Poverty in North Carolina since 2000:

Structural and Cyclical Components

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27 December 2013

Abstract:
The incidence of poverty, as measured by the percentage of individuals with incomes below the national poverty threshold, was declining in North Carolina in the years 1959 through 2000. The trend, observed through the second half of the 20th Century, has been reversed since 2000 – the poverty rate returned in 2011 to a rate last observed in 1980 and has declined only modestly since then.

Econometric investigation indicates that only about half (2.3 percentage points) of the increase in the poverty rate can be attributed to the cyclic effects of high unemployment, and some of this effect (.5 percentage points) was counteracted by the unemployment insurance program. There remains about 2 percentage points in rise of the poverty rate that remains unexplained – not structural, and not unemployment-related. Reliance upon a return to full employment alone as a solution to this surge in poverty may not eliminate this latter increase in the poverty rate.

This research was begun during my fellowship at the Global Research Institute of the University of North Carolina at Chapel Hill. Thanks to Zak Smith and Karina Ibrahim for excellent research assistance.

Poverty in North Carolina until 2000 had been a chronic but declining disease. In 1959, 40.6 percent of the population had incomes below the poverty line; this percentage fell to 20.3 percent in 1969, 14.8 percent in 1979, 13 percent in 1989 and 12.3 percent in 1999.[1] Korstad and Leloudis (2010) document the efforts of the War on Poverty in North Carolina in the 1960s, while Johnson (2003) describes the changed scene in the 1980s and 1990s. The identity of the poor changed over the years, with more of the poor living in cities, coming from ethnic minorities, and living in a female-headed household – but Johnson (2003) is able to conclude that while the number of the poor had risen the percentage had fallen to near the US average.

This positive conclusion has not carried forward into the 21st Century. As indicated in Figure 1, the poverty rate in 2000 was indeed below 12 percent, but by 2011 it had once again risen to nearly 18 percent.[2] This recent rise was not extraordinary among states. As Figure 2 illustrates, all states but Wyoming, Montana and Vermont experienced an increase in the poverty rate over that 12 years: this is evident in the figure by the position of each of the points above the diagonal line. North Carolina is tenth-highest among the 50 states (and the District of Columbia) in the percentage-point increase in the poverty rate over that period (the vertical distance above the diagonal).[3] The period since 2007, product of the recession, has certainly contributed to this increase, but a similar contribution to the rise in the poverty rate was observed in the years 2000-2005.

The poverty rate measures the percent of the population with income less than the poverty threshold.[4] The income threshold for an individual in poverty in 2012 was $11170. Thresholds for individuals who are part of families are higher, but not proportionately higher. The threshold is adjusted upward each year for inflation as measured by the consumer price index (CPI). The income used to determine an individual's (or household's) status relative to the poverty threshold includes earned income, unemployment compensation, Social Security, pensions and transfers.

[1] These statistics are drawn from the decennial censes of the US Census Bureau. The corresponding national poverty rates were 22.1 percent in 1959, 13.7 percent in 1969, 12.4 percent in 1979, 13.1 percent in 1989 and 12.4 percent in 1999. Note that in 1989 and 1999, North Carolina's poverty rate was below the national rate. Johnson (2003) reports that the poverty rate in 1980 was above 16 percent; that is the source of the specific comparison in the abstract and the following paragraph.

[2] The measurements of poverty and median household income used for the 1998-2012 period are taken from the US Bureau of the Census Small Area Income and Poverty Estimates (SAIPE) at http://www.census.gov/did/www/saipe/. These are not statistics calculated directly from a population census, but are estimates derived by US Census staff from American Community Surveys (ACS), Current Population Surveys (CPS) and other sources.

[3] Those with larger percentage-point increases were Mississippi, Arizona, Georgia, Kentucky, South Carolina, Nevada, Missouri, Indiana and Ohio.

[4] The poverty rate is a measure of "absolute poverty", to use the terminology of Niemietz (2011), as distinguished from measures of "relative poverty" that use deciles of the income distribution. The methodology used to calculate poverty rates and poverty thresholds is presented at http://www.census.gov/hhes/www/poverty/methods/definitions.html.

Given the population of North Carolina in 2012, each percentage point of the poverty rate represents 97,500 people living below the poverty line.

The conditions for existence and persistence of poverty in a developed economy have been studied extensively (e.g, O'Connor 2001). There is an extensive literature on what I will call the "structural" determinants of poverty – conditions which lead some groups or regions to maintain elevated poverty rates relative to their peers for extended periods of time. Structural poverty exists in North Carolina: in this paper I will provide evidence, but will not have explanations for its continuation. The focus of this paper is what I will call the "cyclic" determinants of poverty: factors that lead to systematic increases (and reductions) in the poverty rate over the short to medium term. The evolution of the aggregate poverty rate for North Carolina in Figure 1 illustrates this cyclic movement as an overlay to the structural features of poverty statewide.

My research is presented around the research question: is the increase in unemployment the cause of cyclic poverty in North Carolina? I examine this question using a panel database of poverty, income, and unemployment at the county level over the period 1998-2012.[5] The state program of unemployment insurance plays an important role in the evolution of poverty, and so I introduce information on that as well.

The general link between unemployment and poverty is straightforward: conditioning on other factors, those without jobs are more likely to have income falling below the poverty threshold than those with jobs. Those without jobs, however, can be divided into two groups – those who qualify for unemployment compensation and those who do not. Unemployment compensation provides a support that will lift a portion of those receiving it once again above the poverty line. I will demonstrate the importance of these determinants of poverty in three steps.

- Step 1: the relation between the unemployment rate and the percent of the population receiving unemployment insurance payments.
- Step 2: the link from unemployment rate and unemployment insurance payments to the median real household income in each county.
- Step 3: the link from real household income to the poverty rate in each county.

[5] Unemployment data are drawn from the Local Area Unemployment Statistics (LAUS) database, a joint initiative of the US Bureau of the Census and the North Carolina Department of Commerce Division of Employment Security. Data on poverty are provided from the Small Area Income and Poverty Estimates (SAIPE) database of the US Bureau of the Census. Information on unemployment compensation is available from the NC Department of Commerce Division of Employment Security.

I draw three conclusions about the increased incidence of cyclical poverty. First, the increase in unemployment explains just over half of the increase in poverty since 2007. Second, the unemployment insurance program has played an important role in keeping North Carolinians above the poverty line. Third, this leaves a substantial increase in poverty that appears to have different causes. It will be important to uncover and address the cause of this additional increase in poverty, since simple return to full employment will not eliminate this effect.

Unemployment insurance.

The Unemployment Insurance program provides temporary and partial compensation for lost earnings of individuals who become unemployed. The program is designed to be self-financing. Each state has a Trust Fund, and in each state the Trust Fund accumulates reserves from excess employer taxes during periods of economic expansion in order to pay excess benefits during economic downturns. The Trust Fund in each state receives payments from the FUTA (Federal Unemployment Tax Act) tax, a 6.2 percent tax paid by employers on the first $7,000 in wages earned by each employee. Employers residing in states with Unemployment Compensation (UC) programs approved by the Federal government are eligible for a 5.4 percent FUTA tax credit, thus making the effective tax on employers 0.8 percent per dollar in wages.[6]

States are required by Federal law to continue to make unemployment insurance payments even when the Trust Fund hasn't sufficient funds (as, for example, in a high-unemployment episode). The most common way for states to combat fund insolvency is to borrow from the Federal Unemployment Trust Fund Account (FUTFA). States may borrow interest-free from the FUTFA as long as the loan is repaid by September 30th of the year of the loan. If an outstanding loan balance exists on January 1st for two consecutive years, the full amount of the loan must be repaid by November 10th of the second year or employers in the state lose 0.3 percentage points of the FUTA credit each year there is an unpaid balance. An employer in a state with an unpaid FUTFA loan that was one year past due would pay 1.1 percent. States may be relieved from this penalty if they have not taken actions in the previous year that would reduce the solvency of their state trust funds.

The North Carolina Unemployment Insurance Trust Fund (NCTF) has assisted large numbers of out-of-work citizens in recent years: in 2009, for example, there were claims honored each week by on average nearly 189,000 individuals out of work. Its own resources were exhausted quickly in the recession, and it has met its obligations by borrowing from the FUTFA. Figure 3 illustrates the indebtedness of the NCTF to the FUTFA as a percent of the total labor force and

[6] Facts in this paragraph and the following are drawn from GAO (2010).

compares it to the indebtedness observed in other states.[7] As is evident there, only California and Indiana have greater indebtedness per worker.

