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# Have central cities come back?

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## ABSTRACT

Did the residents of large central cities really experience a rebound in their economic fortunes since the 1980s? Much has been made of the revival of distressed cities during the 1990s, yet how much of this asserted revival really worked its way down to residents? We find that residents of distressed central cities were, more often than not, worse off in 2000 than they were in 1980. We first construct a four-variable index of the economic well-being of central city residents, called the Municipal Distress Index, for the 98 central cities that had at least 125,000 residents in 1980 with metropolitan area populations of at least 250,000. We then compare the change in the economic well-being of the residents of the 33 cities with the lowest index scores in 1980 against (1) their own performance over this time period, (2) the performance of the 65 non-distressed central cities, and (3) the performance of the nation. In the third section we build regression models of change in the index and of each of the components of the index to determine what accounts for the improved economic well-being of city residents. In the last section of the paper we examine the residuals of the models to find out which cities performed much better and worse than expected in terms of promoting the economic well-being of their residents. The residual analysis is offered as an objective means for selecting places for case study.

## Introduction

The decade of the 1990s was heralded as the decade of city comeback in the popular press (see, for example, Grogan and Proscio, *Comeback Cities*). Using data assembled for a project funded by the Fannie Mae Foundation we assess the extent to which cities can be said to have "come back" (Wolman, Hill, & Furdell). We take cities that were distressed in 1980, according to an index of municipal distress that we construct, and compare their performance during the 1980s and 1990s to that of the nation as a whole and to cities that were not distressed at the beginning of the 1980s. Did "distressed" cities come back? To what extent did cities that were the most distressed in 1980 continue to be distressed in 2000?

We then examine the performance of all cities over 125,000 in population and ask, which cities *did* perform above the national average during the two decades and what were the characteristics of these cities? We utilize regression analysis to predict city performance based on economic and social structure, while controlling for regional trends affecting the economy. Finally, we examine cities that performed better and worse than expected given our regression model and speculate why their actual performance differed substantially from what the model predicted.

## Identifying Cities with Economically Distressed Populations:

## The Municipal Distress Index

We begin by measuring distress in both 1980 and 2000 using a composite index of municipal level of distress for all cities that had populations of more than 125,000 in 1980 and were in MSAs with populations of more than 250,000 (n=98). The index is made up of standardized values[1] of four indicators of municipal distress:

- Poverty rate
- Unemployment rate
- Change in population over the preceding decade
- Median household income.

All income figures used in the study are adjusted for differences in the cost-of-living among metropolitan areas in 1980 and again in 2000. Typically these differences are not accounted for because cost-of-living indices for all metropolitan areas are not readily available. However, not accounting for cost-of-living ignores differences in the buying power of residents across metropolitan areas and, therefore, distorts measures of their relative well-being. (For a description of the methodology used to adjust income figures for cost-of-living, see Appendix 2.)

Cities in the bottom third of the municipal distress index distribution are designated as distressed (n=33). (See Table 1 for a list of cities and their 1980 and 2000 distress index scores.)

[1] For a description of our standardization methodology, the Median-score, see Appendix 1.

## Comparing the Performance of Distressed Cities

The next step is to examine the performance of these distressed cities during the 1980s and 1990s to determine whether they have really "come back." We begin by noting that the Pearsonian correlation between the 1980 distress index and the 2000 distress index was 0.86, indicating that, on average, city distress relative to other cities did not change much over the 20-year period.

*Compared to themselves*

There are several ways to assess whether cities have "come back," the first of which is to ask whether distressed cities were better off in 2000 than they were in 1980 according to a set of performance measures. Looking first at the indicators used in our municipal distress index, the set of distressed cities was actually worse off in 2000 than they were in 1980. These cities lost an average of 8.5 percent of their populations, and real median household income fell by an average of 6 percent. The average unemployment rate climbed from 9.4 percent to 10.7 percent, and average poverty rate increased by 2.4 percentage-points. The picture looks less dim, however, if we move beyond the indicators in our distress index and examine some additional measures of the economic well-being of city residents. Real per capita income in the distressed cities, for example, rose by an average of 9.9 percent over the two decades, average labor force participation rose by 1.3 percentage-points, and the number of jobs in the cities' MSAs rose by an average of 31.7 percent. (See Table 2)

Of course, not all cities followed the average performance patterns. New York's population grew by 13 percent and Oakland's by 18 percent. Real median income rose by more than 31 percent in Atlanta, and more than 13 percent in New Haven and Norfolk. In Flint, the unemployment rate fell by 7 percentage-points between 1980 and

2000. Jackson, Mississippi, went from having an unemployment rate almost 4 percentage-points higher than the 1980 central city average of 9.4 percent to a rate 2 points below the 2000 average, and Boston and Norfolk both had below-average unemployment rates in both years. Newark and Atlanta both saw significant decreases in their poverty rates (-4.4 percent and -3.1 percent, respectively), but both were still above the average in both years. Akron was well below the average poverty rates in both years.

On those indicators not included in our index of municipal distress, Atlanta saw a 68 percent increase and Cincinnati a 31 percent increase in real per capita income (adjusted for cost-of-living). Akron, Atlanta, and Cincinnati all went from having labor force participation rates around the average in 1980 to being well above the average in 2000. Atlanta experienced job growth of more than 116 percent, and Oakland saw job growth exceed 58 percent.

Several distressed cities showed improvement on multiple performance measures from 1980 to 2000. All distressed cities experienced some job growth, but Boston also improved on every other indicator of performance except the unemployment rate. Atlanta and Norfolk saw improvements on all indicators except population and unemployment rate; Cincinnati and Louisville improved on all measures but poverty rate and population; and Jersey City only failed to improve on the unemployment rate and median household income. (See Table 3 for a list of distressed cities and their successes on individual performance measures.)

*Compared to Non-distressed Central Cities*

So while some cities performed better than the average on individual indicators, distressed cities in general seem to have become more, not less, distressed between

1980 and 2000. However, a better way to assess the performance of these cities is to compare them to that of non-distressed cities over the same time period. Did all cities decline in performance overall, or did distressed cities fall further behind? The performance measures indicate that the latter is the case; the economic position of residents of large central cities that were distressed in 1980 deteriorated over the next 20 years compared to the economic position of residents of the population of large central cities that were not distressed in 1980.

While the population of distressed cities fell, non-distressed cities experienced an average population growth of 27 percent. No single distressed city's growth equaled the average growth of non-distressed cities. The average poverty and unemployment rates for both the distressed and non-distressed cities rose over the two decades, but in each case the distressed cities experienced a larger increase. Again, no distressed city had a poverty rate or an unemployment rate below the average rates of non-distressed cities in 2000. And while real median household income fell for distressed cities, non-distressed cities had an average increase of 3 percent. In this case, however, several distressed cities had increases in median household income that were larger than the average increase for non-distressed cities (Atlanta, Baltimore, Boston, Cincinnati, Louisville, New Haven, New Orleans, Norfolk, and St. Louis).

At first blush distressed central cities appeared to make progress on a number of indicators of the economic well-being of their residents when examined in isolation. However, when the performance of these cities is compared to non-distressed cities their accomplishments begin to pale. The other performance measures that looked promising when examining only distressed cities are less so when compared to the performance of non-distressed cities. Labor force participation increased at a greater average rate for distressed cities than for non-distressed, but in 2000 the average labor force participation rate for distressed cities was still almost six percentage-points lower than the average for non-distressed cities. And though per capita income rose on average for distressed cities, the average increase for non-distressed cities was almost twice as large. There were several distressed cities, however, in which per capita income increased by more than the average increase for non-distressed cities (Atlanta, Birmingham, Cincinnati, Louisville, New Haven, New Orleans, Norfolk, and St. Louis). Finally, while employment grew in the metropolitan areas of distressed cities, the rate of growth was half that experienced in metropolitan areas of the non-distressed cities. In fact, the rate of job growth in only one metropolitan area of a distressed central city, the Atlanta MSA, exceeded the average rate of job growth for non-distressed cities between 1990 and 2000.

*Compared to the nation as a whole*

As the above indicates, not only did distressed cities become more distressed according to several performance indicators, they fell further behind non-distressed cities on income measures and job growth. This method of comparison, however, does not tell us how distressed cities performed relative to the nation as a whole, which is a third way of looking at whether cities have "come back." Turning once again to our distress indicators, the population of the 98 large central cities increased by an average of 14.8 percent, and the national population increased by 24.2 percent, almost twice as fast. However, the non-distressed cities grew slightly faster than the nation, indicating that the cities' poorer performance on this indicator can be ascribed completely to the population loss of distressed cities. Similarly, median household income for the nation and for the set of non-distressed cities increased by 3 percent while real median household income decreased on average for all cities, meaning that it was primarily the distressed cities that saw a decrease in household income from 1980 to 2000.

Large central cities also lagged the nation in both poverty and unemployment rates. The national unemployment rate, already lower than the average unemployment rate for all cities, fell by 1.3 percentage-points over the two decades, while it stayed roughly the same for non-distressed cities and increased an average of 1.4 percentage-points for distressed cities. The national poverty rate was 12.4 percent in both 1980 and 2000, but the average poverty rate for all cities rose by more than 2 percentage-points, from 16.5 to 18.6. Cities' poor performance in comparison to the nation as a whole was not universal, however. Twenty-four cities, all non-distressed in 1980, had unemployment rates below the national average in 2000,[2] and 14 cities, again all non-distressed in 1980, had poverty rates below the 2000 national average.[3]

The only performance measure on which both groups of cities improved relative to the nation was per capita income. National real per capita income fell by more than 5 percent, while it increased by an average of 15 percent for cities. However, when adjusted for cost of living, average per capita income in cities was still well below the national average in 2000. Cities also held their own on labor force participation. The national labor force participation rate increased more over the two decades than did the average rate for cities, but the difference between the average rate for cities and the national rate in 2000 was small (63.3 percent and 63.9 percent, respectively). In fact, the average labor force participation rate for cities in 2000 was 1.3 percentage-points higher than the national average. Finally, the number of jobs in cities' MSAs grew more

[2] Albuquerque, Anaheim, Austin, Charlotte, Colorado Springs, Columbus, Denver, Honolulu, Indianapolis, Jacksonville, Lexington-Fayette, Madison, Minneapolis, Nashville, Oklahoma City, Orlando, Phoenix, Raleigh, San Diego, San Francisco, San Jose, Seattle, Tulsa, and Wichita.

than 9 percent faster than in the nation. Distressed cities, however, experienced much slower job growth than the nation, indicating that the cities' relative good performance is due to the high rate of job growth in the non-distressed cities.

