Effectiveness of the Appalachian Regional Commission's Distressed Counties Program

Author: Lauren Hurring

Boston College Electronic Thesis or Dissertation, 2007

Effectiveness of the Appalachian Regional Commission's Distressed Counties Program

Lauren Hurring

Advisor:
Professor Tresch

May 2007

Introduction

The Federal Government has many agencies whose goal is to promote economic development and alleviate poverty in particular regions of the nation. One such agency is the Appalachian Regional Commission (ARC), established in 1965 to help the historically lagging region. The breadth of the ARC is so large that Wood and Bischak (2000) have claimed that the "ARC's attempt to develop Appalachia is perhaps the most comprehensive regional development effort ever undertaken in this country." In fact, the ARC has spent over $15 billion on economic and social development programs, along with additional contributions by state and local governments (Wood and Bischak 2000, p. 6).

The ARC was one of the first federal development agencies to have a specific regional focus, and there have since been several regional development agencies modeled after the ARC (Wood 2005). Until 1983 the ARC functioned under a growth center strategy that channeled funds to Appalachian areas that were more economically stable and appeared promising. In 1983 the ARC undertook a major change in policy with the introduction of the Distressed Counties Program, which shifted the focus and funds to counties in severe economic duress.

The Appalachian Regional Commission is important to examine because of its prominent role in regional development, and the Distressed Counties Program is particularly important because it marks a significant shift in ARC policy. I used regression analysis to test the effect of the Distressed Counties Program on poverty rates, unemployment rates, and real per capita income of the distressed counties in Appalachia.

Background on the ARC

The Appalachian Regional Commission had an interesting history leading up to its conception. In the early 1960's, the idea that the federal government should play an essential role in improving the social and economic conditions of historically lagging regions was growing. In response to this prevalent national attitude, the Area Redevelopment Act (ARA) was passed to provide aid to poor regions in America and set the stage for the ARC. By 1963 however, some Appalachian politicians were dissatisfied with the ARA because it lacked a specific regional focus and gave little attention to the Appalachian region. At the same time, record floods in Central Appalachia focused media attention on the region. These two factors led to President Kennedy's creation of the President's Appalachian Regional Commission (PARC). This commission had the task of identifying the socioeconomic problems of Appalachia and developing a rough solution for addressing such problems. The PARC's findings revealed the "realities of deprivation" that were present in the Appalachian region, including low income, high unemployment, low urbanization, poor educational attainment, and poor housing quality (Wood and Bischak 2000, p.6). These findings led directly to the passage of the Appalachian Regional Development Act (ARDA) of 1965 (Glasmeier and Fuellhart 1999).

The ARDA recognized the region's insufficient economic base and uneven past development, resulting from heavy dependence on relatively few industries and a marginal agricultural sector. The purpose of the Act was to help the region solve its specific problems and promote economic development. The Act was also intended to establish a framework for joint federal and state efforts, since the states are responsible for recommending projects and they receive the assistance. The Act established the Appalachian Regional Commission, which consists of a Federal Cochairman, appointed by the President with the consent of the Senate, and the governors of the thirteen Appalachian states, with one being elected as the second Cochairmen (Appalachian Regional Development Act 1965). The thirteen Appalachian states include Alabama, Georgia, Kentucky, Maryland, Mississippi, North Carolina, South Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia, and New York. There are currently 410 counties in the Appalachia Region, a number that has remained roughly constant over time.

The ARDA pursued a growth center strategy, which remained in effect until 1983, when the Distressed Counties Program was introduced. The Act states that public investments “shall be concentrated in areas where there is a significant potential for future growth, and where the expected return on public dollars will be the greatest” (Appalachian Regional Development Act 1965, p.3). The hope was to stimulate promising economic areas, mostly urban, so that the region would be able to support itself. The idea was that the development of these areas would eventually “trickle down” to the region’s rural and more economically disadvantaged areas. The growth center strategy was designed in part to move people out of places of little potential and into those that were already more developed (Glasmeier and Fuellhart 1999). Ironically, those counties that needed help the most because they were severely economically depressed did not qualify for aid under the growth center policy of the ARC’s beginning years.

The ARC’s growth center policy remained in effect until 1983. By the early 1980’s, the public was becoming wary of big government programs and many believed that the market mechanism would resolve regional economic problems (Wood and Bischak 2000; Wood 2005). Federal deficits further reduced support for the ARC and, like many other federal development agencies of the time, the ARC was pressured to articulate a finish-up program. Facing possible termination, the thirteen governors of the ARC filed *A Report to Congress from the Appalachian Governors* on December 31, 1981 in an attempt to serve some level of support for the counties that had not benefited from the Program because of their small, rural, and remote conditions. This report contained the beginnings of the Distressed Counties Program, which became effective in 1983.

The Distressed Counties Program initially focused on providing clean water, adequate sewers, and other basic infrastructure projects to those counties most in need. The states are responsible for recommending projects, and they receive a certain level of funding depending on a county's economic status**,** with distressed counties receiving up to 80 percent of project costs as opposed to the usual 50 percent. Unfortunately, the Program's initiation coincided with significant reductions in federal funding for development agencies. As a result, Glasmeier and Fuellhart (1999, p.10), believe that the Program was "not originally empowered with the tools and resources necessary to make major inroads towards resolving some of its communities' most pressing problems."

The criteria for distressed county status have been modified over time. Originally there were four criteria: unemployment rates (as a three-year average), poverty rates, per capita market income (income excluding transfer payments), and infant mortality rates. Infant morality rates were discontinued as a criterion in 1988 when the rates converged to the national rate. Currently, for a county to qualify as distressed it must have a three-year average unemployment rate at least 1.5 times the national average, a per capita market income no greater than two-thirds of the national average, and a poverty rate at least 1.5 times the national average. Or, if the county has twice the national poverty rate, then it need meet only one of the other requirements. Appalachian counties are classified into five economic status designations: distressed, at-risk, transitional, competitive, and attainment. For the fiscal year 2006, 77 counties have been designated as distressed, 81 are at-risk, 222 are transitional, 22 are competitive, and 8 are attainment. The at-risk counties have three-year average unemployment rates at least 1.25 times the national average, per capita income no greater than two-thirds of the national average, and poverty rates at least 1.25 times the national average. Or, if the county meets two of the three criteria for distress, it is categorized as at-risk (ARC County Economic Status Designations 2006).

The Distressed Counties Program recently moved away from the original infrastructure projects towards other development areas. In October of 2000, the ARC approved a new two-part program for distressed counties that consisted of a Capacity-Building Program and a Telecommunications Initiative. The purpose of the Capacity-Building Program is to strengthen communities and to promote learning and leadership through programs such as workshops, outreach efforts to place communities in contact with other resources, and an online resource center (ARC Capacity Building Program). The purpose of the Telecommunications Initiative is to provide adequate telecommunications infrastructures so that the Appalachian region can also enjoy the benefits of the Information Age (ARC Telecommunications Initiative).

It is important to note that other federal programs overlap with the Appalachian Regional Commission. The United States Department of Agriculture (USDA) has setasides for rural development programs covering housing, electricity, water and sewer, empowerment zones, and enterprise communities. The Economic Development Administration (EDA) funds projects in areas of economic distress. There are several Housing and Urban Development (HUD) Programs such as the Agency's Community Development Block Grant and the Home Investment Partnership that have targeted some of their funding to Appalachia (Wood and Bischak 2000; Glasmeier and Fuellhart 1999). Another agency that has provided support for the Appalachian region is the Federal Emergency Management Agency (FEMA), which provides relief after floods, storms, and other natural disasters. The Bureau of Indian Affairs funds projects to promote education and economic opportunity for Native Americans, a significant portion of whom live in the Appalachian region.

Literature Review

The literature on the Distressed Counties Program and economically depressed areas is plentiful. The Appalachian Regional Commission often performs studies of distressed counties. Two studies of particular interest to me are the Wood and Bischak study of 2000 and the Glasmeier and Fuellhart study of 1999. The Wood and Bischak study examines the factors that keep counties in distress and the factors that promote moving them out of distress. This study proved to be the most helpful for my thesis, especially since Wood and Bischak calculated the number of distressed counties in 1960, 1970, 1980, and 1990. They used data from the U.S. Census, the Bureau of Economic Analysis, and the Office of Economic Opportunity, and current distress status standards, except that they did not use a three-year average of unemployment rates, only unemployment rates for census years. According to their calculations, the number of distressed counties has decreased by more than half from 1960 to 1990, and only about one-quarter that were in distress in 1960 have remained in distress. The ARC began categorizing distressed counties in 1983 with the inception of the Distressed Counties Program; it does not have data on the number of distressed counties for any years before 1983.

Wood and Bischak identified many factors affecting distressed county status that were beyond the scope of their study and focused mainly on two logistic regression models. The first was a Socioeconomic Model in which the dependent variable was the probability of a county remaining in or moving out of distressed status given a set of factors or conditions. They used panel data from 1960-1990 on the 214 counties identified as distressed in 1960, in increments of ten years. There were many significant explanatory variables: higher rates of employment in manufacturing, of educational attainment, and of the percentage of population living in urban areas increased the probability that a county moved out of distress. A low percentage of minorities in a county increased the probability that a county moved out of distress. The location of the county in the Southern sub-region of Appalachia increased the probability that a county moved out of distress, and this actually was the most influential variable in predicting distressed status. Wood and Bischak explain that the Southern Appalachian region has benefited from post-World War II economic growth and this is perhaps the reason for its strong influence. Another significant explanatory variable was the population's age distribution. In this model, higher proportions of elderly and children increased the probability that a county moved out of distress. This was misleading, however, because if a high proportion of elderly and children led to more dependents in counties, then those counties were more likely to remain in distress, but if a high proportion of elderly was due to the county attracting retirees, then those counties were more likely to move out of distress. Insignificant explanatory variables included counties adjacent to urban areas, the share of federal ownership of land, and levels of commuting dependence.