In early 2013, the North Carolina legislature passed a massive overhaul of the unemployment compensation system. In an effort to speed up the repayment of North Carolina's debt to FUTFA, there were a number of steps taken to reduce North Carolina's payments to unemployed workers. The maximum weekly payment was reduced to $350, while the number of weeks for which the unemployed could collect benefits was reduced from 26 (i.e., over six months) to between 12 and 20 weeks (i.e., three to five months). This policy adjustment was especially costly to the state because it meant that those unemployed in North Carolina were no longer eligible for Federal extended unemployment benefits. The extended benefits began when residents exhausted their state benefits during times of high unemployment; with the extension, those unemployed could receive up to 63 weeks of benefits under the old system. Anyone who had received benefits longer than 20 weeks but less than 63 weeks was dropped from the program on 1 July 2013 with the change in state unemployment benefits rules. Approximately 70,000 jobless workers lost extended benefits immediately, and another 100,000 will not be eligible for these extended benefits later in 2013. This represents the loss of about $600 million in Federal payments to the unemployed through the second half of 2013.[8]

The unemployment rate and the rate of unemployment compensation.

The unemployment rate measures the share of individuals in the labor market who are willing to work at the current wage but are unable to find a job.[9] While the unemployment rate in North Carolina will differ from the national rate, the two move closely together. Figure 4 illustrates the North Carolina unemployment rate (measured in July of the year) for the period 2001-2012. Prior to 2009, the highest unemployment rate observed was about 7 percent in 2002-2003. In 2009, the rate jumped to 11 percent; by 2012 it remained above 10 percent.

[7] Loan balances as reported by the Department of Labor ETA Division on 12 November 2013. Rankings relative to state GDP are nearly identical. These other measures are available on demand.

[8] The numbers of jobless workers losing benefits and the estimate of forgone Federal payments are provided by Sirota, A. (2013).

[9] This share is measured through surveys of the population. At the national level, the Current Population Survey (CPS) is used; for North Carolina there is the LAUS. In the survey, there are two questions used in creating the unemployment rate. (1) Do you have a job? (2) Are you currently without a job, have actively looked for work in the past 4 weeks, and are currently available to work? If the answer to (1) is yes, then you are employed. If the answer to (1) is no and (2) is yes then you are unemployed. If the answer to (1) and (2) is no, then you are out of the labor force. You don't have to be employed full time (i.e., 40 hours of the week) to be employed. The unemployment rate is the ratio of those unemployed to those in the labor force.

Unemployment insurance is a collection of unemployment benefits offered to those out of work.[10] An individual is eligible to receive unemployment compensation if he/she meets the State requirements for wages earned or time worked during an established period of time referred to as a "base period".[11] He/she must be unemployed through no fault of his/her own. In general, benefits are based on a percentage of an individual's earnings over a recent 52-week period up to a maximum amount. The Division of Employment Security of the NC Department of Commerce reports the average number of weekly claims for each county in North Carolina in each month. It also creates the ratio of this average number of weekly claims of unemployment compensation with the total labor force eligible for unemployment insurance. It calls this the “rate of insured unemployment”; to avoid confusion, I refer to this as the weekly claims ratio. Figure 4 also illustrates the values of the weekly claims ratio for North Carolina as a whole in July of the listed year. The unemployment rate and the weekly claims ratio are highly correlated, but not coincident – not every worker is eligible for unemployment compensation, and not every worker eligible for it will file.[12]

Table 1 reports the correlation between the two variables while controlling for year-specific and county-specific differences. The first column reports a simple regression over the panel of observations from 2001 to 2012 in the weekly claims ratio (w_{jt}) of county j in year t on the unemployment rate (u_{jt}) in county j in year t. The regression has a significant positive intercept and a significant regression coefficient of 0.37 on the unemployment rate: as the unemployment rate rises by 1 percentage point, the weekly claims ratio rises by 0.37.[13] This relationship alone explains 31 percent of the variation in w_{jt}. The second column introduces year-specific effects. The regression coefficient on u_{jt} rises significantly to 0.52 once the year-specific effects are considered. As the excluded year is 2001, the negative and significant coefficients throughout indicate significantly lower claims ratios in these years than in 2001. The period 2010-2012 represents an even more strongly negative shift in weekly claims ratios in those years once the unemployment rate is controlled for.[14] In the third column, I introduce county-specific effects as well. This final specification explains 81 percent of the variation in w_{jt}, and with all of these controls in place the passthrough from unemployment rate to weekly claims ratio remains

[10] State unemployment insurance is the most commonly observed program, but disaster unemployment assistance, unemployment compensation for former Federal employees and unemployment compensation for ex-service members share these characteristics.

[11] In most states, this is four out of the last five completed calendar quarters prior to the time that the claim is filed.

[12] The weekly claims ratio also measures only the payout of the state’s Unemployment Insurance program. Payouts under the Federal extended benefit unemployment compensation or emergency unemployment compensation programs are not included.

[13] Significance is indicated here and in what follows at the 95 percent level of confidence.

[14] I interpret these large negative coefficients as indicators of the increased share of the unemployed who were receiving extended unemployment benefits under the Federal program; those are not included in the weekly claims ratio.

significant and large at 0.39 .[15] This is significantly different from zero, but also from unity – increases in the unemployment rate do not increase the weekly claims ratio proportionally. Figure 4 illustrates another disproportionality: After the initial uptick in weekly claims in 2009, the ratio declined in subsequent years despite persistent high unemployment rate. This was due to the expiration of the UI benefits and the uptake into Federal extended programs for those unemployed more than 26 weeks.

The median real household income.

The median real household income (y_{jt}) of the county provides an important link between unemployment and poverty. As unemployment occurs, individuals and households will observe real income fall. For those already below the median or those sufficiently above the median this has no effect on y_{jt}, but for individuals and households whose income drops from above the median to below the median there is a reduction as well in median real household income. An increase in unemployment is not the only possible reason for a reduction in real household income; any shock placing downward pressure on wages relative to inflation will also have this effect. Competitive downward price pressures from imports can lead to wage stagnation in manufacturing, for example. It can also be the case that those losing higher-wage jobs find employment, but only at lower wages; this will also lower median real household income.

Increased unemployment compensation will, other things equal, raise the median real household income to the extent that households receiving compensation move from the lower half of the income distribution to the upper half. Other things are rarely equal, however, since unemployment compensation must be triggered by an unemployment spell. I anticipate that an increase in u_{jt} will lead to a less-than-proportional increase in w_{jt}, just as described in the previous section, and the joint effect of these two on y_{jt} will be a smaller reduction than would occur if only u_{jt} were to increase.

Real median household income in North Carolina has been declining most years since 2000. Figure 5 illustrates the evolution of this measure for the state as a whole between the years 1998 and 2011. There were two periods of sharp decline, in 2000-2001 and 2008-2011.

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[15] Given the short sample considered here, both data series exhibit non-stationarity by county. The two series should exhibit cointegration, however, and so to exploit this property I also investigate an error-correction form for the estimation equation: $\Delta w_{jt} = a_0 + a_1 \Delta u_{jt} - a_2 (w_{jt-1} - b\, u_{jt-1}) + e_{jt}$, with b the cointegration vector. The estimated passthrough coefficient a_1 (and clustered standard error) is 0.55 (0.02), with error-correction coefficient a_2 = -0.25 (0.03).

In Table 2 I investigate the unemployment rate and weekly claims rate as determinants of real median household income. The first column reports results without controls for time and county-specific effects. There is a pronounced negative effect from increased unemployment rate to reduced median real income, with an increase in the unemployment rate of 1 percentage point associated with a reduction in median real income by $760 (in 1998 prices). The unemployment-compensation effect is negative and insignificant in this specification. The third column provides a specification including county-level fixed effects, and this one takes the form anticipated. As the unemployment rate rises, median real household income falls (with coefficient -0.42, a 1 percentage-point increase leads to a loss of $420 in median real household income). As unemployment compensation claims rise, median real household income rises (with coefficient 0.34). The net effect of the two will be negative. Once we include both county and year-specific fixed effects, the coefficient on u_{jt} remains larger in absolute value (at -0.31) when compared to the coefficient on w_{jt} (at 0.26), but the two coefficients are not significantly different from one another. Even controlling for unemployment rate, the year-specific coefficients are mostly negative and often significantly different from zero: this indicates that there is a recurring problem of those re-employed at lower wages or the newly employed working at below-average wages.