Overall, cities failed to catch up to the rest of the nation, or in some cases fell even further behind. In the next section regression analysis is used to model city performance in 2000 and over the two decades from 1980 to 2000.

## Predicting Performance Using Regression Analysis

What part do cities' economic and social structures play in determining their performance? In the regression models, we test how well these structural factors predict city distress, controlling for region[4] and population size. The economic structure variables of interest are the percent of the labor force that is in manufacturing and the percent in finance, insurance, and real estate (FIRE). The social structure variables are the percent of the population that is dependent, defined here as persons aged 17 or below and 65 or above, and the percent of the population with at least some college. (See Table 4 for a description of all variables.)

We expect that cities with a higher percentage of jobs in manufacturing and FIRE, a higher percentage of the population with some college, and a lower percentage of the population that is dependent will be less distressed.

In Model 1, these variables are used to predict 2000 distress index scores (see Table 5 for complete regression results), controlling for level of distress in 1980 (di80_col). The adjusted-$R^2$ for this model is an impressive 0.81. The coefficient on the 1980 distress index is highly significant with a p-value of 0.000 and has an extremely large effect, with a one point increase in 1980 distress index score leading to a 0.65

[3] Charlotte, Colorado Springs, Des Moines, Greensboro, Honolulu, Indianapolis, Jacksonville, Las Vegas, Omaha, Raleigh, San Francisco, San Jose, Seattle, and Wichita.

increase in 2000 distress index score. (An increase in the distress index indicates a reduction in distress.) This indicates that distress in 1980 is a very good predictor of distress in 2000, showing path dependence at work—it is difficult for residents of large central cities that are distressed to break out of the historical path of their recent economic history.

The natural log of population and the percent of the adult population with some college education are not statistically significant in this model, but both economic structure variables are significant, with positive changes in these variables relating to a decrease in city distress. On the whole region did not play a major role in the performance of large economically distressed central cities. Only the New England regional dummy variable is significant in this model: being in this region is related to a decrease in the 2000 distress index of 0.59, or a greater likelihood of the municipality being in distress.

In Model 2, we attempt to predict the change in the distress index score from 1980 to 2000 using the change in our structural variables over that time period, again controlling for region, population size, and level of distress in 1980 and adding a control for the change in the number of jobs in the cities' MSAs. (See Table 6) The model therefore predicts *relative change* in distress as opposed to level of distress. The percentage-point change in FIRE and the percent change in the number of jobs in the MSA are statistically significant and positively related to the dependent variable, meaning a higher increase in the percentage in FIRE and faster job growth in the MSA translate into higher distress index scores, or a lower level of municipal distress. The change in the dependent population is significant and negatively related to change in

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[4] Regional definitions are listed in Appendix 3.

the distress index, as is the level of distress in 1980, which means that higher distress in 1980 and increases in the dependent population from 1980 to 2000 led to higher levels of municipal distress in 2000. However, the lower adjusted-$R^2$ of 0.48 indicates that much of what causes changes in distress is not included in the model. The Inland Southeast regional dummy variable is significant, with being in the region related to an increase in municipal stress over the two decades.

Models 3 through 7 look at how well economic and social structure predicts changes in the individual components of the index of municipal distress in order to determine which aspects of distress are most affected by these factors. In Model 3, the dependent variable is the percentage-point change in poverty rate from 1980 to 2000 and the independent variables are changes in the structural variables. Poverty rate in 1980 and change in unemployment rate are added to the model as controls. (See Table 7) The percentage-point change in the dependent population is the only significant variable in the model, and is positively related to the dependent variable, indicating that the poverty rate increases as the percent of the population that is dependent (under age 18 or over age 64) increases. The model has a low adjusted-$R^2$ of 0.36, and so does not do a particularly good job of predicting changes in the poverty rate of cities. No regional dummy variables are significant in Model 3.

In Model 4, change in unemployment rate is the dependent variable, and the unemployment rate in 1980 acts as a control. (See Table 8) The adjusted-$R^2$ is a much higher than in the previous model, 0.48, meaning that the model does a better job of predicting changes in unemployment than changes in poverty rates. Once again the economic structure variables are again not significant, nor is the change in the dependent population. However, the change in the percent of the adult population with some college education is statistically significant and negatively related to the dependent variable, meaning that as the percent of the adult population with some college education increases, the unemployment rate decreases. The unemployment rate in 1980 is also significant with a p-value of 0.000, and is negatively related to change in unemployment. This suggests that cities with higher unemployment in 1980 showed more improvement than those with lower rates, indicating that the demand side of the labor market responded to labor availability (which is a regression to the mean effect). Again, no regional dummy variables are significant.

With an adjusted-$R^2$ of 0.66, our model does an even better job predicting changes in real median household income, controlling for 1980 median income. (See Model 5, Table 9) Change in manufacturing is highly significant and positive, and change in the dependent population is also significant and negative. Both have large effects: a 1 percent increase in the percent of the population in manufacturing leads to a 0.84 percent increase in median household income, and a 1 percent decrease in the percent of the population that is dependent leads to a more than 1.3 percent increase in median household income. Change in the number of jobs in the MSA is also significant and is positively related to change in median household income, though the size of the effect is smaller. The Northern Mideast regional dummy variable is significant in this model, and is negatively related to changes in median household income.

Labor force participation is also well-predicted by our model, with an adjusted-$R^2$ of 0.63. Controlling for labor force participation rates in 1980 and for changes in unemployment rates, the coefficients on change in manufacturing, dependent population, and some college are all statistically significant and have the expected signs. (See Model 6, Table 10) The labor force participation rate in 1980 is also significant and negatively related to the dependent variable, suggesting that cities with lower labor force participation in 1980 showed more gains (again, regression to the mean). Several regional dummy variables in the South and West were also significant (Coastal Southeast, Far West, Inland Southeast, and Southwest), which means that those regions experienced other, unaccounted-for, trends during the two decades that influenced participation in the labor force.

Again showing that economic and social structure is a good predictor of income measures, the change in real per capita income model (See Model 7, Table 11) has an adjusted-$R^2$ of 0.68. As with median household income, change in the percentage of adults with some college education and job growth are both significant and positively related to changes in per capita income. Change in the percentage of adults with some college education has a particularly large effect, with a 1 percent increase in the percent of the adult population with at least some college leading to a 1.7 percent increase in per capita income. The Northern Mideast and New England dummy variables are also significant and have extraordinarily large effects. Being in the New England region means a more than 12.6 percent decrease in change in per capita income, while being in the Northern Mideast region leads to an 14.8 percent decrease in change in real per capita income.

Overall, the economic and social structure variables seemed to be good predictors of the income measures (change in real per capita income and change in median household income) and in the change in the labor force participation rate. However, they were not as successful at predicting the unemployment rate and were even less successful at predicting poverty rates. Next we conduct a residuals analysis of our models to see which cities performed better or worse than their regions, population size, and economic and social structures would have predicted.

## Analyzing the Residuals

In this section, we examine both the positive and negative residuals from our regression models to identify cities where either the economy or public policies influenced the economic well-being of city residents in unanticipated ways. In this research we use the residuals as a measure of our ignorance.

Even though there is no obvious specification error in our model and the model performs well, relatively large residuals exist. Are they just random error or do they represent non-random, but idiosyncratic, effects of public policies, economic performance, and other factors? We suspect that these residuals represent local economic development context, public administrative practices, the effectiveness of local public investment and policies, and the performance of local investment and business. None of these “omitted variables” can be captured in the model because the data do not exist, a set of dummy variables that could conceivably capture a long list of policies could never be supported by the number of cases in our population and the actions and activities that result in high and low-performance cities are not know *a priori*.

The residuals measure our lack of understanding as to why particular cities performed unusually well or unusually poorly, but that ignorance can be overcome through case study. A systematic analysis of the residuals is a research method, or technique, for identifying places what public policies or practices could make a difference, positively or negatively, in the economic well-being of local residents. (We have not conducted such case studies for this paper, but we hope to in the future.)

We begin the analysis of the residuals with Model 2, which looks at change in city performance over time from 1980 to 2000 (See Table 13). Fort Wayne, Rockford, and Las Vegas all had residuals that exceeded two standard deviations, meaning these cities performed far better than would have been predicted by the change in economic and social structure. St. Louis and Milwaukee, on the other hand, had residuals that were more than two standard deviations below the mean,[5] indicating they performed much worse than predicted by the model.

In Models 3 through 7, which examine changes in the individual components of the index of municipal distress, several cities exceeded one standard deviation on more than one model. Tables 14 through 18 list the standard deviations of the residuals from the regression equations that model the change in each of the components of the municipal distress index. Table 19 lists those cities that performed substantially better than predicted in at least two of these models. New Haven far exceeded expectations, with standard deviations of more than two standard deviations above the mean in the two models that probe changes in income—percent change in real median household income (Table 16) and percent change in real per capita income (Table 18) . San Antonio also performed better than predicted, exceeding 1.5 standard deviations in the income models and one standard deviation in the model that predicted change in poverty rate (Table 14). Memphis and Norfolk did better than predicted on changes in poverty rate, median household income, and labor force participation rate (Table 17), while Fort Wayne exceeded expectations on changes in the poverty rate, unemployment rate (Table 15), and median household income. And Rockford

[5] The arithmetic mean for the residuals is always zero when using OLS regression.

exceeded 1.5 standard deviations in the models that predicted changes in the unemployment rate, median household income, and per capita income.

At the other end of the spectrum, Spokane, Tucson, and New York all performed worse than expected by at least two standard deviations on the model of the change in real per capita income and in median household income. Spokane also underperformed on the model of the change in the unemployment rate. (See Table 20 for cities that performed worse than expected on at least two of the change in performance measures models.) Providence underachieved by at least one standard deviation on every performance measure except change in unemployment rate. Both Phoenix and Richmond did worse than predicted on the change in income measures, while Phoenix also underperformed in the change in the poverty rate and Richmond in changes in both the poverty and labor force participation rates. Finally, St. Louis and Milwaukee performed worse than expected on changes in the poverty and unemployment rates, with St. Louis also underachieved in terms of change in the in labor force participation and Milwaukee on change in per capita income.

