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T M Tonmoy Islam
University of Kentucky, tmisla2@uky.edu

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T M Tonmoy Islam, Student

Dr. James P. Ziliak, Major Professor

Dr. Aaron Yelowitz, Director of Graduate Studies

ESSAYS ON THE PERSISTENCE OF POVERTY

DISSERTATION

A dissertation submitted in partial fulfillment of the
Requirements for the degree of Doctor of Philosophy in the
College of Business and Economics
at the University of Kentucky

By
T M Tonmoy Islam
Lexington, KY

Director: Dr. James P. Ziliak, Carol Martin Gatton Chair in Microeconomics
and
Director, University of Kentucky Center for Poverty Research

Lexington, KY

2012

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ABSTRACT OF DISSERTATION

ESSAYS ON THE PERSISTENCE OF POVERTY

My dissertation investigates the reasons behind the persistence of income among individuals and US counties. I look at the role of initial conditions in explaining current level of income. In my first essay, I look at how childhood neighborhood conditions affect income of a person. To study persistence, I model income as an autoregressive process where the coefficient on the lagged dependent variable heterogeneous across individuals. In my second essay, I derive a new way to measure chronic poverty, or long term poverty. Current measures of chronic poverty cannot be used to compare improvements of poverty rates over time. Using my measure, one can compare to see if chronic poverty rates changed over time. My third essay looks at the historical reasons behind differences in income between rich and poor counties in the US. There are about 250 counties in the US where poverty rates have been above 20 percent for the last 40 years. I look at whether current and past factors, or differences in technologies is the main reason behind persistence of high rates of poverty in these counties.

Overall, I find that childhood neighborhood conditions have a big effect in determining the coefficient on the lagged dependent variable, that is, childhood neighborhood conditions affect persistence of income. I find that improving neighborhood poverty rates by one percentage point and father's education by one year bring the greatest improvement of social welfare. In my second essay, I show the importance of measuring chronic poverty separately from total poverty; for example, between 2000 and 2005, total poverty declined, but chronic poverty rates actually increased, which shows that the long-term poor got worse off during that time period. In my last essay, I find that some US counties remained poor mainly because of differences in factor endowment, and past and present levels of human capital explain most of the differences in current level of income between poor and non-poor counties. Differences in factor endowments explained 80 percent of income between poor and non-poor counties, while technology accounted for only 20 percent of the difference.

KEYWORDS: Persistence of Income; Childhood Neighborhood; Persistence of Poverty; Chronic Poverty; Growth Regression

T M Tonmoy Islam

July 31, 2012

Date

ESSAYS ON THE PERSISTENCE OF POVERTY

By

T M Tonmoy Islam

Dr. James P. Ziliak

_____

Director of Dissertation

Dr. Aaron Yelowitz

_____

Director of Graduate Studies

July 31, 2012

_____

Date

To my parents, T M Tajul Islam and Tauhida Islam, and their parents

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1 INTRODUCTION

The topic of income and poverty is of crucial interest for both economists and policymakers because analyzing them can help to understand why individuals remain poor and what can be done to improve their earnings. The essays of my dissertation investigates whether historical factors have an influence on current levels of income of a person or a region. One of the goals of the government is to ensure a higher standard of living in the community, which can be obtained by increasing income earned by individuals. Understanding what initial factors affect income and poverty can help policymakers craft policies that can help to increase income of individuals. Two of the papers of my dissertation look at how historical factors affect both individual income and average income of sub-national regions within the US. The results do indicate that historical variables can influence current level of income. My other paper formulates a new way to measure long-term poverty, or chronic poverty, of individuals and highlights the necessity of measuring chronic poverty separately from total poverty in a region.

Usually, different versions of an income equation, where the dependent variable is earned income and independent variables are different individual characteristics, are used to understand income generation process of an entity, such as a person or a region. These studies put forward many different factors that are important in explaining low income or poverty in a person or a region. However, most papers use current levels of individual traits to explain the persistence of income and poverty, and they seldom look beyond these current levels to see why an entity is earning a low income. In my dissertation, I follow a similar path and investigate the reasons behind persistence of income and poverty – that is, why do certain entities have low (or high) levels of income for long

periods of time. However, instead of just considering current factors, I also look at the initial causes of income disparity – that is, what are the historical reasons behind the current level of income of an entity.

My first and third essays study income at the individual and at the US county levels respectively. In the first essay of my dissertation, which is essay 2, I investigate how childhood neighborhood quality affects income earned as an adult. The values of a person are shaped by the place where they spend their childhood, and so, I look at how these childhood neighborhood characteristics affect income fluctuations over time. As an exercise, I also look at which of these childhood neighborhood variables affect adult income the most. In my second essay, which is essay 3, I look at a new way to measure chronic poverty, or long-term poverty. This measure is an improvement on the current measures available to measure long-term poverty, in that it allows a researcher to see if individual well-being is improving over time - something that cannot be done using the prevalent long-term poverty measures. The last essay of my dissertation, which is chapter four, investigates the historical reasons behind low income in certain counties in the US. These low-income counties have poverty rates of over 20 percent or more for the last 40 years, and I look at whether there is a historical basis to explain such low levels of income in those counties.