The Poverty Rate.

The poverty rate (p_{jt}) is a descriptive statistic of the distribution of real household income: it is a measure of the percent of the households in the lower tail of that distribution, with cut-off value determined by the poverty threshold (p^o). The median real household income (y_{jt}) is another descriptive statistic from the same distribution: it represents the location of the midpoint of the distribution for county j. The y_{jt} statistic can vary for one of two general reasons. For given probability distribution $f_j(.)$, county-specific realizations z_{jt} can be uniformly lower or higher; this will cause y_{jt} to be lower or higher as well. Alternatively, for existing range of real household incomes, the distribution of observed household incomes may expand in variance or skew towards lower values. I illustrate the determinants of y_{jt} and p_{jr} for the Pareto distribution in the appendix.

In Table 3 I report the results of a panel-data investigation of the link between poverty rate and median real household income by county in North Carolina. To capture the effects of changes in the shape of the income distribution I include the unemployment rate as a separate regressor. Table 2 illustrated the link from unemployment rate to median real household income, but here the unemployment rate reflects a second channel: the downward income shift in many households due to unemployment. Not only does a rise in the unemployment rate cause the median of the distribution to fall, but it also causes unemployed households in the bottom half of the income distribution to fall into the lower tail of the distribution – and thus into measured poverty. Column (1) of Table 3 illustrates the most parsimonious specification. As median real household income in a county rises by $1000, the poverty rate falls by .61 percentage points. An increase in the unemployment rate by one percentage point will increase the poverty rate by .33 percentage points.[16] Both of these effects are significantly different from zero, and together they explain 69 percent of the county-level variation in the poverty rate over time. In columns (2) through (4) I examine extensions of this regression that allow for time-specific and county-specific effects on the poverty rate. In column (2) I introduce year-specific effects: if there is a common trend in the poverty rate across all counties, these coefficients will reflect that trend. (Since the unemployment rate has just such a state-wide trend as an important component, I also expect that the significance of the unemployment rate as an explanatory power will be reduced.) The year-specific effects trace out a secular upward trend in the poverty rate throughout this period. The coefficient on median real household income is little changed, but the coefficient on the unemployment rate declines (and standard deviation of the coefficient rises) with the introduction of these competing time-specific regressors. Column (3) introduces county-specific differences in the poverty rate but removes the time-specific effects. This should have the same effect on y_{jt} as the year-specific effects of column (2) had on u_{jt}: if median real household income does not embody all county-specific differences in poverty rate, these county effects will do so. As the coefficients of column (3) indicate, coefficients on both y_{jt} and u_{jt} retain their magnitudes and significance, and adding the county-level effects raises the percent of the explained variation in p_{jt} to 0.88. In column (4) both county-specific and year-specific effects are included: this reduces the coefficients on both y_{jt} and u_{jt}, making the latter insignificantly different from zero. My preferred specification of the four will be column (3), as I believe that columns (2) and (4) overfit the time-series dimension by including at the same time both u_{jt} and the year-specific variables.

Structural differences in poverty across counties are evident from the county-specific effects from column (3), but they paint a quite different picture of structural poverty in North Carolina. Once we control for the effects of median real household income and the unemployment rate in each county on the poverty rate, what is the remaining poverty-rate difference? I report the largest positive and negative coefficients from the 100 counties in Figure 6, recalling that these are defined relative to a zero value for Yancey County.[17] The negative coefficients (for Ashe, McDowell, Cherokee, Mitchell and Rockingham counties) indicate that once the median real household income and unemployment rates of the counties are accounted for, the underlying

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[16] This effect is in addition to the impact of the u_{jt} in lowering y_{jt}. I return to that in the next section.

[17] I excluded those coefficients between -1 and +3 for illustrative purposes, but those are available on demand. The counties are identified by the first four letters of their names.

poverty rate is lower than in Yancey County. For the positive coefficients (among the largest being Durham, Orange, Mecklenburg, and Wake counties), the underlying poverty rate is larger than in Yancey County.

This is an odd finding, given that the observed poverty rate in Wake County (for example) is roughly half of that in Yancey County. Table 4 illustrates its derivation. The actual poverty rate is the average for the period 2001-2011 in the two counties, and Wake (at 9.1) is roughly half of Yancey (at 17.5). The average unemployment rate in Wake was also about half of that in Yancey County, while the median real household income in Wake was roughly double that of Yancey County. When I use the coefficients of Table 3, column 3 to predict the poverty rate for the two counties, I obtain the predicted poverty rate of the table below with Wake at 1.5 and Yancey at 17.5. Put differently, given Wake's advantages in terms of higher median real household income and lower unemployment rate, I predict a poverty rate of only 1.5 percent. Given the actual rate of 9.1, the adjusted poverty rate is 7.6 percent. For Yancey County, a similar calculation yields (by construction) an adjusted poverty rate of 0. The adjusted poverty rates for North Carolina counties calculated in this way are the statistics reported in Figure 6.

The concentration of the most urban counties among those with highest adjusted poverty indices is surprising. It is consistent, though, with the findings of the Center for Poverty, Work and Opportunity (2010) of large pockets of urban poverty. The calculations reported in Tables 3 and 4 and illustrated in Figure 6 identify large percentages of households in these more affluent counties that have not shared in the affluence. The mantra "the rising tide lifts all boats" is negated here – counties such as Wake and Mecklenburg have the high median household income and low unemployment rate necessary to "lift all boats", but the observed poverty rates remain stubbornly high.

The impact of increased unemployment on poverty.

The calculations reported in Tables 1 through 3 indicate the cyclic role of unemployment on the poverty rate in North Carolina. In this section I illustrate the implications of a 6 percentage-point increase in unemployment rate on the poverty rate.

Increasing the unemployment rate affects the poverty rate through two channels. First, it shifts down the income distribution: we should observe median real household income fall by $2500 for the unemployment-rate increase. This $2500 fall in y_{jt} is associated with a 1.6 percentage-point increase in the poverty rate. Second, it skews the distribution towards the lower incomes (and thus increased poverty) for given median real household income: we should observe the poverty rate rise by nearly 2 percentage points through this channel. Increasing the unemployment rate by 6 percentage points, then, increases the poverty rate by 3.6 percentage points through these two channels, or about 132,000 households in North Carolina in 2013.

There is a third channel as well: increased unemployment also increases the provision of unemployment-insurance payments. Given the calculations of Table 1, the weekly claims ratio will rise by 2.4 percentage points, and this will (by Table 2) increase median real household income by 0.75 percentage points and thus reduce the poverty rate by 0.5 percentage points, or 18,300 households.

This last calculation yields an identical result to that derivable from the Current Population Survey of the US Census Bureau for 2012.[18] Table 5 reports some detail on poverty at the national level. The poverty rate in the national sample was 15.0 percent in 2012, while in the North Carolina subsample the poverty rate was 17.2 percent. Poverty was relatively concentrated in the young, with 21.8 percent of those under 18 in the national sample (and 24.7 of those in the North Carolina subsample) living in poverty in that year. Poverty rates in both samples decline with the age of the respondent. Comparison of the second and third columns of Table 5 provide the answer to the counterfactual: what percent of those responding to the survey would be thrown into poverty if they did not receive Unemployment Insurance benefits? The answer is evident there: 0.5 percent of the population. This benefit is concentrated in the below-65 age groups, as Unemployment Insurance is relatively unimportant for those of retirement age.

Attributing the systemic county-specific differences in poverty.

The evolution of real household income and the unemployment rate over time provide strong explanations for the evolution of poverty, but leave other cross-county explanations of poverty largely unaddressed. The county-specific differences in poverty rate can be attributed in part to the systemic differences across counties in 1990; in this section I introduce two explanations to check their validity.

Immigration. There is a persistent belief that an inflow of immigrants, especially Hispanic immigrants from Central America and Mexico, has contributed to poverty on a national level. Samuelson (2007) gave voice to this in an opinion piece entitled "Importing Poverty" in which he stated "Only an act of willful denial can separate immigration and poverty". North Carolina has been a leader among states in the growth rate of Hispanic migrants; one explanation of poverty growth in recent years might be found in the growth of these migrants.

[18] The following calculations were performed using the CPS Table Creator on the CPS of 2013 at http://www.census.gov/cps/data/cpstablecreator.html, accessed 27 November 2013.