## Explaining Over- and Underperformance

What might explain why some cities performed substantially better or worse than the models would have predicted? One obvious possibility is that cities (or their states) engaged in actions that served to improve or decrease performance, or possessed institutional or structural characteristics that facilitated or impeded performance.[6] As mentioned above, only case studies can establish why these cities performed unusually

[6] It is also possible that there are other characteristics that were not included in our regression equations, particularly the product in which the area specializes. This would require using 3- or 4-digit SIC codes, which would be impossible to include given the number of cities. When our case studies are conducted, these characteristics along with policy effects will be more easily examined.

well or badly.  There are three sets of explanatory factors that would have to be probed using qualitative research techniques:

(1) State and local public policies.  Were there a set of public investments, policy innovations, or institutional structures that made places perform unusually well — such as public education programs or workforce investments, receptivity to immigrants, physical investments to attract export dollars (such as visitors), or a set of housing or neighborhood investments that changed the position of the city in regional housing markets. The converse of these policy actions holds as the working hypotheses for those places that performed unusually poorly.

(2) Economic development context.  Investment and economic development outcomes are guided by more than a mixture of land, labor, and capital that are poured into a black box that result in a set of outcomes in the product and factor markets.  Tastes in living arrangements, politics, and class arrangements all affect these outcomes, as does the efficiency of the public sector and the psychology that directs flows of investments.  Hill has dubbed these ingredients in economic development success or failure "context."[7]  In the product markets economic context is the aggregation of the competitive strategies of the city's and the region's export business establishments and the age of the region's product on the product cycle.  Economic development investments are also guided by the five components of APPLE—i) **A**ttitudes towards risk taking, ii) **P**ersonalities and motives of those who maintain the civic agenda including (leadership styles), iii) **P**ublic escort efficiency and effectiveness, iv) **L**abor-management relations and the structure of the labor market, and v) **E**lastic civil society, its strength, flexibility, and the permeability of its social structure.

[7] Hill, Edward W. (forthcoming) *The Fundamentals of Economic Development*. The Knight Foundation

(3) Economic efficiency. The residents of some distressed central cities may benefit (or be penalized) by unusually successful or unsuccessful businesses, industry clusters, or strategic private sector investments that drive up demand in the labor markets.

*The Ecological Fallacy and Three Possible Outcomes*

There is the possibility that the ecological fallacy can be at play in interpreting these data. Naïve readers may infer that by comparing the economic well being of city residents over time we are dealing with the same set of residents. Residential mobility, consumer choice, and the regional nature of labor markets and their accompanying housing markets render this interpretation of the data to be false. Assume for a moment that a central city has an unusually proficient private sector; good jobs are created with functioning job ladders so that low income workers, and later their children when they enter the labor market, earn relatively high incomes. Can the central city retain those earners and their families with regionally competitive residential environments and amenity packages (including schools and public safety) at reasonable tax-cost? Central cities may contain educational systems, that combine with industries and employers, to produce unusual social mobility that propel families into nearby suburbs only to be replaced by a new set of low-income city residents.

There are three possibly outcomes from our proposed case studies.

A mayor's dream: The city has an unusually efficient private sector that propels residents up the ladder of social mobility and the city is in the competitive position to retain residents as their incomes increase.

A mayor's nightmare: The city is unusually inefficient with a set of policies and practices that repel investment. Employers view central city locations as places that do not lower their operating costs, increase their revenues, or do not provide them an advantage in the labor market and suburban locations are more efficient.

A mayor's dilemma: The city is competitive as a place to do business and residents make economic progress, but the city offers inferior residential service packages and those who are moving up on the social ladder act in their own best interest and in their family's best interest and move out to suburban communities. The challenge to the long-term health of central cities is that over time the third scenario will become the second.

What are the public policies and actions that produce the first scenario rather than the second or third? What lies behind the unusual success of Las Vegas (other than its unique industrial base and tax structure), Fort Wayne, San Antonio, and Rockford? Can these outcomes be replicated? At the other end of the spectrum what caused the unexpected poor performance of Chattanooga, Gary, Milwaukee and Hartford? What mistakes were made, and can they be avoided by other polities?

TABLE 1: Distress index scores by city, 1980 & 2000 (continued on next page)
High values indicate relatively low levels of economic distress

| City | Distress index 1980 | Rank by 1980 distress index | Distress index 2000 | Rank by 2000 distress index |
|---|---|---|---|---|
| Lexington-Fayette, KY | 1.91 | 1 | 0.87 | 12 |
| San Jose, CA | 1.53 | 2 | 1.13 | 6 |
| Anaheim, CA | 1.44 | 3 | 0.63 | 23 |
| Colorado Springs, CO | 1.39 | 4 | 1.57 | 3 |
| Charlotte, NC | 1.21 | 5 | 1.61 | 2 |
| Houston, TX | 1.20 | 6 | 0.41 | 36 |
| Raleigh, NC | 1.18 | 7 | 1.49 | 5 |
| Phoenix, AZ | 1.15 | 8 | 1.08 | 8 |
| Honolulu, HI | 1.12 | 9 | 0.32 | 39 |
| Wichita, KS | 1.03 | 10 | 0.92 | 11 |
| Tulsa, OK | 1.01 | 11 | 0.51 | 28 |
| Austin, TX | 0.98 | 12 | 1.56 | 4 |
| Oklahoma City, OK | 0.85 | 13 | 0.64 | 21 |
| Albuquerque, NM | 0.84 | 14 | 0.71 | 15 |
| Las Vegas, NV | 0.81 | 15 | 2.21 | 1 |
| Nashville-Davidson, TN | 0.75 | 16 | 0.68 | 17 |
| Little Rock, AR | 0.72 | 17 | 0.47 | 30 |
| Dallas, TX | 0.69 | 18 | 0.46 | 31 |
| Des Moines, IA | 0.67 | 19 | 0.56 | 26 |
| Madison, WI | 0.65 | 20 | 0.64 | 22 |
| Greensboro, NC | 0.65 | 21 | 0.92 | 10 |
| Corpus-Christi, TX | 0.64 | 22 | 0.44 | 34 |
| Riverside, CA | 0.63 | 23 | 0.32 | 38 |
| Fort Lauderdale, FL | 0.60 | 24 | 0.15 | 45 |
| San Diego, CA | 0.58 | 25 | 0.46 | 32 |
| Tucson, AZ | 0.56 | 26 | 0.28 | 40 |
| Chattanooga, TN | 0.55 | 27 | -0.15 | 54 |
| Omaha, NE | 0.50 | 28 | 1.08 | 7 |
| Jacksonville, FL | 0.45 | 29 | 0.98 | 9 |
| Orlando, FL | 0.44 | 30 | 0.56 | 27 |
| Fort Worth, TX | 0.43 | 31 | 0.61 | 24 |
| Evansville, IN | 0.41 | 32 | 0.05 | 46 |
| Baton Rouge, LA | 0.40 | 33 | -0.51 | 64 |
| Seattle, WA | 0.40 | 34 | 0.59 | 25 |
| Montgomery, AL | 0.36 | 35 | 0.23 | 44 |
| Indianapolis, IN | 0.35 | 36 | 0.70 | 16 |
| Shreveport, LA | 0.33 | 37 | -0.52 | 68 |
| Denver, CO | 0.25 | 38 | 0.68 | 18 |
| Worcester, MA | 0.25 | 39 | -0.11 | 49 |
| Minneapolis, MN | 0.21 | 40 | 0.24 | 42 |
| Columbus, OH | 0.21 | 41 | 0.64 | 20 |
| Kansas City, MO | 0.14 | 42 | 0.32 | 37 |
| Milwaukee, WI | 0.10 | 43 | -0.71 | 74 |
| San Antonio, TX | 0.09 | 44 | 0.75 | 14 |
| Fresno, CA | 0.08 | 45 | -0.52 | 67 |
| Portland, OR | 0.08 | 46 | 0.66 | 19 |
| Tacoma, WA | 0.05 | 47 | 0.23 | 43 |
| San Francisco, CA | 0.04 | 48 | 0.50 | 29 |

Table 1: continued

| City | Distress index 1980 | Rank by 1980 distress index | Distress index 2000 | Rank by 2000 distress index |
|---|---|---|---|---|
| Spokane, WA | 0.01 | 49 | -0.11 | 50 |
| Sacramento, CA | -0.01 | 50 | -0.08 | 48 |
| Lansing, MI | -0.01 | 51 | -0.15 | 53 |
| El Paso, TX | -0.04 | 52 | -0.12 | 51 |
| Stockton, CA | -0.05 | 53 | -0.53 | 69 |
| Los Angeles, CA | -0.05 | 54 | -0.51 | 65 |
| Tampa, FL | -0.06 | 55 | 0.00 | 47 |
| Salt Lake City, UT | -0.07 | 56 | 0.46 | 33 |
| Memphis, TN | -0.08 | 57 | -0.13 | 52 |
| Mobile, AL | -0.08 | 58 | -0.29 | 58 |
| Springfield, MA | -0.08 | 59 | -0.83 | 75 |
| Fort Wayne, IN | -0.08 | 60 | 0.80 | 13 |
| Knoxville, TN | -0.16 | 61 | -0.25 | 56 |
| Grand Rapids, MI | -0.17 | 62 | 0.26 | 41 |
| Rockford, IL | -0.23 | 63 | 0.42 | 35 |
| Washington, DC | -0.24 | 64 | -0.68 | 72 |
| Toledo, OH | -0.28 | 65 | -0.34 | 60 |
| Pittsburgh, PA | -0.30 | 66 | -0.88 | 77 |
| Oakland, CA | -0.35 | 67 | -0.32 | 59 |
| Rochester, NY | -0.40 | 68 | -1.06 | 86 |
| Boston, MA | -0.41 | 69 | -0.28 | 57 |
| Norfolk, VA | -0.42 | 70 | -0.39 | 61 |
| Jackson, MS | -0.44 | 71 | -0.64 | 71 |
| Richmond, VA | -0.45 | 72 | -0.52 | 66 |
| Akron, OH | -0.46 | 73 | -0.24 | 55 |
| Syracuse, NY | -0.47 | 74 | -1.23 | 89 |
| Philadelphia, PA | -0.56 | 75 | -1.03 | 84 |
| Chicago, IL | -0.60 | 76 | -0.44 | 62 |
| Louisville, KY | -0.61 | 77 | -0.50 | 63 |
| Miami, FL | -0.64 | 78 | -1.37 | 91 |
| New Orleans, LA | -0.69 | 79 | -1.01 | 82 |
| Providence, RI | -0.70 | 80 | -1.01 | 83 |
| Cincinnati, OH | -0.71 | 81 | -0.62 | 70 |
| Bridgeport, CT | -0.77 | 82 | -0.97 | 81 |
| New York, NY | -0.88 | 83 | -0.93 | 79 |
| Baltimore, MD | -0.90 | 84 | -0.97 | 80 |
| Hartford, CT | -0.94 | 85 | -2.19 | 98 |
| New Haven, CT | -1.00 | 86 | -1.45 | 93 |
| Dayton, OH | -1.01 | 87 | -0.93 | 78 |
| St. Louis, MO | -1.04 | 88 | -1.21 | 88 |
| Birmingham, AL | -1.07 | 89 | -1.12 | 87 |
| Atlanta, GA | -1.09 | 90 | -0.86 | 76 |
| Jersey City, NJ | -1.10 | 91 | -0.69 | 73 |
| Gary, IN | -1.14 | 92 | -1.61 | 96 |
| Cleveland, OH | -1.23 | 93 | -1.33 | 90 |
| Paterson, NJ | -1.45 | 94 | -1.05 | 85 |
| Buffalo, NY | -1.46 | 95 | -1.50 | 95 |
| Flint, MI | -1.68 | 96 | -1.38 | 92 |
| Detroit, MI | -1.98 | 97 | -1.49 | 94 |
| Newark, NJ | -2.30 | 98 | -2.07 | 97 |

