0.25	-0.27	0.05	-0.53	-0.21	-0.15

City	State	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
San Francisco city	California	-0.30	-0.29	0.20	-0.81	-0.15	-0.08
San Jose city	California	0.02	-0.21	0.46	-0.19	-0.31	-0.08
San Leandro city	California	0.08	-0.24	0.36	0.13	-0.46	-0.20
San Marcos city	California	-0.09	-0.43	0.08	0.08	-0.68	-0.43
San Mateo city	California	-0.39	-0.61	0.01	-0.56	-0.70	-0.49
Santa Ana city	California	1.59	0.84	2.31	1.62	0.37	0.98
Santa Barbara city	California	-0.37	-0.40	-0.17	-0.54	-0.38	-0.33
Santa Clara city	California	-0.31	-0.44	0.31	-0.78	-0.41	-0.23
Santa Maria city	California	0.93	0.62	1.37	0.82	0.45	0.73
Santa Monica city	California	-0.91	-0.95	-0.65	-1.13	-0.92	-0.85
Santa Rosa city	California	-0.16	-0.29	-0.06	-0.13	-0.38	-0.28
Simi Valley city	California	-0.54	-0.84	-0.54	-0.23	-1.11	-0.90
Stockton city	California	0.61	0.52	0.70	0.61	0.46	0.53
Sunnyvale city	California	-0.40	-0.54	0.26	-0.94	-0.49	-0.30
Thousand Oaks city	California	-0.74	-0.87	-0.60	-0.74	-0.96	-0.84
Torrance city	California	-0.53	-0.78	-0.19	-0.62	-0.92	-0.70
Tracy city	California	-0.07	-0.50	0.03	0.27	-0.86	-0.55
Turlock city	California	0.34	-0.13	0.49	0.66	-0.51	-0.17
Tustin city	California	-0.13	-0.52	0.38	-0.23	-0.74	-0.40
Union City	California	0.29	-0.15	0.87	0.16	-0.40	-0.01
Upland city	California	-0.28	-0.29	-0.28	-0.28	-0.29	-0.29
Vacaville city	California	-0.41	-0.69	-0.45	-0.09	-0.94	-0.76
Vallejo city	California	-0.01	-0.08	0.07	-0.03	-0.12	-0.06
Victorville city	California	0.52	0.29	0.43	0.84	0.07	0.21
Visalia city	California	0.23	0.06	0.10	0.53	-0.11	-0.02
Vista city	California	0.42	0.22	0.70	0.33	0.13	0.30
West Covina city	California	0.35	0.08	0.50	0.46	-0.12	0.08
Westminster city	California	0.57	-0.09	1.11	0.69	-0.53	-0.01
Arvada city	Colorado	-0.51	-0.71	-0.66	-0.15	-0.93	-0.81

City	State	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Aurora city	Colorado	0.16	0.03	0.19	0.25	-0.07	0.02
Boulder city	Colorado	-1.03	-0.70	-0.65	-1.73	-0.32	-0.48
Colorado Springs city	Colorado	-0.45	-0.40	-0.54	-0.39	-0.39	-0.44
Denver city	Colorado	-0.04	0.10	0.09	-0.32	0.26	0.18
Fort Collins city	Colorado	-0.81	-0.57	-0.75	-1.11	-0.34	-0.50
Greeley city	Colorado	-0.04	-0.07	-0.08	0.02	-0.10	-0.09
Lakewood city	Colorado	-0.33	-0.37	-0.47	-0.14	-0.44	-0.43
Longmont city	Colorado	-0.16	-0.31	-0.07	-0.10	-0.42	-0.30
Pueblo city	Colorado	0.31	0.53	-0.14	0.54	0.61	0.39
Thornton city	Colorado	-0.20	-0.51	-0.28	0.20	-0.81	-0.61
Westminster city	Colorado	-0.48	-0.69	-0.58	-0.17	-0.90	-0.77
Washington city	District of Columbia	-0.25	0.42	-0.10	-1.06	1.04	0.61
Boca Raton city	Florida	-0.62	-0.75	-0.51	-0.59	-0.84	-0.73
Cape Coral city	Florida	-0.17	-0.44	-0.17	0.09	-0.67	-0.49
Clearwater city	Florida	-0.18	-0.29	-0.21	-0.05	-0.40	-0.33
Davie town	Florida	-0.33	-0.50	-0.22	-0.28	-0.62	-0.49
Deerfield Beach city	Florida	0.16	-0.04	0.54	-0.01	-0.12	0.07
Deltona city	Florida	-0.10	-0.48	-0.25	0.42	-0.84	-0.61
Fort Lauderdale city	Florida	-0.09	0.01	-0.16	-0.11	0.08	0.00
Gainesville city	Florida	-0.20	0.25	-0.23	-0.62	0.64	0.33
Hollywood city	Florida	0.06	-0.14	0.31	0.01	-0.26	-0.08
Jacksonville city	Florida	-0.29	-0.25	-0.45	-0.17	-0.26	-0.31
Largo city	Florida	-0.18	-0.44	-0.31	0.23	-0.71	-0.55
Melbourne city	Florida	-0.25	-0.38	-0.36	-0.02	-0.52	-0.45
Miami city	Florida	1.47	1.48	2.34	0.60	1.70	1.83
Miami Beach city	Florida	0.39	0.28	1.22	-0.32	0.38	0.59
Miramar city	Florida	-0.16	-0.45	0.04	-0.06	-0.66	-0.43
Orlando city	Florida	0.10	0.11	0.18	0.01	0.15	0.15

City	State	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Palm Bay city	Florida	-0.11	-0.31	-0.16	0.14	-0.49	-0.37
Pembroke Pines city	Florida	-0.39	-0.63	-0.21	-0.33	-0.79	-0.60
Plantation city	Florida	-0.40	-0.65	-0.32	-0.24	-0.85	-0.67
Pompano Beach city	Florida	0.25	0.04	0.37	0.35	-0.12	0.04
St. Petersburg city	Florida	-0.18	-0.14	-0.36	-0.03	-0.15	-0.20
Sunrise city	Florida	0.04	-0.29	0.22	0.20	-0.54	-0.29
Tallahassee city	Florida	-0.65	-0.37	-0.66	-0.93	-0.12	-0.31
Tampa city	Florida	0.02	0.16	-0.04	-0.05	0.26	0.16
West Palm Beach city	Florida	0.27	0.35	0.41	0.06	0.45	0.42
Atlanta city	Georgia	0.09	0.86	-0.19	-0.39	1.47	0.90
Roswell city	Georgia	-0.85	-1.04	-0.58	-0.92	-1.15	-0.97
Savannah city	Georgia	0.18	0.54	-0.11	0.12	0.79	0.50
Honolulu CDP	Hawaii	-0.31	-0.38	0.05	-0.58	-0.37	-0.26
Boise City	Idaho	-0.53	-0.54	-0.64	-0.42	-0.57	-0.58
Nampa city	Idaho	0.23	0.26	0.05	0.38	0.24	0.20
Aurora city	Illinois	0.24	0.00	0.53	0.21	-0.15	0.06
Champaign city	Illinois	-0.59	-0.30	-0.53	-0.96	-0.02	-0.21
Chicago city	Illinois	0.33	0.65	0.37	-0.01	0.93	0.72
Elgin city	Illinois	0.29	-0.05	0.49	0.45	-0.31	-0.04
Evanston city	Illinois	-1.10	-0.91	-0.92	-1.47	-0.70	-0.80
Joliet city	Illinois	-0.05	-0.22	-0.18	0.25	-0.40	-0.30
Naperville city	Illinois	-1.15	-1.26	-0.94	-1.23	-1.32	-1.21
Peoria city	Illinois	-0.43	0.01	-0.80	-0.51	0.31	-0.05
Rockford city	Illinois	0.24	0.41	-0.07	0.38	0.48	0.32
Schaumburg village	Illinois	-0.57	-0.79	-0.33	-0.58	-0.93	-0.74
Springfield city	Illinois	-0.42	-0.18	-0.75	-0.33	-0.06	-0.27
Waukegan city	Illinois	0.68	0.40	0.93	0.70	0.22	0.44
Bloomington city	Indiana	-0.66	-0.24	-0.46	-1.28	0.17	-0.08
Evansville city	Indiana	0.04	0.19	-0.44	0.35	0.21	0.04

City	State	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Fort Wayne city	Indiana	-0.01	0.14	-0.46	0.30	0.16	-0.01
Hammond city	Indiana	0.57	0.73	0.17	0.80	0.77	0.60
Indianapolis city (balance)	Indiana	-0.07	0.11	-0.41	0.09	0.18	0.01
South Bend city	Indiana	0.29	0.61	-0.08	0.34	0.79	0.52
Cedar Rapids city	Iowa	-0.37	-0.24	-0.65	-0.23	-0.20	-0.33
Davenport city	Iowa	-0.26	-0.07	-0.55	-0.17	0.02	-0.15
Des Moines city	Iowa	-0.30	-0.24	-0.45	-0.23	-0.22	-0.28
Sioux City	Iowa	0.05	0.03	-0.26	0.39	-0.07	-0.10
Kansas City	Kansas	0.57	0.83	0.24	0.65	0.98	0.75
Lawrence city	Kansas	-0.81	-0.59	-0.63	-1.21	-0.36	-0.48
Olathe city	Kansas	-0.80	-0.84	-0.83	-0.72	-0.88	-0.86
Overland Park city	Kansas	-0.94	-1.05	-0.89	-0.87	-1.14	-1.06
Topeka city	Kansas	-0.17	-0.03	-0.56	0.08	0.00	-0.16
Wichita city	Kansas	-0.10	-0.05	-0.35	0.10	-0.06	-0.14
Lexington-Fayette	Kentucky	-0.51	-0.38	-0.61	-0.53	-0.30	-0.40
Baton Rouge city	Louisiana	0.30	0.75	-0.13	0.27	1.04	0.67
Lafayette city	Louisiana	-0.35	-0.25	-0.56	-0.25	-0.22	-0.32
Shreveport city	Louisiana	0.26	0.62	-0.35	0.51	0.78	0.45
Baltimore city	Maryland	0.30	0.91	-0.02	0.01	1.36	0.90
Boston city	Massachusetts	0.02	0.52	0.43	-0.90	1.06	0.78
Brockton city	Massachusetts	0.37	0.38	0.38	0.34	0.39	0.39
Cambridge city	Massachusetts	-0.88	-0.51	-0.28	-1.84	-0.04	-0.20
Fall River city	Massachusetts	0.51	0.55	0.44	0.54	0.57	0.53
Lawrence city	Massachusetts	1.47	2.04	1.85	0.53	2.63	2.30
Lowell city	Massachusetts	0.46	0.71	0.72	-0.06	1.00	0.87
Lynn city	Massachusetts	0.49	0.73	0.71	0.02	0.99	0.86
New Bedford city	Massachusetts	0.60	0.76	0.40	0.63	0.86	0.72
Newton city	Massachusetts	-1.21	-1.20	-0.96	-1.49	-1.12	-1.09

City	State	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Quincy city	Massachusetts	-0.40	-0.58	-0.19	-0.44	-0.68	-0.53
Somerville city	Massachusetts	-0.13	0.12	0.34	-0.84	0.45	0.36
Springfield city	Massachusetts	0.81	1.27	0.50	0.65	1.59	1.24
Worcester city	Massachusetts	0.04	0.34	0.21	-0.43	0.65	0.47
Ann Arbor city	Michigan	-1.00	-0.63	-0.52	-1.84	-0.19	-0.37
Detroit city	Michigan	0.99	1.85	0.24	0.89	2.41	1.72
Grand Rapids city	Michigan	0.17	0.43	-0.02	0.11	0.60	0.40
Lansing city	Michigan	0.19	0.54	-0.11	0.13	0.77	0.49
Livonia city	Michigan	-0.64	-0.96	-0.75	-0.23	-1.26	-1.06
Pontiac city	Michigan	0.87	1.18	0.44	0.98	1.34	1.07
Southfield city	Michigan	-0.27	-0.39	-0.51	0.09	-0.55	-0.51
Sterling Heights city	Michigan	-0.20	-0.54	-0.24	0.17	-0.85	-0.62
Troy city	Michigan	-0.84	-0.96	-0.69	-0.86	-1.04	-0.93
Warren city	Michigan	0.08	-0.14	-0.20	0.58	-0.41	-0.30
Westland city	Michigan	-0.10	-0.29	-0.39	0.37	-0.52	-0.44
Wyoming city	Michigan	0.10	-0.10	-0.02	0.44	-0.32	-0.20
Bloomington city	Minnesota	-0.60	-0.70	-0.62	-0.49	-0.78	-0.72
Brooklyn Park city	Minnesota	-0.22	-0.30	-0.27	-0.10	-0.38	-0.34
Duluth city	Minnesota	-0.63	-0.37	-0.77	-0.75	-0.18	-0.37
Minneapolis city	Minnesota	-0.27	0.22	-0.11	-0.93	0.69	0.38
Plymouth city	Minnesota	-0.90	-1.00	-0.84	-0.87	-1.07	-1.00
Rochester city	Minnesota	-0.82	-0.78	-0.73	-0.94	-0.72	-0.73
St. Paul city	Minnesota	-0.21	0.17	-0.16	-0.65	0.52	0.27
Columbia city	Missouri	-0.76	-0.54	-0.69	-1.05	-0.32	-0.46
Independence city	Missouri	-0.04	-0.14	-0.33	0.36	-0.31	-0.28
Kansas City	Missouri	-0.13	0.15	-0.39	-0.14	0.33	0.10
Lee's Summit city	Missouri	-0.86	-0.95	-0.94	-0.70	-1.04	-1.00
St. Louis city	Missouri	0.35	1.24	-0.20	0.01	1.88	1.20
Springfield city	Missouri	-0.15	0.01	-0.47	0.03	0.06	-0.09

City	State	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Lincoln city	Nebraska	-0.57	-0.49	-0.59	-0.62	-0.43	-0.49
Omaha city	Nebraska	-0.18	-0.02	-0.33	-0.20	0.09	-0.05
Henderson city	Nevada	-0.53	-0.77	-0.64	-0.19	-1.01	-0.86
Las Vegas city	Nevada	0.12	-0.16	0.19	0.34	-0.38	-0.19
North Las Vegas city	Nevada	0.41	0.05	0.57	0.59	-0.21	0.05
Reno city	Nevada	-0.11	-0.16	-0.01	-0.17	-0.17	-0.12
Sparks city	Nevada	-0.13	-0.46	-0.08	0.15	-0.74	-0.51
Manchester city	New Hampshire	-0.24	-0.10	-0.21	-0.41	0.04	-0.06
Nashua city	New Hampshire	-0.52	-0.59	-0.41	-0.56	-0.62	-0.56
Camden city	New Jersey	2.03	3.02	1.76	1.31	3.82	3.11
Clifton city	New Jersey	-0.08	-0.40	0.16	0.01	-0.63	-0.37
Elizabeth city	New Jersey	0.97	0.91	1.35	0.64	0.96	1.06
Jersey City	New Jersey	0.40	0.60	0.80	-0.20	0.88	0.80
Newark city	New Jersey	1.15	1.50	1.35	0.59	1.86	1.65
Passaic city	New Jersey	1.71	1.73	2.45	0.96	1.93	2.03
Paterson city	New Jersey	1.20	1.28	1.56	0.77	1.44	1.44
Trenton city	New Jersey	1.07	1.46	0.92	0.83	1.76	1.47
Albuquerque city	New Mexico	-0.17	-0.20	-0.27	-0.03	-0.26	-0.25
Santa Fe city	New Mexico	-0.34	-0.25	-0.27	-0.50	-0.16	-0.21
Albany city	New York	-0.07	0.80	-0.38	-0.62	1.48	0.85
Buffalo city	New York	0.55	1.45	-0.21	0.42	2.04	1.32
New Rochelle city	New York	-0.21	-0.30	0.05	-0.38	-0.31	-0.21
New York city	New York	0.33	0.52	0.71	-0.23	0.77	0.71
Rochester city	New York	0.77	1.62	0.30	0.40	2.25	1.60
Syracuse city	New York	0.44	1.29	0.00	0.04	1.91	1.28
Yonkers city	New York	0.14	0.14	0.22	0.04	0.17	0.18
Asheville city	North Carolina	-0.49	-0.29	-0.62	-0.55	-0.15	-0.30
Cary town	North Carolina	-0.90	-1.01	-0.69	-1.00	-1.05	-0.94
Charlotte city	North Carolina	-0.25	-0.22	-0.28	-0.27	-0.19	-0.22

City	State	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Durham city	North Carolina	-0.21	-0.08	-0.15	-0.39	0.04	-0.03
Fayetteville city	North Carolina	0.02	0.19	-0.45	0.34	0.21	0.03
Gastonia city	North Carolina	0.40	0.42	0.08	0.69	0.36	0.30
Greensboro city	North Carolina	-0.08	-0.01	-0.21	0.00	0.01	-0.05
High Point city	North Carolina	0.16	0.20	-0.12	0.40	0.17	0.10
Raleigh city	North Carolina	-0.51	-0.32	-0.43	-0.78	-0.14	-0.25
Wilmington city	North Carolina	-0.47	-0.30	-0.55	-0.56	-0.17	-0.30
Winston-Salem city	North Carolina	0.07	0.24	-0.08	0.04	0.36	0.22
Fargo city	North Dakota	-0.65	-0.53	-0.76	-0.68	-0.44	-0.54
Akron city	Ohio	0.12	0.52	-0.33	0.18	0.76	0.42
Cincinnati city	Ohio	0.13	0.89	-0.36	-0.14	1.43	0.85
Cleveland city	Ohio	0.96	1.83	0.17	0.87	2.40	1.69
Columbus city	Ohio	-0.08	0.19	-0.27	-0.16	0.38	0.17
Dayton city	Ohio	0.64	1.41	-0.13	0.64	1.89	1.25
Lorain city	Ohio	0.46	0.58	-0.09	0.89	0.55	0.39
Parma city	Ohio	-0.25	-0.52	-0.47	0.23	-0.81	-0.66
Toledo city	Ohio	0.31	0.64	-0.30	0.60	0.78	0.46
Broken Arrow city	Oklahoma	-0.51	-0.63	-0.75	-0.16	-0.79	-0.75
Edmond city	Oklahoma	-0.90	-0.95	-0.93	-0.82	-1.00	-0.97
Lawton city	Oklahoma	0.18	0.30	-0.32	0.57	0.28	0.12
Norman city	Oklahoma	-0.64	-0.49	-0.73	-0.68	-0.38	-0.50
Oklahoma City	Oklahoma	0.04	0.17	-0.26	0.21	0.21	0.08
Tulsa city	Oklahoma	-0.01	0.14	-0.27	0.10	0.20	0.06
Beaverton city	Oregon	-0.47	-0.61	-0.26	-0.54	-0.68	-0.55
Eugene city	Oregon	-0.54	-0.38	-0.50	-0.75	-0.22	-0.33
Gresham city	Oregon	0.32	0.24	0.33	0.39	0.17	0.22
Hillsboro city	Oregon	0.09	0.13	0.20	-0.07	0.19	0.18
Medford city	Oregon	-0.21	-0.25	-0.37	0.00	-0.33	-0.32
Portland city	Oregon	-0.30	-0.10	-0.27	-0.53	0.08	-0.05

City	State	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Salem city	Oregon	0.15	0.10	0.09	0.25	0.04	0.06
Allentown city	Pennsylvania	0.40	0.82	0.31	0.07	1.17	0.87
Bethlehem city	Pennsylvania	-0.25	-0.17	-0.35	-0.24	-0.12	-0.19
Erie city	Pennsylvania	0.12	0.48	-0.40	0.28	0.66	0.34
Philadelphia city	Pennsylvania	0.45	0.96	0.15	0.23	1.34	0.95
Pittsburgh city	Pennsylvania	-0.08	0.58	-0.48	-0.35	1.07	0.56
Reading city	Pennsylvania	1.34	1.96	1.05	1.00	2.43	1.97
Scranton city	Pennsylvania	0.21	0.55	-0.14	0.20	0.77	0.49
Cranston city	Rhode Island	-0.38	-0.59	-0.39	-0.16	-0.78	-0.63
Pawtucket city	Rhode Island	0.47	0.65	0.42	0.33	0.79	0.66
Providence city	Rhode Island	0.56	1.18	0.74	-0.25	1.77	1.38
Warwick city	Rhode Island	-0.52	-0.75	-0.64	-0.17	-0.98	-0.84
Charleston city	South Carolina	-0.46	-0.12	-0.59	-0.67	0.14	-0.11
Columbia city	South Carolina	-0.31	0.10	-0.48	-0.54	0.42	0.11
Sioux Falls city	South Dakota	-0.45	-0.39	-0.57	-0.39	-0.36	-0.42
Chattanooga city	Tennessee	-0.06	0.29	-0.53	0.06	0.48	0.17
Clarksville city	Tennessee	-0.35	-0.40	-0.60	-0.04	-0.51	-0.51
Knoxville city	Tennessee	-0.06	0.33	-0.42	-0.10	0.58	0.26
Memphis city	Tennessee	0.39	0.68	-0.11	0.59	0.81	0.54
Murfreesboro city	Tennessee	-0.45	-0.31	-0.51	-0.53	-0.21	-0.31
Nashville-Davidson (balance)	Tennessee	-0.19	-0.05	-0.29	-0.24	0.05	-0.06
Abilene city	Texas	0.07	0.12	-0.28	0.36	0.07	-0.01
Amarillo city	Texas	0.09	0.05	-0.16	0.38	-0.05	-0.06
Arlington city	Texas	0.06	-0.12	0.01	0.29	-0.29	-0.17
Austin city	Texas	-0.17	-0.08	-0.03	-0.39	0.03	-0.01
Baytown city	Texas	0.50	0.28	0.26	0.96	0.03	0.14
Beaumont city	Texas	0.29	0.56	-0.20	0.50	0.68	0.42
Bryan city	Texas	0.54	0.56	0.43	0.63	0.55	0.52

City	State	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Carrollton city	Texas	-0.14	-0.52	0.02	0.08	-0.82	-0.54
College Station city	Texas	-0.70	-0.45	-0.39	-1.27	-0.16	-0.28
Corpus Christi city	Texas	0.25	0.18	-0.02	0.59	0.06	0.06
Dallas city	Texas	0.80	0.78	0.97	0.64	0.81	0.85
Denton city	Texas	-0.41	-0.39	-0.33	-0.50	-0.36	-0.36
Fort Worth city	Texas	0.37	0.38	0.30	0.44	0.36	0.35
Garland city	Texas	0.54	0.21	0.61	0.79	-0.05	0.18
Grand Prairie city	Texas	0.33	0.13	0.20	0.65	-0.07	0.04
Houston city	Texas	0.82	0.75	0.94	0.75	0.73	0.79
Irving city	Texas	0.42	0.09	0.71	0.46	-0.13	0.14
Killeen city	Texas	-0.07	-0.03	-0.41	0.24	-0.08	-0.16
Lewisville city	Texas	-0.21	-0.48	-0.16	-0.01	-0.69	-0.51
Lubbock city	Texas	0.00	0.01	-0.30	0.28	-0.05	-0.11
McKinney city	Texas	-0.67	-0.83	-0.64	-0.53	-0.96	-0.85
Mesquite city	Texas	0.28	-0.16	0.17	0.81	-0.57	-0.29
Midland city	Texas	0.10	-0.05	-0.16	0.50	-0.25	-0.18
Odessa city	Texas	0.45	0.30	0.01	1.03	0.06	0.09
Pasadena city	Texas	0.95	0.62	0.99	1.23	0.35	0.57
Plano city	Texas	-0.71	-0.88	-0.55	-0.70	-0.98	-0.85
Richardson city	Texas	-0.58	-0.82	-0.41	-0.50	-0.99	-0.80
Round Rock city	Texas	-0.40	-0.54	-0.50	-0.17	-0.68	-0.60
San Angelo city	Texas	0.08	0.04	-0.28	0.49	-0.09	-0.12
San Antonio city	Texas	0.32	0.26	0.20	0.50	0.17	0.20
Tyler city	Texas	0.19	0.31	-0.13	0.39	0.34	0.21
Waco city	Texas	0.41	0.52	0.19	0.51	0.57	0.46
Wichita Falls city	Texas	-0.05	-0.01	-0.30	0.16	-0.04	-0.10
Ogden city	Utah	0.21	0.53	0.15	-0.03	0.78	0.56
Orem city	Utah	-0.46	-0.56	-0.53	-0.31	-0.65	-0.60
Provo city	Utah	-0.41	-0.09	-0.17	-0.96	0.25	0.07