Loss of manufacturing jobs. North Carolina was the "manufacturing state" of the last quarter of the 20th Century. When measured by employment in manufactures as a share of total employment, North Carolina ranked first among states until the mid-1990s. From that time on, however, North Carolina has been shedding manufacturing jobs at a more rapid rate than other states. This loss of manufacturing jobs necessitates a transition among former manufacturing workers that can mean extended retraining and income loss for affected workers.

A cross-sectional analysis. As an initial step in analyzing the evolution of poverty, I consider a cross-section of four county-level variables: the change in poverty rate by county from 2000 to 2011 (pov_ch), the share of Hispanics in the population in 2000 ($HispShr_{2000}$), the share of employment in manufacturing by county in 2000 ($ManuShr_{2000}$), and the growth of manufacturing employment by county during the period 1990-2000 ($ManuGro_{1990\text{-}2000}$).[19] If there were direct causal effects of these initial conditions on the evolution of poverty in 2000-2011, I expect it to appear in the correlations of these variables. In Table 6 I present the Pearson bivariate correlations. Two important correlations to note:

- The observed change in poverty from 2000 to 2011 depends significantly only on the share of employment in manufacturing in 2000: the larger the share, the greater the change in poverty.
- The share of manufacturing employment in 2000 was positively correlated with the Hispanic share of the population in 2000. The greater the share of employment in manufacturing, the greater the Hispanic share in population. This perhaps reflects the incentives to migrate: the pull of counties with a high percentage of jobs in manufacturing will be greater than the pull of counties with a lower percentage of manufacturing jobs. This effect is evident as well, albeit insignificantly, in the correlation of Hispanic share with the growth in manufacturing jobs in the previous decade.

Table 7 reports the partial correlations among these four variables generated in a regression of the change in poverty on the three "initial conditions". The share of employment in manufacturing in 2000 has a positive and significant correlation, as in Table 6. The partial contributions of $HispShr_{2000}$ and $ManuGro_{1990\text{-}2000}$ are both negative and insignificant. These three initial conditions explain only 11 percent of the variation in the aggregate change in poverty over the period. They also leave unidentified the channel by which each variable might have its effect. For that reason, we turn to extending the dynamic panel regression of Table 3.

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[19] I also considered the growth of the Hispanic population by county in the period 1990-2000 ($HispGro_{1990\text{-}2000}$), but found it to have a 0.96 correlation with $HispShr_{2000}$. It is excluded from Table 6 for that reason.

The dynamic analysis. Table 8 reports five equations that examine the contributions of immigration and manufacturing job loss to the incidence of poverty. The first column reproduces column 3 of Table 3 and represents an explanation for the time-series variation in the county-level poverty rate. The second column reports the incremental impact of $HispShr_{2000}$. The correlation is insignificantly different from zero, and takes the sign of the cross-section coefficient in Table 7: a one percent increase in the Hispanic share of the population is associated with a 0.11 percent reduction in the county poverty rate. The Hispanic share of the population was higher, other things equal, in counties with lower poverty during this period. The third column considers a similar exercise for $ManuShr_{2000}$. This coefficient is also insignificant and negative at -0.11 – a one-percent rise in the share of manufacturing jobs in total employment lowers the poverty rate by 0.11 percentage points. This is a reversal of the result of Table 7, and is due to the fact that in this regression I model explicitly the role played by the unemployment rate. Countries with larger manufacturing sectors in 2000 will have higher unemployment rates in the period 2000-2010, and that effect dominates the result of Tables 6 and 7.

When the two variables are introduced together in column four, both coefficients are significantly different from zero. Counties with larger Hispanic share have larger poverty rates: a one percentage-point increase in Hispanic share is associated with a 0.25 percentage point increase in poverty rate. By contrast (and consistent with priors), a one percentage-point reduction in the share of employment in manufacturing in the county is associated with a 0.36 percentage-point increase in the county-wide poverty rate.

In the fifth column, I introduce $ManuGro_{1990\text{-}2000}$ in addition to the previous two variables. The coefficient on $ManuShr_{2000}$ changes little and remains significantly different from zero at -0.33. The coefficient on $HispShr_{2000}$ rises to 1.04, indicating a stronger positive association of poverty with the share of Hispanics in county population. A one percentage-point reduction in manufacturing employment over the previous decade is associated with a 0.33 percentage-point increase in poverty, other things equal.

Throughout this set of regressions the coefficients on y_{jt} and u_{jt} remain remarkably stable at -0.67 and 0.34, respectively.

Conclusions.

The first finding of this study is one that didn't require such involved econometrics: the increased unemployment rate in North Carolina in the past two years has contributed to pushing large numbers of residents into the ranks of the poor. The point estimate from this study suggests that over 200,000 North Carolina residents had their income fall below the poverty line due to the impact of unemployment.

The second finding relates to the importance of the unemployment insurance program. The econometric results reported here indicate that an additional 18,300 households would have found themselves in poverty without their access to the unemployment insurance payments. The state's Trust Fund has gone deeply into debt to do this, but this has been of benefit for those unemployed who have received it. The decision to reform this program, and the way in which it has been reformed, will accordingly increase the number of households below the poverty line.

The third finding is a quantification of the county-specific composition of poverty. County-specific differences prove to be significant and important in explaining poverty in North Carolina. The derivation of this paper provides an adjusted poverty rate that controls for differences in income and unemployment rate, and that identifies urban counties in North Carolina as pockets of structural poverty. Three characteristics are shown to be significantly associated with this county-specific poverty: the share of Hispanics in the population, the share of manufacturing employment within total employment, and the growth of the share of manufacturing employment in the period 1990-2000.

The fourth finding points to the limits of unemployment explanations for poverty. There was a 3.6 percentage-point increase in the poverty rate from 2007 to 2011 and the estimations here explain only 1.9 percentage points of this through the effects of the increase in the unemployment rate. Moreover, this explanation counts for only a small share of the 2.6 percentage-point increase in the poverty rate between 2000 and 2007. It is not enough to focus simply on renewing employment in order to restore the previous lower poverty rate. It will be important to identify the other cyclic factors that have contributed to this run-up in poverty so that they too can be addressed and eliminated as the state economy recovers. There is a danger that relying solely on the re-establishment of low unemployment rates to fight poverty will lead to a "stair-step" recovery, with higher poverty rates after each recession.

Other results in this analysis suggest directions for further research. The secular decline in real household income is a robust predictor of the increase in poverty in both 2000-2007 and 2007-2011. This is not a double-counting of the loss in real income due to unemployment, but the fall in household income for households employed throughout the period. Providing an explanation for this phenomenon is beyond the scope of this paper, but is of critical importance to our state's structural transition.

The estimation technique of this paper does not identify the causes of the remaining rise in the poverty rate in the 2000s. I conjecture, however, that the root will be found in the productive transformation underway in North Carolina. After a century of reliance upon light manufactures (textiles, apparel, furniture) for employment, the North Carolina economy is in transition to a new mix of productive enterprises. This transition is characterized by layoffs and plant closings in the light manufacturing sector, a product of technological improvement and foreign competition. (Conway (2009) has an analysis of this for the textiles sector.) The workers from light manufactures have found it difficult to start again in the new economy. This is a plausible cause of the unexplained rise in the poverty rate reported here, and is a next step on this research agenda.

Table 1: The Unemployment Rate and Weekly Claims Ratio			
Dependent variable: weekly claims ratio (w_{jt})			
	(1)	(2)	(3)
Intercept	0.84	0.73	3.08
	(0.18)	(0.41)	(0.37)
u_{jt}	0.37	0.52	0.39
	(0.02)	(0.06)	(0.05)
D_{2002}		-0.81	-0.71
		(0.11)	(0.11)
D_{2003}		-0.69	-0.63
		(0.10)	(0.10)
D_{2004}		-1.01	-1.07
		(0.12)	(0.12)
D_{2005}		-0.70	-0.79
		(0.11)	(0.12)
D_{2006}		-0.58	-0.74
		(0.13)	(0.12)
D_{2007}		-0.52	-0.68
		(0.14)	(0.13)
D_{2008}		-0.99	-0.94
		(0.12)	(0.12)
D_{2009}		-0.59	-0.01
		(0.32)	(0.26)
D_{2010}		-2.20	-1.57
		(0.35)	(0.29)
D_{2011}		-2.28	-1.70
		(0.32)	(0.27)
D_{2012}		-2.08	-1.58
		(0.27)	(0.22)
County effects	N	N	Y
N	1198	1198	1198
R^2	0.31	0.40	0.81
RMSE	1.5591	1.4587	0.8458

Excluded year dummy (in columns (2) and (3)): D2001; excluded county dummy (in column (3): Yancey County. County-clustered White standard errors in parentheses.