## TABLE 2: Average performance indicators, 1980-2000

| Indicator | Distressed cities | | | Non-distressed cities | | | All cities | | | National | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1980 | 2000 | Avg % Δ | 1980 | 2000 | Avg % Δ | 1980 | 2000 | Avg % Δ | 1980 | 2000 | Avg % Δ |
| Population (in thousands) | 661.9 | 647.4 | -8.5 | 396.2 | 499.1 | 26.6 | 485.7 | 549 | 14.8 | 226542 | 281422 | 24.2 |
| Median household income | 12379 | 11556 | -6.11 | 15530 | 15955 | 3.1 | 14469 | 14474 | -0.03 | 17710 | 18258 | 3.1 |
| Per capita income | 6015 | 6655 | 9.9 | 7351 | 8681 | 18.1 | 6901 | 7998 | 15.3 | 9940 | 9386 | -5.6 |
| Unemployment rate | 9.4 | 10.7 | 1.4 | 6.6 | 6.7 | 0.1 | 7.56 | 8.03 | 0.5 | 7.1 | 5.8 | -1.3 |
| Labor force participation rate | 58.1 | 59.4 | 1.4 | 64.1 | 65.2 | 1.1 | 62.1 | 63.3 | 1.2 | 62 | 63.9 | 1.9 |
| Poverty rate | 21.2 | 23.6 | 2.3 | 14.1 | 16 | 2 | 16.5 | 18.6 | 2.1 | 12.4 | 12.4 | 0 |
| Jobs by place of work (in thousands) | 1031 | 1363 | 31.7 | 593.1 | 981.7 | 71.3 | 740.5 | 1110 | 57.9 | 110443 | 164174 | 48.7 |

## TABLE 3: Distressed cities' success on performance indicators[8]

x = city improved on the performance indicator between 1980 and 2000

| CITY | Population[8] | Unemployment | Median household income | Poverty rate | Labor force participation | Per capita income |
|---|---|---|---|---|---|---|
| Akron | | x | | | x | |
| Atlanta | | | x | x | x | x |
| Baltimore | | | x | | | x |
| Birmingham | | x | | | x | x |
| Boston | x | | x | x | x | x |
| Bridgeport | | | | x | x | |
| Buffalo | | | | | x | x |
| Chicago | | | | x | x | x |
| Cincinnati | | x | x | | x | x |
| Cleveland | | | | | x | x |
| Dayton | | x | | | x | x |
| Detroit | | x | | | x | |
| Flint | | x | | | x | |
| Gary | | x | | | | x |
| Hartford | | | | | | |
| Jackson | | x | | | | x |
| Jersey City | x | | | x | x | x |
| Louisville | | x | x | | x | x |
| Miami | x | | | | | x |
| New Haven | | | x | | x | x |
| New Orleans | | | x | | x | x |
| New York | x | | | | x | |
| Newark | | | | x | | |
| Norfolk | | | x | x | x | x |
| Oakland | x | | | | x | |
| Paterson | x | | | x | | |
| Philadelphia | | | | | x | x |
| Pittsburgh | | | | | x | x |
| Providence | x | | | | | |
| Richmond | | | | | x | x |
| Rochester | | | | | x | x |
| St. Louis | | | x | | x | x |
| Syracuse | | | | | x | x |

[8] Job growth is not included because all distressed cities experienced job growth during the two decades.

TABLE 4: Description of variables

| Variable | Description |
|---|---|
| chgcoll | Percentage-point change in percent of city residents with at least some college, 1980-2000 |
| chgdepend | Percentage-point change in percent of residents age 17 or under and 65 or over, 1980-2000 |
| chgdi_col | Change in municipal distress index score, adjusted for cost-of-living differences, 1980-2000 |
| chgfire | Percentage-point change in percent of labor force in finance, insurance, and real estate, 1980-2000 |
| chgjobs | Percent change in the number of jobs in city's MSA, 1980-2000 |
| chglabfrc | Percentage-point change in labor force participation rate, 1980-2000 |
| chgman | Percentage-point change in percent of labor force in manufacturing, 1980-2000 |
| chgmedhh_col | Percent change in real median household income in 1980 dollars, adjusted for cost-of-living differences, 1980-2000 |
| chgpercap_col | Percent change in real per capita income in 1980 dollars, adjusted for cost-of-living, 1980-2000 |
| chgpov | Percentage-point change in poverty rate, 1980-2000 |
| chgunemp | Percentage-point change in unemployment rate, 1980-2000 |
| coll00 | Percent of residents with at least some college, 2000 |
| depend00 | Percent of residents age 17 or under and 65 or over, 2000 |
| di00_col | Index of municipal distress score, 2000, adjusted for cost-of-living differences |
| di80_col | Index of municipal distress score, 1980, adjusted for cost-of-living differences |
| fire00 | Percent of labor force in finance, insurance, and real estate, 2000 |
| labfrc80 | Labor force participation rate, 1980 |
| lnpop80 | Natural log of population, 1980 |
| man00 | Percent of labor force in manufacturing, 2004 |
| medhh80_col | Median household income, adjusted for cost-of-living differences, 1980 |
| percap80_col | Per capita income, adjusted for cost-of-living differences, 1980 |
| pov80 | Poverty rate, 1980 |
| unemp80 | Unemployment rate, 1980 |
| coastalse | Coastal Southeast regional dummy variable |
| farwest | Far West regional dummy variable |
| greatlake | Great Lakes regional dummy variable |
| inlandse | Inland Southeast regional dummy variable |
| nthmideast | Northern Mideast regional dummy variable |
| rockymtn | Rocky Mountains regional dummy variable |
| sthmideast | Southern Mideast regional dummy variable |
| newengland | New England regional dummy variable |
| plains | Plains regional dummy variable |
| southwest | Southwest regional dummy variable |

TABLE 5: Regression Model 1 Predicting the Relative Level of Municipal Distress
Dependent variable: 2000 distress index

| Variable | Coefficient | t-statistic | p-value |
|---|---|---|---|
| intercept | 1.190 | 0.83 | 0.406 |
| lnpop80 | -0.105 | -1.72 | 0.090 |
| di80_col | 0.653 | **8.33** | 0.000 |
| man00 | 0.023 | **2.07** | 0.042 |
| fire00 | 0.082 | **3.21** | 0.002 |
| coll00 | 0.010 | 1.13 | 0.260 |
| depend00 | -0.033 | -1.61 | 0.112 |
| coastalse | -0.073 | -0.37 | 0.715 |
| farwest | 0.078 | 0.40 | 0.691 |
| greatlake | 0.043 | 0.22 | 0.823 |
| inlandse | -0.222 | -1.12 | 0.267 |
| nthmideast | -0.332 | -1.48 | 0.142 |
| rockymtn | 0.386 | 1.38 | 0.172 |
| sthmideast | -0.195 | -0.58 | 0.566 |
| newengland | -0.594 | **-2.58** | 0.012 |
| southwest | 0.240 | 1.14 | 0.256 |
| N | | 98 | |
| Adjusted $R^2$ | | 0.8113 | |
| F-statistic$_{15,82}$ | | 28.81 (p-value = 0.000) | |

TABLE 6: Regression Model 2 Change in the Level of Municipal Distress
Dependent variable: change in distress index score 1980-2000

| Variable | Coefficient | t-statistic | p-value |
|---|---|---|---|
| intercept | -0.170 | -0.27 | 0.791 |
| di80_col | -0.243 | **-4.01** | 0.000 |
| lnpop80 | -0.025 | -0.51 | 0.613 |
| chgman | 0.011 | 1.00 | 0.318 |
| chgfire | 0.065 | **2.20** | 0.031 |
| chgcoll | 0.021 | 1.82 | 0.072 |
| chgdepend | -0.046 | **-2.08** | 0.041 |
| chgjobs | -0.005 | **4.11** | 0.000 |
| coastalse | -0.245 | -1.41 | 0.162 |
| farwest | 0.044 | 0.26 | 0.798 |
| greatlake | 0.040 | 0.24 | 0.810 |
| inlandse | -0.370 | **-2.26** | 0.026 |
| nthmideast | -0.276 | -1.41 | 0.163 |
| rockymtn | 0.261 | 1.09 | 0.278 |
| sthmideast | -0.464 | -1.69 | 0.095 |
| newengland | -0.361 | -1.75 | 0.083 |
| southwest | 0.018 | 0.10 | 0.918 |
| N | | 98 | |
| Adjusted $R^2$ | | 0.4794 | |
| F-statistic$_{16,81}$ | | 6.58 (p-value = 0.000) | |