City	State	Index 1: Equal Weight	Index 2: Triple Weight to Poverty and Structural Problems	Index 3: Triple Weight to Immigration and Housing Affordability Factor	Index 4: Hedonic Weights	Index 5: Richardson Weights	Index 6: Partial Hedonic Weights
Salt Lake City	Utah	-0.18	0.05	-0.07	-0.54	0.29	0.15
Sandy city	Utah	-0.72	-0.89	-0.86	-0.42	-1.06	-0.97
West Jordan city	Utah	-0.40	-0.70	-0.48	-0.03	-0.98	-0.79
Alexandria city	Virginia	-0.72	-0.77	-0.18	-1.20	-0.68	-0.57
Chesapeake city	Virginia	-0.46	-0.68	-0.65	-0.05	-0.91	-0.80
Hampton city	Virginia	-0.21	-0.15	-0.48	-0.02	-0.16	-0.24
Newport News city	Virginia	-0.21	-0.12	-0.40	-0.11	-0.09	-0.18
Norfolk city	Virginia	-0.01	0.30	-0.18	-0.15	0.53	0.29
Portsmouth city	Virginia	0.03	0.23	-0.27	0.14	0.33	0.15
Richmond city	Virginia	-0.02	0.38	-0.21	-0.23	0.68	0.39
Roanoke city	Virginia	-0.05	0.14	-0.45	0.16	0.21	0.02
Suffolk city	Virginia	-0.32	-0.35	-0.59	-0.01	-0.44	-0.46
Virginia Beach city	Virginia	-0.53	-0.66	-0.62	-0.30	-0.80	-0.72
Bellevue city	Washington	-0.75	-0.84	-0.30	-1.10	-0.81	-0.68
Bellingham city	Washington	-0.66	-0.44	-0.58	-0.97	-0.23	-0.36
Everett city	Washington	0.02	0.03	0.06	-0.03	0.05	0.05
Kent city	Washington	0.05	-0.05	0.20	-0.01	-0.10	-0.01
Seattle city	Washington	-0.71	-0.55	-0.44	-1.13	-0.34	-0.41
Spokane city	Washington	-0.22	-0.03	-0.45	-0.16	0.07	-0.09
Tacoma city	Washington	-0.03	0.16	-0.09	-0.17	0.32	0.18
Vancouver city	Washington	-0.01	0.06	-0.05	-0.04	0.11	0.06
Yakima city	Washington	0.73	0.71	0.54	0.93	0.65	0.63
Green Bay city	Wisconsin	-0.09	-0.02	-0.23	-0.03	0.01	-0.06
Kenosha city	Wisconsin	-0.10	-0.21	-0.30	0.19	-0.34	-0.30
Madison city	Wisconsin	-0.79	-0.49	-0.61	-1.28	-0.18	-0.36
Milwaukee city	Wisconsin	0.46	0.96	0.19	0.23	1.34	0.96
Waukesha city	Wisconsin	-0.68	-0.83	-0.77	-0.43	-0.98	-0.89

Table A.9. Factor and Equal Weight Index Scores in 2005 and 2000 for 370 Cities

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
Birmingham city	Alabama	222,154	2.46	-1.11	0.26	0.54	1.82	-1.26	0.82	0.46
Huntsville city	Alabama	158,618	-0.05	-1.13	-0.11	-0.43	-0.10	-1.09	0.16	-0.34
Mobile city	Alabama	193,332	1.03	-1.14	0.63	0.17	0.71	-1.17	0.83	0.12
Montgomery city	Alabama	193,042	0.45	-1.26	0.61	-0.07	0.48	-1.25	0.75	-0.01
Anchorage municipality	Alaska	266,281	-0.61	-0.73	-0.06	-0.47	-0.78	-0.66	0.04	-0.47
Avondale city	Arizona	61,666	0.08	0.68	0.48	0.42	-0.42	0.45	0.83	0.29
Chandler city	Arizona	225,725	-1.01	-0.30	-0.07	-0.46	-1.08	-0.28	0.11	-0.42
Glendale city	Arizona	229,913	-0.33	-0.15	0.63	0.05	-0.54	-0.20	0.72	0.00
Mesa city	Arizona	442,445	-0.56	0.05	0.41	-0.03	-0.83	-0.17	0.63	-0.12
Peoria city	Arizona	141,941	-1.16	-0.58	0.41	-0.44	-1.19	-0.65	0.56	-0.43
Phoenix city	Arizona	1,377,980	-0.04	0.70	0.34	0.33	-0.15	0.52	0.52	0.30
Scottsdale city	Arizona	215,933	-1.10	-0.75	-0.70	-0.85	-1.26	-0.71	-0.48	-0.81
Tempe city	Arizona	166,171	-0.69	-0.04	-0.61	-0.44	-0.60	-0.20	-0.64	-0.48
Tucson city	Arizona	507,362	0.26	0.12	0.13	0.17	0.09	0.01	0.37	0.16
Yuma city	Arizona	91,433	-0.37	-0.14	1.33	0.28	-0.52	-0.04	1.55	0.33
Fayetteville city	Arkansas	58,839	-0.02	-0.67	-1.44	-0.71	-0.12	-0.62	-0.89	-0.54
Fort Smith city	Arkansas	81,054	0.26	-0.73	0.87	0.13	-0.04	-0.72	1.20	0.15
Little Rock city	Arkansas	176,924	0.16	-1.06	-0.21	-0.37	0.07	-0.99	0.13	-0.27
Alameda city	California	77,058	-0.48	0.11	-1.30	-0.56	-0.62	0.31	-1.08	-0.46
Alhambra city	California	76,309	-0.40	2.15	-0.64	0.37	-0.45	2.50	-0.03	0.68
Anaheim city	California	329,483	-0.67	1.62	0.92	0.62	-0.61	1.73	0.99	0.70
Antioch city	California	103,339	-0.48	0.07	0.31	-0.03	-0.64	-0.28	0.49	-0.14
Bakersfield city	California	286,316	-0.18	-0.01	0.83	0.21	-0.22	-0.16	1.07	0.23
Baldwin Park city	California	84,812	0.09	2.36	1.50	1.32	-0.25	2.82	1.99	1.52
Bellflower city	California	78,198	0.12	1.07	0.73	0.64	-0.15	1.15	1.12	0.70
Berkeley city	California	90,432	0.08	0.02	-3.22	-1.04	0.19	-0.01	-3.26	-1.03
Buena Park city	California	76,062	-0.94	1.03	0.55	0.21	-0.82	1.16	0.88	0.40

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
Burbank city	California	100,053	-0.84	0.45	-0.35	-0.25	-0.78	0.47	0.08	-0.08
Carlsbad city	California	92,998	-1.30	-0.56	-0.86	-0.91	-1.21	-0.54	-0.56	-0.77
Carson city	California	92,156	-0.74	0.49	1.02	0.26	-0.96	0.66	1.56	0.42
Chico city	California	71,298	0.37	-0.55	-0.87	-0.35	-0.01	-0.36	-0.93	-0.43
Chino city	California	69,732	-1.29	0.23	1.59	0.18	-1.16	0.19	1.85	0.29
Chula Vista city	California	212,954	-0.69	0.67	0.53	0.17	-0.61	0.52	0.65	0.19
Clovis city	California	80,529	-0.79	-0.43	0.38	-0.28	-0.92	-0.65	0.85	-0.24
Concord city	California	116,782	-0.64	0.62	-0.30	-0.11	-0.78	0.42	0.02	-0.12
Corona city	California	162,410	-1.09	0.17	0.86	-0.02	-1.08	0.08	0.92	-0.02
Costa Mesa city	California	105,333	-0.65	1.19	-0.10	0.15	-0.72	0.88	0.22	0.13
Daly City	California	93,513	-0.67	1.78	-0.44	0.22	-0.85	1.50	-0.35	0.10
El Cajon city	California	92,507	-0.06	0.67	0.23	0.28	0.06	0.49	0.58	0.38
Escondido city	California	133,017	-0.69	1.16	0.63	0.37	-0.46	0.98	0.75	0.42
Fairfield city	California	102,642	-0.52	0.21	-0.03	-0.11	-0.56	-0.13	0.27	-0.14
Fontana city	California	158,235	-0.60	1.12	1.35	0.62	-0.54	0.92	1.79	0.72
Fremont city	California	210,387	-1.08	1.26	-1.20	-0.34	-1.15	0.86	-0.86	-0.38
Fresno city	California	477,251	0.51	0.70	0.68	0.63	0.57	0.55	0.97	0.70
Fullerton city	California	142,064	-1.00	0.62	-0.10	-0.16	-0.84	0.65	0.18	0.00
Garden Grove city	California	192,345	-0.66	2.55	0.62	0.83	-0.70	2.28	0.89	0.82
Glendale city	California	194,620	-0.88	2.11	-0.49	0.25	-0.38	2.29	-0.62	0.43
Hawthorne city	California	100,754	0.49	1.70	0.74	0.97	0.28	1.80	1.41	1.16
Hayward city	California	135,474	-0.33	1.00	0.10	0.26	-0.49	1.31	0.35	0.39
Hemet city	California	77,076	-0.26	0.60	1.37	0.57	0.01	0.11	1.34	0.48
Hesperia city	California	79,714	-0.36	0.15	1.39	0.39	-0.47	-0.19	1.80	0.38
Huntington Beach city	California	189,451	-1.16	-0.32	-0.27	-0.58	-1.23	-0.35	0.07	-0.50
Indio city	California	65,091	0.19	2.18	0.89	1.09	0.15	2.00	1.65	1.26
Inglewood city	California	120,204	0.48	1.48	0.91	0.96	0.63	1.47	1.17	1.09
Lakewood city	California	88,253	-1.23	-0.04	0.46	-0.27	-1.18	-0.14	0.87	-0.15

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
Livermore city	California	87,054	-1.06	-0.26	-0.58	-0.63	-1.12	-0.43	-0.09	-0.55
Long Beach city	California	463,956	0.38	1.15	-0.18	0.45	0.62	1.15	0.10	0.62
Los Angeles city	California	3,731,437	0.38	1.88	-0.20	0.69	0.43	2.01	0.18	0.87
Merced city	California	65,391	0.55	0.78	0.95	0.76	0.68	0.79	1.19	0.89
Mission Viejo city	California	90,136	-1.53	-0.72	-0.21	-0.82	-1.55	-0.63	-0.07	-0.75
Modesto city	California	202,971	-0.39	-0.06	0.90	0.15	-0.29	-0.07	1.18	0.27
Mountain View city	California	69,427	-0.88	0.87	-1.79	-0.60	-0.89	1.11	-1.74	-0.51
Napa city	California	73,085	-0.56	0.49	-0.33	-0.14	-0.71	0.34	0.21	-0.05
Norwalk city	California	103,844	-0.84	1.54	1.46	0.72	-0.78	1.49	1.80	0.83
Oakland city	California	373,910	0.88	1.24	-0.95	0.39	0.91	1.22	-0.79	0.45
Oceanside city	California	162,259	-0.98	0.32	0.11	-0.18	-0.58	0.29	0.46	0.06
Ontario city	California	156,679	-0.32	1.43	1.35	0.82	-0.39	1.44	1.57	0.87
Orange city	California	137,994	-1.14	0.37	0.48	-0.10	-1.00	0.37	0.49	-0.05
Oxnard city	California	178,871	0.15	2.21	0.50	0.95	-0.15	2.10	0.82	0.92
Palmdale city	California	145,800	-0.09	0.66	1.36	0.64	-0.38	0.22	1.47	0.44
Pasadena city	California	129,400	-0.21	0.34	-0.97	-0.28	-0.20	0.92	-0.53	0.07
Pleasanton city	California	67,018	-1.22	-0.40	-1.19	-0.93	-1.45	-0.53	-0.68	-0.89
Pomona city	California	161,257	-0.24	2.28	1.22	1.09	0.16	2.11	1.50	1.26
Redding city	California	89,362	-0.51	-0.73	0.31	-0.31	-0.19	-0.73	0.65	-0.09
Redlands city	California	73,548	-0.51	-0.47	-0.10	-0.36	-0.70	-0.38	0.04	-0.35
Redwood City	California	81,195	-0.25	1.34	-0.73	0.12	-1.00	0.82	-0.36	-0.18
Rialto city	California	93,284	-0.67	1.11	1.55	0.66	-0.26	0.65	1.99	0.79
Richmond city	California	96,648	0.38	0.90	-0.27	0.34	0.45	1.01	-0.19	0.42
Riverside city	California	294,059	-0.49	0.63	0.55	0.23	-0.37	0.34	0.88	0.28
Roseville city	California	108,848	-1.15	-0.46	-0.12	-0.58	-1.21	-0.63	0.13	-0.57
Sacramento city	California	445,287	0.52	0.50	-0.24	0.26	0.53	0.42	0.11	0.35
Salinas city	California	156,950	-0.04	2.56	1.44	1.32	-0.31	2.14	1.71	1.18
San Bernardino city	California	204,552	1.28	1.56	0.50	1.11	1.05	1.00	0.90	0.98

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
San Buenaventura (Ventura) city	California	100,154	-0.44	-0.29	-0.59	-0.44	-0.59	-0.19	-0.27	-0.35
San Diego city	California	1,208,331	-0.30	0.51	-0.95	-0.25	-0.28	0.48	-0.52	-0.11
San Francisco city	California	719,077	-0.26	0.95	-1.59	-0.30	-0.32	1.12	-1.44	-0.21
San Jose city	California	887,330	-0.56	1.12	-0.50	0.02	-0.72	1.31	-0.35	0.08
San Leandro city	California	77,631	-0.73	0.77	0.21	0.08	-0.82	0.58	0.27	0.01
San Marcos city	California	77,445	-0.94	0.33	0.34	-0.09	-0.71	0.79	0.64	0.24
San Mateo city	California	93,481	-0.94	0.59	-0.82	-0.39	-1.00	0.52	-0.57	-0.35
Santa Ana city	California	302,302	-0.28	3.39	1.66	1.59	-0.28	3.81	1.96	1.83
Santa Barbara city	California	90,708	-0.45	0.14	-0.79	-0.37	-0.49	0.63	-0.64	-0.17
Santa Clara city	California	102,204	-0.65	1.23	-1.49	-0.31	-0.85	1.14	-1.33	-0.35
Santa Maria city	California	88,817	0.14	2.02	0.65	0.93	0.09	1.91	1.19	1.06
Santa Monica city	California	82,777	-1.00	-0.26	-1.47	-0.91	-0.74	-0.25	-1.22	-0.74
Santa Rosa city	California	146,500	-0.49	0.08	-0.08	-0.16	-0.70	0.03	-0.04	-0.24
Simi Valley city	California	116,722	-1.30	-0.54	0.23	-0.54	-1.18	-0.38	0.38	-0.39
Stockton city	California	278,515	0.38	0.83	0.61	0.61	0.52	0.79	1.01	0.78
Sunnyvale city	California	132,725	-0.75	1.26	-1.73	-0.40	-1.03	1.26	-1.49	-0.42
Thousand Oaks city	California	127,895	-1.07	-0.39	-0.75	-0.74	-1.25	-0.42	-0.40	-0.69
Torrance city	California	138,618	-1.16	0.32	-0.76	-0.53	-1.20	0.25	-0.36	-0.43
Tracy city	California	82,218	-1.15	0.18	0.78	-0.07	-1.21	-0.20	1.14	-0.09
Turlock city	California	74,883	-0.84	0.71	1.14	0.34	-0.38	0.32	1.04	0.33
Tustin city	California	79,811	-1.11	1.13	-0.40	-0.13	-1.08	0.93	0.31	0.06
Union City	California	65,239	-0.82	1.74	-0.04	0.29	-1.06	1.16	0.00	0.03
Upland city	California	74,420	-0.29	-0.29	-0.27	-0.28	-0.70	-0.11	0.40	-0.14
Vacaville city	California	81,117	-1.10	-0.50	0.38	-0.41	-1.05	-0.49	0.74	-0.27
Vallejo city	California	115,657	-0.18	0.19	-0.05	-0.01	-0.41	0.08	0.15	-0.06
Victorville city	California	93,042	-0.04	0.29	1.31	0.52	0.01	-0.04	1.33	0.43
Visalia city	California	108,467	-0.18	-0.10	0.97	0.23	-0.40	-0.16	1.18	0.21
Vista city	California	83,228	-0.06	1.12	0.19	0.42	-0.33	0.94	0.52	0.38

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
West Covina city	California	116,371	-0.33	0.74	0.63	0.35	-0.97	0.60	0.86	0.16
Westminster city	California	97,946	-1.08	1.92	0.88	0.57	-0.77	1.85	0.71	0.60
Arvada city	Colorado	104,766	-1.02	-0.88	0.38	-0.51	-1.04	-0.85	0.37	-0.51
Aurora city	Colorado	291,317	-0.16	0.23	0.40	0.16	-0.44	-0.05	0.37	-0.04
Boulder city	Colorado	83,432	-0.21	-0.08	-2.79	-1.03	-0.33	-0.15	-2.67	-1.05
Colorado Springs city	Colorado	376,985	-0.34	-0.69	-0.31	-0.45	-0.56	-0.72	-0.32	-0.53
Denver city	Colorado	545,198	0.31	0.28	-0.73	-0.04	0.25	0.26	-0.63	-0.04
Fort Collins city	Colorado	122,297	-0.20	-0.67	-1.56	-0.81	-0.52	-0.63	-1.49	-0.88
Greeley city	Colorado	82,836	-0.11	-0.14	0.11	-0.04	-0.09	-0.27	0.29	-0.03
Lakewood city	Colorado	142,434	-0.43	-0.69	0.14	-0.33	-0.74	-0.57	0.05	-0.42
Longmont city	Colorado	76,181	-0.54	0.08	-0.01	-0.16	-0.59	-0.14	0.03	-0.24
Pueblo city	Colorado	101,302	0.86	-0.81	0.88	0.31	0.35	-0.69	1.06	0.24
Thornton city	Colorado	102,331	-0.98	-0.41	0.80	-0.20	-1.00	-0.61	1.09	-0.17
Westminster city	Colorado	99,305	-1.01	-0.72	0.29	-0.48	-1.08	-0.54	0.29	-0.44
Washington city	District of Columbia	515,118	1.41	0.12	-2.28	-0.25	1.31	0.10	-1.74	-0.11
Boca Raton city	Florida	74,361	-0.95	-0.36	-0.55	-0.62	-1.26	-0.47	-0.48	-0.73
Cape Coral city	Florida	134,388	-0.84	-0.16	0.48	-0.17	-1.01	-0.58	0.79	-0.27
Clearwater city	Florida	108,382	-0.46	-0.26	0.16	-0.18	-0.35	-0.34	0.14	-0.18
Davie town	Florida	88,683	-0.75	-0.05	-0.20	-0.33	-0.98	-0.26	0.56	-0.23
Deerfield Beach city	Florida	71,599	-0.34	1.11	-0.27	0.16	-0.57	0.27	0.67	0.12
Deltona city	Florida	85,979	-1.04	-0.47	1.21	-0.10	-0.86	-0.61	1.27	-0.07
Fort Lauderdale city	Florida	141,307	0.15	-0.26	-0.15	-0.09	0.14	0.14	0.12	0.13
Gainesville city	Florida	100,879	0.93	-0.27	-1.26	-0.20	0.24	-0.56	-0.90	-0.41
Hollywood city	Florida	138,412	-0.44	0.68	-0.07	0.06	-0.42	0.29	0.46	0.11
Jacksonville city	Florida	768,537	-0.19	-0.69	0.01	-0.29	-0.23	-0.73	0.38	-0.19
Largo city	Florida	71,269	-0.84	-0.52	0.83	-0.18	-0.75	-0.52	0.83	-0.15
Melbourne city	Florida	76,373	-0.58	-0.51	0.33	-0.25	-0.45	-0.64	0.34	-0.25
Miami city	Florida	361,701	1.48	3.64	-0.70	1.47	1.42	3.61	-0.07	1.65

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
Miami Beach city	Florida	84,086	0.10	2.46	-1.38	0.39	0.84	2.31	-1.32	0.61
Miramar city	Florida	115,444	-0.90	0.35	0.09	-0.16	-0.93	0.41	0.66	0.04
Orlando city	Florida	221,299	0.14	0.29	-0.13	0.10	0.18	0.07	-0.21	0.01
Palm Bay city	Florida	90,102	-0.60	-0.25	0.51	-0.11	-0.65	-0.56	0.92	-0.09
Pembroke Pines city	Florida	159,422	-0.99	0.07	-0.24	-0.39	-1.25	-0.08	0.18	-0.39
Plantation city	Florida	88,859	-1.02	-0.19	0.00	-0.40	-1.24	-0.32	0.13	-0.48
Pompano Beach city	Florida	94,892	-0.28	0.54	0.49	0.25	-0.02	0.18	0.65	0.27
St. Petersburg city	Florida	232,960	-0.08	-0.63	0.18	-0.18	-0.11	-0.62	0.40	-0.11
Sunrise city	Florida	86,586	-0.80	0.48	0.44	0.04	-0.83	0.22	0.52	-0.03
Tallahassee city	Florida	141,148	0.06	-0.67	-1.36	-0.65	0.07	-0.82	-0.97	-0.57
Tampa city	Florida	312,855	0.36	-0.14	-0.15	0.02	0.40	-0.17	0.20	0.15
West Palm Beach city	Florida	86,804	0.46	0.62	-0.25	0.27	0.29	0.44	0.11	0.28
Atlanta city	Georgia	394,929	2.02	-0.63	-1.11	0.09	1.82	-0.58	-0.69	0.18
Roswell city	Georgia	98,137	-1.33	-0.18	-1.03	-0.85	-1.24	-0.19	-0.93	-0.79
Savannah city	Georgia	117,478	1.08	-0.55	0.01	0.18	0.92	-0.57	0.49	0.28
Honolulu CDP	Hawaii	362,252	-0.50	0.57	-0.99	-0.31	-0.54	0.71	-0.65	-0.16
Boise City	Idaho	191,667	-0.54	-0.80	-0.26	-0.53	-0.75	-0.79	-0.16	-0.57
Nampa city	Idaho	67,112	0.31	-0.22	0.60	0.23	-0.27	-0.28	0.88	0.11
Aurora city	Illinois	170,490	-0.38	0.96	0.15	0.24	-0.75	0.46	0.51	0.07
Champaign city	Illinois	65,600	0.15	-0.43	-1.51	-0.59	-0.18	-0.47	-1.62	-0.76
Chicago city	Illinois	2,701,926	1.12	0.42	-0.54	0.33	0.97	0.47	-0.24	0.40
Elgin city	Illinois	93,412	-0.58	0.78	0.68	0.29	-0.80	0.63	0.78	0.20
Evanston city	Illinois	62,258	-0.63	-0.65	-2.02	-1.10	-0.58	-0.47	-1.79	-0.94
Joliet city	Illinois	128,090	-0.47	-0.37	0.69	-0.05	-0.41	-0.39	0.91	0.04
Naperville city	Illinois	147,779	-1.44	-0.64	-1.35	-1.15	-1.48	-0.74	-1.06	-1.10
Peoria city	Illinois	102,136	0.68	-1.35	-0.63	-0.43	0.86	-1.21	-0.25	-0.20
Rockford city	Illinois	139,173	0.67	-0.54	0.59	0.24	0.26	-0.69	0.72	0.10
Schaumburg village	Illinois	77,817	-1.13	0.03	-0.60	-0.57	-1.37	-0.23	-0.18	-0.60

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
Springfield city	Illinois	110,262	0.17	-1.24	-0.20	-0.42	-0.02	-1.13	-0.07	-0.41
Waukegan city	Illinois	82,355	-0.02	1.30	0.75	0.68	-0.08	1.12	1.04	0.69
Bloomington city	Indiana	55,406	0.38	-0.16	-2.21	-0.66	0.09	-0.47	-2.34	-0.90
Evansville city	Indiana	110,708	0.43	-1.16	0.83	0.04	0.19	-1.19	0.88	-0.04
Fort Wayne city	Indiana	219,346	0.36	-1.14	0.76	-0.01	0.18	-1.14	0.82	-0.05
Hammond city	Indiana	72,507	0.97	-0.43	1.15	0.57	0.35	-0.61	1.33	0.36
Indianapolis city (balance)	Indiana	765,310	0.38	-0.91	0.32	-0.07	0.14	-0.99	0.39	-0.15
South Bend city	Indiana	97,070	1.08	-0.63	0.41	0.29	0.65	-0.85	0.74	0.18
Cedar Rapids city	Iowa	119,670	-0.04	-1.07	-0.01	-0.37	-0.62	-0.95	-0.23	-0.60
Davenport city	Iowa	95,382	0.21	-0.99	-0.02	-0.26	0.03	-0.99	0.35	-0.20
Des Moines city	Iowa	196,917	-0.14	-0.66	-0.11	-0.30	-0.10	-0.61	0.28	-0.14
Sioux City	Iowa	78,395	0.00	-0.74	0.90	0.05	-0.31	-0.58	0.77	-0.04
Kansas City	Kansas	142,341	1.22	-0.26	0.76	0.57	0.83	-0.46	0.85	0.41
Lawrence city	Kansas	74,951	-0.27	-0.35	-1.81	-0.81	-0.37	-0.61	-1.44	-0.81
Olathe city	Kansas	107,710	-0.90	-0.88	-0.61	-0.80	-1.18	-0.82	-0.19	-0.73
Overland Park city	Kansas	161,901	-1.22	-0.82	-0.77	-0.94	-1.35	-0.79	-0.68	-0.94
Topeka city	Kansas	117,326	0.19	-1.15	0.45	-0.17	0.03	-1.02	0.31	-0.23
Wichita city	Kansas	354,582	0.04	-0.73	0.39	-0.10	-0.18	-0.75	0.36	-0.19
Lexington-Fayette	Kentucky	255,389	-0.20	-0.76	-0.56	-0.51	-0.29	-0.81	-0.48	-0.53
Baton Rouge city	Louisiana	205,442	1.44	-0.77	0.23	0.30	0.79	-0.85	0.35	0.10
Lafayette city	Louisiana	108,175	-0.10	-0.88	-0.08	-0.35	-0.22	-0.82	0.39	-0.22
Shreveport city	Louisiana	192,531	1.16	-1.26	0.89	0.26	0.91	-1.24	1.10	0.26
Baltimore city	Maryland	608,481	1.82	-0.50	-0.41	0.30	1.63	-0.52	0.20	0.44
Boston city	Massachusetts	520,702	1.27	1.04	-2.27	0.02	0.98	0.88	-1.86	0.00
Brockton city	Massachusetts	91,938	0.40	0.41	0.29	0.37	0.40	0.16	0.28	0.28
Cambridge city	Massachusetts	81,260	0.04	0.61	-3.28	-0.88	-0.03	0.55	-2.67	-0.72
Fall River city	Massachusetts	97,612	0.61	0.34	0.58	0.51	0.52	0.30	1.10	0.64
Lawrence city	Massachusetts	82,191	2.89	2.41	-0.88	1.47	1.88	2.05	-0.24	1.23