Table 2: Median (real) household income				
Dependent variable: median real household income (y_{jt}), in				
	(1)	(2)	(3)	(4)
Intercept	37.38	43.92	28.66	28.58
	(1.01)	(1.74)	(0.39)	(0.53)
u_{jt}	-0.76	-1.46	-0.42	-0.31
	(0.09)	(0.16)	(0.02)	(0.08)
w_{jt}	-0.18	-0.18	0.34	0.26
	(0.22)	(0.22)	(0.04)	(0.07)
D_{2002}		-1.39		-0.14
		(0.25)		(0.09)
D_{2003}		-1.88		-0.28
		(0.30)		(0.10)
D_{2004}		-3.28		-0.24
		(0.48)		(0.15)
D_{2005}		-4.03		-0.78
		(0.54)		(0.19)
D_{2006}		-4.49		-0.58
		(0.60)		(0.201)
D_{2007}		-3.94		-0.01
		(0.60)		(0.21)
D_{2008}		-1.70		0.13
		(0.36)		(0.22)
D_{2009}		3.52		-0.66
		(0.53)		(0.36)
D_{2010}		3.51		-0.43
		(0.44)		(0.43)
D_{2011}				-1.29
				(0.41)
County effects	N	N	Y	Y
N	1099	1099	1099	1099
R^2	0.19	0.30	0.96	0.96
RMSE	4.9055	4.5805	1.32	1.0987

Excluded year dummy (in columns (2) and (3)): D2001; excluded county dummy (in column (3): Yancey County. County-clustered White standard errors in parentheses.

Table 3: Poverty Rate				
Dependent variable: poverty rate (p_{jt})				
	(1)	(2)	(3)	(4)
Intercept	32.92	33.94	32.35	28.80
	(1.87)	(2.27)	(1.75)	(1.50)
y_{jt}	-0.61	-0.62	-0.66	-0.49
	(0.05)	(0.06)	(0.06)	(0.05)
u_{jt}	0.33	0.17	0.34	0.05
	(0.04)	(0.14)	(0.03)	(0.06)
D_{2001}		-1.26		-0.79
		(0.27)		(0.16)
D_{2002}		-1.02		-0.40
		(0.37)		(0.22)
D_{2003}		-0.93		-0.33
		(0.35)		(0.22)
D_{2004}		-0.20		0.27
		(0.23)		(0.18)
D_{2005}		1.32		1.82
		(0.22)		(0.22)
D_{2006}		1.42		1.82
		(0.20)		(0.20)
D_{2007}		1.40		1.71
		(0.18)		(0.19)
D_{2008}		1.53		2.07
		(0.33)		(0.24)
D_{2009}		1.37		2.60
		(0.85)		(0.49)
D_{2010}		2.01		3.32
		(0.95)		(0.50)
D_{2011}		2.04		3.41
		(0.87)		(0.49)
County effects	N	N	Y	Y
N	1200	1200	1200	1200
R^2	0.69	0.75	0.88	0.94
RMSE	2.5928	2.3559	1.6859	1.2268

Excluded year-specific dummy: 2000. Excluded county-specific dummy: Yancey County. County-clustered White standard errors in parentheses.

Table 4: Deriving the Adjusted Poverty Rate for Wake and Yancey Counties

	Wake County	Yancey County
Actual Average Poverty Rate	9.1	17.5
Average Unemployment Rate	5.6	8.8
Median Real Household Income (in thousands)	49.0	27.0
Predicted Poverty Rate	1.5	17.5
Adjusted poverty rate	7.6	0.0

Averages, for the years 2000-2011.

Table 5: Improvement in poverty rate due to Unemployment Insurance transfers in 2012

	Number in thousands	Poverty rate with UI	Poverty rate without UI
Total population in US survey	310548	15	15.5
Broken down by age in US			
Under 18	73719	21.8	22.4
From 18 to 64	193642	13.7	14.3
For 65 and older	43287	9.1	9.2
Total population in NC survey	9634	17.2	17.7
Broken down by age in NC			
Under 18	2330	24.7	25.2
From 18 to 64	5794	15.7	16.4
For 65 and older	1509	11.2	11.2

Source: Current Population Survey Table Creator, 2013.
The reduction in the poverty rate due to the availability of unemployment insurance

Table 6: Correlation of Cross-County Variables				
	$Pov\_ch_{2000\text{-}2010}$	$HispShr_{2000}$	$ManuShr_{2000}$	$ManuGro_{1990\text{-}2000}$
$Pov\_ch_{2000\text{-}2010}$	1.00	0.08	**0.35**	-0.02
$HispShr_{2000}$	0.08	1.00	**0.28**	0.11
$ManuShr_{2000}$	**0.35**	**0.28**	1.00	0.17
$ManuGro_{1990\text{-}2000}$	0.01	0.11	0.17	1.00

Bilateral Pearson correlations. Number of observations: (HispShr, Pov_ch): 100. (Pov_ch, ManuShr): 93. (Pov_ch, ManuGro): 91. (HispShr, ManuShr): 93. (HispShr, ManuGro): 91. (ManuShr, ManuGro): 91. Correlations significantly different from zero at 95 percent confidence level are in bold.

Table 7: Cross-sectional poverty regression:		
Dependent variable $Pov\_ch_{2000\text{-}2011}$		Coefficient
Constant		**4.65**
		(0.61)
$HispShr_{2000}$		-0.06
		(0.10)
$ManuShr_{2000}$		**0.07**
		(0.02)
$ManuGro_{1990\text{-}2000}$		-0.01
		(0.02)
N		101
R^2		0.11
F(3,101)		**3.69**

Table 8: Hispanic Migration, Erosion of Manufacturing and the Poverty Rate					
Dependent variable: poverty rate (p_{jt})					
	(1)	(2)	(3)	(4)	(5)
Intercept	32.35	32.64	35.72	42.87	38.36
	(1.75)	(1.57)	(0.71)	(1.38)	(1.91)
y_{jt}	-0.66	-0.66	-0. 65	-0.65	-0.67
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
u_{jt}	0.34	0.34	0.35	0.35	0.34
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$HispShr_{2000}$		-0.11		0.25	1.04
		(0.07)		(0.06)	(0.02)
$ManuShr_{2000}$			-0.11	-0.36	-0.33
			(0.07)	(0.01)	(0.01)
$ManuGro_{1990\text{-}2000}$					-0.12
					(0.01)
County effects	Y	Y	Y	Y	Y
N	1200	1200	1164	1164	1140
R^2	0.88	0.88	0.88	0.88	0.88

Yancey is the excluded county in columns (1), (2), and (3); Yancey and Yadkin are excluded counties in equation (5).