TABLE 7: Regression Model 3 Change in the Poverty Rate
Dependent variable: percentage-point change in poverty rate 1980-2000

| Variable | Coefficient | t-statistic | p-value |
|---|---|---|---|
| intercept | 11.960 | 2.45 | 0.017 |
| pov80 | -0.126 | -1.58 | 0.118 |
| lnpop80 | -0.418 | -1.10 | 0.276 |
| chgman | -0.045 | -0.55 | 0.583 |
| chgfire | -0.213 | -0.96 | 0.340 |
| chgcoll | -0.133 | -1.47 | 0.147 |
| chgdepend | 0.580 | **3.42** | 0.001 |
| chgunemp | 0.200 | 1.29 | 0.200 |
| chgjobs | -0.013 | -1.57 | 0.120 |
| coastalse | -1.081 | -0.79 | 0.433 |
| farwest | -0.105 | -0.08 | 0.936 |
| greatlake | 1.391 | 1.06 | 0.294 |
| inlandse | 0.182 | 0.14 | 0.889 |
| nthmideast | 1.076 | 0.72 | 0.475 |
| rockymtn | -0.981 | -0.54 | 0.592 |
| sthmideast | -0.103 | -0.05 | 0.961 |
| newengland | 0.185 | 0.12 | 0.908 |
| southwest | 0.052 | 0.04 | 0.970 |
| N | | 98 | |
| Adjusted $R^2$ | | 0.3635 | |
| F-statistic$_{17,80}$ | | 4.26 (p-value = 0.000) | |

TABLE 8: Regression Model 4 Change in the Unemployment Rate
Dependent variable: percentage-point change in unemployment rate 1980-2000

| Variable | Coefficient | t-statistic | p-value |
|---|---|---|---|
| intercept | -0.486 | -0.14 | 0.891 |
| unemp80 | -0.415 | **-4.57** | 0.000 |
| lnpop80 | 0.423 | 1.61 | 0.111 |
| chgman | -0.096 | -1.54 | 0.127 |
| chgfire | -0.148 | -0.97 | 0.336 |
| chgcoll | -0.171 | **-2.46** | 0.016 |
| chgdepend | -0.053 | -0.45 | 0.656 |
| chgjobs | -0.006 | -1.04 | 0.301 |
| chglabfrc | 0.025 | 0.31 | 0.757 |
| coastalse | 1.689 | 1.86 | 0.067 |
| farwest | -0.361 | -0.40 | 0.693 |
| greatlake | -1.221 | -1.35 | 0.181 |
| inlandse | 0.746 | 0.85 | 0.396 |
| nthmideast | 1.614 | 1.60 | 0.114 |
| rockymtn | -1.411 | -1.13 | 0.261 |
| sthmideast | 2.395 | 1.67 | 0.100 |
| newengland | 1.872 | 1.74 | 0.085 |
| southwest | -0.814 | -0.86 | 0.391 |
| N | | 98 | |
| Adjusted $R^2$ | | 0.4815 | |
| F-statistic$_{17,80}$ | | 6.30 (p-value = 0.000) | |

TABLE 9: Regression Model 5 Change in Real Household Income
Dependent variable: percent change in real median household income 1980-2000

| Variable | Coefficient | t-statistic | p-value |
|---|---|---|---|
| intercept | 21.932 | 1.28 | 0.203 |
| medhh80_col | -0.001 | **-2.20** | 0.031 |
| lnpop80 | -0.644 | -0.57 | 0.569 |
| chgman | 0.841 | **3.52** | 0.001 |
| chgfire | 0.805 | 1.24 | 0.220 |
| chgcoll | 0.376 | 1.41 | 0.161 |
| chgdepend | -1.346 | **-2.69** | 0.009 |
| chgunemp | 0.177 | 0.39 | 0.696 |
| chgjobs | 0.092 | **3.73** | 0.000 |
| coastalse | 0.593 | 0.15 | 0.881 |
| farwest | -4.789 | -1.23 | 0.221 |
| greatlake | -7.458 | -1.95 | 0.055 |
| inlandse | -4.009 | -1.09 | 0.280 |
| nthmideast | -13.910 | **-3.09** | 0.003 |
| rockymtn | 4.443 | 0.82 | 0.413 |
| sthmideast | -7.411 | -1.23 | 0.224 |
| newengland | -9.443 | -1.96 | 0.054 |
| southwest | 0.836 | 0.21 | 0.834 |
| N | | 98 | |
| Adjusted $R^2$ | | 0.6612 | |
| F-statistic$_{17,80}$ | | 12.14 (p-value = 0.000) | |

TABLE 10: Regression Model 6 Change in the Labor Force Participation Rate
Dependent variable: percentage-point change in labor force participation 1980-2000

| Variable | Coefficient | t-statistic | p-value |
|---|---|---|---|
| intercept | 24.485 | 4.23 | 0.000 |
| labfrc80 | -0.295 | **-4.55** | 0.000 |
| lnpop80 | -0.513 | -1.58 | 0.118 |
| chgman | 0.250 | **3.60** | 0.001 |
| chgfire | -0.015 | -0.08 | 0.939 |
| chgcoll | 0.362 | **4.64** | 0.000 |
| chgdepend | -0.411 | **-2.95** | 0.004 |
| chgunemp | -0.085 | -0.67 | 0.502 |
| chgjobs | 0.012 | 1.62 | 0.108 |
| coastalse | -2.426 | **-2.13** | 0.036 |
| farwest | -2.233 | **-1.98** | 0.052 |
| greatlake | -0.221 | -0.19 | 0.846 |
| inlandse | -3.370 | **-3.13** | 0.002 |
| nthmideast | -2.125 | -1.63 | 0.107 |
| rockymtn | -0.335 | -0.21 | 0.830 |
| sthmideast | -3.457 | -1.95 | 0.055 |
| newengland | -0.973 | -0.70 | 0.484 |
| southwest | -2.434 | **-2.10** | 0.039 |
| N | | 98 | |
| Adjusted $R^2$ | | 0.6299 | |
| F-statistic$_{17,80}$ | | 10.71 (p-value = 0.000) | |

TABLE 11: Regression Model 7 Change in Real Per Capita Income
Dependent variable: percent change in real per capita income 1980-2000

| Variable | Coefficient | t-statistic | p-value |
|---|---|---|---|
| intercept | 22.684 | 1.12 | 0.266 |
| percap80_col | -0.001 | -0.83 | 0.407 |
| lnpop80 | -1.724 | -1.27 | 0.208 |
| chgman | 0.564 | 1.89 | 0.063 |
| chgfire | -0.044 | -0.06 | 0.956 |
| chgcoll | 1.703 | **5.26** | 0.000 |
| chgdepend | -1.038 | -1.78 | 0.080 |
| chgunemp | 0.933 | 1.77 | 0.081 |
| chgjobs | 0.092 | **3.08** | 0.003 |
| coastalse | 8.672 | 1.82 | 0.072 |
| farwest | -7.533 | -1.59 | 0.116 |
| greatlake | -0.820 | -0.17 | 0.862 |
| inlandse | 6.836 | 1.51 | 0.136 |
| nthmideast | -14.779 | **-2.68** | 0.009 |
| rockymtn | 1.729 | 0.26 | 0.792 |
| sthmideast | 7.289 | 0.99 | 0.325 |
| newengland | -12.650 | **-2.15** | 0.035 |
| southwest | 9.118 | 1.87 | 0.065 |
| N | | 98 | |
| Adjusted $R^2$ | | 0.6828 | |
| F-statistic$_{17,80}$ | | 13.28 (p-value = 0.000) | |

TABLE 12: Model 1 standard deviations of residuals (dependent variable = 2000 distress index)

| City | Standard Deviations | City | Standard Deviations |
|---|---|---|---|
| Las Vegas | 5.168 | Riverside | 0.049 |
| Fort Wayne | 2.010 | Sacramento | 0.040 |
| San Antonio | 1.829 | Denver | -0.040 |
| Rockford | 1.646 | Jackson | -0.054 |
| Paterson | 1.421 | Jersey City | -0.116 |
| Memphis | 1.386 | Albuquerque | -0.138 |
| Jacksonville | 1.350 | Salt Lake City | -0.156 |
| Omaha | 1.278 | San Diego | -0.157 |
| Indianapolis | 1.111 | Dayton | -0.187 |
| Portland | 0.994 | Tucson | -0.232 |
| Worcester | 0.978 | San Francisco | -0.233 |
| Austin | 0.961 | Flint | -0.246 |
| Raleigh | 0.837 | Seattle | -0.277 |
| Nashville-Davidson | 0.826 | Oakland | -0.297 |
| Grand Rapids | 0.806 | San Jose | -0.436 |
| Boston | 0.798 | Shreveport | -0.449 |
| Louisville | 0.696 | Cincinnati | -0.452 |
| Bridgeport | 0.689 | Atlanta | -0.497 |
| Baltimore | 0.653 | Oklahoma City | -0.521 |
| Mobile | 0.613 | Birmingham | -0.532 |
| Tacoma | 0.613 | Lansing | -0.539 |
| Columbus | 0.589 | Spokane | -0.552 |
| Detroit | 0.548 | Evansville | -0.554 |
| Knoxville | 0.532 | Pittsburgh | -0.618 |
| Wichita | 0.529 | Washington | -0.653 |
| Orlando | 0.527 | Rochester | -0.694 |
| Fort Worth | 0.525 | St. Louis | -0.708 |
| Kansas City, Mo | 0.523 | Stockton | -0.762 |
| Montgomery | 0.519 | Minneapolis | -0.764 |
| Norfolk | 0.414 | Cleveland | -0.791 |
| Greensboro | 0.389 | Fresno | -0.806 |
| Akron | 0.372 | Dallas | -0.835 |
| Philadelphia | 0.345 | Des Moines | -0.859 |
| El Paso | 0.297 | Los Angeles | -0.903 |
| Newark | 0.296 | Richmond | -0.973 |
| New York | 0.291 | Honolulu | -1.021 |
| Corpus-Christi | 0.274 | Lexington-Fayette | -1.038 |
| Charlotte | 0.262 | Fort Lauderdale | -1.113 |
| New Orleans | 0.262 | Houston | -1.134 |
| Buffalo | 0.249 | Syracuse | -1.174 |
| Colorado Springs | 0.197 | Tulsa | -1.194 |
| Little Rock | 0.195 | Madison | -1.207 |
| Chicago | 0.179 | Miami | -1.321 |
| Toledo | 0.176 | Anaheim | -1.419 |
| Phoenix | 0.168 | Baton Rouge | -1.453 |
| Providence | 0.142 | Chattanooga | -1.502 |
| Tampa | 0.125 | Gary | -1.509 |
| New Haven | 0.091 | Milwaukee | -1.952 |
| Springfield | 0.085 | Hartford | -2.782 |