Wood and Bischak also employed an Economic Structure model, using the same panel data and the same dependent variable. The results of this model were consistent with those found in the Socioeconomic Model. The significant factors explaining moving out of distress were the ability to attract retirees, high proportions of manufacturing jobs, and location in a metropolitan area. Remaining in distress is explained by high proportions of employment in mining or government.

Wood updated and expanded upon his earlier work with Bischak in *Trends in National and Regional Economic Distress: 1960 – 2000,* published in 2005. Wood re-examined the Appalachia Region by adding data from 2000, and he also examined other regions of the country. His findings for the Appalachian region were very similar to his previous results with Bischak. He employed logistic regression models to assess distressed county status in Appalachia in 2000. The statistically significant factors associated with distress status were high minority populations, low educational attainment, low employment in manufacturing, high employment in mining, low employment in professional services, and metropolitan location.

In addition to the Wood and Bischak 2000 study, the Glasmeier and Fuellhart 1999 study was informative and particularly helpful in providing insight into Appalachian distressed counties. They performed a regression analysis of distressed counties, but they used a modified distress index for their dependent variable. They believe that the Distressed Counties index is limited because it uses poverty rates that are calculated every ten years, which is not very frequent. Their index "takes into account factors such as unemployment, per-capita market income, labor force participation, and share of income from transfer payments" (Glasmeier and Fuellhart 1999, p. 56). They developed a logistic regression model to predict 1994 index levels of 387 ARC counties using 1990 Census variables and a few measures of 1994 income characteristics. Lower index values denoted relatively greater economic health in a county, so a negative coefficient was associated with better economic performance. At the 95% confidence level, the statistically significant explanatory variables, in order from most influential to least, were: the percentage of the population with a BS degree (-); the percentage of the population that was female, single, and had children under 17(+); the female labor force as a percentage of the total (-); the percentage of the population 65 and older (+); the percentage of total income from the government sector (+); county location in the Southern ARC sub-region (+), note that this is the opposite of what Wood and Bischak found; the percentage of total income from the manufacturing sector (-); location in a metropolitan area (-); county location along the "edge" of the ARC region (-); the percentage of establishments that had ten employees or less (+); and, finally, county location in the Central ARC sub-region (+).

The many econometric studies of distressed county status in Appalachia tend to find that roughly the same kind of explanatory variables are statistically significant, as in the three studies discussed above. Therefore, these explanatory variables served as an excellent base for my model. The literature I found concentrated on explaining the factors and conditions that kept counties in distress or helped counties move out of distress. I focus on the effect of the Distressed Counties Program, measured by poverty rates, unemployment rates, and real per capita income.

Methodology

I collected data for the 214 counties that Wood and Bischak identified as distressed in 1960; however, lack of data reduced the number of counties to 200. The data for each county covered the years 1970, 1980, 1990, and 2000. This allowed for my sample to include two dates before the policy change and two dates after. The dependent variables were county poverty rates, unemployment rates, and per capita income, all from the U.S. Department of Commerce, Bureau of the Census. The poverty rate is simply the percent of people living below the national poverty level. Per capita income is adjusted for inflation using state-specific consumer price indices with base year 1969 from the U.S. Census Bureau, *Statistical Abstract of the United States*.

The explanatory variables begin with a Distressed Counties Program dummy that equals zero for 1970 and 1980 and one for 1990 and 2000 for all counties. There is a Southern and Northern dummy variable to denote the county as located in the Southern region of Appalachia, Northern region, or Central region. A county in the Central region is designated by both the Southern and Northern dummies equaling zero. There was one more dummy variable that equaled one if the county was designated as metropolitan. These data came from the Appalachian Regional Commission. Other explanatory variables include: manufacturing employment as a percent of total employment; government employment as a percent of total employment (Regional Economic Information System, Bureau of Economic Analysis); the percent of the population 65 and older; the percent of the population that is non-white, or minority (Population Estimates

Program, U.S. Census Bureau); the percent of adults with a high school diploma; the percent of adults with a BS degree (Census of Population and Housing, U.S. Census Bureau); national unemployment rates; the ten year average of national unemployment; national poverty rates (U.S. Department of Commerce, Bureau of the Census); and real GDP growth rate from the equation (for the 1960's) $Y_{70} = Y_{60}*(1+r_{70})^10$ where Y_{70} is real GDP for 1970, Y_{60} is real GDP for 1960, and r_{70} is the average annual growth rate during the decade. These national measures were used to account for trends in the three dependent variables. For example, unemployment rates tended to be low for 1970, high for 1980, high for 1990, and low for 2000. As mentioned earlier, most of data I collected were the explanatory variables from the literature that seem most applicable as factors contributing to a county's economic status.

The only data I was unable to collect that would have been very useful was Appalachian Regional Commission spending. The level of funding is very important because ARC funding decreased drastically during the 1980's and has remained relatively low. Wood and Bischak identified a correlation between distressed status and the level of ARC spending. In their 2000 study, p.16, they note that "distress trends in Appalachia mirrors ARC spending, with relatively high expenditures and corresponding improvement in the number of distressed counties until the 1980s. The increase in the number of distressed Appalachian counties parallels the substantial decline in ARC expenditures beginning in the 1980s." According to Wood and Bischak, there were 214 distressed counties in 1960, 161 in 1970, 78 in 1980, 106 in 1990, and 111 in 2000. There were 77 in 2006. Unfortunately, I was unable to obtain these data. Recent annual total ARC funding is around $65 million, which is spread across the entire region (410 counties and 77 distressed counties). This amount does seem relatively small, and perhaps ARC spending data would have been insignificant in my regressions.

Empirical Results

My hypothesis is that the Distressed Counties Program should have a statistically significant negative effect on poverty rates, negative effect on unemployment rates, and positive effect on real per capita income. I had originally planned to use ordinary least squares (OLS) regression analysis; however, fixed effects regression analysis is more appropriate since it captures unobservable county-specific effects. The Southern, Northern, and Metropolitan dummies were consequently dropped because their values were the same for the four dates for each county.

200 County Sample

Poverty Rates

The first regression using the dataset of 200 counties has poverty rates as the dependent variable (Table A). The Distressed Counties Program dummy (DCPdum) has a negative coefficient, as expected. Poverty rates decreased by 2.9% after the institution of the program. The percent of manufacturing employment (manufacturing) coefficient is negative, which is expected because a higher rate of manufacturing employment is associated with better economic status. The percent of government employment (government) coefficient is positive, which is consistent with the literature since high rates of government employment are associated with poorer economic status. The percent of the population 65 and older (elderly) coefficient is positive, following the logic that more dependents would increase the poverty rate. The percent of population that is non-white (minorities) coefficient is positive; often higher percentages of minorities are associated with poorer economic status. The percent of adults with a high school degree (high school) coefficient is negative, so a higher rate of high school graduates decreases the poverty rate in a county. However the percent of adults with a BS degree (college) has no statistically significant effect on poverty rates. The national poverty rate coefficient is positive and has a high magnitude, especially compared with the other explanatory variables. When national poverty rates increase by one percent, county poverty rates increase by almost seven percent, revealing that these Appalachian counties are very sensitive to changes in the national economy. Besides the Distressed Counties Program dummy and the national poverty rates, the percentage of the population 65 and older has the most impact on poverty rates; a 1% increase causes the poverty rates to increase by 0.34. The percentage minorities has the next largest effect on poverty rates; a 1% increase causes the poverty rate to increase by 0.24. Interestingly the percent of adults with a high school degree had a relatively small effect on poverty rates; a 1% increase causes the poverty rate to decrease by 0.09. This regression using poverty rates as my dependent variable gave the best results, meaning those most consistent with expectations.

Unemployment rates

The next fixed effects regression has unemployment rates as the dependent variable (Table B). The Distressed Counties Program dummy coefficient has the opposite sign than expected. According to this regression, unemployment rates increased by 3.4% with the onset of the Distressed Counties Program. However, this dummy may simply be capturing a trend in unemployment rates since it is a time dummy that equals zero for 1970 and 1980 and one for 1990 and 2000. Or perhaps I am leaving out some important labor factors that are necessary for explaining unemployment. This could lead to omitted variable bias that could change the signs on the coefficients on the other explanatory variables. The percent of the population that is 65 and older and the percent of minorities are statistically insignificant. The other variables' coefficients all have the expected sign. Disregarding the Distressed Counties Program dummy, national unemployment had the largest impact on county unemployment; a 1% increase causes a 1.43 increase in county unemployment rates. The percent of adults with a BS degree also has a high magnitude; a 1% increase causes unemployment to decrease by 0.226. Manufacturing and government employment have a statistically significant effect on unemployment, where a 1% increase in manufacturing employment causes unemployment to decrease by 0.08 and a 1% increase in government employment causes unemployment to increase by 0.09. Unfortunately this regression using unemployment as the dependent variable did not provide the expected result for the Distressed Counties Program. At best we can disregard the dummy coefficient as resulting from a poor model specification since it does not make much sense that the program would increase county unemployment rates.

Per Capita Income

The last fixed effects regression with my original sample of 200 counties has real per capita income as the dependent variable (Table C). The Distressed Counties Program dummy has a positive coefficient as expected (note that all the expected signs on the variables are reversed with per capita income instead of poverty rates or unemployment). Per capita income increased by $131.48 after the inception of the Distressed Counties Program. The average per capita income for these counties over the four dates is

$3,351.56, so this increase of $131.48 would be a four percent improvement. The percent of people 65 and older, the percent of minorities, and the real GDP growth rate are statistically insignificant. Only the manufacturing employment coefficient has an opposite sign than expected. The most important factors seem to be the percent of adults with a high school degree and the percent of adults with a college degree. A 1% increase in the former causes a $34.76 increase in county per capita income and a 1% increase in the later causes a $77.95 increase. This regression supports the hypothesis that the Distressed Counties Program has a statistically significant positive effect on per capita income.