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
Lowell city	Massachusetts	96,876	1.10	1.10	-0.83	0.46	0.65	0.64	-0.33	0.32
Lynn city	Massachusetts	83,419	1.09	1.04	-0.67	0.49	0.66	0.78	-0.33	0.37
New Bedford city	Massachusetts	84,898	1.01	0.10	0.68	0.60	0.97	0.30	0.98	0.75
Newton city	Massachusetts	82,383	-1.18	-0.57	-1.89	-1.21	-1.25	-0.43	-1.68	-1.12
Quincy city	Massachusetts	84,080	-0.85	0.12	-0.48	-0.40	-0.69	0.08	-0.49	-0.37
Somerville city	Massachusetts	74,869	0.48	1.05	-1.91	-0.13	-0.12	0.87	-1.61	-0.28
Springfield city	Massachusetts	146,948	1.96	0.04	0.42	0.81	1.32	-0.18	0.42	0.52
Worcester city	Massachusetts	154,398	0.80	0.47	-1.14	0.04	0.67	0.12	-0.50	0.09
Ann Arbor city	Michigan	98,743	-0.08	0.19	-3.10	-1.00	-0.33	0.01	-2.99	-1.10
Detroit city	Michigan	836,056	3.13	-0.88	0.73	0.99	2.59	-1.00	0.95	0.85
Grand Rapids city	Michigan	193,568	0.81	-0.32	0.03	0.17	0.42	-0.38	0.13	0.06
Lansing city	Michigan	119,675	1.06	-0.55	0.04	0.19	0.57	-0.61	0.25	0.07
Livonia city	Michigan	103,497	-1.42	-0.91	0.40	-0.64	-1.44	-0.95	0.62	-0.59
Pontiac city	Michigan	59,472	1.64	-0.20	1.16	0.87	1.41	-0.33	1.13	0.74
Southfield city	Michigan	75,053	-0.56	-0.87	0.62	-0.27	-0.71	-0.67	0.43	-0.32
Sterling Heights city	Michigan	123,368	-1.05	-0.29	0.73	-0.20	-1.27	-0.47	0.83	-0.30
Troy city	Michigan	83,958	-1.15	-0.47	-0.89	-0.84	-1.48	-0.44	-0.68	-0.87
Warren city	Michigan	134,901	-0.48	-0.62	1.33	0.08	-0.85	-0.55	1.64	0.08
Westland city	Michigan	80,284	-0.57	-0.82	1.08	-0.10	-0.90	-0.68	1.33	-0.08
Wyoming city	Michigan	68,960	-0.41	-0.21	0.93	0.10	-0.75	-0.52	1.00	-0.09
Bloomington city	Minnesota	80,055	-0.84	-0.64	-0.32	-0.60	-1.12	-0.62	-0.08	-0.61
Brooklyn Park city	Minnesota	66,408	-0.42	-0.34	0.08	-0.22	-0.79	-0.44	0.10	-0.38
Duluth city	Minnesota	76,918	0.02	-0.98	-0.93	-0.63	-0.04	-1.00	-0.57	-0.54
Minneapolis city	Minnesota	350,260	0.95	0.14	-1.91	-0.27	0.75	0.07	-1.75	-0.31
Plymouth city	Minnesota	68,978	-1.15	-0.74	-0.81	-0.90	-1.38	-0.78	-0.67	-0.94
Rochester city	Minnesota	88,338	-0.72	-0.61	-1.12	-0.82	-0.62	-0.57	-0.92	-0.70
St. Paul city	Minnesota	261,559	0.75	-0.09	-1.30	-0.21	0.61	0.01	-1.24	-0.21
Columbia city	Missouri	82,103	-0.20	-0.59	-1.49	-0.76	-0.17	-0.69	-1.43	-0.76

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
Independence city	Missouri	111,842	-0.30	-0.76	0.95	-0.04	-0.55	-0.85	1.02	-0.12
Kansas City	Missouri	440,885	0.57	-0.79	-0.16	-0.13	0.39	-0.79	0.04	-0.12
Lee's Summit city	Missouri	86,357	-1.08	-1.05	-0.46	-0.86	-1.20	-1.07	-0.13	-0.80
St. Louis city	Missouri	333,730	2.57	-1.03	-0.50	0.35	2.43	-1.02	-0.09	0.44
Springfield city	Missouri	139,600	0.24	-0.96	0.28	-0.15	0.01	-0.98	0.43	-0.18
Lincoln city	Nebraska	226,062	-0.38	-0.62	-0.70	-0.57	-0.55	-0.70	-0.51	-0.59
Omaha city	Nebraska	373,215	0.23	-0.55	-0.23	-0.18	-0.15	-0.65	-0.18	-0.33
Henderson city	Nevada	223,776	-1.13	-0.79	0.31	-0.53	-1.20	-0.72	0.55	-0.46
Las Vegas city	Nevada	538,653	-0.58	0.29	0.66	0.12	-0.57	0.18	0.83	0.15
North Las Vegas city	Nevada	165,061	-0.47	0.82	0.87	0.41	-0.35	0.99	1.33	0.66
Reno city	Nevada	204,478	-0.22	0.15	-0.26	-0.11	-0.39	0.11	0.02	-0.09
Sparks city	Nevada	76,405	-0.96	0.00	0.57	-0.13	-0.90	0.01	0.77	-0.04
Manchester city	New Hampshire	109,308	0.12	-0.17	-0.67	-0.24	-0.12	-0.22	-0.29	-0.21
Nashua city	New Hampshire	84,632	-0.69	-0.25	-0.62	-0.52	-0.69	-0.48	-0.22	-0.46
Camden city	New Jersey	73,305	4.51	1.36	0.23	2.03	3.62	0.77	0.77	1.72
Clifton city	New Jersey	72,667	-0.89	0.51	0.14	-0.08	-1.02	0.46	0.44	-0.04
Elizabeth city	New Jersey	121,137	0.83	1.93	0.14	0.97	0.45	2.32	0.59	1.12
Jersey City	New Jersey	246,335	0.91	1.40	-1.11	0.40	0.71	1.32	-0.49	0.52
Newark city	New Jersey	254,217	2.02	1.65	-0.24	1.15	2.21	1.27	0.44	1.30
Passaic city	New Jersey	68,422	1.76	3.56	-0.18	1.71	0.93	3.35	0.18	1.49
Paterson city	New Jersey	148,353	1.40	2.09	0.13	1.20	1.17	1.92	0.61	1.23
Trenton city	New Jersey	77,471	2.04	0.69	0.47	1.07	1.84	0.15	0.59	0.86
Albuquerque city	New Mexico	488,133	-0.26	-0.42	0.18	-0.17	-0.31	-0.53	0.26	-0.19
Santa Fe city	New Mexico	66,453	-0.12	-0.15	-0.75	-0.34	-0.40	-0.14	-0.22	-0.25
Albany city	New York	78,402	2.10	-0.84	-1.45	-0.07	1.53	-0.82	-1.07	-0.12
Buffalo city	New York	256,492	2.79	-1.35	0.23	0.55	2.66	-1.36	0.33	0.55
New Rochelle city	New York	75,961	-0.43	0.44	-0.64	-0.21	-0.65	0.29	-0.30	-0.22

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
New York city	New York	7,956,113	0.79	1.28	-1.08	0.33	0.88	1.38	-0.60	0.55
Rochester city	New York	189,312	2.90	-0.41	-0.17	0.77	2.42	-0.70	0.09	0.60
Syracuse city	New York	132,495	2.55	-0.66	-0.56	0.44	2.02	-0.74	-0.33	0.32
Yonkers city	New York	193,327	0.15	0.35	-0.10	0.14	0.17	0.43	0.08	0.23
Asheville city	North Carolina	74,889	0.01	-0.81	-0.65	-0.49	0.07	-0.75	-0.27	-0.32
Cary town	North Carolina	107,446	-1.17	-0.37	-1.16	-0.90	-1.33	-0.49	-1.26	-1.03
Charlotte city	North Carolina	601,598	-0.16	-0.32	-0.28	-0.25	-0.38	-0.36	-0.15	-0.30
Durham city	North Carolina	191,731	0.11	-0.06	-0.67	-0.21	0.03	-0.33	-0.40	-0.23
Fayetteville city	North Carolina	128,777	0.43	-1.17	0.82	0.02	0.17	-1.10	0.72	-0.07
Gastonia city	North Carolina	72,183	0.46	-0.40	1.14	0.40	0.25	-0.49	0.91	0.23
Greensboro city	North Carolina	208,552	0.08	-0.42	0.11	-0.08	-0.24	-0.63	0.11	-0.25
High Point city	North Carolina	101,852	0.26	-0.55	0.76	0.16	-0.15	-0.51	0.65	-0.01
Raleigh city	North Carolina	315,249	-0.04	-0.31	-1.19	-0.51	-0.36	-0.30	-0.87	-0.51
Wilmington city	North Carolina	91,207	-0.05	-0.67	-0.69	-0.47	0.30	-0.67	-0.45	-0.27
Winston-Salem city	North Carolina	183,467	0.50	-0.30	0.00	0.07	0.17	-0.54	0.08	-0.09
Fargo city	North Dakota	88,809	-0.33	-0.92	-0.71	-0.65	-0.60	-0.79	-0.61	-0.67
Akron city	Ohio	200,181	1.12	-1.00	0.26	0.12	0.84	-1.03	0.51	0.11
Cincinnati city	Ohio	287,540	2.03	-1.09	-0.54	0.13	1.75	-1.02	-0.49	0.08
Cleveland city	Ohio	414,534	3.14	-1.00	0.73	0.96	2.52	-0.97	0.72	0.75
Columbus city	Ohio	693,983	0.59	-0.56	-0.27	-0.08	0.23	-0.70	-0.14	-0.20
Dayton city	Ohio	132,679	2.56	-1.28	0.64	0.64	1.92	-1.41	0.55	0.35
Lorain city	Ohio	65,476	0.76	-0.91	1.53	0.46	0.62	-0.76	1.42	0.43
Parma city	Ohio	79,708	-0.93	-0.80	0.96	-0.25	-1.10	-0.76	1.25	-0.21
Toledo city	Ohio	285,937	1.14	-1.23	1.03	0.31	0.72	-1.18	1.00	0.18
Broken Arrow city	Oklahoma	85,039	-0.80	-1.11	0.37	-0.51	-1.19	-1.02	0.46	-0.58
Edmond city	Oklahoma	71,658	-1.02	-0.98	-0.70	-0.90	-1.12	-0.94	-0.56	-0.87
Lawton city	Oklahoma	79,486	0.48	-1.09	1.15	0.18	0.31	-1.21	0.96	0.02
Norman city	Oklahoma	97,484	-0.27	-0.88	-0.76	-0.64	-0.56	-0.75	-0.73	-0.68

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
Oklahoma City	Oklahoma	515,751	0.37	-0.71	0.46	0.04	0.20	-0.75	0.59	0.01
Tulsa city	Oklahoma	370,447	0.36	-0.66	0.27	-0.01	-0.04	-0.80	0.46	-0.13
Beaverton city	Oregon	83,447	-0.81	0.05	-0.65	-0.47	-0.85	-0.04	-0.44	-0.44
Eugene city	Oregon	142,716	-0.13	-0.44	-1.06	-0.54	-0.28	-0.61	-0.92	-0.60
Gresham city	Oregon	95,334	0.11	0.35	0.50	0.32	-0.43	-0.09	0.45	-0.02
Hillsboro city	Oregon	82,732	0.19	0.37	-0.30	0.09	-0.74	0.32	-0.10	-0.17
Medford city	Oregon	73,782	-0.31	-0.62	0.31	-0.21	-0.27	-0.59	0.56	-0.10
Portland city	Oregon	513,627	0.20	-0.22	-0.88	-0.30	-0.14	-0.18	-0.63	-0.31
Salem city	Oregon	142,006	0.02	0.00	0.42	0.15	-0.17	-0.32	0.66	0.06
Allentown city	Pennsylvania	105,231	1.46	0.17	-0.44	0.40	0.89	-0.06	0.21	0.35
Bethlehem city	Pennsylvania	68,144	-0.04	-0.49	-0.23	-0.25	0.20	-0.43	-0.17	-0.13
Erie city	Pennsylvania	91,423	1.02	-1.18	0.53	0.12	0.93	-1.13	0.79	0.20
Philadelphia city	Pennsylvania	1,406,415	1.74	-0.29	-0.09	0.45	1.49	-0.37	0.33	0.48
Pittsburgh city	Pennsylvania	284,366	1.58	-1.07	-0.76	-0.08	1.26	-1.14	-0.22	-0.03
Reading city	Pennsylvania	81,302	2.89	0.62	0.50	1.34	2.04	0.12	0.63	0.93
Scranton city	Pennsylvania	67,314	1.07	-0.65	0.20	0.21	0.28	-0.95	0.62	-0.02
Cranston city	Rhode Island	77,025	-0.91	-0.40	0.17	-0.38	-0.90	-0.62	0.75	-0.26
Pawtucket city	Rhode Island	72,896	0.92	0.34	0.13	0.47	0.50	0.49	0.53	0.50
Providence city	Rhode Island	160,264	2.12	1.01	-1.46	0.56	2.04	0.86	-1.00	0.63
Warwick city	Rhode Island	85,804	-1.09	-0.83	0.36	-0.52	-1.10	-0.81	0.62	-0.43
Charleston city	South Carolina	109,151	0.38	-0.78	-0.98	-0.46	0.24	-0.85	-0.65	-0.42
Columbia city	South Carolina	88,450	0.72	-0.75	-0.89	-0.31	0.93	-0.85	-0.43	-0.12
Sioux Falls city	South Dakota	132,358	-0.29	-0.75	-0.30	-0.45	-0.61	-0.73	-0.24	-0.52
Chattanooga city	Tennessee	139,158	0.81	-1.24	0.24	-0.06	0.57	-1.07	0.56	0.02
Clarksville city	Tennessee	107,130	-0.48	-0.98	0.43	-0.35	-0.51	-0.99	0.86	-0.21
Knoxville city	Tennessee	168,744	0.91	-0.96	-0.15	-0.06	0.66	-0.90	-0.04	-0.09
Memphis city	Tennessee	642,251	1.12	-0.86	0.90	0.39	0.89	-0.93	1.17	0.38
Murfreesboro city	Tennessee	83,822	-0.10	-0.59	-0.65	-0.45	-0.42	-0.65	-0.23	-0.44

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
Nashville-Davidson (balance)	Tennessee	522,662	0.17	-0.45	-0.30	-0.19	-0.04	-0.58	-0.09	-0.24
Abilene city	Texas	105,165	0.19	-0.79	0.80	0.07	-0.11	-0.90	1.01	0.00
Amarillo city	Texas	176,999	-0.01	-0.54	0.82	0.09	-0.11	-0.63	0.93	0.06
Arlington city	Texas	348,965	-0.39	-0.06	0.63	0.06	-0.62	-0.18	0.48	-0.11
Austin city	Texas	678,457	0.05	0.17	-0.73	-0.17	-0.25	0.24	-0.58	-0.20
Baytown city	Texas	61,504	-0.05	-0.09	1.65	0.50	-0.12	-0.03	1.69	0.51
Beaumont city	Texas	107,876	0.97	-0.92	0.81	0.29	0.64	-1.01	1.04	0.22
Bryan city	Texas	56,277	0.59	0.27	0.76	0.54	0.09	-0.02	0.95	0.34
Carrollton city	Texas	122,699	-1.10	0.26	0.42	-0.14	-1.11	-0.01	0.12	-0.33
College Station city	Texas	65,370	-0.08	0.08	-2.12	-0.70	-0.40	-0.14	-1.97	-0.84
Corpus Christi city	Texas	280,002	0.09	-0.43	1.09	0.25	0.00	-0.43	1.38	0.32
Dallas city	Texas	1,144,946	0.76	1.22	0.41	0.80	0.38	0.97	0.44	0.60
Denton city	Texas	87,766	-0.37	-0.22	-0.63	-0.41	-0.32	-0.17	-0.43	-0.31
Fort Worth city	Texas	604,538	0.38	0.20	0.54	0.37	0.20	0.17	0.78	0.38
Garland city	Texas	235,750	-0.27	0.72	1.17	0.54	-0.73	0.26	1.14	0.22
Grand Prairie city	Texas	148,677	-0.16	0.02	1.13	0.33	-0.42	-0.04	1.27	0.27
Houston city	Texas	1,941,430	0.65	1.13	0.66	0.82	0.34	0.91	0.77	0.67
Irving city	Texas	212,262	-0.41	1.16	0.51	0.42	-0.57	0.85	0.35	0.21
Killeen city	Texas	98,434	0.03	-0.91	0.69	-0.07	-0.13	-0.65	0.62	-0.05
Lewisville city	Texas	81,484	-0.87	-0.08	0.30	-0.21	-1.08	-0.37	0.36	-0.36
Lubbock city	Texas	199,789	0.03	-0.74	0.70	0.00	-0.11	-0.69	0.68	-0.04
McKinney city	Texas	92,337	-1.07	-0.60	-0.33	-0.67	-0.95	-0.27	0.07	-0.38
Mesquite city	Texas	126,895	-0.82	0.02	1.62	0.28	-0.93	-0.58	1.47	-0.02
Midland city	Texas	100,799	-0.27	-0.54	1.11	0.10	-0.38	-0.68	1.02	-0.01
Odessa city	Texas	94,329	0.08	-0.65	1.91	0.45	0.05	-0.62	2.13	0.52
Pasadena city	Texas	150,180	0.14	1.05	1.66	0.95	-0.13	0.70	1.85	0.81
Plano city	Texas	251,648	-1.13	-0.31	-0.68	-0.71	-1.30	-0.49	-0.72	-0.84
Richardson city	Texas	107,892	-1.19	-0.17	-0.39	-0.58	-1.20	-0.18	-0.38	-0.59

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
Round Rock city	Texas	81,639	-0.74	-0.65	0.18	-0.40	-1.14	-0.51	0.33	-0.44
San Angelo city	Texas	82,293	-0.03	-0.83	1.11	0.08	-0.04	-0.71	1.23	0.16
San Antonio city	Texas	1,202,223	0.17	0.02	0.77	0.32	0.05	-0.04	1.05	0.35
Tyler city	Texas	87,687	0.50	-0.62	0.70	0.19	0.09	-0.55	0.71	0.08
Waco city	Texas	107,146	0.69	-0.14	0.67	0.41	0.69	-0.35	0.89	0.41
Wichita Falls city	Texas	88,861	0.04	-0.67	0.48	-0.05	-0.12	-0.84	0.88	-0.03
Ogden city	Utah	79,171	1.00	0.04	-0.40	0.21	0.64	-0.20	0.06	0.17
Orem city	Utah	85,616	-0.69	-0.63	-0.07	-0.46	-0.85	-0.58	0.07	-0.46
Provo city	Utah	101,164	0.39	0.18	-1.79	-0.41	0.24	-0.04	-1.62	-0.47
Salt Lake City	Utah	182,670	0.41	0.10	-1.06	-0.18	0.23	0.14	-0.97	-0.20
Sandy city	Utah	88,189	-1.13	-1.07	0.04	-0.72	-1.29	-0.96	0.10	-0.71
West Jordan city	Utah	101,626	-1.14	-0.59	0.52	-0.40	-1.10	-0.77	0.72	-0.38
Alexandria city	Virginia	133,479	-0.85	0.64	-1.93	-0.72	-0.51	0.60	-1.72	-0.54
Chesapeake city	Virginia	214,835	-1.00	-0.94	0.56	-0.46	-0.92	-0.91	0.63	-0.40
Hampton city	Virginia	133,584	-0.05	-0.88	0.28	-0.21	-0.31	-0.88	0.59	-0.20
Newport News city	Virginia	176,591	0.01	-0.68	0.05	-0.21	-0.01	-0.73	0.32	-0.14
Norfolk city	Virginia	206,172	0.76	-0.44	-0.35	-0.01	0.70	-0.49	-0.01	0.07
Portsmouth city	Virginia	95,183	0.53	-0.73	0.30	0.03	0.35	-0.73	0.80	0.14
Richmond city	Virginia	180,757	0.98	-0.49	-0.55	-0.02	1.22	-0.52	-0.51	0.06
Roanoke city	Virginia	90,074	0.43	-1.06	0.48	-0.05	0.50	-0.91	0.75	0.12
Suffolk city	Virginia	77,922	-0.39	-1.00	0.45	-0.32	-0.26	-0.84	0.96	-0.05
Virginia Beach city	Virginia	430,856	-0.86	-0.75	0.04	-0.53	-0.98	-0.74	0.27	-0.48
Bellevue city	Washington	114,748	-0.98	0.37	-1.64	-0.75	-1.12	0.12	-1.27	-0.76
Bellingham city	Washington	69,057	-0.11	-0.44	-1.44	-0.66	-0.19	-0.50	-0.94	-0.54
Everett city	Washington	88,850	0.04	0.13	-0.11	0.02	-0.07	-0.01	0.15	0.03
Kent city	Washington	84,979	-0.20	0.43	-0.09	0.05	-0.32	0.09	0.08	-0.05
Seattle city	Washington	536,946	-0.31	-0.04	-1.77	-0.71	-0.32	-0.11	-1.55	-0.66
Spokane city	Washington	192,777	0.25	-0.81	-0.09	-0.22	0.20	-0.74	-0.11	-0.22

City	State	2005 Population	2005 Factor 1	2005 Factor 2	2005 Factor 3	2005 Equal Weight Index	2000 Factor 1	2000 Factor 2	2000 Factor 3	2000 Equal Weight Index
Tacoma city	Washington	191,934	0.45	-0.17	-0.38	-0.03	0.35	-0.24	-0.23	-0.04
Vancouver city	Washington	155,488	0.17	-0.11	-0.08	-0.01	-0.31	-0.09	0.06	-0.11
Yakima city	Washington	79,517	0.68	0.26	1.24	0.73	0.61	0.15	1.55	0.77
Green Bay city	Wisconsin	94,242	0.09	-0.44	0.06	-0.09	-0.29	-0.55	0.10	-0.24
Kenosha city	Wisconsin	95,440	-0.36	-0.58	0.63	-0.10	-0.47	-0.64	0.80	-0.10
Madison city	Wisconsin	203,704	-0.04	-0.32	-2.02	-0.79	-0.27	-0.36	-2.04	-0.89
Milwaukee city	Wisconsin	556,948	1.72	-0.21	-0.12	0.46	1.29	-0.34	0.12	0.36
Waukesha city	Wisconsin	62,690	-1.05	-0.91	-0.06	-0.68	-1.09	-0.72	0.21	-0.53