Figure 1: Poverty Rate for North Carolina

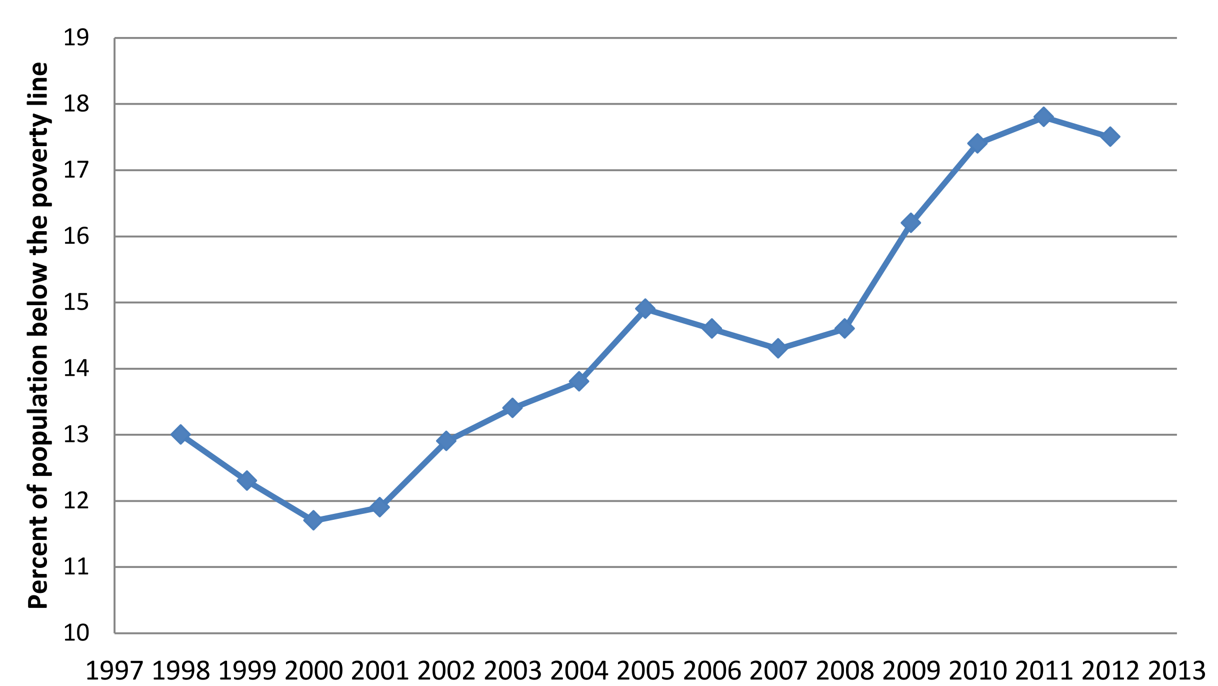


Figure 2: Poverty Rate by State

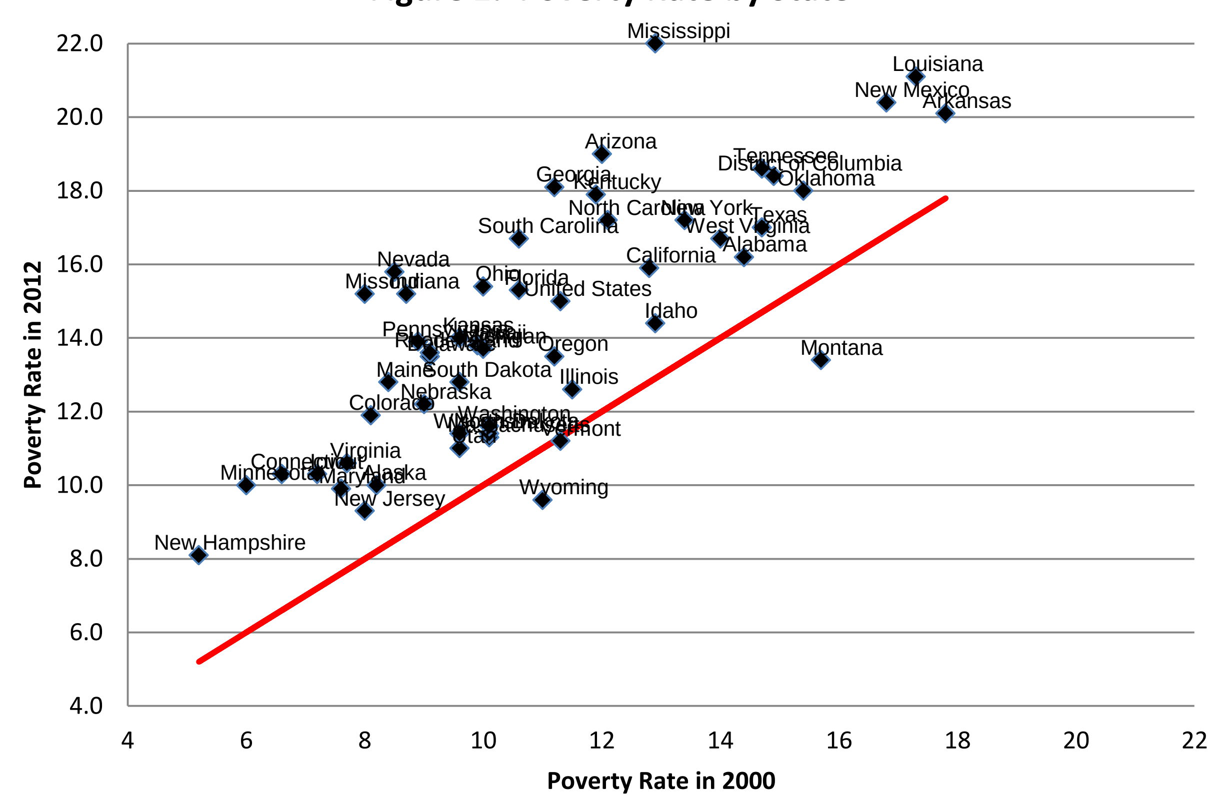


Figure 3: Federal Unemployment Insurance Trust Fund Indebtedness in October 2013

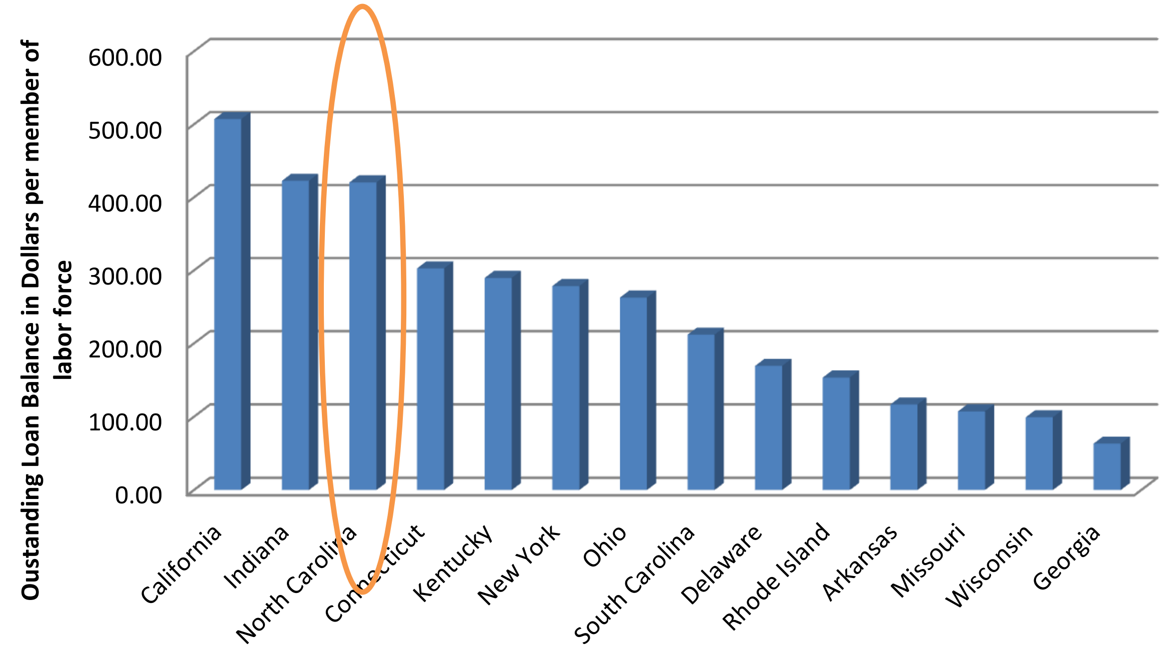