These fixed effects regressions on the 200 counties that Wood and Bischak designated as distressed in 1960 give reasonably good results. For poverty rates and per capita income, the Distressed Counties Program proved to be statistically significant and improved both. Unemployment, however, was a different story, and although the Distressed Counties Program dummy was statistically significant, the direction of its effect was opposite of expected. Yet I would hesitate to conclude that the Distressed Counties Program increased unemployment. Instead, I explain this result as a consequence of a poorly specified model or perhaps an insufficiency in capturing the Program through a simple time dummy that can easily pick up other effects. Overall, I am impressed by the results of these regressions. The fact that the Distressed Counties Program had an effect on lowering poverty rates and increasing per capita income is promising since the ARC funding was low and these counties have historically been plagued by poverty. The ARC does aim to make "strategic investments that encourage other Federal, State, local and private participation and dollars" (The Budget for Fiscal

Year 2000). Perhaps some of the effects captured by the Distressed Counties Program dummy is the success of the ARC strategic investments since ARC funding itself is low and is most likely too small to make a significant impact in these areas by itself.

Chow Test

I also did a Chow test for each of the dependent variables. This tests for a structural break or regime change by allowing for the coefficients to be different before and after the Program was instituted. Three regressions are run to obtain the Chow statistic. The first is the constrained regression in which the coefficients are the same before and after the change. In my case, this change would be the initiation of the Distressed Counties Program. I did a fixed effects regression for years 1970, 1980, 1990, 2000. The second regression is before the regime change, so I did a fixed effects regression for only 1970 and 1980. The third regression is after the regime change, for 1990 and 2000. The Chow statistic is derived from the equation $[(RSS_c - (RSS_b + RSS_a))/k] / [(RSS_b + RSS_a) / (n_b + n_a - 2k)]$ where RSS is the residual sum of squares for the constrained regression (denoted by c), the before regression (b), and the after regression (a), k is the number of parameters, and n is the number of observations. If the Chow statistic is greater than $F(k, n_b + n_a - 2k)$, which is found using a F distribution table, then you can reject the null hypothesis that there is no structural break. For poverty rates as the dependent variable, the Chow statistic was greater than F so we can reject the null hypothesis (Table D). The results were the same using unemployment rates and per capita income as the dependent variable. The Chow test showed that there was a statistically significant structural break after the onset of the Distressed Counties Program. This was confirmed for poverty rates, unemployment, and per capita income.

Poverty Rates

A closer look at the Chow regression with poverty rates as the dependent variable, shows that manufacturing employment and the percent of adults with a high school degree are statistically significant at the 90% confidence level and have the expected sign only for the after regression (Table E). Government employment and the percent of minorities are statistically significant and have the correct sign only for the before regression. The percent of the population 65 and older and national poverty rates are statistically significant and have the correct signs for both regressions. The percent of the population 65 and older has a higher coefficient in the before regression (0.21) than in the after regression (0.07). This is true for national poverty rates as well; in the before regression its coefficient is 10.51, which seems very high, and in the after regression its coefficient is 3.84. This perhaps indicates a positive influence of the Distressed Counties Program since after its inception these counties are not as sensitive to changes in national poverty rates. The percent of adults with a BS degree is statistically insignificant in both regressions.

Unemployment Rates

When unemployment rates are used as the dependent variable for the Chow test, manufacturing employment and the ten year average of national unemployment rates are statistically significant at the 90% confidence level and have the correct sign in both regressions (the ten year average of national unemployment is used instead of national unemployment because it gives better results) (Table F). The magnitude of the manufacturing employment coefficient is greater in the after regression (-0.21) than in the before regression (-0.07). So manufacturing after the institution of the Distressed

Counties Program decreases unemployment more than before the Program. The ten year average of national unemployment coefficient is 0.65 in the before regression and 1.65 in the after regression. This is not expected since one would think that after the beginning of the Program, county unemployment would be less influenced by national levels. Government employment is statistically significant and has the correct sign only in the before regression. The percent of the population 65 and older, the percent of minorities, the percent of adults with a high school degree, and the percent of adults with a BS degree are statistically insignificant in both regressions.

Per Capita Income

When per capita income is used as the dependent variable for the Chow test, manufacturing employment and the percent of adults with a high school degree are statistically insignificant in both regressions (Table G). Government employment and national poverty rates are statistically significant and have the expected signs for both regressions (national poverty rates are used in place of the growth rate of national GDP because the former is statistically significant and gives better regression results). Government employment has a coefficient of -9.42 in the before regression and -16.40 in the after regression. This would not be expected since one would hope that after the institution of the Program high government employment would not have such a negative effect on per capita income. The national poverty rate has a coefficient of -543.23 in the before regression and -780.26 in the after regression. Again this would not be expected because this result shows that after the institution of the Program per capita levels were even more sensitive to changes in national poverty levels. The percent of the population 65 and older and the percent of minorities are statistically significant only in the before regression, and they have the expected signs. These results are good because they show that the percent of the population 65 and older and the percent of minorities do not have a statistically significant negative affect on per capita income after the institution of the Program. The percent of adults with a BS degree is statistically significant only in the after regression and it has the expected sign. This is an interesting result and shows that only after the institution of the Program does the percent of adults with a BS degree have a statistically significant positive affect on per capita income.

Considerations

A concern arose about possibly having an endogenous model since about half of the 1960 distressed counties were no longer distressed in 1990 and 2000. If some of the counties were not classified as distressed and assuming that the Distressed Counties Program only helps distressed counties, then the causal relationship would be going in both directions in my sample. To avoid this I modified my dataset to create two new datasets. The first dataset consists of 57 counties that were distressed in 1960, 1970, 1980, 1990, and 2000. The second dataset consists of counties that were distressed in 1990 and 2000, regardless of their status before the inception of the Distressed Counties Program.

57 County Sample

Poverty Rates

The first regression with the 57 county dataset has poverty rates as the dependent variable, and again I used fixed effects (Table H). The Distressed Counties Program dummy coefficient is -4.4, which is the expected sign. The Distressed Counties Program dummy is -2.9 in the regression using the 200 county dataset, implying that the Program had a greater effect on poverty rates in the counties that were distressed from 1960 to 2000. However, there are a lot of statistically insignificant variables in this regression. Only the dummy, government employment, and national poverty rates are statistically significant. The national poverty rates increased to 9.3, as opposed to 6.9 in the previous regression, suggesting that national poverty rates has a more dominant effect on the poverty rate in these 57 counties. This number actually seems too large, since a 1% increase in national poverty rates would cause a 9.3 increase in county poverty rates; even 6.9 seems too high.

I tried using different national variables such as national unemployment and the ten year average of national unemployment. When national unemployment is used in place of national poverty rates, the Distressed Counties Program dummy has a positive sign and the national unemployment coefficient is negative, so both were the opposite of expected and not logical since an increase in unemployment should not decrease the poverty rate. It is the same story when the ten year average of national unemployment is used. When national unemployment is used along with national poverty rates, the Distressed Counties Program dummy is negative as expected, but the national unemployment coefficient was negative, and the national poverty rate coefficient is still very high at 7.85. When the ten year average of national unemployment is used with national poverty rates, the Distressed Counties Program dummy is statistically insignificant, the sign is wrong on average national unemployment, and the coefficient on the national poverty rates is even higher at 8.31. So changing the national variables does not help lower the national poverty rate effect and using only the national poverty rates gives the best results in terms of what was expected.

Unemployment Rates

The second regression using the 57 county dataset has unemployment rates as the dependent variable, and again I used fixed effects (Table I). The Distressed Counties Program dummy still has the opposite sign than expected. The percent of the population 65 and the older and percent of minorities are statistically insignificant, as they are in the 200 county dataset regression, and percent of adults with a BS degree is statistically insignificant. It is interesting that the percent of adults with a BS degree does not have a statistically significant effect on unemployment for these 57 counties. Perhaps this is because the percent is lower in these counties; the average is 6.87% over the four dates and across the 57 counties and 7.83% across the 200 counties. The remaining variables, all statistically significant, have the expected signs on the coefficients. Also the magnitudes of the effect on unemployment are greater for manufacturing employment, government employment, percent of adults with high school degrees, and national unemployment than in the 200 county dataset regression.

In an attempt to get the expected negative sign on the Distressed Counties Program dummy when unemployment is the dependent variable, I tried different national variables. I used the ten year average of national unemployment, national poverty rates, the real GDP growth rate, and the growth rate of county per capita income, which is derived from the equation (for 1980) $Y_{80} = Y_{70}*(1+r_{80})$ ^10 where Y_{80} is the county per capita income for 1980, Y_{70} is the county per capita income for 1970, and r_{780} is the average annual growth rate. Only the years 1980, 1990, and 2000 are included when the growth rate of county per income is used since I do not have the 1960 per capita income for each of the counties. When the ten year average of national unemployment is used, the results are very similar to when national unemployment is used, and only the magnitudes of the coefficients change slightly. The regressions with national poverty rates and real GDP growth rate still gave a positive coefficient for the Distressed Counties Program dummy. When the growth rate of county per capita income is used, even in conjunction with the other national variables, the Distressed Counties Program dummy always remains positive.

Per Capita Income

The third fixed effects regression using the 57 county dataset has per capita income as the dependent variable (Table J). The Distressed Counties Program dummy is statistically insignificant, unlike it is in the 200 county dataset regression. Manufacturing employment, the percent of the population 65 and older, the percent of minorities, the percent of adults with BS degree, and real GDP growth rate were also statistically insignificant. Government employment and the percent of adults with high school degrees are the only statistically significant variables, and their coefficients are very close to those in the 200 county dataset regression.