Table A.10. Adjusted Needs Index for 234 Cities

City	State	Population	Standardized Equal Weight Index	Standardized Real Fiscal Capacity Index	Adjusted Needs Index	Equal Weight Index Rank	Adjusted Needs Index Rank
Birmingham city	Alabama	222,154	1.00	0.71	0.29	34	98
Huntsville city	Alabama	158,618	-0.87	1.40	-2.27	188	214
Mobile city	Alabama	193,332	0.30	0.60	-0.30	80	130
Anchorage municipality	Alaska	266,281	-0.95	-0.85	-0.10	198	114
Chandler city	Arizona	225,725	-0.93	-0.98	0.05	194	109
Mesa city	Arizona	442,445	-0.10	-1.29	1.18	117	67
Peoria city	Arizona	141,941	-0.90	-1.32	0.43	190	89
Phoenix city	Arizona	1,377,980	0.61	-0.96	1.57	55	45
Scottsdale city	Arizona	215,933	-1.69	1.54	-3.23	227	227
Tempe city	Arizona	166,171	-0.90	-0.05	-0.85	191	162
Tucson city	Arizona	507,362	0.29	-1.07	1.36	83	56
Fort Smith city	Arkansas	81,054	0.22	2.04	-1.82	88	200
Little Rock city	Arkansas	176,924	-0.76	2.02	-2.78	182	221
Anaheim city	California	329,483	1.17	-0.93	2.10	26	26
Bakersfield city	California	286,316	0.37	-1.10	1.48	76	51
Berkeley city	California	90,432	-2.05	0.07	-2.12	233	207
Burbank city	California	100,053	-0.52	0.90	-1.42	165	193
Chula Vista city	California	212,954	0.29	-0.75	1.05	82	72
Concord city	California	116,782	-0.25	-0.66	0.40	135	92
Corona city	California	162,410	-0.08	-0.48	0.40	116	93
El Cajon city	California	92,507	0.50	-0.85	1.35	63	58
Escondido city	California	133,017	0.67	-0.57	1.24	50	65
Fairfield city	California	102,642	-0.26	-1.31	1.05	137	71
Fullerton city	California	142,064	-0.35	-0.65	0.30	143	96
Garden Grove city	California	192,345	1.58	-1.44	3.01	17	11
Glendale city	California	194,620	0.44	-0.61	1.05	71	70
Hayward city	California	135,474	0.46	-0.82	1.28	68	63
Hemet city	California	77,076	1.06	-1.49	2.55	30	17
Inglewood city	California	120,204	1.81	-1.81	3.62	14	7
Long Beach city	California	463,956	0.83	-1.29	2.12	41	25
Los Angeles city	California	3,731,437	1.29	-0.96	2.25	24	22
Modesto city	California	202,971	0.25	-0.93	1.18	85	68
Oakland city	California	373,910	0.72	-0.99	1.71	47	39
Oceanside city	California	162,259	-0.39	-0.70	0.31	150	95
Ontario city	California	156,679	1.55	-0.73	2.28	18	21
Oxnard city	California	178,871	1.81	-1.13	2.93	15	12
Pasadena city	California	129,400	-0.58	0.34	-0.92	171	168
Pomona city	California	161,257	2.07	-1.69	3.76	10	5
Redwood City	California	81,195	0.19	1.02	-0.83	93	159
Richmond city	California	96,648	0.61	-1.04	1.65	53	42
Riverside city	California	294,059	0.41	-0.99	1.40	74	54
Roseville city	California	108,848	-1.16	0.29	-1.45	212	195
Sacramento city	California	445,287	0.47	-0.80	1.26	66	64

City	State	Population	Standardized Equal Weight Index	Standardized Real Fiscal Capacity Index	Adjusted Needs Index	Equal Weight Index Rank	Adjusted Needs Index Rank
Salinas city	California	156,950	2.52	-1.24	3.76	6	4
San Bernardino city	California	204,552	2.12	-1.53	3.65	9	6
San Buenaventura (Ventura) city	California	100,154	-0.90	0.18	-1.08	189	179
San Diego city	California	1,208,331	-0.52	0.32	-0.84	164	161
San Francisco city	California	719,077	-0.62	0.26	-0.88	173	164
San Jose city	California	887,330	0.00	-0.47	0.46	107	87
Santa Ana city	California	302,302	3.04	-1.24	4.29	2	1
Santa Barbara city	California	90,708	-0.76	1.45	-2.20	181	212
Santa Clara city	California	102,204	-0.63	-0.63	-0.01	177	110
Santa Monica city	California	82,777	-1.81	2.52	-4.33	229	231
Santa Rosa city	California	146,500	-0.35	0.48	-0.83	142	160
Stockton city	California	278,515	1.13	-1.34	2.48	27	19
Vallejo city	California	115,657	-0.07	-0.86	0.79	114	77
Arvada city	Colorado	104,766	-1.02	-0.92	-0.10	203	116
Aurora city	Colorado	291,317	0.26	-1.07	1.33	84	60
Boulder city	Colorado	83,432	-2.03	2.54	-4.57	232	232
Colorado Springs city	Colorado	376,985	-0.90	-0.31	-0.59	192	146
Denver city	Colorado	545,198	-0.13	0.35	-0.48	120	139
Fort Collins city	Colorado	122,297	-1.61	-0.41	-1.20	225	185
Greeley city	Colorado	82,836	-0.12	-0.54	0.42	119	91
Lakewood city	Colorado	142,434	-0.67	-0.23	-0.44	178	137
Longmont city	Colorado	76,181	-0.35	-0.11	-0.24	141	129
Westminster city	Colorado	99,305	-0.97	-0.78	-0.19	200	123
Washington city	District of Columbia	515,118	-0.52	0.72	-1.24	163	186
Cape Coral city	Florida	134,388	-0.37	-0.50	0.12	147	107
Clearwater city	Florida	108,382	-0.40	1.24	-1.64	153	197
Fort Lauderdale city	Florida	141,307	-0.21	1.58	-1.79	130	199
Gainesville city	Florida	100,879	-0.42	-0.07	-0.36	155	134
Hollywood city	Florida	138,412	0.07	-0.48	0.55	99	84
Jacksonville city	Florida	768,537	-0.61	-0.56	-0.05	172	112
Largo city	Florida	71,269	-0.38	-0.22	-0.16	148	119
Melbourne city	Florida	76,373	-0.53	-0.34	-0.19	166	124
Miami Beach city	Florida	84,086	0.72	0.11	0.61	46	81
Miami city	Florida	361,701	2.82	-0.12	2.93	3	13
Orlando city	Florida	221,299	0.15	1.28	-1.13	94	181
Pompano Beach city	Florida	94,892	0.45	0.16	0.28	69	99
St. Petersburg city	Florida	232,960	-0.38	0.42	-0.80	149	155
Tallahassee city	Florida	141,148	-1.31	0.08	-1.38	215	191
Tampa city	Florida	312,855	0.01	1.04	-1.03	104	176

City	State	Population	Standardized Equal Weight Index	Standardized Real Fiscal Capacity Index	Adjusted Needs Index	Equal Weight Index Rank	Adjusted Needs Index Rank
West Palm Beach city	Florida	86,804	0.49	1.64	-1.15	65	182
Atlanta city	Georgia	394,929	0.14	2.32	-2.18	95	211
Savannah city	Georgia	117,478	0.31	1.34	-1.03	79	175
Honolulu CDP	Hawaii	362,252	-0.63	0.29	-0.92	176	169
Boise City	Idaho	191,667	-1.08	1.41	-2.49	209	218
Aurora city	Illinois	170,490	0.43	-1.12	1.56	72	46
Chicago city	Illinois	2,701,926	0.61	-0.63	1.24	54	66
Evanston city	Illinois	62,258	-2.17	0.92	-3.09	234	226
Joliet city	Illinois	128,090	-0.14	-1.08	0.94	121	75
Rockford city	Illinois	139,173	0.42	0.18	0.24	73	102
Springfield city	Illinois	110,262	-0.86	0.19	-1.05	187	177
Bloomington city	Indiana	55,406	-1.32	0.83	-2.15	217	210
Evansville city	Indiana	110,708	0.03	0.63	-0.60	103	147
Fort Wayne city	Indiana	219,346	-0.05	-0.25	0.19	110	104
Indianapolis city (balance)	Indiana	765,310	-0.18	0.26	-0.44	125	136
South Bend city	Indiana	97,070	0.52	0.26	0.26	62	100
Cedar Rapids city	Iowa	119,670	-0.76	1.19	-1.95	183	204
Davenport city	Iowa	95,382	-0.55	0.77	-1.32	169	189
Des Moines city	Iowa	196,917	-0.63	0.26	-0.89	175	165
Kansas City	Kansas	142,341	1.07	-1.38	2.45	29	20
Overland Park city	Kansas	161,901	-1.86	1.17	-3.03	230	224
Topeka city	Kansas	117,326	-0.37	0.44	-0.82	146	157
Wichita city	Kansas	354,582	-0.23	-0.02	-0.21	132	127
Lexington-Fayette	Kentucky	255,389	-1.02	0.63	-1.65	202	198
Baton Rouge city	Louisiana	205,442	0.54	0.40	0.14	61	106
Lafayette city	Louisiana	108,175	-0.73	0.54	-1.27	180	187
Shreveport city	Louisiana	192,531	0.46	-0.27	0.73	67	79
Baltimore city	Maryland	608,481	0.54	0.37	0.17	60	105
Boston city	Massachusetts	520,702	-0.01	1.42	-1.43	108	194
Brockton city	Massachusetts	91,938	0.67	-0.35	1.02	51	74
Cambridge city	Massachusetts	81,260	-1.74	3.17	-4.91	228	233
Fall River city	Massachusetts	97,612	0.95	-0.78	1.74	35	36
Lawrence city	Massachusetts	82,191	2.81	-1.01	3.82	4	3
Lowell city	Massachusetts	96,876	0.85	-0.70	1.54	39	47
Lynn city	Massachusetts	83,419	0.90	-0.51	1.41	36	53
New Bedford city	Massachusetts	84,898	1.12	-0.78	1.90	28	30
Quincy city	Massachusetts	84,080	-0.82	0.14	-0.97	185	171
Somerville city	Massachusetts	74,869	-0.28	-0.24	-0.04	138	111
Springfield city	Massachusetts	146,948	1.52	-0.41	1.93	20	28
Worcester city	Massachusetts	154,398	0.04	0.25	-0.21	101	126
Ann Arbor city	Michigan	98,743	-1.98	0.84	-2.82	231	222
Detroit city	Michigan	836,056	1.89	-1.46	3.34	11	9
Grand Rapids city	Michigan	193,568	0.29	-0.17	0.46	81	86

City	State	Population	Standardized Equal Weight Index	Standardized Real Fiscal Capacity Index	Adjusted Needs Index	Equal Weight Index Rank	Adjusted Needs Index Rank
Sterling Heights city	Michigan	123,368	-0.43	-0.08	-0.35	156	133
Warren city	Michigan	134,901	0.11	-0.45	0.56	96	83
Westland city	Michigan	80,284	-0.24	-1.11	0.87	133	76
Bloomington city	Minnesota	80,055	-1.21	2.60	-3.81	213	230
Duluth city	Minnesota	76,918	-1.26	0.78	-2.05	214	205
Minneapolis city	Minnesota	350,260	-0.57	0.85	-1.42	170	192
Rochester city	Minnesota	88,338	-1.62	0.87	-2.49	226	217
St. Paul city	Minnesota	261,559	-0.45	0.16	-0.62	159	148
Columbia city	Missouri	82,103	-1.52	0.85	-2.37	223	215
Independence city	Missouri	111,842	-0.12	-0.41	0.29	118	97
Kansas City	Missouri	440,885	-0.29	0.50	-0.79	139	153
Springfield city	Missouri	139,600	-0.32	1.28	-1.61	140	196
St. Louis city	Missouri	333,730	0.63	0.19	0.44	52	88
Lincoln city	Nebraska	226,062	-1.14	-0.50	-0.64	211	149
Omaha city	Nebraska	373,215	-0.40	0.17	-0.57	151	144
Henderson city	Nevada	223,776	-1.08	-0.96	-0.12	208	118
Las Vegas city	Nevada	538,653	0.20	-1.11	1.31	91	61
Reno city	Nevada	204,478	-0.26	-0.07	-0.19	136	122
Manchester city	New Hampshire	109,308	-0.50	1.41	-1.92	162	202
Nashua city	New Hampshire	84,632	-1.05	2.25	-3.30	206	228
Clifton city	New Jersey	72,667	-0.20	0.31	-0.50	128	140
Elizabeth city	New Jersey	121,137	1.84	-0.73	2.56	12	16
Jersey City	New Jersey	246,335	0.74	-0.62	1.36	45	57
Newark city	New Jersey	254,217	2.18	-0.70	2.89	8	14
Passaic city	New Jersey	68,422	3.28	-0.96	4.24	1	2
Paterson city	New Jersey	148,353	2.29	-0.98	3.28	7	10
Albuquerque city	New Mexico	488,133	-0.36	-0.20	-0.17	144	120
Santa Fe city	New Mexico	66,453	-0.70	1.44	-2.14	179	208
Albany city	New York	78,402	-0.17	0.63	-0.80	124	154
Buffalo city	New York	256,492	1.03	-1.18	2.21	32	23
New York city	New York	7,956,113	0.60	-1.03	1.64	56	43
Rochester city	New York	189,312	1.46	-0.28	1.74	22	37
Syracuse city	New York	132,495	0.82	-0.56	1.39	42	55
Yonkers city	New York	193,327	0.22	-1.29	1.51	87	48
Asheville city	North Carolina	74,889	-0.98	1.85	-2.84	201	223
Charlotte city	North Carolina	601,598	-0.53	0.36	-0.89	168	166
Durham city	North Carolina	191,731	-0.45	0.13	-0.58	157	145
Fayetteville city	North Carolina	128,777	0.01	-0.34	0.34	105	94
Greensboro city	North Carolina	208,552	-0.19	0.84	-1.03	126	174
Raleigh city	North Carolina	315,249	-1.04	0.32	-1.36	204	190
Wilmington city	North Carolina	91,207	-0.95	0.99	-1.94	199	203
Winston-Salem city	North Carolina	183,467	0.09	0.20	-0.11	97	117

City	State	Population	Standardized Equal Weight Index	Standardized Real Fiscal Capacity Index	Adjusted Needs Index	Equal Weight Index Rank	Adjusted Needs Index Rank
Fargo city	North Dakota	88,809	-1.31	1.72	-3.03	216	225
Akron city	Ohio	200,181	0.20	-0.45	0.65	90	80
Cincinnati city	Ohio	287,540	0.21	0.72	-0.50	89	141
Cleveland city	Ohio	414,534	1.81	-0.39	2.21	13	24
Columbus city	Ohio	693,983	-0.19	-0.14	-0.05	127	113
Dayton city	Ohio	132,679	1.20	-0.24	1.44	25	52
Toledo city	Ohio	285,937	0.57	-0.46	1.03	59	73
Oklahoma City	Oklahoma	515,751	0.03	-0.22	0.26	102	101
Tulsa city	Oklahoma	370,447	-0.06	0.49	-0.55	113	143
Eugene city	Oregon	142,716	-1.09	-0.13	-0.96	210	170
Gresham city	Oregon	95,334	0.58	-1.09	1.67	57	41
Portland city	Oregon	513,627	-0.62	0.12	-0.74	174	152
Salem city	Oregon	142,006	0.24	-0.52	0.77	86	78
Bethlehem city	Pennsylvania	68,144	-0.53	0.15	-0.69	167	150
Erie city	Pennsylvania	91,423	0.19	-0.01	0.20	92	103
Philadelphia city	Pennsylvania	1,406,415	0.83	-0.74	1.58	40	44
Pittsburgh city	Pennsylvania	284,366	-0.20	0.99	-1.20	129	183
Reading city	Pennsylvania	81,302	2.55	-0.28	2.83	5	15
Scranton city	Pennsylvania	67,314	0.36	0.30	0.06	77	108
Cranston city	Rhode Island	77,025	-0.77	-0.47	-0.31	184	131
Pawtucket city	Rhode Island	72,896	0.86	-1.12	1.98	37	27
Providence city	Rhode Island	160,264	1.04	-0.83	1.87	31	32
Warwick city	Rhode Island	85,804	-1.05	-0.14	-0.90	205	167
Charleston city	South Carolina	109,151	-0.93	4.35	-5.28	195	234
Sioux Falls city	South Dakota	132,358	-0.91	1.36	-2.27	193	213
Chattanooga city	Tennessee	139,158	-0.16	0.91	-1.07	122	178
Knoxville city	Tennessee	168,744	-0.17	1.03	-1.20	123	184
Memphis city	Tennessee	642,251	0.71	-0.58	1.29	48	62
Nashville-Davidson (balance)	Tennessee	522,662	-0.42	0.12	-0.53	154	142
Arlington city	Texas	348,965	0.08	-1.27	1.35	98	59
Austin city	Texas	678,457	-0.36	-0.04	-0.33	145	132
Corpus Christi city	Texas	280,002	0.44	-1.06	1.50	70	49
Dallas city	Texas	1,144,946	1.51	-0.24	1.74	21	35
Fort Worth city	Texas	604,538	0.68	-1.05	1.73	49	38
Garland city	Texas	235,750	1.00	-1.55	2.55	33	18
Houston city	Texas	1,941,430	1.54	-0.36	1.91	19	29
Irving city	Texas	212,262	0.77	0.87	-0.10	43	115
Laredo	Texas	199,789	-0.05	-1.88	1.84	109	33
Mesquite city	Texas	126,895	0.49	-1.39	1.88	64	31
Pasadena city	Texas	150,180	1.79	-1.56	3.36	16	8
San Antonio city	Texas	1,202,223	0.58	-1.24	1.82	58	34
Tyler city	Texas	87,687	0.33	0.51	-0.18	78	121
Waco city	Texas	107,146	0.75	-0.40	1.15	44	69

City	State	Population	Standardized Equal Weight Index	Standardized Real Fiscal Capacity Index	Adjusted Needs Index	Equal Weight Index Rank	Adjusted Needs Index Rank
Ogden city	Utah	79,171	0.38	-0.09	0.47	75	85
Orem city	Utah	85,616	-0.94	-0.12	-0.83	197	158
Provo city	Utah	101,164	-0.83	-0.01	-0.82	186	156
Salt Lake City	Utah	182,670	-0.40	1.66	-2.06	152	206
Alexandria city	Virginia	133,479	-1.43	1.20	-2.63	221	219
Chesapeake city	Virginia	214,835	-0.94	0.07	-1.01	196	173
Hampton city	Virginia	133,584	-0.46	-0.23	-0.23	160	128
Newport News city	Virginia	176,591	-0.45	0.24	-0.69	158	151
Norfolk city	Virginia	206,172	-0.06	0.41	-0.47	111	138
Richmond city	Virginia	180,757	-0.08	1.02	-1.10	115	180
Virginia Beach city	Virginia	430,856	-1.06	0.24	-1.30	207	188
Bellevue city	Washington	114,748	-1.49	2.29	-3.77	222	229
Bellingham city	Washington	69,057	-1.33	0.81	-2.14	218	209
Everett city	Washington	88,850	0.00	0.85	-0.85	106	163
Kent city	Washington	84,979	0.05	0.26	-0.21	100	125
Seattle city	Washington	536,946	-1.41	1.28	-2.69	220	220
Spokane city	Washington	192,777	-0.46	-0.09	-0.37	161	135
Vancouver city	Washington	155,488	-0.06	-0.48	0.42	112	90
Yakima city	Washington	79,517	1.37	-0.32	1.69	23	40
Green Bay city	Wisconsin	94,242	-0.22	0.76	-0.98	131	172
Kenosha city	Wisconsin	95,440	-0.24	-0.81	0.57	134	82
Madison city	Wisconsin	203,704	-1.58	0.86	-2.44	224	216
Milwaukee city	Wisconsin	556,948	0.86	-0.64	1.49	38	50
Waukesha city	Wisconsin	62,690	-1.35	0.49	-1.84	219	201

Appendix B—Using Regression Analysis to Develop a Community Needs Index

This report uses factor analysis to identify common themes in the needs of cities and to measure the needs represented by those common themes. Chapter 3 points out that factor analysis has several conceptual weaknesses. The main flaws of factor analysis are:

- It assumes the existence of unobservable factors that cause the observed needs. The existence of these factors cannot be proved.

- There are no definite ways to determine how many factors are at work or to select among all the possible "rotations" of the factors. We resorted to some common rules of thumb and judgment to select the factors used to analyze cities needs in Chapter 4.

- Judgment must be used to choose weights to combine the factors into a single-value index of need.

- The individual factor scores and any index created by combining them are unitless measures of need—that is, a factor score of 1.0 says that that city is one standard deviation above the average of all cities on that factor; it does not provide any information on how serious a 1.0 score is.

At the project's Orientation Meeting on October 12, 2006, George Galster suggested an alternative to factor analysis that would avoid all of these weaknesses. This appendix describes this alternative approach, explains how we implemented it, and presents the results. The alternative approach produced some interesting findings, but we were unable to translate the results into a comprehensive assessment of community needs. The problem was that some community needs, such as the lack of affordable housing, cannot be measured using the alternative approach. For this reason, we used factor analysis to measure needs and relegated our experience with the alternative approach to this appendix. The concluding section of the appendix contains a summary of the insights we gained from the alternative approach.

B.1. General Concept, Model Specification, and Difficulties

B.1.1. General Concept

The alternative approach is derived from, but is not the same as, two methods employed in economics. The first is a methodology used to explain price differences across similar products with different characteristics. This "hedonic" model was originally developed to explain the variation in prices of cars that have different features. The model has since been applied frequently to explain differences in the price of individual houses based on such features as house size; the condition of the house; lot size; location with respect to employment centers, good schools, and shopping; amenities such as air conditioning, garage, and decks; and the quality of the neighborhood. These applications use data on the price and the features of specific houses.

The second method uses variations in median house prices across metropolitan areas to measure the market valuation of amenities associated with living in these various places, such as climate, culture, and sports teams. This method uses housing prices and amenities measured at the metropolitan scale. The proposed methodology draws from the intuitions and conclusions of both prior strands of work, but at an intermediate spatial scale. It attempts to explain variation in the median price of houses across census tracts in various cities. It uses census information on various characteristics of the census tracts and the information produced by this study on the characteristics of the cities in which the tracts are located. Drawing upon the central insight of both prior strands of work—that the housing market effectively capitalizes the value placed by consumers on characteristics of the geography surrounding the dwelling—this approach seeks to find how aspects of the political jurisdiction that have been associated traditionally with "distress" are capitalized, controlling for characteristics of the dwellings, neighborhoods, and larger metropolitan area.

The "hedonic" model starts from recognizing two facts: (1) house prices vary significantly across the country, and (2) the value of a house depends upon the characteristics of the house, the characteristics of the immediate neighborhood in which the house is located, and the characteristics of the political jurisdiction and the broader metropolitan market in which the house is located.[49] To the extent that a city has problems, the value of houses in that city should be lower than the value of comparable housing in comparable neighborhoods in a city without such problems. For example, consider two identical neighborhoods in two different cities in the same metropolitan area. Because the neighborhoods have similar housing and are located in the same housing market, one would expect that the median price of houses in the two neighborhoods would be equal unless one city was a more desirable place to live than the other city. The goal is to use regression analysis to determine how much effect particular city-level problems have on the value of homes in those cities.

If one can successfully isolate these effects, then one has a direct measure of the impact of the problems we have been considering. The measure is a "dollars and cents" measure, and therefore the effects of different problems can be added together. In this way, one could determine the combined effects of a number of city-level problems and could also assess which problems have the greatest negative impact. The key advantage here is that the respective coefficients measuring these effects provide guidance about how the market evaluates the various problematic characteristics of the city, without the imposition of value judgments from the researcher.

[49] While it is a misnomer to call the techniques employed in this appendix hedonic models, we shall use the "hedonic" label for convenience and because the reasoning behind the model draws on the hedonic literature.

From the 2000 decennial census, we have information on owners' assessments of the value of their homes.[50] In particular, we know the median value (as reported by owners) of the owner-occupied homes in 26,287 census tracts in the 370 cities for which we have data on our 24 needs indicators.

B.1.2. Model Specification[51]

The house prices (P_{ijk}) in the ith neighborhood located in the jth political jurisdiction in the kth metro area is a function of the myriad characteristics (C) of these various scales of geography. For example, C_i includes housing characteristics, C_j includes municipal tax rate, and C_k includes climate and housing supply elasticity. Symbolically:

[1] $P_{ijk} = f(C_i, C_j, C_k)$

But because many (not all) of the characteristics of jurisdictions (demographic, economic, social, etc.) are mathematical summations of the corresponding characteristics of the constituent neighborhoods, we can write:

[2] $C_j = g(C_i)$

Other characteristics of the jurisdiction (like tax rate) can be symbolized C_{j*}. Thus, [1] can be written:

[3] $P_{ijk} = f(C_i, [Cj_*, g(C_i)] , C_k)$

From the perspective of a community needs index, the only level of geography that is directly relevant is the jurisdictional j level. Certainly, variations among neighborhoods in j may matter for needs, but such variation should be captured with variables measured at the community j scale to be operational, e.g., percentage of tracts in a community exceeding 40 percent poverty.

If we were to run a regression using median census tract housing prices as the dependent variable for a large set of tracts across j jurisdictions and k different metropolitan areas, C_k could be measured by a dummy variable for each metropolitan area. $[C_{j*}, g(C_i)]$ will be measured with the variables used for input into the factor analysis; coefficients of these variables would be the key item of interest that weight the various attributes of the jurisdiction. The Ci term is trickiest. We certainly can measure many tract characteristics using census data, but others of interest (like crime rates) we cannot for the entire nation. So, there will be some omitted variables of interest. It is likely, however, that many of these will be highly correlated with others that we can measure.

[50] The ACS will provide same information at the census-tract level beginning in 2010.
[51] George Galster drafted this formal presentation of the hedonic-like model.

The measure of community needs would be the sum of the product of $[C_{j^*}, g(C_i)]$ and its coefficients. Its interpretation is straightforward. Community conditions in city A reduce the median price of houses in city A by X dollars.

B.1.3. Difficulties

The statistical problem is how to relate the variation in median home values to the information we have about the tract and the local market.[52] Because city-level problems are likely to have less impact on the values of the houses in a tract than the characteristics of the houses themselves and their neighborhood, it is very important to have good information on the houses and the tract. This is the first problem that must be overcome.