Figure 4: Weekly Claims Ratio and Unemployment Rate in North Carolina

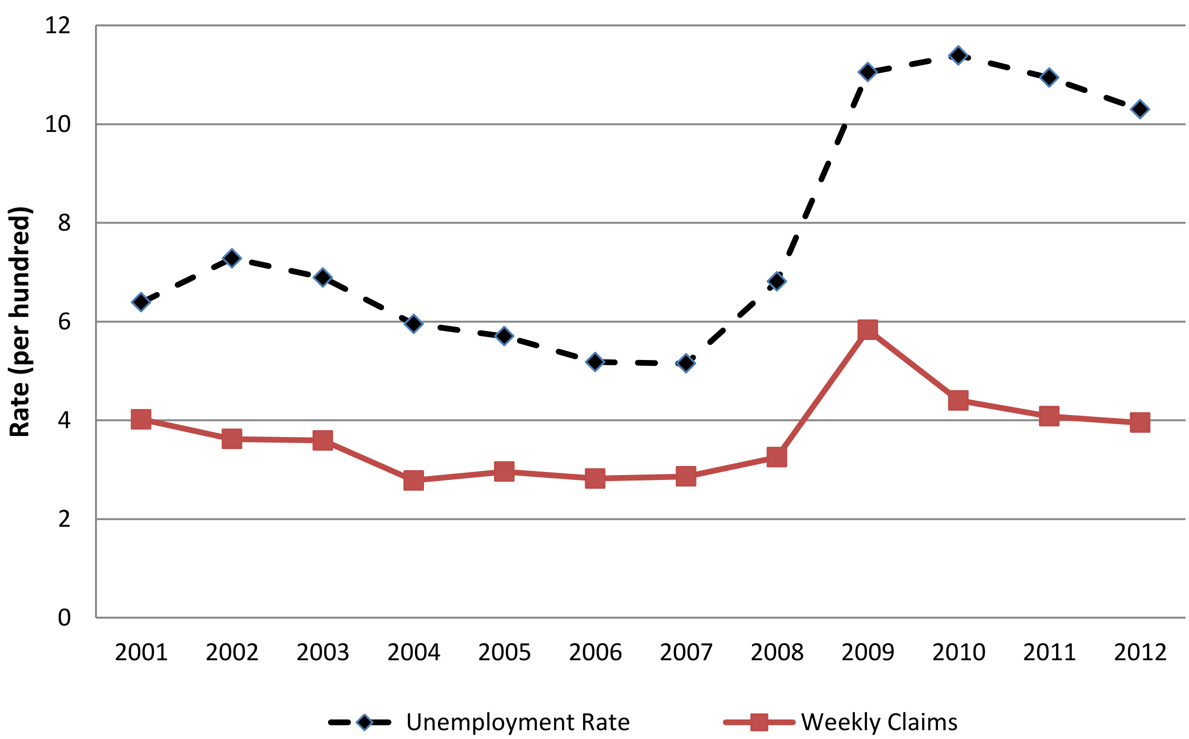


Figure 5: Real Median Household Income in North Carolina

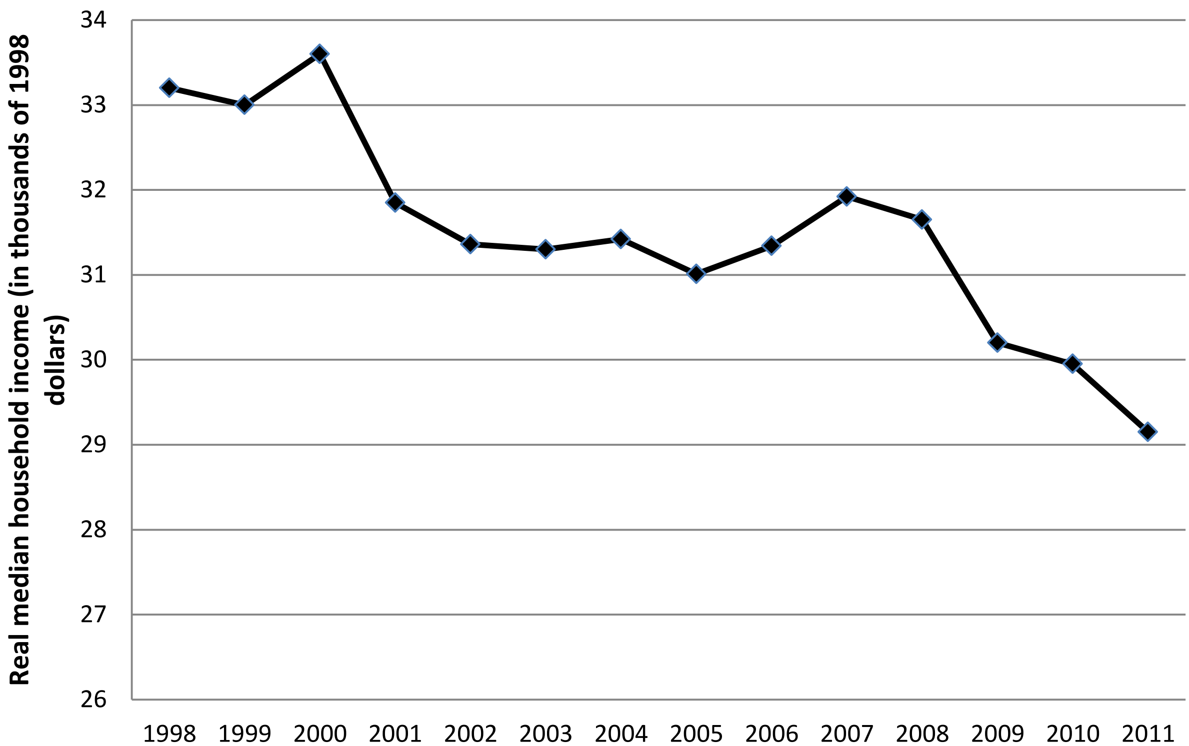
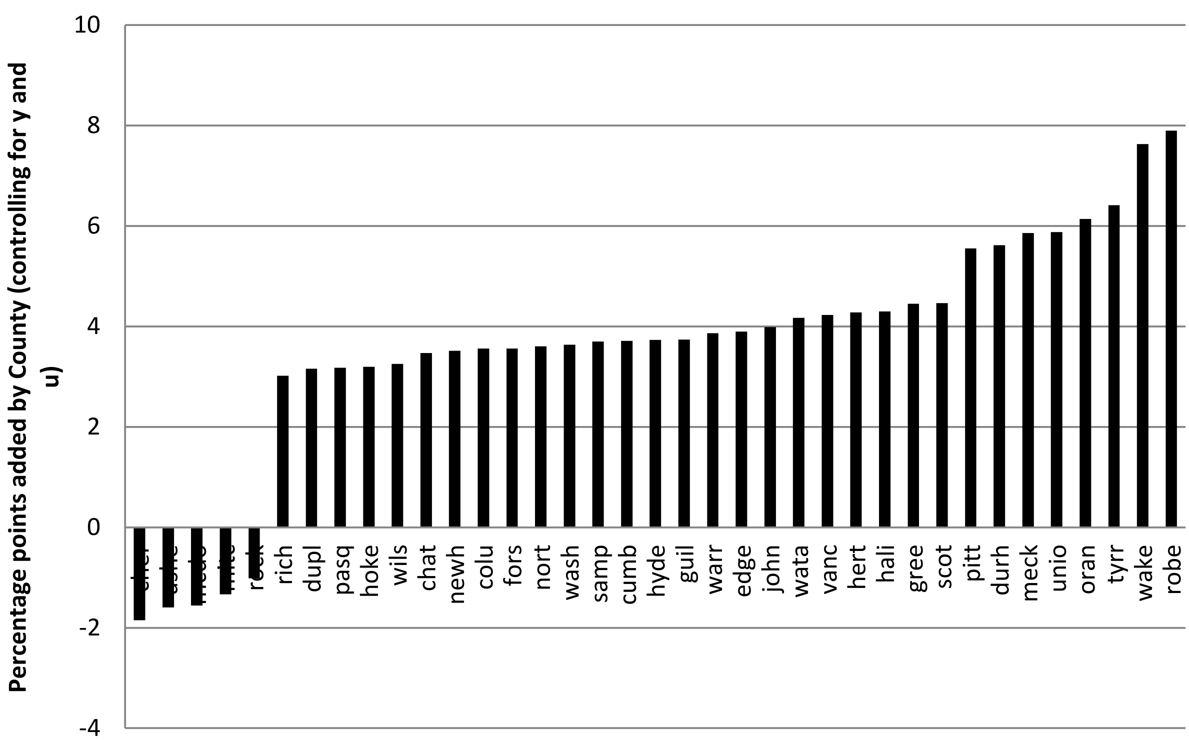