Chow Test

Poverty Rates

I also performed Chow tests using the 57 county dataset and poverty rates, unemployment rates, and per capita income as the dependent variables (Table K). The results are the same as with the 200 county dataset, and in each case I am able to reject the null hypothesis that there was no structural break. This again confirms that there was a significant change with the onset of the Distressed Counties Program. Specifically, with poverty rates as the dependent variable, manufacturing employment, the percent of the population 65 and older, and the percent of adults with a high school degree are statistically significant at the 90% confidence level in the after regression and have the expected sign (Table L). But they are statistically insignificant in the before regression. Perhaps the Distressed Counties Program indirectly influenced the effect that manufacturing employment and the percent of adults with high school degrees had on county poverty rates. Government employment and national poverty rates are statistically significant in both regressions and have the correct sign. The magnitude of their coefficients is lower in the after regression, especially for national poverty rates, which is 7.73 before and 3.36 after, suggesting that after the Program these counties are not as subject to national trends in poverty rates as before the Program. The percent of minorities is statistically significant and has the correct sign on its coefficient only in the before regression. The percent of adults with a BS degree is statistically insignificant in both regressions.

Unemployment Rates

When unemployment rates are used as the dependent variable, manufacturing employment is statistically significant only in the after regression, and it has the correct sign (Table M). Government employment is statistically significant only in the before regression and has the expected sign. The percent of population 65 and older, the percent of minorities, the percent of adults with a high school degree, and the percent of adults with a BS degree are all statistically insignificant in both regressions. The ten year average of national unemployment (avgnatlunemp) is statistically significant only in the after regression and has the correct sign. Unfortunately, these results to do not give much insight into the regime change, before and after the institution of the Distressed Counties Program.

Per Capita Income

When per capita income is used as the dependent variable, manufacturing employment is statistically significant only in the before regression but it does not have the expected sign (Table N). Government employment and national poverty rates are statistically significant and have the correct sign on the coefficient for both regressions. The magnitude of government employment's coefficient is lower in the after regression, so having high government employment has less of a negative effect on per capita income after the beginning of the Program. The opposite is true for national poverty rates because after the Program, national poverty rates have even more of an effect on per capita income; a 1% increase in national poverty rates decreases county per capita income by $993.74. The percent of the population 65 and older, the percent of minorities, the percent of adults with a high school degree, and the percent of adults with a BS degree are all statistically insignificant in both regressions.

91 County Sample

The 57 county dataset is useful since it eliminates the possibility of endogeneity. However this significantly reduces the number of counties in my dataset and these are the counties that we already know do not move out of distressed status. The results suggest something different about the Distressed Counties Program effect on per capita income since it is statistically insignificant (it was statistically significant using the 200 county dataset). I decided to also use a dataset of 91 counties that were distressed in 1990 and

2000, after the beginning of the Program. This allows for a larger number of counties and does not restrict the dataset to those distressed in 1970 and 1980 as well.

As one might imagine, the results are basically the same as those found using the 57 county dataset. When poverty rates are used as the dependent variable, the Distressed Counties Program dummy is negative and its magnitude of -4.0 falls between that of the 200 county dataset (-2.9) and the 57 county dataset (-4.4) (Table O). The national poverty rate coefficient is very high at 9.6, and as before I tried different national variables but had no success. When unemployment is used as the dependent variable, the Distressed Counties Program dummy is positive, as it was in the regressions using the other two datasets (Table P). When per capita income is used as the dependent variable, the Distressed Counties Program dummy is statistically insignificant (Table Q). I also did Chow tests with this dataset for poverty rates, unemployment rates, and per capita income I am able to reject the null hypothesis that there was no structural break or regime change.

200 County Sample

In comparing my three datasets, the 200 county set gives the most expected results since the Distressed Counties Program dummy in the per capita income regression is statistically significant and had the correct sign on it. In the other two datasets it is statistically insignificant, which may simply reveal that the Program was not aiming to increase per capita income and was focusing its attention elsewhere. In all three datasets, the Distressed Counties Program has a statistically significant positive effect on poverty rates (it brought poverty rates down). Also in all three datasets, the Distressed Counties Program dummy has the wrong sign in the unemployment regression. As mentioned earlier, this is most likely because my model is missing some important explanatory variables or because the dummy is picking up other effects.

Altering the Dummy

I also tried defining my dummy differently to capture the effects of the Distressed Counties Program. The first alteration was to use my 200 county set but to have the dummy equal one for only those counties that were distressed in 1990 and 2000. In effect the dummy would represent the eligibility for Distressed Counties Grants, so those counties that were not classified as distressed in 1990 and 2000 have the dummy equal to zero. The results are not good for this regression because the dummy coefficient had the opposite sign than expected for poverty rates, unemployment, and per capita income (Tables R, S, and T). Instead of capturing the Distressed Counties Program, this dummy simply captures the fact that these counties were distressed, characterized by high poverty and unemployment rates and low per capita income. In this light, the signs on the dummy are reasonable.

The second alteration is to have the dummy capture targeted aid. The idea was that non-distressed counties in 1970 and 1980 would be receiving ARC aid under the growth center policy and that distressed counties would be receiving ARC aid in 1990 and 2000. So the dummy equaled one for non-distressed counties in 1970 and 1980 and it equaled one for distressed counties in 1990 and 2000. When poverty rates are used as the dependent variable, the dummy is statistically insignificant (Table U). When unemployment is the dependent variable, the dummy has the opposite sign than expected and suggests that when ARC funding was targeted to that type of county the unemployment increased by 0.36 (Table V). When per capita income is used as the dependent variable, the dummy had the opposite effect than expected, implying that when ARC funding is targeted to that type of county the per capita income decreases by $111.66 (Table W).

These results are not reasonable and this is most likely because the idea behind the dummy variable was faulty. The counties that were non-distressed in 1970 and 1980 probably would not have been the counties receiving aid under the growth center policy because the counties in my dataset were still very poor even though they were not technically distressed. These counties were all distressed in 1960 and it is unlikely that they made large strides in ten or twenty years to become one of the promising urban centers to which the ARC was targeting its aid. Also it is reasonable to assume that a least a good number of these counties remained at a poor economic level through 2000 and would be on the margin, at-risk, in 1990 and 2000. In this case most of the counties in the sample would be among the poorest counties in Appalachia and the shift in ARC policy, represented by the Distressed Counties Program, does not exclusively aid distressed counties.

The 2006 Budget of the United States Government states that the ARC's "area development funds are allocated…for projects that promote sustainable regional economic development, with assistance targeted at the most distressed and underdeveloped counties and areas…those communities with the greatest needs." There are two important insights in this statement. First as discussed, assistance is targeted not only to distressed counties but those with greatest needs, which at least some of the non-distressed counties in my 200 county dataset would most likely fall under. Second, the projects are aimed at regional development. It would not be unreasonable that the non-distressed counties in my dataset border the distressed counties because there seem to be pockets of poverty. Even by looking at the distressed counties in 2006 one can see that there are clusters of distressed counties (Table X). So perhaps the 1990 and 2000 non-distressed counties are benefiting from ARC regional development projects.

Using this logic, the 200 county dataset with the original Distressed Counties Program dummy is the most appropriate dataset. Also using fixed effects takes into account the fact that some of these counties are doing slightly better, moving out of distress. In addition, using the 57 or 91 county datasets in a sense restricts the effects of the Distressed Counties Program since these counties never move out of distress; therefore, their poverty and unemployment rates never move below a certain level and their per capita income never moves above a certain level. Looking at the empirical results, the F values are much better for the regressions using the 200 county dataset, but this most likely is because of a larger sample size.

Interacting the Dummy

Poverty Rates

I also tried interacting the Distressed Counties Program dummy. I interacted the dummy with manufacturing employment, the percent of adults with a high school degree, and the percent of adults with a BS degree. When I used the 200 county dataset and poverty rates as the dependent variable, the Distressed Counties Program dummy, the dummy interacted with manufacturing employment, and the dummy interacted with the percent of adults with a BS degree have the expected signs and are statistically significant. However, the signs on manufacturing employment and the percent of adults with a BS degree were not as expected and therefore the shift in their slopes, their coefficients, does not make sense.

Unemployment Rates

When I used the 200 county dataset and unemployment rates as the dependent variable, the Distressed Counties Program dummy has the opposite sign than expect, as usual. But, the dummy interacted with manufacturing employment and the dummy interacted with the percent of adults with a BS degree have the correct signs and are statistically significant. Manufacturing employment has the correct sign and is statistically significant, yet the percent of adults with a BS degree is not statistically significant. This regression shows that before the program a 1% increase in manufacturing employment caused unemployment to decrease by 0.07. After the program this effect was even larger, decreasing unemployment by an additional 0.06 (0.13 total). However this may also simply mean that manufacturing has a greater impact in more recent years, 1990 and 2000, than in earlier year, which is perhaps more reasonable since the Distressed Counties Program does not specifically have the goal of increasing manufacturing jobs. The Program would be more likely to effect education, such as the percentage of adults with high school degrees. The percent of adults with a BS degree decreases the unemployment rate by an additional 0.14 after the inception of the Program.

Per Capita Income

When I used the 200 county dataset and per capita income as the dependent variable, the Distressed Counties Program dummy has the opposite sign than expected, suggesting that per capita income decreased by $509.51 with the onset of the Program.

As with the poverty rate and unemployment regressions, the percent of adults with high school degrees interacted with the dummy is statistically insignificant and the other two interacted dummies are statistically significant. Manufacturing employment has the opposite sign than expected (-9.26) and with the change after the Program (add 11.71 to the coefficient) this amounts only to a $2.45 increase in per capita income when manufacturing employment increases by 1%. The percent of adults with BS degrees makes more sense and the coefficient before the Program is 46.32 and 67.33 after the Program. Again though, this may simply reflect that a college education has a greater impact in recent years than in the past.