A second problem is the possibility that not all city-level problems will be associated with lower house values. An example of such a situation is housing affordability. The needs indicators in Table 1 include several measures of possible housing market problems. While the lack of affordable rental housing (LACKAFFDRENTALS) given the city's income level is definitely a legitimate city-level problem, it is likely to be associated with high housing prices, not low housing prices.

There are also situations where the functioning of private markets may run counter to public perception of what is desirable and what is not. For example, city-level diversity in terms of income and racial or ethnic composition is considered desirable from the perspective of public policy, but some homebuyers may pay a premium to live in cities that are homogenous in terms of income or race or ethnicity. If enough homebuyers value racial and income homogeneity, then the implicit prices derived from the hedonic model will represent the *market value* but not the *social value* of diversity.

B.2. Implementing the "Hedonic" Approach for City-Level Needs Indicators

B.2.1. Choice of Database

As noted above, we have data on median housing values for 26,287 census tracts. After eliminating tracts with missing values for various variables, this left 21,375 for our first regression. In reviewing earlier versions of this model, some HUD staff members expressed concern about using median values in the regression because housing values can vary significantly within a tract. At HUD's suggestion, we experimented with eliminating tracts where housing values vary greatly within the tract. We dropped roughly 25 percent of the tracts—those with the greatest variation relative to the

[52] The *Final Work Plan* for this project contains the formal presentation of this model.

median.[53] This resulted in a database of 20,485 tracts, of which we used 16,096 in the second regression.

The two regressions produced similar results, and neither set of results was clearly superior to the other.[54] Table B.10 at the end of this appendix contains the complete results from the regression using the full set of tracts, while Table B.11 contains the complete results from the regression using the tracts with less dispersion in house values. The discussion in this chapter will focus on the regression based on the tracts with less dispersion—that is, the regression reported in Table B.11. Both models fit the data well. The regression using the restricted data set explains 77 percent of the variation in median house prices, and the probability that the reduction in variance is due to chance is less than 1 in 10,000.

B.2.2. The Tract-Level Variables

To isolate the effects of city-level needs indicators on median house prices, we used 20 control variables defined at the tract level. Table B.1 lists the tract-level variables.

In choosing these variables, we looked first for information that might describe the characteristics of the houses whose median value we are trying to explain. The decennial census has two tables that contain relevant information: a distribution of owner-occupied homes by the number of rooms in the home and a distribution of owner-occupied housing by the year the unit was built. We use the median number of rooms and create five variables to characterize the age of the owner-occupied housing in the tract.[55]

Next, we use the decennial census to provide information about the housing and people in the tract that might relate to the value of owner-occupied housing. Table B.1 contains variables that describe the tenure pattern and the type of structures in the tract and a variable that measures the proportion of overcrowded units in the tract. The decennial census provides information on the poverty rate in the tract and the racial and ethnic composition of the tract. It also provides information at the tract level on populations that we include in the city-level needs indicators—namely, single-parent families, recent immigrants, and linguistically isolated households.

---

[53] We calculated the ratio of (3rd quartile value – 1st quartile value)/median and eliminated all tracts where this ratio equaled or exceeded 0.56. The distribution of this ratio had a first quartile of 0.30, a median of 0.41, and a third quartile of 0.56.

[54] Both regressions use the natural log of the median house value as the dependent variable. This means that independent variables have a multiplicative effect on median house price—that is, if a variable has a value of 1.0 and its coefficient is 1.04, then the impact of that variable is to increase the median value of the homes in that tract by 4 percent. Those with positive coefficients increase median house price, while those with negative coefficients decrease median house price.

[55] Our age-of-housing variables segment age into six periods. We use only five of them, because in regression analysis if there is a group of mutually exclusive categories, one must category must serve as the point of comparison. With a set of categorical variables, the coefficients tell how much impact each of the included variables has compared to the excluded variable, for example, by what percentage the median value of a units built after 1989 is greater or less the median value of a units built in the 1970s, the omitted age category.

Table B.1. Tract-Level Variables Used in Regressions

Variable Name	Explanation
Characteristics of owner-occupied housing in the tract	
ROOMS	Median number of rooms in owner-occupied houses.
BUILTB50	Percent of owner-occupied was built before 1950
BUILT50S	Percent of owner-occupied was built the 1950s
BUILT60S	Percent of owner-occupied was built the 1960s
BUILT80S	Percent of owner-occupied was built the 1970s
BUILTA89	Percent of owner-occupied was built after 1989
Characteristics of the tract	
ORATE	Percent of the occupied units that are owner-occupied
PCTSFDETACHED	Percent of the units that are in single-family detached structures
PCT5PLUSUNITS	Percent of the units that are in structures containing 5 or more units
OVERCROWD2000_TR	Percent of households in the tract living in units where the number of person per room is 1.01 or greater.
HISPAN	Percent of the population that is Hispanic
NHBLACK	Percent of the population that is non-Hispanic Black
NHOTHER	Percent of the population that is non-Hispanic and not White alone or Black alone
POV10_19	The poverty rate in the tract is greater than or equal to 10 percent and less than 20 percent.
POV20_29	The poverty rate in the tract is greater than or equal to 20 percent and less than 30 percent.
POV30_39	The poverty rate in the tract is greater than or equal to 10 percent and less than 40 percent.
POV40PLUS	The poverty rate in the tract is greater than or equal to 40 percent.
SGLPRNTFAM_TR	Percent of families in the tract that are single parent-headed with own children under 18.
RCNTIMMIG_TR	Percent of household population in the tract that is foreign born and entered the United States within the last 15 years.
LINGISOL_TR	Percent of households in the tract that are "linguistically isolated" according to the definition in Table 1.

Table B.2 shows that the tract-level variables perform very well. Median housing value is positively and significantly related to the median number of rooms. All the year-built coefficients are statistically significant, except the coefficient for houses built in the 1960s. The sign and size of the coefficients suggest that older housing is less valuable than more recently built housing, with the exception that houses built before 1950 are more valuable than those built in the 1950s.[56]

[56] One possible explanation for this result is that "being built before 1950" proxies for other features of a housing unit that are not picked up by the other variables, for example, being located close to the central business district where land prices are high.

Table B.2. Parameter Estimates for Tract-Level Variables

Variable Name	Parameter Estimate	Probability Estimate Different from zero
Characteristics of owner-occupied housing in the tract		
ROOMS	0.06354	<.0001
BUILTB50	-0.07358	<.0001
BUILT50S	-0.17592	<.0001
BUILT60S	0.04551	0.0629
BUILT80S	0.0719	0.0038
BUILTA89	0.38942	<.0001
Characteristics of the tract		
ORATE	-0.11829	<.0001
PCTSFDETACHED	-0.01155	0.5314
PCT5PLUSUNITS	0.26393	<.0001
OVERCROWD2000_TR	-0.01706	0.6733
HISPAN	-0.92027	<.0001
NHBLACK	-0.71908	<.0001
NHOTHER	-0.61469	<.0001
POV10_19	-0.02347	0.0011
POV20_29	-0.03605	0.0002
POV30_39	-0.05207	<.0001
POV40PLUS	-0.03562	0.0187
SGLPRNTFAM_TR	-0.27932	<.0001
RCNTIMMIG_TR	-0.00535	0.0001
LINGISOL_TR	0.1206	0.0078

Only two of the four variables that describe the housing in the tract are significant. The signs of these two variables are different than anticipated and suggest that they are acting as proxies for other factors. According to the coefficient of PCT5PLUSUNITS, neighborhoods with more multifamily housing have higher median house values. Higher density development is usually the response of the housing market to high land prices. One can suppose that the median value of owner-occupied housing in tracts where land prices are high would also be higher. The negative coefficient for the homeownership rate is more puzzling; neighborhoods with higher homeownership rates appear to have lower median house values. One possibility is that we are not taking into account the relationship between the homeownership rate and the type of housing in a tract. Homeownership rates vary systematically by type of structure; they are highest for single-family detached structures, lower for single-family attached structures, lower still for two-to-four unit structures, and lowest for five-plus unit structures. The omitted group in this analysis consists of the combination of single-family attached units and units in two-to-four unit structures. The equation does not take the relationship between tenure and structure type into account and the failure to do so may have biased the coefficient of the homeownership rate variable.

All but one of the variables that describe the demographic composition of the tract have statistically significant coefficients. The race and ethnicity coefficients indicate that the larger the percentage of persons other than non-Hispanic Whites in the tract, the lower the median house value. This negative relationship may result from non-Hispanic Whites having higher incomes on average and, therefore, being able to afford more expensive housing, or it may represent a premium on neighborhoods with a higher proportion of non-Hispanic White residents. The coefficients of all the poverty variables are negative, indicating that poverty is associated with lower house values. In general, where the poverty rate is higher, the value of houses is disproportionately lower. Finally, housing values are lower in neighborhoods with a higher percentage of single-parent households or recent immigrants.

B.2.3. Variation Across Core-Based Statistical Areas

Our sample includes tracts in 191 core-based statistical areas. We included 190 dummy variables in the equation to account for unspecified, metro-wide amenity, housing supply elasticity, and speculative dynamic features unique to each of those housing markets. There was no dummy variable included for Birmingham-Hoover, so all the effects are measured relative to this CBSA.

These variables also performed according to prior expectations. Housing values are highest in the San Jose, Honolulu, San Francisco, and Santa Barbara metropolitan areas and lowest in the Pittsburgh, Buffalo, Syracuse, and Youngstown metropolitan areas.

B.2.4. City-Level Needs Indicators

The model fits well, and both the tract-level variables and metropolitan-area dummy variables are controlling for housing and tract characteristics and broader market characteristics. Thus now we can feel comfortable in looking at the impact of the city-level needs indicators on median house values.

As expected, the effect of the city-level indicators is small relative to the other variables. The adjusted R-square is 0.73 without the city-level needs indicators, and increases to 0.77 with these variables. The F statistic increases from 220.05 to 225.36; the 5-percent gain in explained variance is partially offset by the increase in the number of variables.

Table B.3 provides the estimated coefficients for the 24 city-level needs indicators. The results are organized into four subgroups.

Table B.3. Estimated Coefficients for City-Level Needs Indicators

Variable Name	Parameter Estimate	Probability Estimate Different from Zero
Variables that describe market conditions		
LACKAFFDRENTALS_2000	3.60592	<.0001
PR70RENTPOV_2000	3.98406	<.0001
OVERCROWD_2000	0.97017	<.0001
Variables not statistically significant at the 0.05 level		
SGLPRNTFAM_2000	-0.19016	0.5071
POORPERS_2000	-0.71551	0.4368
LINGISOL_2000	0.23691	0.3735
SCHPOPPOOR_2000	-0.91598	0.3324
PCTVACMODPOVCITY_2000	1.05775	0.2383
EXCSINFRA_2000	-0.18106	0.1234
CHNGEMPLBASE	0.04516	0.1221
POORCHILD_2000	1.75478	0.0944
UNEMPCEN_2000	-0.89899	0.0873
CHGLOWINCCON_2000	0.03215	0.0507
Statistical Significant Need Variables with Unanticipated Signs		
DENIAL	0.99676	0.0008
POOROVER74_2000	1.03706	<.0001
UNEDUCADULTS_2000	1.05456	<.0001
MINCON_2000	0.097	<.0001
Statistical Significant Need Variables with Anticipated Signs		
RCNTIMMIG_2000	-0.42276	0.0479
POVCON_2000	-0.08581	0.0211
PCTPOPHIGHPOVNGHS_2000	-0.52367	0.0145
LWINCHHDS_2000	-0.47981	0.0016
PCTPOPMODPOVNGHS_2000	-0.41167	<.0001
MEDINCCBS2CITY_2000	-0.57655	<.0001
UNDEREDWORKAGE_2000	-1.61828	<.0001

The first group contains three variables that describe conditions in the housing market: lack of affordable housing, poor households renting older units, and overcrowded units. Each variable has a statistically significant positive sign, indicating that—other things being equal—cities with higher values on these variables are associated with higher median house prices. Care must be taken in interpreting these results. These variables are problematic for use in a hedonic model because they do not measure attributes of communities that can independently be priced by the housing market. Rather, they are variables that are the result of housing market conditions themselves; causation is reversed from the typical hedonic model specification. Thus, in this case, we believe that all three variables probably reflect higher housing costs and therefore higher housing values, instead of signaling that consumers "value" these conditions more highly.

The second group contains 10 needs indicators that have coefficients that are not statistically significant. Three would be statistically significant at the 0.10 level, and one of these (CHGLOWNINCCON) is almost significant at the 0.05 level.

CHGLOWNINCCON is a trend variable that compares the proportion of families in the bottom 20 percent of the national family income distribution in 2000 to the proportion in 1970. The sign of the coefficient of CHGLOWNINCCON suggests that a growing low-income population is associated with higher housing prices—an unexpected result.

The third group contains four needs indicators that have statistically significant coefficients with unexpected positive signs. These are the mortgage denial rate (DENIAL), the percent of the population over 74 who are poor (POOROVER74), the percent of the working-age adults without a high school diploma (UNEDUCADULTS), and the minority share of the city population relative to the minority share of the metropolitan population (MINCON). We defined UNDEREDWORKAGE in such a way that it includes working-age persons without a high school diploma. While the base groups are different (all adults verses working-age adults), it makes sense to consider these two variables together. Their coefficients sum to -0.56, which has the appropriate sign. We have no ready explanations for the signs of the other variables. The sign of the coefficient of the MINCON variable is inconsistent with the sign on the ethnic and racial tract-level variables.

The last group contains seven needs indicators that have statistically significant coefficients, and the coefficients have the expected negative sign. This group includes two of the city/suburb disparity variables, POVCON and MEDINCCBS2CITY. It also includes the two variables (PCTPOPHIGHPOVNGHS and PCTPOPMODPOVNGHS) that measure the extent to which poverty is concentrated in certain neighborhoods. The last three variables measure the relative importance of certain populations: recent immigrants (RCNTIMMIG), households that are low income but above the poverty level (LWINCHHDS), and working-age adults without a college degree (UNDEREDWORKAGE).

B.3. Modified Specification of the Hedonic Model

From the initial analysis, we concluded that some variables, namely those in the top panel of Table B.3, are not appropriate for the hedonic model because they are the result of high housing prices. With this in mind, we estimated a new regression using all the same variables except for LACKAFFDRENTALS_2000, PR70RENTPOV_2000, and OVERCROWD_2000.

Table B.4 presents the results for the tract-level variables. The elimination of the three housing-market related variables had very little effect on the results for the tract-level variables. There are only two noteworthy changes. Now the coefficient of OVERCROWD2000_TR is positive and nearly significant; previously, it had a negative coefficient of very low significance. After dropping the city-level overcrowding variable, the tract-level variable now appears to be picking the impact of housing market conditions. The other noteworthy change involves LINGISOL_TR. Previously this variable had a positive significant coefficient; now the coefficient is still positive but insignificant.

Table B.4. Parameter Estimates for Tract-Level Variables with Modified Specification

Variable Name	Parameter Estimate	Probability Estimate Different from zero
Characteristics of owner-occupied housing in the tract		
ROOMS	0.06484	<.0001
BUILTB50	-0.06862	0.0001
BUILT50S	-0.16982	<.0001
BUILT60S	0.04634	0.0599
BUILT80S	0.07176	0.0041
BUILTA89	0.38898	<.0001
Characteristics of the tract		
ORATE	-0.10577	<.0001
PCTSFDETACHED	-0.03583	0.0526
PCT5PLUSUNITS	0.26388	<.0001
OVERCROWD2000_TR	0.07004	0.0789
HISPAN	-0.92366	<.0001
NHBLACK	-0.71292	<.0001
NHOTHER	-0.61038	<.0001
POV10_19	-0.02522	0.0005
POV20_29	-0.03892	<.0001
POV30_39	-0.05484	<.0001
POV40PLUS	-0.03883	0.0109
SGLPRNTFAM_TR	-0.30528	<.0001
RCNTIMMIG_TR	-0.00544	0.0001
LINGISOL_TR	0.06017	0.1834

Table B.5 presents the result for the city-level variables, using the same categories as Table B.3. The first panel in Table B.3 is dropped in Table B.5 because the modified specification eliminates these variables from the regression. The second panel in Table B.3 included 10 variables that were not statistically significant in the initial regression. Nine of the 10 are still insignificant; only LINGISOL_2000 is significant in the modified regression. We anticipated a negative coefficient for the percentage of households that are linguistically isolated (LINGISOL) because we thought the extra services required by such households would increase the tax burden. In the modified regression, LINGISOL_2000 has a positive coefficient; this unexpected result may be a result of the correlation between LINGISOL_2000 and OVERCROWD2000 or because immigrants may be attracted to cities that are more economically vibrant.

The third panel in Table B.3 included four variables whose coefficients were statistically significant and, contrary to our expectations, had positive signs. The results in Table B.5 for these four variables are substantively the same as those in B.3. The discussion of B.3 explained that the correct interpretation is to combine the coefficient of UNEDUCADULTS_2000 with the coefficient of UNDEREDWORKAGE_2000. In the initial specification, the combined value of these coefficients was -0.56; in the modified specification, the combined value is -0.42. In both equations, the combined effect of a low level of education level is to lower median house prices; this effect is stronger in the initial specification.

Table B.5. Estimated Coefficients for City-Level Needs Indicators with Modified Specification

Variable Name	Parameter Estimate	Probability Estimate Different from Zero
Variables not statistically significant at the 0.05 level in initial specification		
SGLPRNTFAM_2000	0.11269	0.6934
POORPERS_2000	-0.3083	0.7371
LINGISOL_2000	0.76863	0.002
SCHPOPPOOR_2000	1.11468	0.2344
PCTVACMODPOVCITY_2000	0.41418	0.639
EXCSINFRA_2000	-0.13529	0.2453
CHNGEMPLBASE	0.00307	0.9166
POORCHILD_2000	-0.43336	0.6741
UNEMPCEN_2000	-0.60749	0.242
CHGLOWINCCON_2000	0.01802	0.2741
Statistical significant need variables with unanticipated signs in initial specification		
DENIAL	1.03135	0.0004
POOROVER74_2000	1.2255	<.0001
UNEDUCADULTS_2000	1.55449	<.0001
MINCON_2000	0.1155	<.0001
Statistical significant need variables with anticipated signs in initial specification		
RCNTIMMIG_2000	-0.08441	0.6648
POVCON_2000	-0.058	0.0955
PCTPOPHIGHPOVNGHS_2000	0.000347	0.9987
LWINCHHDS_2000	-0.39888	0.0089
PCTPOPMODPOVNGHS_2000	-0.39901	<.0001
MEDINCCBS2CITY_2000	-0.12208	0.1368
UNDEREDWORKAGE_2000	-1.97809	<.0001

The final panel contains seven variables whose coefficients were statistically significant in the initial specification and had the anticipated negative signs. In the modified specification, only two of the seven have statistically significant signs.

We conclude that, while we cannot give the three housing market-related variables a "community needs" interpretation in the hedonic model, their inclusion is important in the specification of the model. The three variables appear to account for the effect of important housing market conditions.

B.4. Interpreting the Coefficients of City-Level Needs Indicators

For this analysis, we use the results from the initial specification reported in Table B.3. But instead of using estimates of the regular coefficient, we use estimates of the beta coefficients. The beta coefficient of variable x measures the impact of a one-standard-deviation change in variable x on the dependent variable—in this case, on the log of median house prices. Table B.6 reports the beta coefficients and transforms them into the percentage effect that a one-standard-deviation change will have on the median price.

Table B.6. Percentage Decline in Median House Prices Caused by a One-Standard-Deviation Worsening in a Need Indicator[57]

Need Indicator	Beta Coefficient	Percentage Impact
RCNTIMMIG_2000	-0.051	-0.050
POVCON_2000	-0.068	-0.065
PCTPOPHIGHPOVNGHS_2000	-0.043	-0.042
LWINCHHDS_2000	-0.072	-0.069
PCTPOPMODPOVNGHS_2000	-0.098	-0.093
MEDINCCBS2CITY_2000	-0.222	-0.199
UNDEREDWORKAGE_2000	-0.263	-0.231

The percentage impacts range from a 4-percent decline to a 23-percent decline in median house value. The first five needs indicators have approximately the same impact: a 4- to 7-percent decline. This is to be expected, given that several indicators measure similar aspects of disadvantaged communities. The relatively high impact of MEDINCCBS2CITY suggests that housing prices vary substantially inside of metropolitan areas where income inequality is significant across jurisdictions. The strong impact of UNDEREDWORKAGE suggests that we should group it with UNEDUADULTS as discussed above. If we were to use the combined coefficients, the estimated impact of a one standard deviation worsening on both indicators would be an 8-percent decline, an impact in line with the earlier variables.

B.5. Use of the "Hedonic" Approach for Assessing Importance of Factors

In Chapter 3, we used factor analysis to identify three factors underlying the 24 needs indicators. In Chapter 4, we reported a score on each factor for 370 cities. In this section, we substitute the factor scores for the 24 need variables and use the hedonic approach to measure the impact of the factors on median house value. In particular, we are interested in using the measured impact to inform our choice of weights for combining the factors into a single index of community need.

We used the factor scores in regressions using both all the census tracts and only the census tracts with limited dispersion of home values. The two regressions produced similar results. The discussion in this section will focus on the regression based on the tracts with less dispersion; Table B.12 at the end of this appendix contains the complete results from that regression. The model fit the data well, explaining 75 percent of the variation in median house prices, and the probability that the reduction in variance is due to chance is less than 1 in 10,000. The effect of adding the factor score variables is small relative to the other variables. The adjusted R-square is 0.73 without the city-level needs indicators, and increases to 0.75 with these variables. The F statistic increases from 220.05 to 232.98.

[57] The formula used to estimate the impact was: exp(beta coefficient*one standard deviation) – 1, which equals the change in median value over the original median value.

Table B.7 presents the parameter estimates for the three factor scores. All three coefficients are highly significant, and two of the three have the expected negative sign. The coefficient for Factor 2 has a positive sign. This factor had high factor loadings for overcrowded housing (OVERCROWD2000) and the lack of affordable rental housing (LACKAFFDRENTALS)—two needs indicators that had significant positive coefficients in the regression with the city-level need variables. Therefore, it is not surprising that this factor also has a positive coefficient.

Table B.7. Estimated Coefficients for the Three Factors

Variable	Parameter Estimate	Probability Estimate Different from Zero
Factor 1	-0.05551	<.0001
Factor 2	0.09500	<.0001
Factor 3	-0.19129	<.0001

As explained above, we believe that OVERCROWD2000 and LACKAFFDRENTALS had positive coefficients because they were produced by higher housing prices, not because markets positively value overcrowding or lack of affordable housing. For this reason, we did not think it appropriate to use the estimated impact of these variables on median prices in Table B.3 to measure the "social costs" of these conditions. Similarly, we will not try to use the hedonic model to estimate the social costs of the conditions measured by Factor 2. We will, however, explore what the hedonic model tells us about the relative social costs of Factors 1 and 3.

Table B.8 calculates the impact on median home values of a one-standard-deviation increase in the scores for Factors 1 and 3. A one-standard-deviation increase in the score for Factor 1 lowers the median house price by 5 percent, while a one-standard-deviation increase in the score for Factor 3 lowers the median house price by 16 percent. Higher values of Factors 1 and 3 are associated with lower median home values; the impact of a one-standard-deviation increase is approximately three times worse for Factor 3. This suggests that elements of community need associated with economic prospects (Factor 3) are approximately three times more important to consumers in the market than elements of community need associated with poverty and structural problems (Factor 1). We used this information to create Index 4, which weights the three factors 0.20, 0.20, and 0.60.[58]

Table B.8. Percentage Change in Median House Prices Caused by a One-Standard-Deviation Worsening in a Factor Score

	Standard Deviation	Percentage Impact
Factor 1	0.84	-0.05
Factor 3	0.88	-0.16

[58] We experimented with a regression containing only scores for Factors 1 and 3. (This is parallel to the analysis in Section 4.3 where we modified the regression containing the city-level needs indicators by dropping the three indicators associated with high-priced housing markets.) The coefficients from this regression suggest that the market values a one-standard-deviation change in Factor 3 seven times more than it values a one-standard-deviation change in Factor 1.

B.6. Use of Information on City-Level Variables to Create Factor Weights

B.6.1. The Relationship between Beta Coefficients and Standardized Scoring Coefficients

Table B.6 made use of beta coefficients. There is a parallel interpretation that can be given to beta coefficients and the standardized scoring coefficients derived in factor analysis. [59]

- Beta coefficients measure the impact of a one-standard-deviation change in a need indicator on the log of median housing prices. In the hedonic analysis, the change in the log of median housing prices is the measuring stick, or metric, used to gauge the impact of a variable.

- Standardized scoring coefficients measure the impact of a one-standard-deviation change in a need indicator on the estimated factor score. In factor analysis, the change in a factor score is the metric used to gauge the impact of a variable.

When we create a single-value index, we take a linear combination of the standardized scoring coefficients and convert them into a measure of the impact of a one-standard-deviation change in a variable on the index score, the metric used to gauge the overall impact of a variable.