Figure 6: County-specific Components of NC Poverty Rate



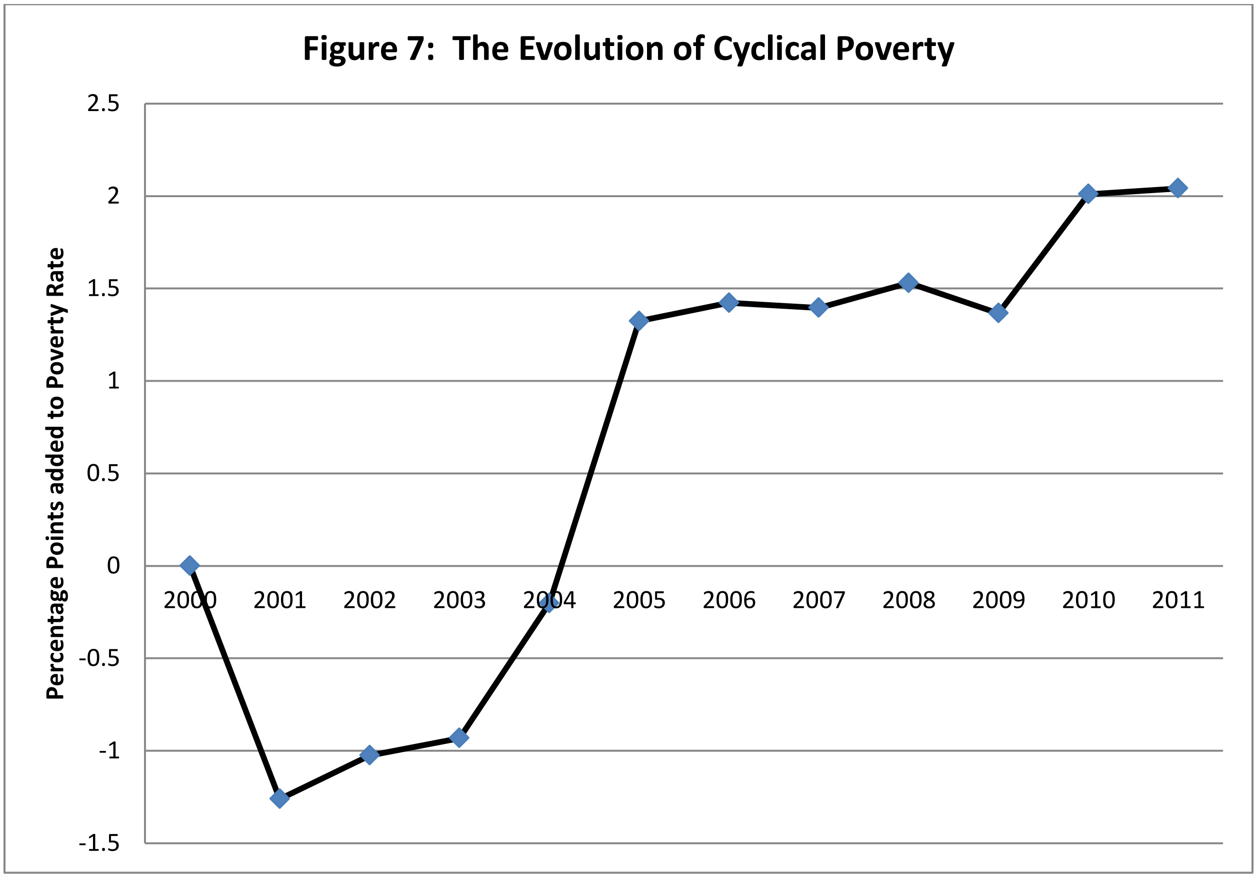


Figure 7: The Evolution of Cyclical Poverty
Percentage Points added to Poverty Rate
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011

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US Census Bureau: Poverty Statistics of Decennial Censes, by State. Table CPH-L-162. PERSONS BY POVERTY STATUS IN 1959, 1969, 1979, 1989, AND 1999 BY STATE. http://www.census.gov/hhes/www/poverty/data/census/1960/index.html

Appendix: **Derivation of Estimating Equations Using a Specific Income Distribution**

I illustrate the comparative statics discussed in the paper through use of the Pareto distribution.[20] Consider household income indexed by z and defined on the range of household incomes with lower bound of 1. There is a county-specific component to median household income, κ_j, that will for higher values indicate proportionally higher household incomes in that county. There is also a shape parameter μ, assumed to be shared by all counties. Figure 6 illustrates this distribution for μ=.25; note the greater density at the lower values of incomes z. Using this parameterization, the probability density becomes

$$f_j(z) = \mu/z^{\mu+1} \qquad \text{with shape parameter } \mu \tag{1}$$

$$y_{jt} = \kappa_{jt}\,(.5)^{-1/\mu} \tag{2}$$

and

$$p_{jt} = F(p^o/\kappa_{jt}) = 1- (\kappa_{jt}/p^o)^{\mu} = 1 - 2(y_{jt}/p^o)^{\mu} \tag{3}$$

The median real household income y_{jt} is calculated for this distribution in (2), and as is evident there can be used to identify those county-specific differences in income κ_{jt}. The poverty rate for the Pareto distribution is given in (3), and the third equality substitutes the median real household income for κ_{jt}. The evolution of y_{jt} and p_{jt} over time is described in (4) and (5).

$$dy_{jt} = (\kappa_{jt}\,(.5)^{-1/\mu})[d\kappa_{jt}/\kappa_{jt} + (\ln(.5)/\mu)\, d\mu/\mu] \tag{4}$$

$$dp_{jt} = (y_{jt}/p^o)^{\mu}\,\{2\ln(y_{jt}/p^o)\, d\mu - \mu\, [(dy_{jt}/y_{jt}) - dp^o/p^o]\} \tag{5}$$

Equation (4) indicates that county median real household income will be larger with higher κ_{jt}; it will be smaller as μ rises (and the distribution becomes more skewed towards lower incomes). The poverty rate in (5) will be lower for counties with higher y_{jt} and will rise as the poverty line rises. The poverty rate will also rise as μ rises for given $y_{jt.}$

[20] Pareto (1964) introduced this distribution to explain the large concentration of the population at the low end of the wealth and income distributions. Clementi and Gallegati (2005) demonstrate that it is a preferred approximation to the upper tail of the observed distribution in the US, UK and Germany, while the lower portion of the distribution is better represented by a log-normal distribution. I use the Pareto distribution for the entire economy here because of the ease of illustrating the differing roles of distribution central tendency (y_{jt}) and shape (μ).

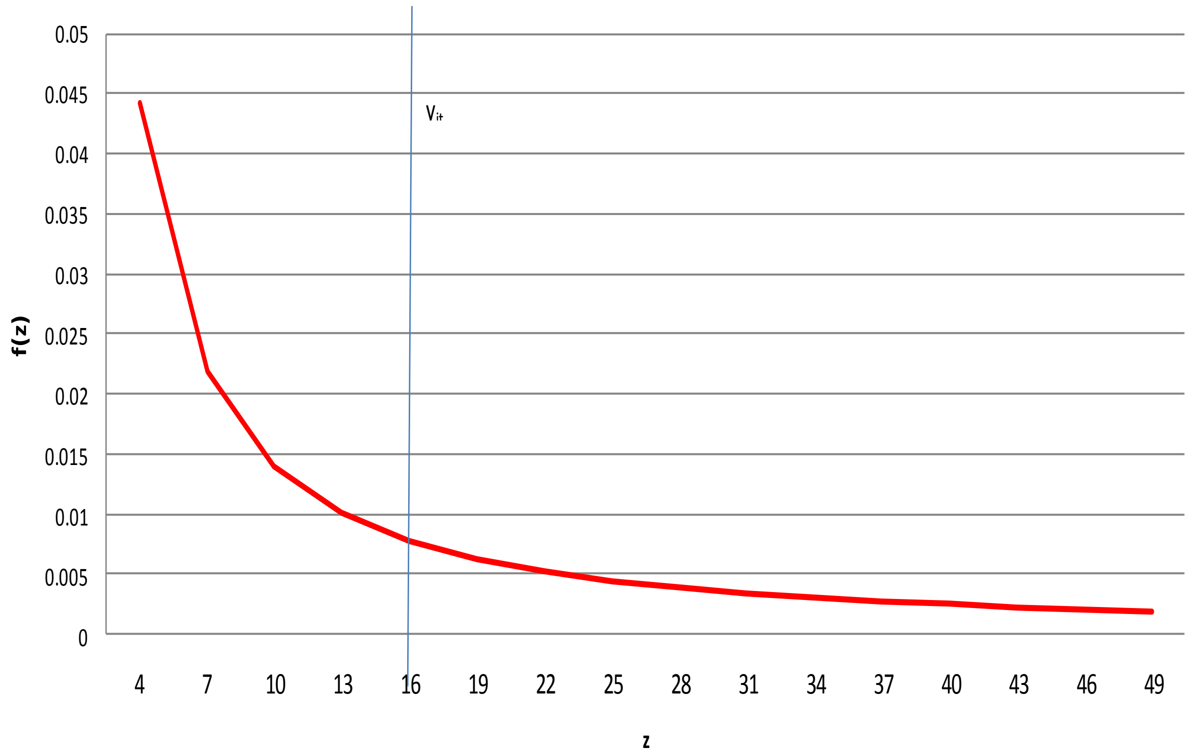

Figure A1: Pareto Distribution of Household Income (μ=.25)