Conclusions

While the regressions with the interacted dummy are interesting, I hesitate to draw any definite conclusions from them. I will focus more on my results from the fixed effects regressions using the 200 county dataset that was derived from Wood and Bischak's designation of 1960 distressed counties. These empirical results are very favorable for the Distressed Counties Program since they showed that the Program is making inroads in improving poverty rates and per capita income. Furthermore, at the beginning of this process I was not sure if the Program would have any statistically significant effect on poverty rates, unemployment, or per capita income. Unfortunately the unemployment regressions do not produce the expected sign for the Distressed Counties Program.

But the unemployment results aside, the ARC seems to have been successful in its attempts to provide help to the most distressed counties that did not receive aid in the early years under the growth center strategy. Even with cuts in funding the ARC was able to improve poverty rates and per capita income in the distressed counties. This is impressive since agencies have certain goals in mind but they are not always met. The ARC is noteworthy not only to have recognized their earlier mistake of providing aid to the more promising areas while neglecting those who needed aid the most, but then to have corrected this problem in an effective way. It is certainly not easy to improve areas of poverty, especially with little funds, so even small increases in per capita income or a slight decrease in poverty rates is respectable. Perhaps one of the reasons the ARC has been successful is because of their deep understanding of the Appalachian region and the explanatory factors behind poverty.

The most influential study in writing my thesis was from the ARC and their website is full of articles and numerous econometric studies on all different aspects of poverty and possible solutions. I must admit that I tended towards the pessimistic side when I began my thesis and did not expect the Distressed Counties Program to have much of an effect, if any, on poverty rates, unemployment, and per capita income. I was pleasantly surprised to find some evidence that the government is using their money efficiently in this area to produce real results for these counties. While some wonder about the culture of poverty, especially in the Appalachian region, my results certainly suggest that something can be done to fight poverty and help those who have been historically plagued by economic hardship.

Table A.
Fixed Effects Regression, Poverty Rates as Dependent Variable
200 county dataset

Number of obs = 800 **R-sq: within = 0.7505** **F(8,592) = 222.57**
Number of groups = 200 **between = 0.1698** **Prob > F = 0.0000**
overall = 0.4053

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	-	-2.93662	-3.3	0.001	-4.6853	-1.18795
Manufacturing	-	-0.09024	-3.3	0.001	-0.14399	-0.0365
Government	+	0.162149	3.5	0.001	0.071062	0.253236
Elderly	+	0.342342	2.55	0.011	0.078594	0.60609
Minorities	+	0.243517	2.03	0.043	0.007415	0.479619
High School	-	-0.09333	-2.23	0.026	-0.17547	-0.01118
College	-	0.049581	0.49	0.622	-0.14795	0.24711
natlpovrates	+	6.858649	12.99	0.000	5.821315	7.895983
_cons		-65.4716	-7.42	0.000	-82.8084	-48.1348

F test that all u_i=0: F(199, 592) = 5.43 Prob > F = 0.0000 e(rss) = 7363.100871907654

Table B.
Fixed Effects Regression, Unemployment as Dependent Variable
200 county dataset

Number of obs = 800 **R-sq: within = 0.3720** **F(8,592) = 43.84**
Number of groups = 200 **between = 0.2707** **Prob > F = 0.0000**
overall = 0.3082

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	-	3.479503	10.49	0	2.827925	4.13108
Manufacturing	-	-0.08438	-5.75	0	-0.11321	-0.0555538
Government	+	0.090666	3.69	0	0.042434	0.1388977
Elderly	+	-0.02394	-0.33	0.74	-0.16545	0.1175675
Minorities	-	-0.04433	-0.67	0.503	-0.17432	0.0856602
High School	-	-0.03108	-2.19	0.029	-0.05894	-0.0032126
College	-	-0.22631	-4.27	0	-0.33051	-0.1221153
NatlUnemp	+	1.430875	12.84	0	1.211982	1.649768
_cons		2.344633	2.02	0.044	0.065792	4.623473

F test that all u_i=0: F(199, 592) = 2.54 Prob > F = 0.0000 e(rss) = 2067.204895418046

Table C.
Fixed Effects Regression, Per Capita Income as Dependent Variable
200 county dataset

Number of obs	**= 800**	**R-sq: within = 0.8886**	**F(8,592)**	**=**	**590.28**
Number of groups	**= 200**	**between = 0.2712**	**Prob > F**	**=**	**0.0000**
		overall = 0.6798			

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	**+**	131.4791	2.57	0.01	31.0409	231.9172
Manufacturing	**+**	-5.89657	-2.47	0.014	-10.5869	-1.20623
Government	**-**	-16.9062	-4.23	0	-24.7516	-9.06081
Elderly	**-**	-8.68811	-0.74	0.459	-31.7299	14.35368
Minorities	**-**	9.903746	0.94	0.349	-10.8551	30.66259
High School	**+**	34.75888	12.99	0	29.50355	40.01421
College	**+**	77.94694	9.02	0	60.98143	94.91244
GDPr	**+**	36.71283	0.78	0.436	-55.8842	129.3099
_cons		1314.728	4.1	0	685.4136	1944.042

F test that all u_i=0: F(199, 592) = 4.00 Prob > F = 0.0000 e(rss) = 54674829.28245717

Table D.
Chow Test Results
200 county dataset

Chow Equation:
[RSSc - (RSSb + RSSa)] / k
(RSSb + RSSa) / (nb + na - 2k)

1. Poverty Rates

RSSb	2442.326
RSSa	681.9449
RSSc	7498.399
Nb	400
Na	400
k	8
CHOW	**137.2047**
at alpha=.05	
F(8,inf) =	2.9276

*Can reject Ho that there is no structural break

2. Unemployment

RSSb	505.12
RSSa	625.2995
RSSc	2109.375
Nb	400
Na	400
k	8
CHOW	**84.86904**
at alpha=.05	
F(8,inf) =	2.9276

*Can reject Ho that there is no structural break

3. Per Capita Income

RSSb	9572366
RSSa	7075314
RSSc	55657704
Nb	400
Na	400
k	8
CHOW	**229.6406**
at alpha=.05	
F(8,inf) =	2.9276

*Can reject Ho that there is no structural break

Table E.
Chow Test Regressions, Poverty Rate as Dependent Variable
200 county dataset

Before Regression (1970 and 1980)

Number of obs = 400 **R-sq: within = 0.8401** **F(7,193) = 144.85**
Number of groups = 200 **between = 0.0085** **Prob > F = 0.0000**
overall = 0.1583

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
Manufacturing	-	0.008358	0.13	0.894	-0.11498	0.131699
Government	+	0.209979	2.83	0.005	0.063892	0.356067
Elderly	+	1.273236	3.95	0	0.637722	1.908751
Minorities	+	0.533258	1.88	0.061	-0.02487	1.091389
High School	-	0.062081	0.66	0.507	-0.12229	0.246453
College	-	0.369053	1.39	0.167	-0.15558	0.893685
natlpovrates	+	10.51642	9.92	0	8.425942	12.60689
_cons		-136.747	-7.26	0	-173.898	-99.5955

F test that all u_i=0: F(199, 193) = 4.53 Prob > F = 0.0000 e(rss) = 2442.325724576856

After Regression (1990 and 2000)

Number of obs = 400 **R-sq: within = 0.6886** **F(7,193) = 60.98**
Number of groups = 200 **between = 0.0254** **Prob > F = 0.0000**
overall = 0.0695

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
Manufacturing	-	-0.08605	-2.78	0.006	-0.14706	-0.02504
Government	+	0.073375	1.13	0.261	-0.05489	0.201637
Elderly	+	0.346307	1.79	0.075	-0.03516	0.727771
Minorities	+	-0.22777	-1.28	0.204	-0.58	0.124453
High School	-	-0.1224	-2.66	0.008	-0.21299	-0.0318
College	-	0.119967	1.01	0.313	-0.11408	0.354014
natlpovrates	+	3.841059	4.82	0	2.270354	5.411765
_cons		-24.4269	-1.75	0.081	-51.8819	3.028073

F test that all u_i=0: F(199, 193) = 10.61 Prob > F = 0.0000 e(rss) = 681.9449014128

Table F.
Chow Test Regressions, Unemployment as Dependent Variable
200 county dataset

Before Regression (1970 and 1980)

Number of obs = 400 **R-sq: within = 0.3771** **F(7,193) = 16.69**
Number of groups = 200 **between = 0.0668** **Prob > F = 0.0000**
overall = 0.1093

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
Manufacturing	-	-0.07409	-2.61	0.01	-0.13018	-0.018
Government	+	0.075661	2.25	0.026	0.009224	0.142097
Elderly	+	0.228985	1.56	0.12	-0.06003	0.518
Minorities	+	-0.14729	-1.14	0.254	-0.40112	0.10653
High School	-	0.02849	0.67	0.504	-0.05536	0.112337
College	-	-0.10972	-0.91	0.366	-0.34831	0.128867
AvgNatlUnemp	+	0.652208	1.73	0.086	-0.09278	1.397197
_cons		1.121853	0.57	0.569	-2.75755	5.001254

F test that all u_i=0: F(199, 193) = 2.22 Prob > F = 0.0000 e(rss) = 505.1200128175456

After Regression (1990 and 2000)

Number of obs = 400 **R-sq: within = 0.4638** **F(7,193) = 23.85**
Number of groups = 200 **between = 0.0897** **Prob > F = 0.0000**
overall = 0.1423