Table B.9 has five columns. The second column contains the beta coefficients for the seven variables that had statistically significant coefficients of the correct sign. The only difference is that the last row contains the sum of the beta coefficients for UNDEREDWORKAGE and UNEDUCADULTS because we concluded that these coefficients should be considered jointly. Columns three, four, and five contain the standardized scoring coefficients for these variables.

We can combine Factors 1, 2, and 3 into a single-valued index by selecting weights for the factors. What if we selected the weights to make the sum of the standardized coefficients in columns three, four, and five as close as possible to the beta coefficients in column two? The result would be a single-valued index that approximated the impact of these eight variables on median housing prices.

[59] George Galster pointed out the relationship between beta coefficients and the standardized scoring coefficients. However, he is not responsible for any erroneous use of this relationship by the principal investigator.

Table B.9. Beta Coefficients and Standardized Scoring Coefficients for Needs Indicators with Valid Hedonic Coefficients

		Standardized Scoring Coefficients		
Variable	**beta Coefficient**	**Factor 1**	**Factor 2**	**Factor 3**
RCNTIMMIG	-0.051	-0.008	0.247	-0.186
POVCON	-0.068	0.098	0.006	-0.429
PCTPOPHIGHPOVNGHS	-0.043	0.014	-0.010	-0.042
LWINCHHDS	-0.072	0.028	0.099	-0.104
PCTPOPMODPOVNGHS	-0.098	0.009	0.045	0.021
MEDINCCBS2CITY	-0.222	0.204	0.102	-0.014
UNDEREDWORKAGE + UNEDUCADULTS	-0.122	-0.098	0.081	0.835

We used ordinary least squares regression to estimate raw weights that would make the weighted sum of the standardized scoring coefficients as close as possible to the beta coefficients. The raw coefficients were: -0.98, -0.45, and -0.19. When we adjust the raw weights so that the coefficients sum to 1.00, the weights become 0.60, 0.28, and 0.12. These are the weights we used in Index 6, the partial hedonic weights index.

This approach was purely experimental. It ignores all the needs indicators for which the hedonic-type equation failed to find valid coefficients. Yet it generated reasonable results. Index 6 is a blend of Index 2 and Index 5.

B.6.2. Extension of Experimental Use of Beta Coefficients to Guide Selection of Weights

In the last stages of writing the second draft report, the principal investigator had an idea on how to extend the analysis in Section B.4.1 that produced Index 6. Here is the extension of the rationale used in B.4.1.

Table 3 in section 3.2.5 contains the factor loadings (based on an orthogonal rotation) for the factors used in this report. In the case of each factor, some of the factor loadings are negative. This is not surprising. In factor analysis, the first unrotated factor will have all positive factor loading; the other unrotated factors will always have some negative factor loadings. After rotation, all factors will have some negative factor loadings. The existence of some negative factor loading results from the mathematics used to identify the factors.

In Table A.7 in Appendix A, there are negative standardized scoring coefficients for each factor. Table 9 in section 3.4.3 converts the standard scoring coefficients for the individual factors into the weights applied to the needs indicators to generate four of the six single-valued indices. Each of the single-value indices in Table 9 employs some negative weights.

The preceding section described a parallelism between the beta coefficients from the hedonic analysis and the weights derived from the standardized scoring coefficients.

Both the beta coefficients and the weights estimate the impact of a one-standard-deviation change in a need indicator on a metric. In the case of the regression analysis, the metric is the log of median housing value; in the case of the single-value index, the metric is the weighted sum of the factor scores.

In B.4.1, we limited our attention to the seven needs indicators that had significant coefficients with the correct sign in the regression analysis. In the regression, sign was important; but for the standardized scoring coefficients, it appears to be less important.

With this in mind, we used an OLS regression to fit the standardized scoring coefficients to the beta coefficients for all the variables except LACKAFFDRENTALS and OVERCROWD, which are variables that clearly do not fit the rationale of the regression model.[60] The raw coefficients were: -0.11, -0.40, and -0.10. When we adjust the raw weights so that the coefficients sum to 1.00, the weights become 0.18, 0.66, and 0.16. These are similar to the weights used in Index 3, the triple weight to the immigration and housing affordability factor.

We were unable to work through the implications of this analysis or to investigate its weaknesses. Therefore, we cannot claim that this analysis provides a justification for choosing Index 3. We present the results to call attention to the relationship between the regression analysis and the factor analysis and to the need to explore this relationship in greater depth.

B.7. Insights Gained from the Hedonic-type Analysis

Initially the project focused solely on factor analysis as the technique to be used in constructing a community needs index. At the Orientation Meeting, George Galster suggested using a hedonic analysis in order to resolve some of the uncertainties in factor analysis.

As reported in this appendix, the hedonic approach cannot put a price on community needs related to affordability housing. This limitation prevents the hedonic approach from being a substitute for factor analysis. In addition, because housing affordability is a core element in the dimension of need represented by Factor 2, the hedonic approach cannot determine the relative weight of Factor 2.

The work described in this appendix did provide some valuable insights related to community needs. The two most important were:

- Consistent with previous literature, the regression model shows that city-level characteristics are reflected in median housing values at the tract level. This provides proof that, at least, some of the conditions that we include among community needs have a detrimental impact on city residents.

[60] Again, we summed the beta coefficients and the standardized scoring coefficients for UNDEREDWORKAGE and UNEDUCADULTS before running the OLS regression.

- The model was able to provide reasonable estimates of how large an impact the following conditions may have on median house values:

    - Having a high proportion of low-income households.
    - Having a high proportion of residents living in neighborhoods with poverty rates over 40 percent.
    - Having a high proportion of residents living in neighborhoods with poverty rates over 20 percent but less than 40 percent.
    - Having a high proportion of working-age residents without a college degree.
    - Having a city poverty rate that is high relative to the metropolitan poverty rate.
    - Having city median income that is low relative to the metropolitan median income.

  The estimated impacts were sizable, particularly the impact of differences in median income.

The discussion in this appendix has also shown that the regression methodology and the factor analysis methodology are not unrelated. There are parallels in both the objectives of the two methodologies and in the statistical techniques employed. Understanding how the two methodologies are related may provide insights that will guide future research into community needs. One possible avenue of research would be to consider principal components as a bridge between the two methodologies.

Tables B.10, B.11, and B.12 contain the full regression results. Table B.10 contains the results for the regression over all tracts using the need indicators as independent variables. Table B.11 contains the results for the regression over the tracts with less house value dispersion using the need indicators as independent variables. Tables B.10 and B.11 are discussed in section B.2.1. Table B.12 contains the regression results for the regression over the tracts with less house value dispersion using the factor scores as independent variables instead of the need indicators. Table B.12 is discussed in section B.5.

Table B.10. Regressions Using All Tracts with Median House Values

THE HEDONIC MODEL USING 20 TRACT VARIABLES, 24 CITY VARIABLES AND 191 (203-12) metro DUMMIES					
DEPENDENT VARIABLE Natural log of median housing price: ln (H076001)					
Dependent Variable: LNVALUE					
Number of Observations Read			26287		
Number of Observations Used			21375		
Number of Observations with Missing Values			4912		
Analysis of Variance					
		Sum of	Mean		
Source	DF	Squares	Square	F Value	Pr > F
Model	234	7943.464	33.94643	284.57	<.0001
Error	21140	2521.795	0.11929		
Corrected Total	21374	10465			
Root MSE	0.34538	R-Square	0.759		
Dependent Mean	11.70984	Adj R-Sq	0.7564		
Coeff Var	2.94952				
Parameter Estimates					
		Parameter	Standard		
Variable	DF	Estimate	Error	t Value	Pr > |t|
Intercept	1	12.35706	0.11572	106.78	<.0001
ROOMS	1	0.06753	0.00427	15.83	<.0001
ORATE	1	-0.09851	0.02486	-3.96	<.0001
BUILTB50	1	-0.03393	0.01807	-1.88	0.0604
BUILT50S	1	-0.13859	0.02043	-6.78	<.0001
BUILT60S	1	0.08409	0.02597	3.24	0.0012
BUILT80S	1	0.11951	0.02606	4.59	<.0001
BUILTA89	1	0.42183	0.01957	21.56	<.0001
PCTSFDETACHED	1	-0.0036	0.01823	-0.2	0.8433
PCT5PLUSUNITS	1	0.36086	0.01788	20.19	<.0001
HISPAN	1	-1.08989	0.01675	-65.07	<.0001
NHBLACK	1	-0.87194	0.01141	-76.42	<.0001
NHOTHER	1	-0.73878	0.03094	-23.88	<.0001
POV10_19	1	-0.0174	0.00724	-2.41	0.0162
POV20_29	1	-0.02829	0.00965	-2.93	0.0034
POV30_39	1	-0.06768	0.01205	-5.62	<.0001
POV40PLUS	1	-0.08843	0.01423	-6.22	<.0001

SGLPRNTFAM_TR	1	-0.33302	0.02935	-11.35	<.0001
RCNTIMMIG_TR	1	-0.00842	0.00153	-5.5	<.0001
OVERCROWD2000_TR	1	0.06022	0.04117	1.46	0.1435
LINGISOL_TR	1	0.06294	0.04544	1.39	0.166
LACKAFFDRENTALS_2000	1	4.16489	0.44378	9.38	<.0001
CHGLOWINCCON_2000	1	0.05786	0.01723	3.36	0.0008
chngemplbase	1	0.06896	0.03064	2.25	0.0244
DENIAL	1	0.52985	0.30034	1.76	0.0777
EXCSINFRA_2000	1	-0.38307	0.1105	-3.47	0.0005
LINGISOL_2000	1	0.19548	0.2776	0.7	0.4813
LWINCHHDS_2000	1	-0.51596	0.1594	-3.24	0.0012
MEDINCCBS2CITY_2000	1	-0.69046	0.10478	-6.59	<.0001
MINCON_2000	1	0.13255	0.02107	6.29	<.0001
OVERCROWD_2000	1	0.86862	0.18575	4.68	<.0001
PCTPOPHIGHPOVNGHS_2000	1	-0.30971	0.21464	-1.44	0.1491
PCTPOPMODPOVNGHS_2000	1	-0.32628	0.09248	-3.53	0.0004
PCTVACMODPOVCITY_2000	1	-0.73593	0.79317	-0.93	0.3535
POORCHILD_2000	1	1.4214	1.06529	1.33	0.1821
POOROVER74_2000	1	0.81763	0.24188	3.38	0.0007
POORPERS_2000	1	-1.45744	0.93481	-1.56	0.119
POVCON_2000	1	-0.02125	0.03774	-0.56	0.5735
PR70RENTPOV_2000	1	4.52297	0.45901	9.85	<.0001
RCNTIMMIG_2000	1	-0.60178	0.22422	-2.68	0.0073
SCHPOPPOOR_2000	1	-0.3664	0.96535	-0.38	0.7043
SGLPRNTFAM_2000	1	-0.46251	0.29514	-1.57	0.1171
UNDEREDWORKAGE_2000	1	-1.59802	0.10246	-15.6	<.0001
UNEDUCADULTS_2000	1	1.32086	0.2002	6.6	<.0001
UNEMPCEN_2000	1	-0.06319	0.52636	-0.12	0.9044
Abilene_TX	1	-0.54106	0.08515	-6.35	<.0001
Akron_OH	1	-0.09629	0.06819	-1.41	0.158
Albany_GA	1	-0.2584	0.08975	-2.88	0.004
Albany_Schenectady_Troy_NY	1	-0.37119	0.09301	-3.99	<.0001
Albuquerque_NM	1	0.48704	0.06404	7.61	<.0001
Allentown_Bethlehem_Easton_PA_NJ	1	-0.19006	0.08373	-2.27	0.0232
Amarillo_TX	1	-0.18867	0.07065	-2.67	0.0076
Anchorage_AK	1	0.57395	0.07652	7.5	<.0001
Ann_Arbor_MI	1	0.11825	0.09327	1.27	0.2049
Appleton_WI	1	0.05857	0.10447	0.56	0.5751
Asheville_NC	1	-0.23004	0.09522	-2.42	0.0157
Atlanta_SandySprings_Marietta_GA	1	0.31578	0.06903	4.57	<.0001
Austin_Round_Rock_TX	1	0.23569	0.06559	3.59	0.0003
Bakersfield_CA	1	0.17576	0.07616	2.31	0.021
Baltimore_Towson_MD	1	0.09904	0.06271	1.58	0.1143
Baton_Rouge_LA	1	0.05705	0.06476	0.88	0.3783
Beaumont_Port_Arthur_TX	1	-0.29618	0.08018	-3.69	0.0002

Bellingham_WA	1	0.15348	0.12011	1.28	0.2014
Bend_OR	1	0.19986	0.12051	1.66	0.0972
Billings_MT	1	-0.0984	0.09731	-1.01	0.3119
Bloomington_IN	1	-0.6786	0.11334	-5.99	<.0001
Bloomington_Normal_IL	1	-0.08398	0.09711	-0.86	0.3871
Boise_City_Nampa_ID	1	0.02208	0.07683	0.29	0.7738
Boston_Cambridge_Quincy_MA_NH	1	0.50352	0.06472	7.78	<.0001
Boulder_CO	1	0.58623	0.08795	6.67	<.0001
Buffalo_Niagara_Falls_NY	1	-0.52216	0.07037	-7.42	<.0001
Canton_Massillon_OH	1	-0.1872	0.09272	-2.02	0.0435
Cape_Coral_Fort_Myers_FL	1	0.09997	0.09294	1.08	0.2821
Cedar_Rapids_IA	1	-0.02369	0.08729	-0.27	0.7861
Champaign_Urbana_IL	1	-0.38321	0.1055	-3.63	0.0003
Charleston_North_Charleston_SC	1	0.13113	0.0763	1.72	0.0857
Charlotte_Gastonia_Concord_NC_SC	1	0.15606	0.06018	2.59	0.0095
Chattanooga_TN_GA	1	-0.31599	0.07269	-4.35	<.0001
Chicago_Naperville_Joliet_IL_IN	1	0.56731	0.05433	10.44	<.0001
Chico_CA	1	0.04538	0.10799	0.42	0.6743
Cincinnati_Middletown_OH_KY_IN	1	-0.16788	0.06997	-2.4	0.0164
Clarksville_TN_KY	1	-0.21985	0.091	-2.42	0.0157
Cleveland_Elyria_Mentor_OH	1	0.1117	0.05777	1.93	0.0532
College_Station_Bryan_TX	1	-0.19731	0.08957	-2.2	0.0276
Colorado_Springs_CO	1	0.35995	0.0692	5.2	<.0001
Columbia_MO	1	-0.32383	0.10692	-3.03	0.0025
Columbia_SC	1	0.07747	0.07144	1.08	0.2782
Columbus_OH	1	-0.01512	0.06097	-0.25	0.8041
Corpus_Christi_TX	1	-0.20687	0.07398	-2.8	0.0052
Dallas_Fort_Worth_Arlington_TX	1	0.07344	0.05658	1.3	0.1943
Davenport_Moline_Rock_Island_IA	1	-0.14088	0.08413	-1.67	0.094
Dayton_OH	1	-0.00538	0.06692	-0.08	0.9359
Decatur_IL	1	-0.21275	0.08125	-2.62	0.0088
Deltona_Daytona_Beach_Ormond_FL	1	-0.21663	0.13239	-1.64	0.1018
Denver_Aurora_CO	1	0.62122	0.06167	10.07	<.0001
Des_Moines_IA	1	0.01039	0.07395	0.14	0.8883
Detroit_Warren_Livonia_MI	1	0.38657	0.0573	6.75	<.0001
Duluth_MN_WI	1	-0.35563	0.08159	-4.36	<.0001
Durham_NC	1	0.03869	0.07338	0.53	0.598
Erie_PA	1	-0.57339	0.0859	-6.67	<.0001
Eugene_Springfield_OR	1	0.05661	0.08547	0.66	0.5077
Evansville_IN_KY	1	-0.23815	0.07782	-3.06	0.0022
Fargo_ND_MN	1	-0.13151	0.10541	-1.25	0.2122
Fayetteville_NC	1	-0.07988	0.08068	-0.99	0.3221
Fayetteville_Springdale_AR_MO	1	-0.30134	0.11117	-2.71	0.0067
Flint_MI	1	-0.19732	0.07821	-2.52	0.0116
Fort_Collins_Loveland_CO	1	0.19266	0.08875	2.17	0.03
Fort_Smith_AR_OK	1	-0.37366	0.09635	-3.88	0.0001
Fort_Wayne_IN	1	-0.15878	0.06927	-2.29	0.0219

Fresno_CA	1	0.13313	0.07248	1.84	0.0663
Gainesville_FL	1	-0.21756	0.10479	-2.08	0.0379
Grand_Rapids_Wyoming_MI	1	0.04878	0.06954	0.7	0.4831
Greeley_CO	1	0.2582	0.09463	2.73	0.0064
Green_Bay_WI	1	0.19492	0.09105	2.14	0.0323
Greensboro_High_Point_NC	1	-0.02609	0.06558	-0.4	0.6908
Greenville_NC	1	-0.14274	0.10525	-1.36	0.175
Gulfport_Biloxi_MS	1	-0.26297	0.09169	-2.87	0.0041
Honolulu_HI	1	1.29919	0.0778	16.7	<.0001
Houston_Baytown_Sugar_Land_TX	1	0.06153	0.05769	1.07	0.2862
Huntsville_AL	1	-0.049	0.07258	-0.68	0.4996
Indianapolis_IN	1	0.08265	0.06263	1.32	0.1869
Jackson_MS	1	-0.08067	0.0674	-1.2	0.2314
Jacksonville_FL	1	0.05102	0.06316	0.81	0.4193
Kalamazoo_Portage_MI	1	-0.18026	0.09742	-1.85	0.0643
Kansas_City_MO_KS	1	-0.06304	0.05605	-1.12	0.2607
Killeen_Temple_Fort_Hood_TX	1	0.11341	0.10281	1.1	0.27
Knoxville_TN	1	-0.3554	0.07256	-4.9	<.0001
Lafayette_LA	1	-0.02434	0.07794	-0.31	0.7548
Lake_Charles_LA	1	-0.05051	0.08145	-0.62	0.5352
Lakeland_FL	1	-0.18879	0.08932	-2.11	0.0346
Lansing_East_Lansing_MI	1	0.01996	0.07837	0.25	0.799
Las_Vegas_Paradise_NV	1	0.302	0.06613	4.57	<.0001
Lawrence_KS	1	-0.13828	0.10461	-1.32	0.1862
Lawton_OK	1	-0.13014	0.08532	-1.53	0.1272
Lexington_Fayette_KY	1	-0.06153	0.07146	-0.86	0.3892
Lincoln_NE	1	-0.01104	0.07917	-0.14	0.8891
Little_Rock_North_Little_Rock_AR	1	-0.18258	0.07296	-2.5	0.0123
Longview_TX	1	-0.23432	0.09384	-2.5	0.0125
LosAngeles_LongBeach_SantaAna_CA	1	0.84023	0.06159	13.64	<.0001
Lubbock_TX	1	-0.42982	0.07447	-5.77	<.0001
Lynchburg_VA	1	-0.23863	0.09395	-2.54	0.0111
Macon_GA	1	0.03729	0.07826	0.48	0.6337
Madison_WI	1	0.04788	0.086	0.56	0.5777
Manchester_Nashua_NH	1	0.04756	0.08254	0.58	0.5645
Medford_OR	1	0.0847	0.11063	0.77	0.4439
Memphis_TN_MS_AR	1	0.00882	0.0582	0.15	0.8796
Merced_CA	1	0.46135	0.11125	4.15	<.0001
Miami_Fort_Lauderdale_Miami_FL	1	0.2799	0.06114	4.58	<.0001
Midland_TX	1	-0.21241	0.08664	-2.45	0.0142
Milwaukee_Waukesha_West_Allis_WI	1	0.00562	0.06053	0.09	0.926
Minneapolis_St_Paul_MN_WI	1	0.23074	0.07258	3.18	0.0015
Mobile_AL	1	-0.1817	0.06659	-2.73	0.0064
Modesto_CA	1	0.34971	0.07943	4.4	<.0001
Montgomery_AL	1	-0.11058	0.06795	-1.63	0.1037
Muncie_IN	1	-0.5804	0.09347	-6.21	<.0001
Napa_CA	1	1.02033	0.10587	9.64	<.0001

Nashville_Murfreesboro_TN	1	0.08022	0.06283	1.28	0.2017
NewYork_N_NJ_LongIsland_NY_NJ_PA	1	0.68255	0.05813	11.74	<.0001
Odessa_TX	1	-0.42231	0.09065	-4.66	<.0001
Ogden_Clearfield_UT	1	0.2624	0.1032	2.54	0.011
Oklahoma_City_OK	1	-0.17471	0.05442	-3.21	0.0013
Omaha_Council_Bluffs_NE_IA	1	-0.05705	0.06455	-0.88	0.3768
Orlando_FL	1	0.0181	0.08436	0.21	0.8301
Oxnard_Thousand_Oaks_Ventura_CA	1	0.98926	0.06827	14.49	<.0001
Palm_Bay_Melbourne_Titusville_FL	1	-0.10723	0.09252	-1.16	0.2464
Peoria_IL	1	-0.38694	0.08138	-4.75	<.0001
Philadelphia_Camden_PA_NJ_DE_MD	1	-0.08523	0.05325	-1.6	0.1095
Phoenix_Mesa_Scottsdale_AZ	1	0.31493	0.05874	5.36	<.0001
Pittsburgh_PA	1	-0.72159	0.0755	-9.56	<.0001
Portland_Vancouver_OR_WA	1	0.5228	0.06117	8.55	<.0001
Providence_Fall_River_RI_MA	1	0.06255	0.06455	0.97	0.3325
Provo_Orem_UT	1	0.16217	0.09287	1.75	0.0808
Pueblo_CO	1	0.27169	0.07909	3.43	0.0006
Racine_WI	1	0.14412	0.09573	1.51	0.1322
Raleigh_Cary_NC	1	0.25525	0.06982	3.66	0.0003
Reading_PA	1	-0.53845	0.09639	-5.59	<.0001
Redding_CA	1	0.17502	0.10098	1.73	0.0831
Reno_Sparks_NV	1	0.45325	0.08174	5.55	<.0001
Richmond_VA	1	0.09209	0.07529	1.22	0.2213
Riverside_San_Bernardino_Ont_CA	1	0.56192	0.06272	8.96	<.0001
Roanoke_VA	1	-0.11941	0.09221	-1.29	0.1954
Rochester_MN	1	0.01463	0.09015	0.16	0.8711
Rochester_NY	1	-0.39128	0.07145	-5.48	<.0001
Rockford_IL	1	-0.08064	0.07245	-1.11	0.2657
Sacramento_Arden_Roseville_CA	1	0.56968	0.06617	8.61	<.0001
Salem_OR	1	0.29188	0.08495	3.44	0.0006
Salinas_CA	1	0.9546	0.09748	9.79	<.0001
Salt_Lake_City_UT	1	0.44892	0.0699	6.42	<.0001
San_Angelo_TX	1	-0.28251	0.09283	-3.04	0.0023
San_Antonio_TX	1	0.02422	0.06214	0.39	0.6967
San_Diego_Carlsbad_San_Marcos_CA	1	0.85281	0.06142	13.89	<.0001
San_Francisco_Oakland_Fremont_CA	1	1.23172	0.06179	19.93	<.0001
San_Jose_Sunnyvale_St_Clara_CA	1	1.4657	0.06869	21.34	<.0001
Santa_Barbara_Maria_Goleta_CA	1	1.09522	0.08308	13.18	<.0001
Santa_Fe_NM	1	0.75498	0.09667	7.81	<.0001
Santa_Rosa_Petaluma_CA	1	0.96654	0.08605	11.23	<.0001
Savannah_GA	1	0.17328	0.07248	2.39	0.0168
Scranton_Wilkes_Barre_PA	1	-0.37611	0.09229	-4.08	<.0001
Seattle_Tacoma_Bellevue_WA	1	0.67053	0.06243	10.74	<.0001
Shreveport_Bossier_City_LA	1	-0.13435	0.06443	-2.09	0.0371
Sioux_City_IA_NE_SD	1	-0.27551	0.09366	-2.94	0.0033
Sioux_Falls_SD	1	-0.00363	0.09272	-0.04	0.9687
South_Bend_Mishawaka_IN_MI	1	-0.27853	0.07137	-3.9	<.0001