TABLE 13: Model 2 standard deviations of residuals (dependent variable = change in distress index 1980-2000)

| City | Standard Deviation | City | Standard Deviation |
|---|---|---|---|
| Fort Wayne | 2.995 | San Jose | 0.010 |
| Rockford | 2.853 | Springfield | -0.050 |
| Las Vegas | 2.453 | San Diego | -0.060 |
| Greensboro | 1.818 | New Orleans | -0.080 |
| Paterson | 1.730 | Dallas | -0.174 |
| Jacksonville | 1.647 | Lansing | -0.262 |
| San Francisco | 1.567 | Toledo | -0.270 |
| Raleigh | 1.540 | Des Moines | -0.280 |
| Wichita | 1.522 | Tulsa | -0.314 |
| Omaha | 1.353 | Dayton | -0.348 |
| Portland | 1.137 | Shreveport | -0.373 |
| Memphis | 1.095 | Philadelphia | -0.375 |
| San Antonio | 1.001 | Birmingham | -0.394 |
| Jackson | 0.994 | Seattle | -0.417 |
| Charlotte | 0.923 | New Haven | -0.431 |
| Indianapolis | 0.866 | Honolulu | -0.435 |
| New York | 0.829 | Salt Lake City | -0.466 |
| Louisville | 0.815 | Madison | -0.476 |
| Mobile | 0.795 | Riverside | -0.521 |
| Baltimore | 0.783 | Phoenix | -0.590 |
| Flint | 0.774 | Anaheim | -0.616 |
| Grand Rapids | 0.716 | Fresno | -0.728 |
| Norfolk | 0.694 | Spokane | -0.773 |
| Little Rock | 0.671 | Washington | -0.783 |
| Detroit | 0.626 | Tucson | -0.799 |
| Newark | 0.619 | Houston | -0.803 |
| Fort Worth | 0.602 | Syracuse | -0.846 |
| Boston | 0.588 | Minneapolis | -0.850 |
| Bridgeport | 0.583 | Richmond | -0.859 |
| Austin | 0.547 | Cleveland | -0.862 |
| Akron | 0.429 | Miami | -0.869 |
| Denver | 0.429 | Stockton | -0.885 |
| Worcester | 0.330 | Cincinnati | -0.967 |
| Kansas City, Mo | 0.327 | Rochester | -0.975 |
| Montgomery | 0.280 | Evansville | -1.002 |
| Knoxville | 0.267 | Sacramento | -1.036 |
| Buffalo | 0.243 | Tampa | -1.056 |
| Oakland | 0.205 | Orlando | -1.062 |
| El Paso | 0.203 | Hartford | -1.132 |
| Oklahoma City | 0.166 | Chattanooga | -1.305 |
| Jersey City | 0.159 | Fort Lauderdale | -1.361 |
| Nashville-Davidson | 0.150 | Baton Rouge | -1.361 |
| Corpus-Christi | 0.148 | Pittsburgh | -1.383 |
| Providence | 0.111 | Gary | -1.409 |
| Los Angeles | 0.084 | Atlanta | -1.415 |
| Chicago | 0.078 | Lexington-Fayette | -1.554 |
| Colorado Springs | 0.037 | Columbus | -1.627 |
| Tacoma | 0.015 | St. Louis | -2.072 |
| Albuquerque | 0.010 | Milwaukee | -2.114 |

TABLE 14: Model 3 standard deviations of residuals (dependent variable = percentage-point change in poverty rate 1980-2000)

| City | Standard Deviation | City | Standard Deviation |
|---|---|---|---|
| Providence | 2.856 | Knoxville | -0.060 |
| Flint | 2.565 | Charlotte | -0.062 |
| Rochester | 2.123 | San Diego | -0.088 |
| Fresno | 1.796 | Spokane | -0.106 |
| Fort Lauderdale | 1.785 | Evansville | -0.141 |
| Syracuse | 1.694 | Grand Rapids | -0.151 |
| Minneapolis | 1.665 | Riverside | -0.176 |
| St. Louis | 1.531 | Fort Worth | -0.187 |
| Phoenix | 1.485 | Mobile | -0.205 |
| Richmond | 1.316 | Dayton | -0.257 |
| Buffalo | 1.225 | Omaha | -0.260 |
| Milwaukee | 1.156 | Baltimore | -0.313 |
| Sacramento | 1.137 | Tulsa | -0.372 |
| Jackson | 1.072 | Corpus-Christi | -0.412 |
| Salt Lake City | 1.043 | Austin | -0.438 |
| Birmingham | 1.002 | Philadelphia | -0.439 |
| Baton Rouge | 1.000 | Akron | -0.454 |
| Houston | 0.891 | Anaheim | -0.456 |
| Stockton | 0.832 | Hartford | -0.478 |
| Detroit | 0.720 | Madison | -0.492 |
| Los Angeles | 0.715 | Jersey City | -0.544 |
| Louisville | 0.646 | Columbus | -0.546 |
| Tucson | 0.612 | Oakland | -0.603 |
| Seattle | 0.501 | Chattanooga | -0.606 |
| Oklahoma City | 0.489 | El Paso | -0.612 |
| Shreveport | 0.479 | San Jose | -0.617 |
| Tampa | 0.464 | Raleigh | -0.624 |
| Toledo | 0.454 | Albuquerque | -0.685 |
| Worcester | 0.440 | Indianapolis | -0.725 |
| Cincinnati | 0.430 | Little Rock | -0.765 |
| Pittsburgh | 0.404 | New Haven | -0.810 |
| Dallas | 0.363 | Des Moines | -0.866 |
| Washington | 0.313 | Lexington-Fayette | -0.866 |
| Miami | 0.312 | Montgomery | -0.890 |
| Springfield | 0.297 | Greensboro | -0.893 |
| Nashville-Davidson | 0.278 | Rockford | -0.915 |
| New Orleans | 0.276 | Chicago | -1.038 |
| Orlando | 0.270 | Fort Wayne | -1.071 |
| Tacoma | 0.266 | San Francisco | -1.074 |
| Gary | 0.225 | Colorado Springs | -1.080 |
| Cleveland | 0.207 | San Antonio | -1.134 |
| Portland | 0.070 | Jacksonville | -1.292 |
| Atlanta | 0.050 | Norfolk | -1.325 |
| Boston | 0.046 | Memphis | -1.360 |
| Denver | 0.038 | Wichita | -2.017 |
| Lansing | 0.034 | Paterson | -2.128 |
| Las Vegas | 0.029 | Honolulu | -2.225 |
| New York | 0.002 | Newark | -2.338 |
| Kansas City, Mo | -0.054 | Bridgeport | -2.349 |

TABLE 15: Model 4 standard deviations of residuals (dependent variable = percentage-point change in unemployment rate 1980-2000)

| City | Standard Deviation | City | Standard Deviation |
|---|---|---|---|
| Atlanta | 3.535 | Denver | -0.055 |
| Hartford | 2.482 | Lexington-Fayette | -0.078 |
| St. Louis | 2.129 | Rochester | -0.134 |
| New Haven | 2.092 | Knoxville | -0.209 |
| Gary | 1.734 | Colorado Springs | -0.217 |
| Stockton | 1.685 | Oklahoma City | -0.222 |
| Milwaukee | 1.567 | Anaheim | -0.258 |
| Cleveland | 1.558 | Montgomery | -0.305 |
| Fresno | 1.557 | Portland | -0.348 |
| Tampa | 1.324 | Fort Worth | -0.361 |
| Spokane | 1.278 | Seattle | -0.400 |
| New Orleans | 1.218 | Syracuse | -0.451 |
| Pittsburgh | 1.189 | Los Angeles | -0.474 |
| Chicago | 1.174 | Phoenix | -0.474 |
| Las Vegas | 1.151 | Little Rock | -0.480 |
| Shreveport | 1.070 | Nashville-Davidson | -0.481 |
| Newark | 0.998 | Riverside | -0.518 |
| Dayton | 0.775 | Akron | -0.529 |
| Miami | 0.662 | Providence | -0.571 |
| Washington | 0.652 | Toledo | -0.583 |
| Corpus-Christi | 0.598 | Charlotte | -0.619 |
| Memphis | 0.558 | Louisville | -0.621 |
| Chattanooga | 0.558 | Norfolk | -0.623 |
| Madison | 0.544 | Albuquerque | -0.637 |
| Birmingham | 0.531 | Baltimore | -0.652 |
| Detroit | 0.474 | Grand Rapids | -0.668 |
| Houston | 0.444 | Bridgeport | -0.680 |
| Richmond | 0.416 | Fort Lauderdale | -0.682 |
| Columbus | 0.406 | Wichita | -0.723 |
| Sacramento | 0.376 | Raleigh | -0.755 |
| El Paso | 0.373 | Boston | -0.760 |
| Austin | 0.353 | Orlando | -0.765 |
| Cincinnati | 0.346 | Indianapolis | -0.784 |
| Jersey City | 0.274 | Kansas City, Mo | -0.795 |
| Salt Lake City | 0.272 | Paterson | -0.811 |
| Baton Rouge | 0.194 | San Diego | -0.866 |
| Tacoma | 0.182 | Omaha | -0.869 |
| Philadelphia | 0.182 | Greensboro | -0.915 |
| Honolulu | 0.173 | Springfield | -0.939 |
| Des Moines | 0.163 | Fort Wayne | -1.122 |
| Mobile | 0.151 | Lansing | -1.383 |
| Buffalo | 0.143 | New York | -1.389 |
| Minneapolis | 0.095 | Flint | -1.507 |
| Oakland | 0.041 | San Francisco | -1.538 |
| Evansville | 0.032 | Jacksonville | -1.578 |
| Tulsa | -0.008 | Worcester | -1.623 |
| Tucson | -0.014 | Rockford | -2.035 |
| Dallas | -0.025 | San Jose | -2.041 |
| San Antonio | -0.027 | Jackson | -2.107 |