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
Manufacturing	-	-0.21149	-7.14	0	-0.26991	-0.15307
Government	+	0.083716	1.34	0.18	-0.0391	0.206536
Elderly	+	0.110811	0.6	0.55	-0.25447	0.476089
Minorities	+	-0.00735	-0.04	0.966	-0.34463	0.329933
High School	-	-0.01257	-0.29	0.775	-0.09932	0.074184
College	-	0.031845	0.28	0.78	-0.19227	0.255961
AvgNatlUnemp	+	1.654711	4.49	0	0.927259	2.382163
_cons		-0.91061	-0.14	0.887	-13.5172	11.69599

F test that all u_i=0: F(199, 193) = 3.08 Prob > F = 0.0000 e(rss) = 625.2995007601

Table G.
Chow Test Regressions, Per Capita Income as Dependent Variable
200 county dataset

Before Regression (1970 and 1980)

Number of obs = 400 **R-sq: within = 0.8396** **F(7,193) = 144.36**
Number of groups = 200 **between = 0.0032** **Prob > F = 0.0000**
overall = 0.1328

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
Manufacturing	+	-5.18998	-1.33	0.187	-12.9117	2.53175
Government	-	-9.42532	-2.03	0.043	-18.5711	-0.27954
Elderly	-	-54.1734	-2.69	0.008	-93.9596	-14.3871
Minorities	-	-35.9744	-2.03	0.044	-70.9161	-1.03264
High School	+	-2.11938	-0.36	0.718	-13.6619	9.423168
College	+	13.91807	0.84	0.404	-18.9264	46.76256
natlpovrates	-	-543.232	-8.19	0	-674.106	-412.358
_cons		10960.48	9.29	0	8634.629	13286.34

F test that all u_i=0: F(199, 193) = 3.71 Prob > F = 0.0000 e(rss) = 9572365.799846392

After Regression (1990 and 2000)

Number of obs = 400 **R-sq: within = 0.8876** **F(7,193) = 217.65**
Number of groups = 200 **between = 0.4197** **Prob > F = 0.0000**
overall = 0.5108

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
Manufacturing	+	-0.7868	-0.25	0.803	-7.00131	5.427709
Government	-	-16.4013	-2.48	0.014	-29.466	-3.33665
Elderly	-	6.255553	0.32	0.751	-32.5999	45.11099
Minorities	-	-5.11403	-0.28	0.779	-40.9915	30.7634
High School	+	6.303305	1.35	0.179	-2.92475	15.53136
College	+	46.18352	3.82	0	22.34381	70.02323
natlpovrates	-	-780.26	-9.62	0	-940.25	-620.27
_cons		13327.38	9.4	0	10530.85	16123.91

F test that all u_i=0: F(199, 193) = 9.95 Prob > F = 0.0000 e(rss) = 7075313.5139198

Table H.
Fixed Effects Regression, Poverty Rates as Dependent Variable
57 county dataset (counties distressed in 1960, 1970, 1980, 1990, and 2000)

Number of obs = 228 | **R-sq: within = 0.8000** | **F(8,163) = 81.51**
Number of groups = 57 | **between = 0.0193** | **Prob > F = 0.0000**
overall = 0.3774

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	-	-4.38739	-1.98	0.05	-8.767384	-0.00739
Manufacturing	-	-0.0984	-1.65	0.101	-0.2163238	0.019521
Government	+	0.323261	3.7	0	0.1508572	0.495664
Elderly	+	0.571124	1.58	0.115	-0.1411095	1.283358
Minorities	+	0.24996	1	0.319	-0.2439489	0.743869
High School	-	-0.03643	-0.37	0.711	-0.2304528	0.157602
College	-	-0.03916	-0.13	0.897	-0.6377641	0.559448
natlpovrates	+	9.297451	7.16	0	6.732454	11.86245
_cons		-96.6378	-4.54	0	-138.6874	-54.5881

F test that all u_i=0: F(56, 163) = 4.16 Prob > F = 0.0000

Table I.
Fixed Effects Regression, Unemployment as Dependent Variable
57 county dataset (counties distressed in 1960, 1970, 1980, 1990, and 2000)

Number of obs = 228 | **R-sq: within = 0.4927** | **F(8,163) = 19.79**
Number of groups = 57 | **between = 0.1182** | **Prob > F = 0.0000**
overall = 0.1988

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	-	5.172276	7.66	0	3.839705	6.504847
Manufacturing	-	-0.15505	-5.17	0	-0.214296	-0.09581
Government	+	0.184062	4.16	0	0.0967431	0.271381
Elderly	+	0.039476	0.22	0.825	-0.3130554	0.392008
Minorities	-	-0.0982	-0.76	0.45	-0.3543302	0.157937
High School	-	-0.10148	-3.46	0.001	-0.1593566	-0.04359
College	-	-0.12139	-0.84	0.404	-0.4080221	0.165246
NatlUnemp	+	1.726036	7.87	0	1.292796	2.159276
_cons		1.969409	0.7	0.484	-3.572023	7.510841

F test that all u_i=0: F(56, 163) = 2.72 Prob > F = 0.0000

Table J.
Fixed Effects Regression, Per Capita Income as Dependent Variable
57 county dataset (counties distressed in 1960, 1970, 1980, 1990, and 2000)

Number of obs = 228 **R-sq: within = 0.8784** **F(8,163) = 147.18**
Number of groups = 57 **between = 0.2730** **Prob > F = 0.0000**
overall = 0.5807

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	+	28.4022	0.31	0.755	-151.2417	208.0461
Manufacturing	+	-1.34467	-0.32	0.746	-9.525015	6.83567
Government	-	-19.469	-3.19	0.002	-31.52958	-7.40842
Elderly	-	-11.9259	-0.48	0.631	-60.87014	37.01841
Minorities	-	23.7313	1.33	0.184	-11.42166	58.88425
High School	+	40.51718	8.78	0	31.40244	49.63191
College	+	31.60242	1.55	0.122	-8.583521	71.78837
GDPr	+	32.62462	0.4	0.692	-129.7117	194.9609
_cons		1120.918	2.05	0.042	43.39959	2198.437

F test that all u_i=0: F(56, 163) = 2.00 Prob > F = 0.0004

Table K.
Chow Test Results
57 county dataset (counties distressed in 1960, 1970, 1980, 1990, and 2000)

Chow Equation:

$$\frac{[RSSc - (RSSb + RSSa)] / k}{(RSSb + RSSa) / (nb + na - 2k)}$$

1. Poverty Rate		**2. Unemployment**		**3. Per Capita Income**	
RSSb	900.9375027	RSSb	149.3100146	RSSb	1673202.168
RSSa	228.4166127	RSSa	147.6827658	RSSa	1426432.57
RSSc	2578.641418	RSSc	669.4264964	RSSc	11761879.61
Nb	114	Nb	114	Nb	114
Na	114	Na	114	Na	114
k	8	k	8	k	8
CHOW	**34.00714886**	**CHOW**	**33.23142556**	**CHOW**	**74.05694814**
at alpha=.05		at alpha=.05		at alpha=.05	
F(8,200) =	2.9669	F(8,200) =	2.9669	F(8,200) =	2.9669

*Can reject Ho that there is no structural break

*Can reject Ho that there is no structural break

*Can reject Ho that there is no structural break

Table L.
Chow Test Regressions, Poverty Rate as Dependent Variable
57 county dataset (counties distressed in 1960, 1970, 1980, 1990, and 2000)

Before Regression (1970 and 1980)

Number of obs = 114 **R-sq: within = 0.8699** **F(7,50) = 47.77**
Number of groups = 57 **between = 0.0077** **Prob > F = 0.0004**
overall = 0.1054

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
Manufacturing	-	0.202755	1.17	0.247	-0.14509	0.550603
Government	+	0.587261	3.58	0.001	0.25744	0.917082
Elderly	+	-0.00766	-0.01	0.992	-1.5566	1.541285
Minorities	+	1.00966	1.74	0.088	-0.15584	2.175162
High School	-	-0.06776	-0.25	0.801	-0.60614	0.470624
College	-	-0.67897	-0.9	0.374	-2.19978	0.841851
natlpovrates	+	7.731676	2.68	0.01	1.944596	13.51876
_cons		-80.078	-1.62	0.112	-179.479	19.32325

F test that all u_i=0: F(56, 50) = 2.99 Prob > F = 0.0001 e(rss) = 900.9375026748784

After Regression (1990 and 2000)

Number of obs = 114 **R-sq: within = 0.8131** **F(7,50) = 31.08**
Number of groups = 57 **between = 0.0487** **Prob > F = 0.0004**
overall = 0.1159

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
Manufacturing	-	-0.10564	-1.8	0.078	-0.22376	0.012485
Government	+	0.297988	2.49	0.016	0.057724	0.538252
Elderly	+	1.281942	2.3	0.026	0.162409	2.401476
Minorities	+	-0.33167	-0.93	0.354	-1.04429	0.380953
High School	-	-0.22629	-2.32	0.025	-0.42259	-0.03
College	-	-0.48749	-1.47	0.147	-1.15239	0.177417
natlpovrates	+	3.361387	1.91	0.062	-0.17646	6.899235
_cons		-15.2776	-0.5	0.623	-77.2564	46.7012

F test that all u_i=0: F(56, 50) = 4.62 Prob > F = 0.0000 e(rss) = 228.4166126655165

Table M.
Chow Test Regressions, Unemployment as Dependent Variable
57 county dataset (counties distressed in 1960, 1970, 1980, 1990, and 2000)

Before Regression (1970 and 1980)

Number of obs = 114 **R-sq: within = 0.4007** **F(7,50) = 4.78**
Number of groups = 57 **between = 0.0850** **Prob > F = 0.0004**
overall = 0.0863