Spokane_WA	1	0.1193	0.07122	1.68	0.0939
Springfield_IL	1	-0.10948	0.0752	-1.46	0.1455
Springfield_MA	1	0.21599	0.08513	2.54	0.0112
Springfield_MO	1	-0.34164	0.07552	-4.52	<.0001
St_Cloud_MN	1	-0.1274	0.12609	-1.01	0.3123
St_Joseph_MO_KS	1	-0.41145	0.08561	-4.81	<.0001
St_Louis_MO_IL	1	0.08682	0.07546	1.15	0.2499
Stockton_CA	1	0.51968	0.07494	6.93	<.0001
Syracuse_NY	1	-0.72491	0.07931	-9.14	<.0001
Tallahassee_FL	1	-0.07902	0.0839	-0.94	0.3463
Tampa_St_Petersburg_Clwater_FL	1	-0.01435	0.05897	-0.24	0.8078
Toledo_OH	1	-0.14222	0.06239	-2.28	0.0227
Topeka_KS	1	-0.31523	0.0799	-3.95	<.0001
Trenton_Ewing_NJ	1	0.33843	0.09898	3.42	0.0006
Tucson_AZ	1	0.30822	0.06522	4.73	<.0001
Tulsa_OK	1	-0.13173	0.05985	-2.2	0.0278
Tuscaloosa_AL	1	-0.10535	0.08617	-1.22	0.2215
Tyler_TX	1	-0.21119	0.08591	-2.46	0.014
Vallejo_Fairfield_CA	1	0.87619	0.07443	11.77	<.0001
Virginia_Beach_Norfolk_VA_NC	1	0.23105	0.05983	3.86	0.0001
Visalia_Porterville_CA	1	0.20604	0.10185	2.02	0.0431
Waco_TX	1	-0.45084	0.08453	-5.33	<.0001
Washington_Arl_Alex_DC_VA_MD_WV	1	0.85627	0.08215	10.42	<.0001
Waterloo_Cedar_Falls_IA	1	-0.34838	0.08709	-4	<.0001
Wichita_Falls_TX	1	-0.52884	0.08086	-6.54	<.0001
Wichita_KS	1	-0.20276	0.06304	-3.22	0.0013
Wilmington_NC	1	-0.05655	0.09838	-0.57	0.5654
Winston_Salem_NC	1	0.02539	0.07235	0.35	0.7256
Worcester_MA	1	0.03909	0.08083	0.48	0.6286
Yakima_WA	1	0.13032	0.11493	1.13	0.2568
Youngstown_Warren_Boardman_OH_PA	1	-0.68743	0.09237	-7.44	<.0001
Yuma_AZ	1	-0.00583	0.10301	-0.06	0.9549

Table B.11. Regressions on Tracts with Less Dispersion in Median Prices

THE HEDONIC MODEL USING 20 TRACT VARIABLES, 24 CITY VARIABLES					
AND 191 (203-12) metro dUMMIES					
DEPENDENT VARIABLE Natural log of median housing price: ln (H076001)					
where SPECIAL LE .56					
Dependent Variable: LNVALUE					
Number of Observations Read			20485		
Number of Observations Used			16096		
Number of Observations with Missing Values			4389		
Analysis of Variance					
		Sum of	Mean		
Source	DF	Squares	Square	F Value	Pr > F
Model	234	4846.302	20.71069	225.36	<.0001
Error	15861	1457.622	0.0919		
Corrected Total	16095	6303.924			
Root MSE	0.30315	R-Square	0.7688		
Dependent Mean	11.7506	Adj R-Sq	0.7654		
Coeff Var	2.57987				
Parameter Estimates					
		Parameter	Standard		
Variable		Estimate	Error	t Value	Pr > |t|
Intercept		12.0885	0.12086	100.02	<.0001
ROOMS		0.06354	0.00435	14.6	<.0001
ORATE		-0.11829	0.02562	-4.62	<.0001
BUILTB50		-0.07358	0.01775	-4.15	<.0001
BUILT50S		-0.17592	0.01944	-9.05	<.0001
BUILT60S		0.04551	0.02447	1.86	0.0629
BUILT80S		0.0719	0.02482	2.9	0.0038
BUILTA89		0.38942	0.0186	20.93	<.0001
PCTSFDETACHED		-0.01155	0.01845	-0.63	0.5314
PCT5PLUSUNITS		0.26393	0.01844	14.31	<.0001
HISPAN		-0.92027	0.01703	-54.05	<.0001
NHBLACK		-0.71908	0.01232	-58.37	<.0001
NHOTHER		-0.61469	0.03014	-20.39	<.0001
POV10_19		-0.02347	0.00718	-3.27	0.0011
POV20_29		-0.03605	0.00984	-3.66	0.0002
POV30_39		-0.05207	0.01272	-4.09	<.0001
POV40PLUS		-0.03562	0.01515	-2.35	0.0187

SGLPRNTFAM_TR		-0.27932	0.03077	-9.08	<.0001
RCNTIMMIG_TR		-0.00535	0.0014	-3.83	0.0001
OVERCROWD2000_TR		-0.01706	0.04048	-0.42	0.6733
LINGISOL_TR		0.1206	0.04535	2.66	0.0078
LACKAFFDRENTALS_2000		3.60592	0.42479	8.49	<.0001
CHGLOWINCCON_2000		0.03215	0.01645	1.95	0.0507
chngemplbase		0.04516	0.02921	1.55	0.1221
DENIAL		0.99676	0.2974	3.35	0.0008
EXCSINFRA_2000		-0.18106	0.11751	-1.54	0.1234
LINGISOL_2000		0.23691	0.26618	0.89	0.3735
LWINCHHDS_2000		-0.47981	0.15164	-3.16	0.0016
MEDINCCBS2CITY_2000		-0.57655	0.10209	-5.65	<.0001
MINCON_2000		0.097	0.02082	4.66	<.0001
OVERCROWD_2000		0.97017	0.17949	5.41	<.0001
PCTPOPHIGHPOVNGHS_2000		-0.52367	0.21423	-2.44	0.0145
PCTPOPMODPOVNGHS_2000		-0.41167	0.09011	-4.57	<.0001
PCTVACMODPOVCITY_2000		1.05775	0.89695	1.18	0.2383
POORCHILD_2000		1.75478	1.04911	1.67	0.0944
POOROVER74_2000		1.03706	0.23313	4.45	<.0001
POORPERS_2000		-0.71551	0.92003	-0.78	0.4368
POVCON_2000		-0.08581	0.03719	-2.31	0.0211
PR70RENTPOV_2000		3.98406	0.44457	8.96	<.0001
RCNTIMMIG_2000		-0.42276	0.21372	-1.98	0.0479
SCHPOPPOOR_2000		-0.91598	0.94506	-0.97	0.3324
SGLPRNTFAM_2000		-0.19016	0.28668	-0.66	0.5071
UNDEREDWORKAGE_2000		-1.61828	0.10227	-15.82	<.0001
UNEDUCADULTS_2000		1.05456	0.19703	5.35	<.0001
UNEMPCEN_2000		-0.89899	0.52569	-1.71	0.0873
Abilene_TX		-0.30477	0.10261	-2.97	0.003
Akron_OH		0.05554	0.07178	0.77	0.4391
Albany_GA		-0.0643	0.09395	-0.68	0.4938
Albany_Schenectady_Troy_NY		-0.20011	0.09666	-2.07	0.0384
Albuquerque_NM		0.52279	0.06762	7.73	<.0001
Allentown_Bethlehem_Easton_PA_NJ		0.03917	0.08886	0.44	0.6593
Amarillo_TX		-0.04372	0.07695	-0.57	0.5699
Anchorage_AK		0.69935	0.07848	8.91	<.0001
Ann_Arbor_MI		0.26431	0.09835	2.69	0.0072
Appleton_WI		0.23745	0.10111	2.35	0.0189
Asheville_NC		-0.08851	0.10509	-0.84	0.3997
Atlanta_SandySprings_Marietta_GA		0.3062	0.07333	4.18	<.0001
Austin_Round_Rock_TX		0.25751	0.06942	3.71	0.0002
Bakersfield_CA		0.28697	0.08076	3.55	0.0004
Baltimore_Towson_MD		0.23928	0.06857	3.49	0.0005
Baton_Rouge_LA		0.2176	0.07261	3	0.0027
Beaumont_Port_Arthur_TX		-0.22713	0.11959	-1.9	0.0575

Bellingham_WA		0.40534	0.12107	3.35	0.0008
Bend_OR		0.35234	0.13063	2.7	0.007
Billings_MT		0.04631	0.09517	0.49	0.6265
Bloomington_IN		-0.46117	0.11835	-3.9	<.0001
Bloomington_Normal_IL		0.0495	0.09619	0.51	0.6068
Boise_City_Nampa_ID		0.11606	0.07946	1.46	0.1441
Boston_Cambridge_Quincy_MA_NH		0.68356	0.07154	9.56	<.0001
Boulder_CO		0.68413	0.0933	7.33	<.0001
Buffalo_Niagara_Falls_NY		-0.54614	0.07501	-7.28	<.0001
Canton_Massillon_OH		0.00683	0.10198	0.07	0.9466
Cape_Coral_Fort_Myers_FL		0.19777	0.09531	2.08	0.038
Cedar_Rapids_IA		0.11871	0.09005	1.32	0.1874
Champaign_Urbana_IL		-0.31142	0.11197	-2.78	0.0054
Charleston_North_Charleston_SC		0.00627	0.09606	0.07	0.948
Charlotte_Gastonia_Concord_NC_SC		0.19505	0.06555	2.98	0.0029
Chattanooga_TN_GA		-0.10972	0.08426	-1.3	0.1929
Chicago_Naperville_Joliet_IL_IN		0.6131	0.06015	10.19	<.0001
Chico_CA		0.2417	0.11044	2.19	0.0287
Cincinnati_Middletown_OH_KY_IN		-0.08625	0.07443	-1.16	0.2465
Clarksville_TN_KY		-0.09387	0.10787	-0.87	0.3842
Cleveland_Elyria_Mentor_OH		0.18059	0.06136	2.94	0.0033
College_Station_Bryan_TX		-0.10283	0.09718	-1.06	0.29
Colorado_Springs_CO		0.44595	0.0722	6.18	<.0001
Columbia_MO		-0.30199	0.12027	-2.51	0.0121
Columbia_SC		0.04587	0.07733	0.59	0.5531
Columbus_OH		0.06535	0.06502	1.01	0.3149
Corpus_Christi_TX		-0.12055	0.08034	-1.5	0.1335
Dallas_Fort_Worth_Arlington_TX		0.10698	0.06123	1.75	0.0806
Davenport_Moline_Rock_Island_IA		0.00994	0.0873	0.11	0.9094
Dayton_OH		-0.0444	0.07122	-0.62	0.533
Decatur_IL		-0.02509	0.10243	-0.24	0.8065
Deltona_Daytona_Beach_Ormond_FL		-0.08684	0.12865	-0.68	0.4997
Denver_Aurora_CO		0.7208	0.06575	10.96	<.0001
Des_Moines_IA		0.14221	0.07788	1.83	0.0679
Detroit_Warren_Livonia_MI		0.56204	0.06209	9.05	<.0001
Duluth_MN_WI		-0.19807	0.08927	-2.22	0.0265
Durham_NC		0.04939	0.07589	0.65	0.5152
Erie_PA		-0.45312	0.09016	-5.03	<.0001
Eugene_Springfield_OR		0.22649	0.08911	2.54	0.011
Evansville_IN_KY		-0.09678	0.08067	-1.2	0.2303
Fargo_ND_MN		0.03814	0.10127	0.38	0.7065
Fayetteville_NC		-0.03441	0.08239	-0.42	0.6762
Fayetteville_Springdale_AR_MO		-0.11734	0.13145	-0.89	0.3721
Flint_MI		-0.18226	0.09183	-1.98	0.0472
Fort_Collins_Loveland_CO		0.35723	0.09064	3.94	<.0001
Fort_Smith_AR_OK		-0.35488	0.11031	-3.22	0.0013
Fort_Wayne_IN		-0.02872	0.07269	-0.4	0.6928

Fresno_CA		0.26975	0.0767	3.52	0.0004
Gainesville_FL		-0.07339	0.11235	-0.65	0.5136
Grand_Rapids_Wyoming_MI		0.1963	0.07336	2.68	0.0075
Greeley_CO		0.34292	0.0962	3.56	0.0004
Green_Bay_WI		0.34747	0.09238	3.76	0.0002
Greensboro_High_Point_NC		0.00421	0.07067	0.06	0.9525
Greenville_NC		-0.09324	0.11938	-0.78	0.4348
Gulfport_Biloxi_MS		-0.27602	0.10039	-2.75	0.006
Honolulu_HI		1.44719	0.08262	17.52	<.0001
Houston_Baytown_Sugar_Land_TX		0.08725	0.06189	1.41	0.1586
Huntsville_AL		-0.06043	0.07621	-0.79	0.4279
Indianapolis_IN		0.09643	0.06516	1.48	0.1389
Jackson_MS		-0.12784	0.07433	-1.72	0.0855
Jacksonville_FL		0.07758	0.06953	1.12	0.2646
Kalamazoo_Portage_MI		-0.04987	0.10961	-0.45	0.6491
Kansas_City_MO_KS		0.10913	0.06134	1.78	0.0752
Killeen_Temple_Fort_Hood_TX		0.18234	0.0994	1.83	0.0666
Knoxville_TN		-0.24437	0.07805	-3.13	0.0017
Lafayette_LA		0.02529	0.10951	0.23	0.8174
Lake_Charles_LA		0.06006	0.0883	0.68	0.4964
Lakeland_FL		-0.14718	0.10156	-1.45	0.1473
Lansing_East_Lansing_MI		0.11677	0.08112	1.44	0.15
Las_Vegas_Paradise_NV		0.43187	0.07142	6.05	<.0001
Lawrence_KS		-0.04195	0.10577	-0.4	0.6916
Lawton_OK		-0.11731	0.08713	-1.35	0.1782
Lexington_Fayette_KY		-0.02488	0.07597	-0.33	0.7433
Lincoln_NE		0.10606	0.08116	1.31	0.1913
Little_Rock_North_Little_Rock_AR		-0.16585	0.08341	-1.99	0.0468
Longview_TX		-0.19355	0.1128	-1.72	0.0862
LosAngeles_LongBeach_SantaAna_CA		0.9646	0.06762	14.27	<.0001
Lubbock_TX		-0.38731	0.08284	-4.68	<.0001
Lynchburg_VA		-0.12824	0.11561	-1.11	0.2673
Macon_GA		-0.08535	0.08768	-0.97	0.3304
Madison_WI		0.24536	0.08952	2.74	0.0061
Manchester_Nashua_NH		0.24318	0.08496	2.86	0.0042
Medford_OR		0.2525	0.10837	2.33	0.0198
Memphis_TN_MS_AR		-0.03273	0.06069	-0.54	0.5897
Merced_CA		0.59994	0.1106	5.42	<.0001
Miami_Fort_Lauderdale_Miami_FL		0.31523	0.06693	4.71	<.0001
Midland_TX		-0.16258	0.09676	-1.68	0.0929
Milwaukee_Waukesha_West_Allis_WI		0.17229	0.0661	2.61	0.0092
Minneapolis_St_Paul_MN_WI		0.36836	0.07676	4.8	<.0001
Mobile_AL		-0.17661	0.07466	-2.37	0.018
Modesto_CA		0.48982	0.08281	5.92	<.0001
Montgomery_AL		-0.13255	0.07297	-1.82	0.0693
Muncie_IN		-0.41326	0.09843	-4.2	<.0001
Napa_CA		1.15046	0.11065	10.4	<.0001

Nashville_Murfreesboro_TN		0.15974	0.06806	2.35	0.0189
NewYork_N_NJ_LongIsland_NY_NJ_PA		0.82946	0.06492	12.78	<.0001
Odessa_TX		-0.36904	0.10077	-3.66	0.0003
Ogden_Clearfield_UT		0.46515	0.10267	4.53	<.0001
Oklahoma_City_OK		-0.1149	0.05958	-1.93	0.0538
Omaha_Council_Bluffs_NE_IA		0.0937	0.07012	1.34	0.1815
Orlando_FL		0.05323	0.08878	0.6	0.5488
Oxnard_Thousand_Oaks_Ventura_CA		1.10356	0.0723	15.26	<.0001
Palm_Bay_Melbourne_Titusville_FL		-0.00867	0.09612	-0.09	0.9282
Peoria_IL		-0.13402	0.09559	-1.4	0.1609
Philadelphia_Camden_PA_NJ_DE_MD		0.02546	0.0587	0.43	0.6645
Phoenix_Mesa_Scottsdale_AZ		0.37127	0.06439	5.77	<.0001
Pittsburgh_PA		-0.67064	0.08602	-7.8	<.0001
Portland_Vancouver_OR_WA		0.63741	0.06709	9.5	<.0001
Providence_Fall_River_RI_MA		0.21488	0.07027	3.06	0.0022
Provo_Orem_UT		0.29563	0.09358	3.16	0.0016
Pueblo_CO		0.37537	0.08093	4.64	<.0001
Racine_WI		0.29251	0.09763	3	0.0027
Raleigh_Cary_NC		0.29144	0.07387	3.95	<.0001
Reading_PA		-0.40604	0.09936	-4.09	<.0001
Redding_CA		0.31348	0.10307	3.04	0.0024
Reno_Sparks_NV		0.56874	0.08476	6.71	<.0001
Richmond_VA		0.15943	0.08159	1.95	0.0507
Riverside_San_Bernardino_Ont_CA		0.68707	0.06879	9.99	<.0001
Roanoke_VA		-0.01715	0.0949	-0.18	0.8566
Rochester_MN		0.13019	0.0932	1.4	0.1625
Rochester_NY		-0.33743	0.07386	-4.57	<.0001
Rockford_IL		0.05556	0.0758	0.73	0.4636
Sacramento_Arden_Roseville_CA		0.66794	0.07085	9.43	<.0001
Salem_OR		0.42147	0.08564	4.92	<.0001
Salinas_CA		1.11718	0.09549	11.7	<.0001
Salt_Lake_City_UT		0.55884	0.07269	7.69	<.0001
San_Angelo_TX		-0.21813	0.11518	-1.89	0.0583
San_Antonio_TX		0.03624	0.06605	0.55	0.5833
San_Diego_Carlsbad_San_Marcos_CA		0.97065	0.06767	14.34	<.0001
San_Francisco_Oakland_Fremont_CA		1.33513	0.06656	20.06	<.0001
San_Jose_Sunnyvale_St_Clara_CA		1.54372	0.07215	21.4	<.0001
Santa_Barbara_Maria_Goleta_CA		1.19215	0.08946	13.33	<.0001
Santa_Fe_NM		0.75551	0.09826	7.69	<.0001
Santa_Rosa_Petaluma_CA		1.06617	0.08803	12.11	<.0001
Savannah_GA		0.07082	0.08416	0.84	0.4001
Scranton_Wilkes_Barre_PA		-0.2391	0.09563	-2.5	0.0124
Seattle_Tacoma_Bellevue_WA		0.78121	0.0682	11.45	<.0001
Shreveport_Bossier_City_LA		-0.2115	0.07289	-2.9	0.0037
Sioux_City_IA_NE_SD		-0.18902	0.09907	-1.91	0.0564
Sioux_Falls_SD		0.11364	0.0934	1.22	0.2238
South_Bend_Mishawaka_IN_MI		-0.18462	0.07426	-2.49	0.0129

Spokane_WA		0.22543	0.07511	3	0.0027
Springfield_IL		-0.00835	0.07811	-0.11	0.9149
Springfield_MA		0.25335	0.08736	2.9	0.0037
Springfield_MO		-0.21719	0.07843	-2.77	0.0056
St_Cloud_MN		0.00619	0.12643	0.05	0.9609
St_Joseph_MO_KS		-0.14809	0.11089	-1.34	0.1817
St_Louis_MO_IL		0.02149	0.07938	0.27	0.7866
Stockton_CA		0.65459	0.07877	8.31	<.0001
Syracuse_NY		-0.53325	0.08275	-6.44	<.0001
Tallahassee_FL		-0.00834	0.08939	-0.09	0.9257
Tampa_St_Petersburg_Clwater_FL		0.01739	0.06615	0.26	0.7927
Toledo_OH		0.00582	0.0667	0.09	0.9305
Topeka_KS		-0.19351	0.08402	-2.3	0.0213
Trenton_Ewing_NJ		0.2694	0.09981	2.7	0.007
Tucson_AZ		0.3522	0.0693	5.08	<.0001
Tulsa_OK		-0.10254	0.06416	-1.6	0.11
Tuscaloosa_AL		-0.11362	0.09421	-1.21	0.2278
Tyler_TX		-0.13077	0.12686	-1.03	0.3026
Vallejo_Fairfield_CA		0.96565	0.07669	12.59	<.0001
Virginia_Beach_Norfolk_VA_NC		0.31641	0.06683	4.73	<.0001
Visalia_Porterville_CA		0.30273	0.11435	2.65	0.0081
Waco_TX		-0.34872	0.10122	-3.45	0.0006
Washington_Arl_Alex_DC_VA_MD_WV		0.95056	0.08615	11.03	<.0001
Waterloo_Cedar_Falls_IA		-0.19408	0.09743	-1.99	0.0464
Wichita_Falls_TX		-0.4187	0.09302	-4.5	<.0001
Wichita_KS		-0.10938	0.06676	-1.64	0.1014
Wilmington_NC		-0.04251	0.11594	-0.37	0.7139
Winston_Salem_NC		0.06889	0.08158	0.84	0.3984
Worcester_MA		0.16624	0.08752	1.9	0.0575
Yakima_WA		0.23051	0.12054	1.91	0.0559
Youngstown_Warren_Boardman_OH_PA		-0.48621	0.11728	-4.15	<.0001
Yuma_AZ		-0.01662	0.10992	-0.15	0.8798

Table B.12. Regressions on Tracts with Less Dispersion in Median Prices Using Factor Scores

THE HEDONIC MODEL USING 20 TRACT VARIABLES, 3 2000					
FACTOR SCORES AND (203) metro dUMMIES					
DEPENDENT VARIABLE Natural log of median housing price					
where SPECIAL LE .56: ln (H076001)					
Dependent Variable: LNVALUE					
Number of Observations Read					20485
Number of Observations Used					16096
Number of Observations with Missing Values					4389
Analysis of Variance					
		Sum of	Mean		
Source	DF	Squares	Square	F Value	Pr > F
Model	213	4775.534	22.42035	232.98	<.0001
Error	15882	1528.39	0.09623		
Corrected Total	16095	6303.924			
Root MSE	0.31022	R-Square	0.7575		
Dependent Mean	11.7506	Adj R-Sq	0.7543		
Coeff Var	2.64				
Parameter Estimates					
		Parameter	Standard		
Variable	DF	Estimate	Error	t Value	Pr > |t|
Intercept	1	11.67077	0.05571	209.49	<.0001
ROOMS	1	0.07169	0.00439	16.33	<.0001
ORATE	1	-0.11065	0.02605	-4.25	<.0001
BUILTB50	1	-0.06047	0.01801	-3.36	0.0008
BUILT50S	1	-0.16268	0.01978	-8.22	<.0001
BUILT60S	1	0.0556	0.02495	2.23	0.0258
BUILT80S	1	0.07399	0.02534	2.92	0.0035
BUILTA89	1	0.38087	0.01895	20.1	<.0001
PCTSFDETACHED	1	-0.03267	0.01868	-1.75	0.0804
PCT5PLUSUNITS	1	0.28452	0.01872	15.2	<.0001
HISPAN	1	-0.89505	0.01714	-52.23	<.0001
NHBLACK	1	-0.68054	0.01236	-55.04	<.0001
NHOTHER	1	-0.58534	0.02984	-19.61	<.0001
POV10_19	1	-0.02889	0.0073	-3.96	<.0001
POV20_29	1	-0.04846	0.00999	-4.85	<.0001

POV30_39	1	-0.06432	0.01294	-4.97	<.0001
POV40PLUS	1	-0.05452	0.01537	-3.55	0.0004
SGLPRNTFAM_TR	1	-0.31284	0.03124	-10.01	<.0001
RCNTIMMIG_TR	1	-0.00518	0.00143	-3.62	0.0003
OVERCROWD2000_TR	1	0.12258	0.03984	3.08	0.0021
LINGISOL_TR	1	0.0492	0.04508	1.09	0.2752
Factor 1	1	-0.05551	0.00505	-11	<.0001
Factor 2	1	0.095	0.00614	15.46	<.0001
Factor 3	1	-0.19129	0.00589	-32.5	<.0001
Abilene_TX	1	-0.4806	0.09694	-4.96	<.0001
Akron_OH	1	-0.23545	0.06134	-3.84	0.0001
Albany_GA	1	0.07687	0.08704	0.88	0.3772
Albany_Schenectady_Troy_NY	1	-0.35326	0.08446	-4.18	<.0001
Albuquerque_NM	1	0.20864	0.05471	3.81	0.0001
Allentown_Bethlehem_Easton_PA_NJ	1	-0.37837	0.06882	-5.5	<.0001
Amarillo_TX	1	-0.32767	0.0701	-4.67	<.0001
Anchorage_AK	1	0.07285	0.06345	1.15	0.2509
Ann_Arbor_MI	1	-0.33176	0.08274	-4.01	<.0001
Appleton_WI	1	-0.49689	0.0834	-5.96	<.0001
Asheville_NC	1	-0.2553	0.08974	-2.84	0.0044
Atlanta_SandySprings_Marietta_GA	1	-0.02446	0.05767	-0.42	0.6714
Austin_Round_Rock_TX	1	-0.23524	0.05398	-4.36	<.0001
Bakersfield_CA	1	0.07171	0.06059	1.18	0.2367
Baltimore_Towson_MD	1	-0.18325	0.05287	-3.47	0.0005
Baton_Rouge_LA	1	0.10633	0.06522	1.63	0.103
Beaumont_Port_Arthur_TX	1	-0.2749	0.11806	-2.33	0.0199
Bellingham_WA	1	-0.1745	0.10855	-1.61	0.108
Bend_OR	1	-0.15741	0.11899	-1.32	0.1859
Billings_MT	1	-0.3319	0.08261	-4.02	<.0001
Bloomington_IN	1	-0.80301	0.09892	-8.12	<.0001
Bloomington_Normal_IL	1	-0.49504	0.08337	-5.94	<.0001
Boise_City_Nampa_ID	1	-0.34716	0.06709	-5.17	<.0001
Boston_Cambridge_Quincy_MA_NH	1	0.1686	0.05252	3.21	0.0013
Boulder_CO	1	0.06597	0.07846	0.84	0.4005
Buffalo_Niagara_Falls_NY	1	-0.31702	0.06226	-5.09	<.0001
Canton_Massillon_OH	1	-0.18331	0.08898	-2.06	0.0394
Cape_Coral_Fort_Myers_FL	1	-0.34935	0.08341	-4.19	<.0001
Cedar_Rapids_IA	1	-0.51652	0.07615	-6.78	<.0001
Champaign_Urbana_IL	1	-0.91988	0.10141	-9.07	<.0001
Charleston_North_Charleston_SC	1	-0.12862	0.08971	-1.43	0.1517
Charlotte_Gastonia_Concord_NC_SC	1	-0.16388	0.05441	-3.01	0.0026
Chattanooga_TN_GA	1	-0.14825	0.07809	-1.9	0.0577
Chicago_Naperville_Joliet_IL_IN	1	0.22152	0.04716	4.7	<.0001
Chico_CA	1	-0.21522	0.09515	-2.26	0.0237
Cincinnati_Middletown_OH_KY_IN	1	-0.19744	0.05727	-3.45	0.0006