TABLE 16: Model 5 standard deviations of residuals (dependent variable = percent change in real median household income 1980-2000)

| City | Standard Deviations | City | Standard Deviations |
|---|---|---|---|
| New Haven | 2.721 | Houston | 0.042 |
| Fresno | 1.773 | Fort Worth | -0.009 |
| San Antonio | 1.705 | Montgomery | -0.012 |
| Rockford | 1.670 | Columbus | -0.021 |
| Baltimore | 1.630 | New Orleans | -0.027 |
| Paterson | 1.519 | Minneapolis | -0.030 |
| Fort Wayne | 1.483 | Pittsburgh | -0.051 |
| Indianapolis | 1.410 | Syracuse | -0.079 |
| Memphis | 1.406 | Anaheim | -0.079 |
| San Diego | 1.360 | San Jose | -0.141 |
| Buffalo | 1.357 | Dallas | -0.147 |
| Atlanta | 1.184 | Worcester | -0.194 |
| Little Rock | 1.138 | Des Moines | -0.225 |
| Norfolk | 1.114 | Kansas City, Mo | -0.227 |
| Austin | 1.109 | Detroit | -0.233 |
| El Paso | 1.092 | Denver | -0.245 |
| Wichita | 1.044 | Salt Lake City | -0.380 |
| Los Angeles | 0.990 | Bridgeport | -0.388 |
| Greensboro | 0.959 | Chattanooga | -0.511 |
| Chicago | 0.832 | Oakland | -0.578 |
| Jacksonville | 0.821 | Milwaukee | -0.618 |
| Cincinnati | 0.793 | Cleveland | -0.650 |
| Corpus-Christi | 0.787 | Newark | -0.657 |
| Stockton | 0.667 | Knoxville | -0.724 |
| Tampa | 0.662 | Orlando | -0.731 |
| Colorado Springs | 0.625 | Sacramento | -0.745 |
| Tacoma | 0.604 | Hartford | -0.790 |
| Rochester | 0.553 | St. Louis | -0.801 |
| Boston | 0.540 | Honolulu | -0.801 |
| Portland | 0.530 | Las Vegas | -0.813 |
| Louisville | 0.452 | Springfield | -0.826 |
| Raleigh | 0.431 | Flint | -0.840 |
| Nashville-Davidson | 0.417 | Birmingham | -0.996 |
| San Francisco | 0.366 | Gary | -1.020 |
| Charlotte | 0.343 | Phoenix | -1.034 |
| Riverside | 0.292 | Providence | -1.064 |
| Philadelphia | 0.281 | Seattle | -1.094 |
| Madison | 0.257 | Toledo | -1.143 |
| Omaha | 0.239 | Fort Lauderdale | -1.167 |
| Grand Rapids | 0.232 | Lansing | -1.197 |
| Shreveport | 0.208 | Evansville | -1.350 |
| Dayton | 0.207 | Albuquerque | -1.366 |
| Akron | 0.186 | Washington | -1.630 |
| Jackson | 0.178 | Miami | -1.644 |
| Tulsa | 0.160 | Baton Rouge | -1.757 |
| Lexington-Fayette | 0.135 | Richmond | -1.972 |
| Oklahoma City | 0.129 | Spokane | -2.329 |
| Mobile | 0.093 | Tucson | -2.467 |
| Jersey City | 0.085 | New York | -3.008 |

TABLE 17: Model 6 standard deviations of residuals (dependent variable = percentage-point change in labor force participation rate 1980-2000)

| City | Standard Deviations | City | Standard Deviations |
|---|---|---|---|
| Raleigh | 2.492 | Worcester | 0.036 |
| Bridgeport | 1.875 | Fort Wayne | 0.031 |
| Greensboro | 1.639 | Oklahoma City | 0.008 |
| Tacoma | 1.593 | Denver | 0.000 |
| Rochester | 1.592 | Dallas | -0.025 |
| Akron | 1.494 | New York | -0.051 |
| Portland | 1.257 | Colorado Springs | -0.059 |
| Tulsa | 1.171 | Pittsburgh | -0.069 |
| Memphis | 1.094 | Evansville | -0.080 |
| Norfolk | 1.080 | Cincinnati | -0.096 |
| Spokane | 1.077 | Rockford | -0.108 |
| Lexington-Fayette | 1.031 | Tucson | -0.150 |
| Buffalo | 0.974 | Little Rock | -0.166 |
| Fort Worth | 0.914 | Sacramento | -0.180 |
| Jacksonville | 0.910 | Omaha | -0.186 |
| Louisville | 0.862 | Baltimore | -0.195 |
| Minneapolis | 0.832 | San Antonio | -0.217 |
| Phoenix | 0.819 | Shreveport | -0.225 |
| Des Moines | 0.817 | Toledo | -0.242 |
| Austin | 0.758 | Chattanooga | -0.299 |
| Oakland | 0.756 | Birmingham | -0.332 |
| Los Angeles | 0.708 | Jackson | -0.333 |
| Madison | 0.696 | San Francisco | -0.370 |
| Columbus | 0.671 | Grand Rapids | -0.379 |
| Syracuse | 0.631 | Hartford | -0.563 |
| New Haven | 0.600 | New Orleans | -0.637 |
| Philadelphia | 0.597 | Detroit | -0.659 |
| Fresno | 0.589 | Chicago | -0.667 |
| Baton Rouge | 0.547 | Kansas City, Mo | -0.746 |
| Seattle | 0.525 | Boston | -0.785 |
| Milwaukee | 0.487 | Fort Lauderdale | -0.819 |
| Knoxville | 0.466 | Houston | -0.821 |
| Riverside | 0.456 | Gary | -0.823 |
| Nashville-Davidson | 0.446 | San Jose | -0.952 |
| Charlotte | 0.441 | Mobile | -1.004 |
| Albuquerque | 0.433 | Dayton | -1.085 |
| Wichita | 0.381 | St. Louis | -1.098 |
| Stockton | 0.374 | Newark | -1.119 |
| Lansing | 0.341 | Paterson | -1.216 |
| San Diego | 0.328 | Corpus-Christi | -1.284 |
| Anaheim | 0.252 | Providence | -1.294 |
| Cleveland | 0.221 | Jersey City | -1.338 |
| Washington | 0.195 | Richmond | -1.355 |
| Tampa | 0.134 | Montgomery | -1.450 |
| Springfield | 0.131 | El Paso | -1.605 |
| Indianapolis | 0.121 | Orlando | -1.660 |
| Flint | 0.075 | Honolulu | -2.101 |
| Atlanta | 0.066 | Miami | -2.928 |
| Salt Lake City | 0.059 | Las Vegas | -4.313 |

TABLE 18: Model 7 standard deviations of residuals (dependent variable = percent change in real per capita income 1980-2000)

| City | Standard Deviations | City | Standard Deviations |
|---|---|---|---|
| Atlanta | 2.525 | Columbus | -0.038 |
| New Haven | 2.524 | Jacksonville | -0.040 |
| Rockford | 1.892 | Dallas | -0.051 |
| San Antonio | 1.878 | Paterson | -0.065 |
| Los Angeles | 1.698 | Shreveport | -0.086 |
| Cincinnati | 1.606 | Montgomery | -0.100 |
| Fresno | 1.553 | Honolulu | -0.130 |
| Indianapolis | 1.389 | Colorado Springs | -0.159 |
| Buffalo | 1.347 | Des Moines | -0.223 |
| Austin | 1.290 | Knoxville | -0.265 |
| El Paso | 1.202 | Raleigh | -0.274 |
| Seattle | 1.166 | Tacoma | -0.311 |
| Greensboro | 1.138 | Las Vegas | -0.344 |
| San Diego | 1.010 | Chicago | -0.382 |
| Baltimore | 0.998 | Albuquerque | -0.454 |
| Denver | 0.981 | Newark | -0.462 |
| Tampa | 0.965 | Evansville | -0.489 |
| Charlotte | 0.962 | Bridgeport | -0.563 |
| Little Rock | 0.923 | St. Louis | -0.606 |
| Riverside | 0.884 | Oklahoma City | -0.610 |
| Memphis | 0.846 | Springfield | -0.615 |
| Pittsburgh | 0.824 | Toledo | -0.656 |
| Rochester | 0.804 | San Jose | -0.681 |
| Kansas City, Mo | 0.723 | Grand Rapids | -0.681 |
| Jackson | 0.711 | Lansing | -0.721 |
| Corpus-Christi | 0.697 | Minneapolis | -0.725 |
| Syracuse | 0.659 | Hartford | -0.737 |
| Wichita | 0.617 | Birmingham | -0.769 |
| Boston | 0.556 | Fort Lauderdale | -0.808 |
| Houston | 0.507 | Miami | -0.822 |
| Flint | 0.506 | Salt Lake City | -0.822 |
| Philadelphia | 0.455 | New Orleans | -0.893 |
| Dayton | 0.444 | Sacramento | -0.919 |
| Fort Wayne | 0.430 | Cleveland | -0.947 |
| Louisville | 0.291 | Oakland | -0.950 |
| Akron | 0.249 | Jersey City | -0.980 |
| Chattanooga | 0.237 | Washington | -0.998 |
| Worcester | 0.217 | Detroit | -1.076 |
| Omaha | 0.213 | Fort Worth | -1.102 |
| San Francisco | 0.192 | Baton Rouge | -1.187 |
| Mobile | 0.174 | Anaheim | -1.257 |
| Norfolk | 0.145 | Phoenix | -1.267 |
| Madison | 0.113 | Orlando | -1.342 |
| Stockton | 0.102 | Providence | -1.382 |
| Lexington-Fayette | 0.096 | Milwaukee | -1.644 |
| Nashville-Davidson | 0.022 | Spokane | -2.003 |
| Tulsa | 0.005 | Tucson | -2.094 |
| Gary | 0.003 | Richmond | -2.448 |
| Portland | -0.010 | New York | -2.581 |

TABLE 19: Cities that exceeded expectations on at least two of the performance measure regression models

+ indicates the city's residual was above one standard deviation on the performance measure

| City | Model 4 (poverty rate) | Model 5 (unemployment rate) | Model 6 (median house-hold income) | Model 7 (labor force participation rate) | Model 8 (per capita income) |
|---|---|---|---|---|---|
| Atlanta | | | + | | + |
| Austin | | | + | | + |
| Bridgeport | + | | | + | |
| Buffalo | | | + | | + |
| El Paso | | | + | | + |
| Fort Wayne | + | + | + | | |
| Fresno | | | + | | + |
| Greensboro | | | | + | + |
| Indianapolis | | | + | | + |
| Jacksonville | + | + | | | |
| Memphis | + | | + | + | |
| New Haven | | | + | | + |
| Norfolk | + | | + | + | |
| Paterson | + | | + | | |
| Rockford | | + | + | | + |
| San Antonio | + | | + | | + |
| San Diego | | | + | | + |
| San Francisco | + | + | | | |
| Wichita | + | | + | | |

TABLE 20: Cities that performed worse than expected on at least two of the performance measure regression models

- indicates the city's residual was below one standard deviation on the performance measure

| City | Model 4 (poverty rate) | Model 5 (unemployment rate) | Model 6 (median house-hold income) | Model 7 (labor force participation) | Model 8 (per capita income) |
|---|---|---|---|---|---|
| Baton Rouge | | | - | | - |
| Fort Lauderdale | - | | - | | |
| Fresno | - | - | | | |
| Gary | | - | - | | |
| Las Vegas | | - | | - | |
| Miami | | | - | - | |
| Milwaukee | - | - | | | - |
| New York | | | - | | - |
| Orlando | | | | - | - |
| Phoenix | - | | - | | - |
| Providence | - | | - | - | - |
| Richmond | - | | - | - | - |
| Spokane | | - | - | | - |
| St. Louis | - | - | | - | |
| Tucson | | | - | | - |

APPENDIX 1: Median-scores and index formation

Distributions of the size of cities, whether measured by population or income, as well as measures of the income distribution, are highly skewed with long right-hand tails and densities concentrated on the left side of the distribution. These data typically have means to the right of the median and large standard deviations. The shapes of these distributions cause both real and conceptual problems when constructing indices using standardized (z) scores that use the mean as their measure of central tendency.