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
Manufacturing	-	-0.1109	-1.57	0.122	-0.2525	0.03071
Government	+	0.239819	3.59	0.001	0.10555	0.374087
Elderly	+	-0.10038	-0.32	0.75	-0.73095	0.530187
Minorities	+	-0.29303	-1.24	0.221	-0.76751	0.181438
High School	-	-0.02448	-0.22	0.823	-0.24365	0.194695
College	-	-0.16776	-0.54	0.589	-0.78688	0.45136
AvgNatlUnemp	+	1.288684	1.4	0.167	-0.55746	3.134827
_cons		3.471941	0.82	0.413	-4.98318	11.92706

F test that all u_i=0: F(56, 50) = 1.71 Prob > F = 0.0272 e(rss) = 149.3100145721238

After Regression (1990 and 2000)

Number of obs = 114 **R-sq: within = 0.6585** **F(7,50) = 13.77**
Number of groups = 57 **between = 0.0001** **Prob > F = 0.0004**
overall = 0.0621

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
Manufacturing	-	-0.17593	-3.72	0.001	-0.27091	-0.08095
Government	+	0.098246	1.02	0.312	-0.09495	0.291438
Elderly	+	0.514749	1.15	0.256	-0.38545	1.414947
Minorities	+	-0.03088	-0.11	0.914	-0.60388	0.542129
High School	-	0.036117	0.46	0.648	-0.12172	0.193955
College	-	0.468875	1.76	0.084	-0.06576	1.003513
AvgNatlUnemp	+	2.746434	4.01	0	1.370554	4.122314
_cons		-19.3337	-1.57	0.122	-44.0376	5.370159

F test that all u_i=0: F(56, 50) = 3.26 Prob > F = 0.0000 e(rss) = 147.6827658335847

Table N.
Chow Test Regressions, Per Capita Income as Dependent Variable
57 county dataset (counties distressed in 1960, 1970, 1980, 1990, and 2000)

Before Regression (1970 and 1980)

Number of obs = 114 **R-sq: within = 0.8807** **F(7,50) = 52.71**
Number of groups = 57 **between = 0.0019** **Prob > F = 0.0004**
overall = 0.1908

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
Manufacturing	**+**	-12.8144	-1.72	0.092	-27.8049	2.176104
Government	**-**	-37.5372	-5.3	0	-51.7509	-23.3236
Elderly	**-**	-0.75262	-0.02	0.982	-67.5042	65.99895
Minorities	**-**	-19.1422	-0.77	0.448	-69.3695	31.08511
High School	**+**	-3.20672	-0.28	0.782	-26.4082	19.9948
College	**+**	43.33183	1.33	0.19	-22.2078	108.8714
natlpovrates	**-**	-379.444	-3.06	0.004	-628.838	-130.05
_cons		8203.688	3.85	0	3919.99	12487.39

F test that all u_i=0: F(56, 50) = 2.32 Prob > F = 0.0014 e(rss) = 1673202.168436158

After Regression (1990 and 2000)

Number of obs = 114 **R-sq: within = 0.9038** **F(7,50) = 67.11**
Number of groups = 57 **between = 0.1352** **Prob > F = 0.0004**
overall = 0.5223

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
Manufacturing	**+**	3.03767	0.65	0.516	-6.29704	12.37238
Government	**-**	-20.0151	-2.12	0.039	-39.0019	-1.02834
Elderly	**-**	-55.9894	-1.27	0.21	-144.46	32.48115
Minorities	**-**	4.130933	0.15	0.883	-52.1835	60.44534
High School	**+**	-2.90589	-0.38	0.708	-18.418	12.60619
College	**+**	-10.4558	-0.4	0.691	-62.9995	42.08785
natlpovrates	**-**	-993.739	-7.14	0	-1273.32	-714.162
_cons		17371.29	7.12	0	12473.45	22269.14

F test that all u_i=0: F(56, 50) = 4.59 Prob > F = 0.0000 e(rss) = 1426432.569743338

Table O.
Fixed Effects Regression, Poverty Rates as Dependent Variable
91 county dataset (counties distressed in 1990 and 2000)

Number of obs = 364 **R-sq: within = 0.7553** **F(8,265) = 102.27**
Number of groups = 91 **between = 0.0203** **Prob > F = 0.0000**
overall = 0.2847

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	**-**	-3.99352	-2.44	0.015	-7.211141	-0.7759
Manufacturing	**-**	-0.14737	-2.78	0.006	-0.2517591	-0.04297
Government	**+**	0.19133	2.82	0.005	0.057913	0.324748
Elderly	**+**	1.008229	3.99	0	0.5109839	1.505474
Minorities	**+**	0.258644	1.25	0.214	-0.1501099	0.667398
High School	**-**	-0.02928	-0.39	0.695	-0.1763289	0.117773
College	**-**	0.217328	0.93	0.351	-0.2409654	0.675622
Natlpovrates	**+**	9.626804	10.12	0	7.754436	11.49917
_cons		-109.032	-6.95	0	-139.9263	-78.1372

F test that all u_i=0: F(90, 265) = 4.89 Prob > F = 0.0000

Table P.
Fixed Effects Regression, Unemployment as Dependent Variable
91 county dataset (counties distressed in 1990 and 2000)

Number of obs = 364 **R-sq: within = 0.4943** **F(8,265) = 32.38**
Number of groups =
91 **between = 0.1510** **Prob > F = 0.0000**
overall = 0.2744

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	**-**	4.958223	9.48	0	3.928475	5.987972
Manufacturing	**-**	-0.14237	-5.37	0	-0.1945938	-0.09015
Government	**+**	0.112187	3.28	0.001	0.0449258	0.179448
Elderly	**+**	0.306704	2.46	0.015	0.0607559	0.552653
Minorities	**-**	-0.03344	-0.3	0.761	-0.2498053	0.182921
High School	**-**	-0.09892	-4.24	0	-0.1448115	-0.05303
College	**-**	-0.16958	-1.49	0.138	-0.3937959	0.054632
NatlUnemp	**+**	1.506345	8.76	0	1.167656	1.845034
_cons		0.742411	0.36	0.721	-3.345184	4.830007

F test that all u_i=0: F(90, 265) = 2.60 Prob > F = 0.0000

Table Q.
Fixed Effects Regression, Per Capita Income as Dependent Variable
91 county dataset (counties distressed in 1990 and 2000)

Number of obs = 364 **R-sq: within = 0.8417** **F(8,265) = 176.17**
Number of groups = 91 **between = 0.1391** **Prob > F = 0.0000**
overall = 0.4287

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	+	24.53565	0.31	0.755	-130.1643	179.2356
Manufacturing	+	-0.96977	-0.24	0.813	-9.048624	7.109074
Government	-	-13.8681	-2.63	0.009	-24.26674	-3.46949
Elderly	-	-45.5782	-2.35	0.019	-83.70389	-7.45242
Minorities	-	39.35974	2.35	0.02	6.354291	72.3652
High School	+	37.31677	9.06	0	29.2057	45.42784
College	+	21.6737	1.22	0.224	-13.3333	56.6807
GDPr	+	-166.4	-2.34	0.02	-306.5729	-26.2269
_cons		2309.014	5.14	0	1424.27	3193.758

F test that all u_i=0: F(90, 265) = 2.75 Prob > F = 0.0000

Table R.
Fixed Effects Regression, Poverty Rate as Dependent Variable
200 county dataset
Modified Distressed Counties Dummy (=1 only for distressed counties in 1990 and 2000)

Number of obs = 800 **R-sq: within = 0.7507** **F(8,592) = 222.81**
Number of groups = 200 **between = 0.6177** **Prob > F = 0.0000**
overall = 0.5968

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	-	1.665521	3.37	0.001	0.694759	2.636284
Manufacturing	-	-0.11936	-4.36	0	-0.17309	-0.06563
Government	+	0.150529	3.23	0.001	0.059044	0.242014
Elderly	+	0.218979	1.72	0.086	-0.03128	0.469236
Minorities	+	0.149959	1.24	0.214	-0.08696	0.386876
High School	-	-0.25674	-9.92	0	-0.30758	-0.20591
College	-	0.122424	1.19	0.235	-0.07961	0.324462
natlpovrates	+	5.126858	15.73	0	4.486907	5.766809
_cons		-34.6441	-6.9	0	-44.5032	-24.7851

F test that all u_i=0: F(199, 592) = 5.91 Prob > F = 0.0000

Table S.
Fixed Effects Regression, Unemployment as Dependent Variable
200 county dataset
Modified Distressed Counties Dummy (=1 only for distressed counties in 1990 and 2000)

Number of obs = 800 | **R-sq: within = 0.3405** | **F(8,592) = 38.21**
Number of groups = 200 | **between = 0.1745** | **Prob > F = 0.0000**
overall = 0.2013

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	-	2.285068	8.74	0	1.771845	2.79829
Manufacturing	-	-0.07938	-5.28	0	-0.10888	-0.04987
Government	+	0.05319	2.11	0.035	0.003749	0.102632
Elderly	+	0.258639	3.8	0	0.124963	0.392316
Minorities	-	-0.14532	-2.14	0.033	-0.2786	-0.01203
High School	-	0.012646	1	0.317	-0.01216	0.037449
College	-	-0.16363	-2.94	0.003	-0.27304	-0.05421
NatlUnemp	+	0.956969	9.81	0	0.765368	1.148569
_cons		0.854963	0.73	0.464	-1.43484	3.144771

F test that all u_i=0: F(199, 592) = 2.64 Prob > F = 0.0000

Table T.
Fixed Effects Regression, Per Capita Income as Dependent Variable
200 county dataset
Modified Distressed Counties Dummy (=1 only for distressed counties in 1990 and 2000)

Number of obs = 800 | **R-sq: within = 0.8949** | **F(8,592) = 630.29**
Number of groups = 200 | **between = 0.3252** | **Prob > F = 0.0000**
overall = 0.6781