Clarksville_TN_KY	1	-0.3777	0.10025	-3.77	0.0002
Cleveland_Elyria_Mentor_OH	1	0.00653	0.04944	0.13	0.895
College_Station_Bryan_TX	1	-0.45403	0.08656	-5.25	<.0001
Colorado_Springs_CO	1	-0.0938	0.05858	-1.6	0.1094
Columbia_MO	1	-0.7767	0.1136	-6.84	<.0001
Columbia_SC	1	-0.15849	0.07348	-2.16	0.031
Columbus_OH	1	-0.29074	0.05074	-5.73	<.0001
Corpus_Christi_TX	1	-0.03904	0.06863	-0.57	0.5694
Dallas_Fort_Worth_Arlington_TX	1	-0.23624	0.04836	-4.88	<.0001
Davenport_Moline_Rock_Island_IA	1	-0.3788	0.07741	-4.89	<.0001
Dayton_OH	1	-0.19617	0.06538	-3	0.0027
Decatur_IL	1	-0.31459	0.09965	-3.16	0.0016
Deltona_Daytona_Beach_Ormond_FL	1	-0.36133	0.11902	-3.04	0.0024
Denver_Aurora_CO	1	0.20352	0.04961	4.1	<.0001
Des_Moines_IA	1	-0.43792	0.0626	-7	<.0001
Detroit_Warren_Livonia_MI	1	0.20343	0.04747	4.29	<.0001
Duluth_MN_WI	1	-0.73214	0.07605	-9.63	<.0001
Durham_NC	1	-0.10269	0.06757	-1.52	0.1286
Erie_PA	1	-0.52718	0.08074	-6.53	<.0001
Eugene_Springfield_OR	1	-0.12875	0.07177	-1.79	0.0729
Evansville_IN_KY	1	-0.38298	0.07115	-5.38	<.0001
Fargo_ND_MN	1	-0.60924	0.08639	-7.05	<.0001
Fayetteville_NC	1	-0.14937	0.07048	-2.12	0.0341
Fayetteville_Springdale_AR_MO	1	-0.67793	0.1191	-5.69	<.0001
Flint_MI	1	-0.07169	0.08524	-0.84	0.4003
Fort_Collins_Loveland_CO	1	-0.29184	0.0735	-3.97	<.0001
Fort_Smith_AR_OK	1	-0.41433	0.10362	-4	<.0001
Fort_Wayne_IN	1	-0.3621	0.06358	-5.7	<.0001
Fresno_CA	1	0.09294	0.05454	1.7	0.0884
Gainesville_FL	1	-0.38594	0.10411	-3.71	0.0002
Grand_Rapids_Wyoming_MI	1	-0.24632	0.06163	-4	<.0001
Greeley_CO	1	-0.01088	0.08992	-0.12	0.9037
Green_Bay_WI	1	-0.32992	0.07593	-4.35	<.0001
Greensboro_High_Point_NC	1	-0.21785	0.05695	-3.83	0.0001
Greenville_NC	1	-0.33542	0.10818	-3.1	0.0019
Gulfport_Biloxi_MS	1	-0.19985	0.09386	-2.13	0.0332
Honolulu_HI	1	0.9186	0.06373	14.41	<.0001
Houston_Baytown_Sugar_Land_TX	1	-0.16051	0.04957	-3.24	0.0012
Huntsville_AL	1	-0.30784	0.06663	-4.62	<.0001
Indianapolis_IN	1	-0.24477	0.05083	-4.82	<.0001
Jackson_MS	1	-0.01233	0.06926	-0.18	0.8587
Jacksonville_FL	1	-0.38143	0.05539	-6.89	<.0001
Kalamazoo_Portage_MI	1	-0.48395	0.10018	-4.83	<.0001
Kansas_City_MO_KS	1	-0.33362	0.04931	-6.77	<.0001
Killeen_Temple_Fort_Hood_TX	1	-0.3401	0.08783	-3.87	0.0001
Knoxville_TN	1	-0.45555	0.06642	-6.86	<.0001
Lafayette_LA	1	-0.17428	0.10378	-1.68	0.0931

Lake_Charles_LA	1	0.02718	0.07939	0.34	0.7321
Lakeland_FL	1	-0.31726	0.08943	-3.55	0.0004
Lansing_East_Lansing_MI	1	-0.33757	0.06973	-4.84	<.0001
Las_Vegas_Paradise_NV	1	-0.04667	0.05312	-0.88	0.3797
Lawrence_KS	1	-0.58682	0.09552	-6.14	<.0001
Lawton_OK	1	-0.2432	0.08217	-2.96	0.0031
Lexington_Fayette_KY	1	-0.50416	0.06533	-7.72	<.0001
Lincoln_NE	1	-0.54824	0.06611	-8.29	<.0001
Little_Rock_North_Little_Rock_AR	1	-0.30143	0.07736	-3.9	<.0001
Longview_TX	1	-0.38551	0.10776	-3.58	0.0003
LosAngeles_LongBeach_SantaAna_CA	1	0.75216	0.04942	15.22	<.0001
Lubbock_TX	1	-0.47904	0.07148	-6.7	<.0001
Lynchburg_VA	1	-0.31301	0.11239	-2.79	0.0054
Macon_GA	1	-0.01637	0.08335	-0.2	0.8443
Madison_WI	1	-0.45961	0.06727	-6.83	<.0001
Manchester_Nashua_NH	1	-0.34424	0.0662	-5.2	<.0001
Medford_OR	1	-0.0672	0.09441	-0.71	0.4766
Memphis_TN_MS_AR	1	0.01004	0.05175	0.19	0.8462
Merced_CA	1	0.2562	0.09024	2.84	0.0045
Miami_Fort_Lauderdale_Miami_FL	1	-0.02714	0.05235	-0.52	0.6042
Midland_TX	1	-0.4143	0.09181	-4.51	<.0001
Milwaukee_Waukesha_West_Allis_WI	1	-0.23531	0.05015	-4.69	<.0001
Minneapolis_St_Paul_MN_WI	1	-0.38009	0.05199	-7.31	<.0001
Mobile_AL	1	-0.04918	0.06811	-0.72	0.4702
Modesto_CA	1	0.23241	0.06327	3.67	0.0002
Montgomery_AL	1	-0.08913	0.06945	-1.28	0.1994
Muncie_IN	1	-0.43734	0.09135	-4.79	<.0001
Napa_CA	1	0.56122	0.10129	5.54	<.0001
Nashville_Murfreesboro_TN	1	-0.20111	0.05306	-3.79	0.0002
NewYork_N_NJ_LongIsland_NY_NJ_PA	1	0.5207	0.04854	10.73	<.0001
Odessa_TX	1	-0.24229	0.0944	-2.57	0.0103
Ogden_Clearfield_UT	1	-0.14999	0.08585	-1.75	0.0806
Oklahoma_City_OK	1	-0.40658	0.05201	-7.82	<.0001
Omaha_Council_Bluffs_NE_IA	1	-0.42278	0.05562	-7.6	<.0001
Orlando_FL	1	-0.26063	0.06586	-3.96	<.0001
Oxnard_Thousand_Oaks_Ventura_CA	1	0.58537	0.05707	10.26	<.0001
Palm_Bay_Melbourne_Titusville_FL	1	-0.4792	0.08438	-5.68	<.0001
Peoria_IL	1	-0.37497	0.08716	-4.3	<.0001
Philadelphia_Camden_PA_NJ_DE_MD	1	-0.32447	0.04933	-6.58	<.0001
Phoenix_Mesa_Scottsdale_AZ	1	-0.11279	0.04856	-2.32	0.0202
Pittsburgh_PA	1	-0.63708	0.06186	-10.3	<.0001
Portland_Vancouver_OR_WA	1	0.04363	0.05076	0.86	0.39
Providence_Fall_River_RI_MA	1	-0.10821	0.05307	-2.04	0.0415
Provo_Orem_UT	1	-0.30503	0.07427	-4.11	<.0001
Pueblo_CO	1	0.22105	0.07143	3.09	0.002
Racine_WI	1	-0.15952	0.08935	-1.79	0.0742
Raleigh_Cary_NC	1	-0.2096	0.06049	-3.47	0.0005

Reading_PA	1	-0.66826	0.0804	-8.31	<.0001
Redding_CA	1	-0.02051	0.08972	-0.23	0.8191
Reno_Sparks_NV	1	0.03366	0.06624	0.51	0.6113
Richmond_VA	1	-0.21911	0.06499	-3.37	0.0008
Riverside_San_Bernardino_Ont_CA	1	0.33481	0.05015	6.68	<.0001
Roanoke_VA	1	-0.24505	0.0853	-2.87	0.0041
Rochester_MN	1	-0.54847	0.08006	-6.85	<.0001
Rochester_NY	1	-0.3149	0.05905	-5.33	<.0001
Rockford_IL	1	-0.31468	0.0661	-4.76	<.0001
Sacramento_Arden_Roseville_CA	1	0.18116	0.05566	3.25	0.0011
Salem_OR	1	0.03054	0.07247	0.42	0.6734
Salinas_CA	1	0.80124	0.07889	10.16	<.0001
Salt_Lake_City_UT	1	-0.03296	0.05773	-0.57	0.568
San_Angelo_TX	1	-0.3801	0.11261	-3.38	0.0007
San_Antonio_TX	1	-0.14877	0.05101	-2.92	0.0035
San_Diego_Carlsbad_San_Marcos_CA	1	0.48229	0.04986	9.67	<.0001
San_Francisco_Oakland_Fremont_CA	1	0.76054	0.05118	14.86	<.0001
San_Jose_Sunnyvale_St_Clara_CA	1	0.92824	0.05476	16.95	<.0001
Santa_Barbara_Maria_Goleta_CA	1	0.79819	0.07584	10.52	<.0001
Santa_Fe_NM	1	0.52152	0.0851	6.13	<.0001
Santa_Rosa_Petaluma_CA	1	0.45127	0.07438	6.07	<.0001
Savannah_GA	1	-0.12671	0.07709	-1.64	0.1003
Scranton_Wilkes_Barre_PA	1	-0.45236	0.07883	-5.74	<.0001
Seattle_Tacoma_Bellevue_WA	1	0.16125	0.05218	3.09	0.002
Shreveport_Bossier_City_LA	1	-0.14616	0.06807	-2.15	0.0318
Sioux_City_IA_NE_SD	1	-0.53363	0.0921	-5.79	<.0001
Sioux_Falls_SD	1	-0.5515	0.07932	-6.95	<.0001
South_Bend_Mishawaka_IN_MI	1	-0.27955	0.06902	-4.05	<.0001
Spokane_WA	1	-0.30505	0.0634	-4.81	<.0001
Springfield_IL	1	-0.44426	0.07006	-6.34	<.0001
Springfield_MA	1	0.06333	0.07186	0.88	0.3782
Springfield_MO	1	-0.53358	0.06822	-7.82	<.0001
St_Cloud_MN	1	-0.73529	0.11337	-6.49	<.0001
St_Joseph_MO_KS	1	-0.36591	0.10775	-3.4	0.0007
St_Louis_MO_IL	1	-0.34546	0.05822	-5.93	<.0001
Stockton_CA	1	0.32382	0.06076	5.33	<.0001
Syracuse_NY	1	-0.51576	0.06465	-7.98	<.0001
Tallahassee_FL	1	-0.4147	0.07368	-5.63	<.0001
Tampa_St_Petersburg_Clwater_FL	1	-0.34974	0.05269	-6.64	<.0001
Toledo_OH	1	-0.16477	0.0577	-2.86	0.0043
Topeka_KS	1	-0.54898	0.07529	-7.29	<.0001
Trenton_Ewing_NJ	1	-0.25884	0.08595	-3.01	0.0026
Tucson_AZ	1	-0.08815	0.05507	-1.6	0.1095
Tulsa_OK	1	-0.36288	0.05287	-6.86	<.0001
Tuscaloosa_AL	1	-0.16586	0.08714	-1.9	0.057
Tyler_TX	1	-0.2555	0.12539	-2.04	0.0416
Vallejo_Fairfield_CA	1	0.37098	0.06282	5.91	<.0001

Virginia_Beach_Norfolk_VA_NC	1	-0.1418	0.04906	-2.89	0.0039
Visalia_Porterville_CA	1	0.15583	0.10062	1.55	0.1215
Waco_TX	1	-0.5323	0.09392	-5.67	<.0001
Washington_Arl_Alex_DC_VA_MD_WV	1	0.17325	0.05393	3.21	0.0013
Waterloo_Cedar_Falls_IA	1	-0.59191	0.08949	-6.61	<.0001
Wichita_Falls_TX	1	-0.56496	0.08751	-6.46	<.0001
Wichita_KS	1	-0.51891	0.0573	-9.06	<.0001
Wilmington_NC	1	-0.39179	0.10804	-3.63	0.0003
Winston_Salem_NC	1	-0.17344	0.07072	-2.45	0.0142
Worcester_MA	1	-0.30127	0.07368	-4.09	<.0001
Yakima_WA	1	0.20396	0.11286	1.81	0.0707
Youngstown_Warren_Boardman_OH_PA	1	-0.41408	0.09971	-4.15	<.0001
Yuma_AZ	1	-0.13035	0.09781	-1.33	0.1826

Appendix C—Comparison of Factor Analysis for 2000 with Richardson Factor Analysis for 2000

Originally we had hoped to construct community needs indices using both factor analysis and the regression method. One advantage of having two different methodologies would have been the ability to compare the results and use one approach to check for weaknesses in the other approach. This mutual checking against each other would have been valuable, because there is no external standard to compare a community needs index against.

We were unable, however, to use the regression results to build a needs index, so we must identify another way to test the index that we derived from factor analysis. HUD suggested trying to compare our index to the index constructed by Richardson for the 2000 decennial census data in the study published in 2005.

This appendix makes that comparison. There is one important difference between the results used in this appendix and the results reported elsewhere in the report. In Chapter 4, we used factors derived using 2005 data and obtained standardized scoring coefficients based on those factors. We then estimated factor scores for 2000 using 2000 data for the needs indicators but standardizing those data using means and standard deviations from 2005. In this appendix, we used factors derived from 2000 data and obtain standardized scoring coefficients based of those factors. We then estimated factor scores for 2000 using 2000 data for the needs indicators, but standardized those data using means and standard deviations from 2000. In other words, we conducted a new factor analysis using 2000 as the base. These results are more comparable to Richardson (2005) in approach than the factor analysis reported in Chapter 3 and should produce a clearer comparison.

While there are important similarities between the needs indicators used by Richardson (2005) and those used in this study, there are important differences. As a result, the factors identified by Richardson (2005) and those identified by us are only partially similar. Despite the differences the scores on the two indices correlate highly, but the rankings of a number of cities change substantially. This comparison provided little useful information for benchmarking purposes.

C.1. Comparison of Index Structure

There are several similarities and some differences in how Richardson (2005) constructed his needs index and how the equal weight index used in this study was constructed:

- Richardson (2005) based his selection of indicators on needs eligible for assistance under the Community Development Block Grant (CDBG) program; this study uses a slightly broader concept of need focusing on HUD's overall community development mission.

- Richardson (2005) used 17 needs indicators; this study uses 24 indicators.

- There are significant overlaps in 11 indicators used in both studies (see Table C.1):

  - Six indicators are identical in terms of definition and data source.

  - Five indicators are essentially identical in concept but are implemented somewhat differently in terms of definition and data.

- This research also attempted to use a crime variable similar to the one used in Richardson (2005), but the crime variable was dropped because of missing values for a large number of cities.

- Both Richardson (2005) and this study used factor analysis to extract factors from a larger number of indicators. There were differences in how the factors were extracted, but these differences are minor.[61]

- Because of differences in the needs indicators used, the factor analyses produced significantly different results. Richardson (2005) found four factors which he characterized as: poverty/age/decline, overcrowding/immigration, poverty concentration, and income growth. We characterized our three factors as: poverty and structural problems, immigration and housing affordability, and limited economic prospects.

- Richardson (2005) used 0.80, 0.15, 0.05, and 0.00 respectively, as weights for his four factors; this study used an equal weight index to combine its three factors.

[61] Richardson uses the principal components method to extract initial factors; we used principal factors. Richardson used unrotated factors; we used a varimax rotation. Richardson used factor loading to create factor scores; we used standardized scoring coefficients. The use of factor loadings is consistent with the use of principal components whereas the use of standardized scoring coefficients is consistent with the use of principal factors.

Table C.1. Identical or Similar Indicators in Richardson (2005) and This Study

Description of Indicator	Name Used in This Study
Used same data	
Percent of housing units with more than 1.01 persons per room.	OVERCROWD2000
Occupied housing units that are pre-1970 and occupied by a poverty renter.	PR70RENTPOV
Percent of city population living in census tracts with poverty rates of 40 percent or higher.	PCTPOPHIGHPOVNGHS
Persons in poverty (excluding students living off campus) – Richardson (2005) used 2000 data, this study used 2005 data on all poor but subtracted Richardson's 2000 count of students.	POORPERS
Percent of adult population without a high school diploma – Richardson (2005) used 2000 data; this study used 2005 data.	UNEDUCADULTS
Percent of persons age 16 years or older in the labor force that was unemployed.	UNEMPCEN
Used similar concept	
Fiscal disparity: Richardson (2005) used the ratio of city per capita income to metro per capita income; this study used the ratio of median metro family income to median city family income.	MEDINCCBS2CITY
Children in one parent households: Richardson (2005) used female headed families; this study used single-parent households.	SGLPRNTFAM
Lack of ethnic and racial diversity: Richardson (2005) used a segregation index weighted by the proportion of minorities in population; this study used the minority proportion of the population in the city divided by the proportion in the metropolitan area.	MINCON
Long term population decline: Richardson (2005) used population loss between 1960 and 2000; this study uses the ratio of households in 1970 to maximum count of households in the years 1980, 1990, 2000, and 2005.	EXCSINFRA
Growth in low-income households: Richardson (2005) used the percentage point change in the poverty rate between 1990 and 2000; this study used the ratio of the proportion of families in the bottom quintile nationally in 2005 to the proportion in 1970.	CHGLOWINCCON

C.2. Comparison of Need Scores

Richardson (2005) was able to estimate need scores for 416 of our 473 cities; we were able to estimate scores for 415 of the 473 in 2000. Richardson (2005) was unable to calculate factor scores and therefore index scores for some cities, mainly because of missing crime data; this study was unable to calculate factor scores for some cities mainly because of missing data on the change in employment base indicator. There are 379 cities that have index scores in 2000 from both Richardson (2005) and this study.

Table C.2 provides a statistical overview of the index scores from Richardson (2005) and this study for the 379 cities.

Table C.2. Comparison of Richardson (2005) Index Scores and the Equal Weight Index Scores

	Richardson (2005) Index Score	Equal weight Index Score
Mean	0.16	-0.02
Standard Deviation	0.81	0.52
Range	4.98	2.92
Highest Score	3.39	1.78
Median	-0.05	-0.09
Lowest score	-1.59	-1.14
Number of cities within ½ standard deviation of mean	168	165
Number of cities within 1 standard deviation from mean	260	276
Number of cities within 1 ½ standard deviations from mean	327	339
Number of cities within 2 standard deviations from mean	358	361
Number of cities within 2 ½ standard deviations from mean	373	368

The scores from both indices are distributed nearly normally.[62] Richardson (2005)'s index scores have a higher standard deviation and therefore a greater range. The correlation between the two need scores is 0.87. On the basis of these statistics, the two indices appear to perform very similarly.

We next examined the ranking of cities under both indices, where a higher rank (a low number) means a city has serious problems, and a low rank (a high number) means a city is well off. Camden had the number-one ranking under the Richardson (2005) index and was number 9 under the equal weight index, whereas El Monte, CA had the number-one ranking under the equal weight index and was number 12 under the Richardson (2005) index. Newport Beach, CA was number 379 in the Richardson (2005) ranking and number 375 in the equal weight ranking. Ann Arbor was ranked number 379 under the equal weight index and 297 under the Richardson (2005) index. Of the 379 cities, 307 places changed rank by more than 50 places.

We were surprised by the number of large shifts in rank despite the high correlation between the two indices. To see how the weighting affected the ranking, we substituted index 5, which uses weights based on the Richardson (2005) index, for the equal weight index. The change in weights had little impact on the correlation between an index built on our factors and an index built on Richardson's (2005) factors but did affect the change in rankings. The correlation increased from 0.87 to 0.89; but now, of the 379 cities, only 97 change rank by more than 50 places. As noted earlier in the report, the index scores

[62] We compared the percentage of cases within each of the standard deviation ranges with a normal distribution, and the percentages match the percentages from a normal distribution almost perfectly. Each index score is a linear combination of the needs indicators. If every need indicator were normally distributed, then the index scores would have to be normally distributed. However, we have no a priori reason to believe that all the needs indicators are normally distributed and the indicators are certainly not independently distributed, so this result was not preordained. The result is obviously an example of the law of large numbers at work even when all the conditions are not satisfied.

are approximately normally distributed. This means that the distribution is tightly packed in the middle; therefore, small changes in scores can result in large changes in rankings.

C.3. Conclusion

The selection of need indices is the most important step in developing measures to track changes in community needs. Despite an apparent overlap in 11 needs indicators, the factor analysis conducted in this report and that conducted by Richardson resulted in sets of factors that differ significantly. As a result, it is difficult to use either result to benchmark the other. Nevertheless, despite the differences, the two approaches produced index scores that were highly correlated. Within this high correlation, a large number of cities had substantially different ranks. The number of cities with substantially differences declined when we substituted Richardson (2005)'s weights for our equal weights. This confirms the observation in section 3.4.3 that the choice of weights is more important to the ranking of individual cities than it is to a general understanding of community needs.

References

American Community Survey, Puerto Rico Community Survey, 2005 Subject Definitions, p. 31. http://www.census.gov/acs/www/Downloads/2005/usedata/Subject_Definitions.pdf.

Bunce, Harold L. 1976. *An Evaluation of the Community Development Block Grant Formula*. Washington, DC: U.S. Department of Housing and Urban Development.

Bunce, Harold L. and Robert L. Goldberg. 1979. *City Need and Community Development Funding*. Washington, DC: U.S. Department of Housing and Urban Development.

Bunce, Harold L., Sue G. Neal, and John L. Gardner. 1983. *Effects of the 1980 Census on Community Development Funding*. Washington, DC: U.S. Department of Housing and Urban Development.

Federal Bureau of Investigation. 2005. "Crime in the United States 2005, Offenses Known to Law Enforcement by State by City, 2005." Washington, DC: U.S. Department of Justice, Federal Bureau of Investigation. http://www.fbi.gov/ucr/05cius/data/table_08.html.

Kim, Jae-On and Charles W. Mueller. 1978. *Introduction to Factor Analysis: What It Is and How to Do It.* Sage University Series on Quantitative Applications in the Social Sciences, 07-013. Newbury Park, CA: Sage.

———. 1978. *Factor Analysis: Statistical Methods and Practical Issues.* Sage University Series on Quantitative Applications in the Social Sciences, 07-014. Newbury Park, CA: Sage.

Neary, Kevin and Todd Richardson. 1995. *Effect of the 1990 Census on CDBG Program Funding*. Washington, DC: U.S. Department of Housing and Urban Development.

Richardson, Todd. 2005. *CDBG Formula Targeting to Community Needs*. Washington, DC: U.S. Department of Housing and Urban Development.

———. 2007. "Analyzing a Community Development Needs Index," *Cityscape: A Journal of Policy Development and Research*, Vol. 9, No. 1: 47-72.

U.S. Department of Housing and Urban Development, *HUD Strategic Plan FY 2006 – FY 2011*, March 31, 2006.