Indices are constructed when it is desirable to operationalize concepts with multiple indicators, each of which imperfectly measures the underlying concept of interest. Standardized scores are used in index creation when the variables used to capture different aspects of the underlying concept, such as economic or social well being, have different units of measure — dollars, percentages, growth rates, etc. — making it impossible to simply to add the variables together and then to weight the results. Hamilton writes that “standard scores are convenient when variables have no natural units, or when we want to compare variables measured in different units or with different standard deviations” (Hamilton 1991, p.256). This is because standardized variables are expressed, or measured, in terms of their relative distance from the mean, using standard deviation units as the metric. Standardized scores have an additional advantage over more abstract means of index creation, such as factor analysis, because it is easier to intuitively understand and interpret the result — the index score is interpreted in terms of distance from a measure of central tendency.

*Resistance Outliers, and Index Creation*

Lanzante (1996) defines statistical “resistance” as the tolerance of a statistical technique (either an estimator or a test) to the presence of outliers, where outliers are not characteristic of the “bulk of the data.” Most distributions that are relevant to cities and to measuring economic well-being have distributions that are severely skewed to the right and both the mean and standard deviation of the distributions are susceptible to the tug and pull of outliers. The means and standard deviations of these distributions are not resistant to outliers. Resistance is contrasted to a second important property of a statistics—its statistical efficiency, a relative measure of sampling variability. Lanzante states that many commonly used statistical techniques have no resistance at all, but that alternatives exist at the cost of efficiency. He begins his article with a discussion of the mean and standard deviation.

Using the mean as the measure of central tendency can present a distorted picture of the behavior of the center of the population and distance measures that rely on the mean and standard deviation will be distorted. In particular, z-scores to the right of the mean will be understated; those to the left of the mean, but to the right of the median will have the wrong sign; and all distance measures to the left of the mean being overstated. There is also a problem with the standard deviation in skewed distribution. The mean is used in the calculation and the deviations are squared, leading the standard deviation to be sensitive to extreme outliers.

Frequently there is confusion between the standardized normal, or z-distribution, and the z-score (Hamilton 1991). Standardized scores can be calculated on any variable, and the interpretation of the transformed variable remains the same — it measures the standardized distance from the mean of the data vector. It does not make the variable's distribution normal; it simply provides a common unit of measure across variables.

If a standardized score is to be used for just one variable, issues of the bias entered by the measure of centrality would cause some trouble in interpretation, but the statistical properties of the measure would not be altered because calculating a standardized score is a monotonic (or linear) transformation of the variable. However, if a skewed index number is combined with other sub-indices, then the issue of skew becomes more important to the overall index. This is the reason why a resistant alternative to the z-score may be desirable in index creation where distance form the center of the distribution is a desirable property of the components of the index.

The z-transformation makes no assumption about the distribution of the underlying data, but it does force the data to take a very specific form: the mean of the transformed vector is 0.0 and the standard deviation is 1.0. The standardization that results measures each observation in terms of its distance from the mean of the distribution using standard deviations as the unit of measure. This standardized distance measure, coupled with the ease of performing the calculation and the direct interpretation of the z-scores are major attractions when several variables, with different units of measure, are added in multi-dimensional index construction.

However, the validity of the transformation is called into question when populations are distributed so that the median is some distance from the mean. There are two possible responses to this problem. The first is to change the shape of the data by using a nonlinear transformation to form an intervening variable and then standardize the intervening variable.[9] The disadvantages of this approach are that (1) the resulting

[9] Lee C. Hamilton suggested that the authors of this article use a logarithmic transformation, either ln(x) or $\log_{10}(x)$ to reduce positive skew. Other possible transformations include taking the square root of the data value for less

intermediate variable is extremely hard to interpret, (2) the method is computationally complex, and (3) face validity is lost. The second approach is to find a transformation that retains the desirable computational and interpretive properties of a z-score but is outlier-resistant. Our candidate is calculating a standardized variable based on the median of the distribution rather than the mean. We refer to this transformation as a Median-score.[10]

The Median-score is analogous to the z-score but it uses a set of measures that are less susceptible to the influence of outliers than z-scores. The z-transformation is given in equation 1 and the Median-transformation in equation (2).

The z-score is defined as:

$$z_i = (x_i - \mu) / \sigma \qquad (1)$$

Where: $z_i$ is the transformed observation of variable x

$x_i$ is the observation

$\mu$ is the mean of the distribution of x

$\sigma$ is the standard deviation of variable x

While the Median-score is:

$$M_i = (x_i - M) / PSD \qquad (2)$$

---

severe positive skew or [–1/square root(x)] for more severe positive skewed distributions. A final approach would be to use Box-Cox transformations.

[10] The Median-score was suggested to Wolman and Hill by a colleague as being superior to the z-score in response to an earlier article (Hill, Wolman, and Brennan, 1998). The transformation was termed an n-score. However, an extended search Hill, Wolman, and Brennan and then by Furdell could not find a reference to n-scores in the literature. We did ascertain that the name n-score created a great deal of confusion in search engines. It was frequently confused with the number of observations (n) in a distribution and Japanese dart-scoring software. Seeing that the term n-score does not appear to exist in the published statistical literature we decided to rename the statistic the Median-score to emphasize its conceptual similarity to the z-score but that it is centered on the median of a distribution. John Brennan performed a series of comparisons between z- and Median-transformations in preparation of Hill et al. (1998) that demonstrated its robust properties. We use this section to explain the properties of Median-scores and offer them as an alternative to z-scores for index creation when the variables used have highly skewed distributions.

Where: $M_i$ is the transformed observation of variable x

$x_i$ is the observation

M is the median of the distribution

PSD is the pseudo-standard deviation, or pseudo-sigma, defined as the interquartile range (IQR) divided by 1.349.

$IQR = q_{0.75} - q_{0.25}$[11]

Both the mean and standard deviation have no resistance, but the median (M) and the pseudo-standard deviation are resistant estimators of the distribution. The median is the middle value of the sample. The PSD is based on the interquartile range, which is the difference between the first and third quartile and captures the width, or spread, of the middle half of the distribution. The PSD is divided by 1.349, which is frequently rounded to1.35, because in the case of the normal distribution the ratio of the IQR to 1.349 is equal to the standard deviation.[12]

The median and IQR are both easy to compute and to understand. They clearly represent the centrality of a population and the spread of the middle 50 percent of the observations and both are highly resistant to the tug and pull of outliers. However, they are not terribly efficient. A review of several literatures shows that the PSD is being used as an estimator where there is highly skewed data with a high frequency of positive outliers. Del Boca and her co-authors (2002) wrote in their review of investment research that the PSD is used as a "more robust measure of variability" (p. 6). The PSD is also used in climatologically research where data are highly uncertain.

[11] Sometimes the IQR is written ($Q_3 - Q_1$)

[12] Lanzante writes that "For a Gaussian distribution the IQR is 1.349 times the standard deviation; therefore the pseudo-standard deviation ($s_{ps}$) may be defined as the IQR divided by 1.349." 1.349 is equal to (2*0.674), which is 50 percent of the spread in the normal distribution. If the distribution were normal the standard deviation and the PSD would be equal.

Combining the properties of the median (M) and the PSD in the Median-score provides a highly resistant standardized transformation that accurately represents the middle portion of a distribution and distance from the middle. In the case of the indices created in this article, the loss in statistical efficiency is warranted because the rightward skew of the data will give too much weight to extremely large metropolitan areas or central cities as well as to those with high incomes in the case of measures of the income distribution.

## APPENDIX 2: Adjusting for cost-of-living differences

The ACCRA Cost-of-Living index, which measures relative price levels among metropolitan statistical areas (MSAs), is currently the most widely available and reliable source of cost-of-living information. We attempted to use the ACCRA indices for 1980 and 2000 to adjust our income measures (this study uses both per capita and median household income data) for differences in cost-of-living across cities. However, the index does not include all MSAs or even a consistent set of MSAs from one year to the next. We therefore used ACCRA data for the available cities to predict a cost-of-living index for the missing cities.

We began by using the 2000 ACCRA index of those cities in our database for which the index was available as the dependent variable in a regression, with median home value, the natural log of population, and regional dummy variables as the independent variables. We then used this regression model to predict cost-of-living indices of those cities in our database for which ACCRA data was unavailable. The process was then repeated using 1980 data, and the resulting ACCRA and predicted indices were applied to the income measures. The R-squared for the 2000 regression model was 0.78, and for the 1980 was 0.84, meaning both models were highly predictive.

APPENDIX 3: Regions used in regression analysis

New England
Connecticut
Maine
Massachusetts
New Hampshire
Rhode Island
Vermont

Southern Mideast
Delaware
District of Columbia
Maryland

Northern Mideast
New Jersey
New York
Pennsylvania

Great Lakes
Illinois
Indiana
Michigan
Ohio
Wisconsin

Plains
Iowa
Kansas
Minnesota
Missouri
Nebraska
North Dakota
South Dakota

Coastal Southeast
Florida
Georgia
North Carolina
South Carolina
Virginia

Inland Southeast
Alabama
Arkansas
Kentucky
Louisiana
Mississippi
Tennessee
West Virginia

Southwest
Arizona
New Mexico
Oklahoma
Texas

Rocky Mountain
Colorado
Idaho
Montana
Utah
Wyoming

Far West
California
Nevada
Oregon
Alaska
Hawaii

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