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	+	-260.279	-6.53	0	-338.54	-182.018
Manufacturing	+	-2.32273	-1	0.317	-6.87509	2.229625
Government	-	-15.7883	-4.07	0	-23.4064	-8.1702
Elderly	-	4.533778	0.43	0.666	-16.1006	25.16813
Minorities	-	16.8638	1.63	0.103	-3.41563	37.14324
High School	+	46.06506	21.59	0	41.875	50.25513
College	+	62.52007	7.27	0	45.6238	79.41633
GDPr	+	126.8445	3.11	0.002	46.66406	207.0249
_cons		392.8398	1.54	0.123	-107.276	892.9553

Table U.
Fixed Effects Regression, Poverty Rate as Dependent Variable
200 county dataset
Second Modified Dummy (=1 for non-distressed counties in 1970 and 1980 and =1 for distressed counties in 1990 and 2000)

Number of obs = 800 **R-sq: within = 0.7469** **F(8,592) = 218.42**
Number of groups = 200 **between = 0.3891** **Prob > F = 0.0000**
between = 0.3891

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	-	-0.48641	-1.56	0.12	-1.09976	0.126948
Manufacturing	-	-0.09565	-3.44	0.001	-0.15027	-0.04103
Government	+	0.174099	3.71	0	0.081889	0.266309
Elderly	+	0.185119	1.44	0.151	-0.06771	0.437951
Minorities	+	0.220566	1.82	0.069	-0.01695	0.458084
High School	-	-0.20385	-9.03	0	-0.24818	-0.15951
College	-	0.010117	0.1	0.923	-0.19476	0.214989
natlpovrates	+	5.317289	16.35	0	4.67854	5.956038
_cons		-39.0468	-8.06	0	-48.5579	-29.5357

Table V.
Fixed Effects Regression, Unemployment as Dependent Variable
200 county dataset
Second Modified Dummy (=1 for non-distressed counties in 1970 and 1980 and =1 for distressed counties in 1990 and 2000)

Number of obs = 800 **R-sq: within = 0.2604** **F(8,592) = 26.05**
Number of groups = 200 **between = 0.0968** **Prob > F = 0.0000**
overall = 0.1320

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	-	0.362461	2.01	0.045	0.008625	0.716297
Manufacturing	-	-0.0619	-3.89	0	-0.09314	-0.03067
Government	+	0.064726	2.42	0.016	0.012188	0.117263
Elderly	+	0.289612	3.98	0	0.146676	0.432549
Minorities	-	-0.11996	-1.65	0.099	-0.26249	0.022571
High School	-	0.056355	4.53	0	0.031903	0.080806
College	-	-0.25191	-4.28	0	-0.36756	-0.13626
NatlUnemp	+	0.729836	6.87	0	0.521157	0.938515
_cons		-0.14554	-0.12	0.907	-2.5821	2.291032

Table W.
Fixed Effects Regression, Per Capita Income as Dependent Variable
200 county dataset
Second Modified Dummy (=1 for non-distressed counties in 1970 and 1980 and =1 for distressed counties in 1990 and 2000)

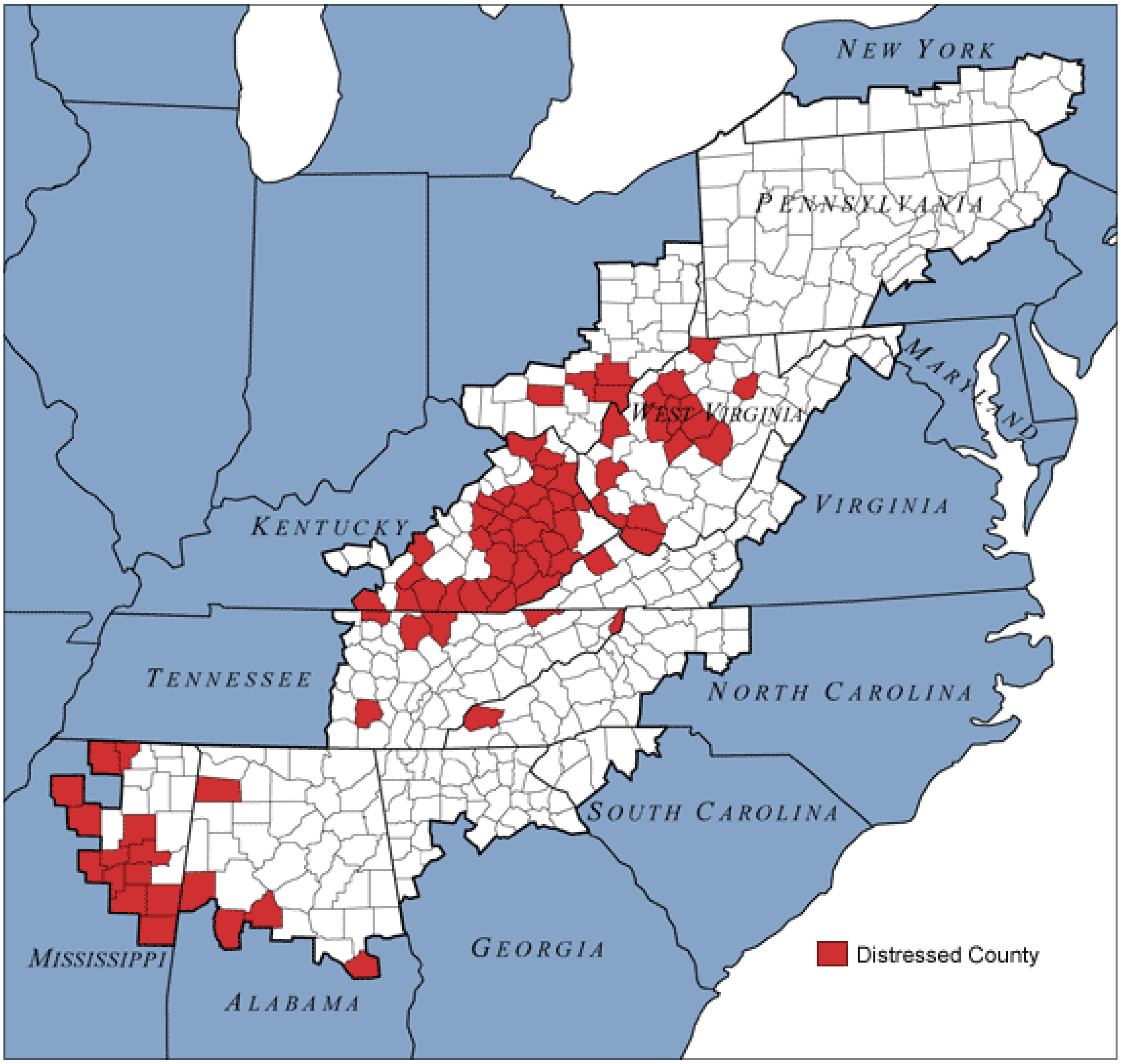
Number of obs = 800	**R-sq: within = 0.8905**	**F(8,592) = 601.96**
Number of groups = 200	**between = 0.2720**	**Prob > F = 0.0000**
	overall = 0.6673	

	Expected Sign	Coef.	t	P>t	[95% Conf.	Interval]
DCPdum	+	-111.655	-4.14	0	-164.641	-58.6697
Manufacturing	+	-3.23701	-1.37	0.172	-7.88211	1.408092
Government	-	-15.8336	-3.98	0	-23.6381	-8.0291
Elderly	-	-3.95391	-0.36	0.716	-25.2681	17.36031
Minorities	-	16.14475	1.52	0.128	-4.67157	36.96108
High School	+	40.74684	20.95	0	36.92787	44.56582
College	+	67.29651	7.67	0	50.05429	84.53872
GDPr	+	35.09445	0.8	0.422	-50.6619	120.8508
_cons		1057.64	4.09	0	550	1565.281

F test that all u_i=0: F(199, 592) = 5.72 Prob > F = 0.0000

Table X.

ARC-Designated Distressed Counties, Fiscal Year 2006



Prepared by the Appalachian Regional Commission

Data Sources:
Unemployment data: U.S. Department of Labor, Bureau of Labor Statistics, 2001--2003
Income data: U.S. Department of Commerce, Bureau of Economic Analysis, 2002
Poverty data: U.S. Department of Commerce, Census Bureau, 2000

Reference Section

Aldrich, Lorna and Lorin Kusmin. *Rural Economic Development: What Makes Rural Communities Grow?* An Economic Research Service Report. United States Department of Agriculture, Economic Research Service, September 1997.

Appalachian Regional Commission (ARC). *Appalachian Regional Development Act*. Originally U.S. Congress Public Law 94-188. Washington, DC: Government Printing Office, 1965. Reprinted by the Appalachian Regional Commission.

Appalachian Regional Commission (ARC). *Capacity-Building Program.* Washington, DC: Appalachian Regional Commission.

Appalachian Regional Commission (ARC). *County Economic Status Designations in the Appalachian Region, Fiscal Year 2006.* Washington, DC: Appalachian Regional Commission, 2006.

Appalachian Regional Commission (ARC). *Telecommunications Initiative.* Washington, DC: Appalachian Regional Commission.

The Budget of the United States for Fiscal Year 2000 and 2006.

Glasmeier, Amy K., and Kurtis G. Fuellhart. *Building on Past Experiences: Creating a New Future for Distressed Counties.* State College, PA: Institute for Policy Research and Evaluation, 1999.

Wood, Lawrence E. and Gregory Bischak. *Progress and Challenges in Reducing Economic Distress in Appalachia: An Analysis of National Trends since 1960.* Washington, DC: Appalachian Regional Commission, 2000.

Wood, Lawrence E. *Trends in National and Regional Economic Distress: 1960 – 2000*. Ohio University, 2005.