2 CHILDHOOD NEIGHBORHOOD CONDITIONS AND THE PERSISTENCE OF ADULT INCOME

2.1 Introduction

Understanding income dynamics is a big research agenda for labor economists, and a result, a huge literature has emerged explaining individual evolution of income over time. A number of papers have shown that unfavorable neighborhood conditions can adversely affect various individual outcomes such as income, education attainment, delinquency rates and IQ scores (Aaronson, 1998; Brooks-Gunn et al., 1993; Crane, 1991; Cutler and Glaeser, 1997; Datcher, 1982; Duncan, 1994; Galster et al., 2007; Peeples and Loebler, 1994; Plotnick and Hoffman, 1999). Identifying the childhood neighborhood and family variables that have the largest impact on individual outcomes have become an important research agenda, because growing up in adverse conditions can potentially have serious macroeconomic consequences. For example, Holzer, et al (2007) estimate that children growing up in poor households cost the US about $500 billion annually. Thus far, researchers have only focused on how family background and childhood neighborhood quality affect the level of individual income (Corcoran et al., 1992; Datcher, 1982; Galster et al., 2007, Lee and Solon, 2009; Mazumder, 2005; Solon, 1992; Solon et al., 2000; Zimmerman, 1992). However, persistence can be important in explaining income. Besides using it to calculate the long-run coefficients in an income equation, persistence of income can also explain phenomena such as the likelihood of an individual to be trapped in a low-income trap, and the speed of adjustment of individual income when hit by an adverse shock. Analyzing income persistence can help researchers determine the underlying factors influencing these phenomena. While the existing

literature indicates a relationship between childhood neighborhood quality and individual outcomes, there is little evidence showing how neighborhood and family characteristics affect income persistence. My research fills that void and shows that childhood neighborhood characteristics can affect the level and persistence of income, after controlling for different individual and family characteristics.

While explaining individual outcomes, most of the literature emphasizes the importance of family characteristics over childhood neighborhood quality (among many, Solon et al, 2000, Page and Solon, 2003a). However, there are some papers showing or inferring the link between neighborhood quality and individual outcomes. Neighborhood variables can affect spells of poverty (Quillen, 2003), and people who suffer from poverty in their adult life have lived in lower-quality neighborhoods during childhood (Brooks-Gunn et al., 1993). Poorer quality neighborhoods can also increase delinquency among boys and reduce graduation rates (Aaronson, 1998; Cutler and Glaeser, 1997; Datcher, 1982; Duncan, 1994; Peeples and Loeber, 1994), which indicates that human capital accumulation can be affected by the quality of neighborhood where a person grows up. Alesina et al (1999) shows that the composition of a neighborhood can affect the availability of public services, such as good roads and schooling, in that neighborhood. However, improving neighborhood quality may not have the desired effect in the short run as shown by the Moving to Opportunity (MTO) experiment. The MTO was a randomized trial that moved some families from neighborhoods with high rates of poverty and crime to those with lower rates of poverty and crime. The preliminary investigation of the MTO did not show any significant effect on earnings, employment or welfare receipts of the household head; but indicators of well-being such as health

showed some improvement when compared to that of the control group (Katz et al., 2001; Ludwig et al., 2008). In the short run, the MTO reduced youth crime among girls, but the result for boys was mixed (Kling et al, 2005). The long-term effect of the MTO has not been studied yet, since it is a relatively new experiment. Even though none of the abovementioned studies exclusively look at how childhood neighborhood quality affects income persistence, overall, they indicate that neighborhood quality during childhood can be important in determining adult income directly, or indirectly through human capital accumulation.

In this chapter, I study individual income equation by modeling it as an autoregressive process. I introduce individual-level heterogeneity on the coefficient of the lagged dependent variable by making it a correlated random coefficient (Altonji and Dunn, 1996b; Heckman and Vytlacil, 1998). I parameterize this coefficient using different childhood neighborhood and family variables, making it possible to indicate which variables influence income persistence. I apply a two-step generalized method of moments (GMM) estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) on the Survey Research Center (SRC) section of the Panel Study of Income Dynamics (PSID) data to estimate my model of income persistence. The PSID is a long panel containing data on many individual and family-level characteristics. It interviewed 5000 families in the year 1968 and continues to interview them today, including the offspring who left the original family unit of 1968 and created their own families. It also has sensitive geocodes of an individual's place of residence during childhood and adulthood which can be used to match local macroeconomic data (from the Census Bureau) with individual characteristics. All these information allows a researcher to link individual level data with

parents' data and the place of their current and past residence. With all these data, I look at how childhood neighborhood characteristics affect the persistence of income, how this persistence coefficient vary by income group, and which neighborhood variables affect income the most.

My results indicate that besides family characteristics, certain childhood neighborhood variables not only affect the level of income of a person, but also its persistence. The baseline model shows that education level in the childhood neighborhood affects both the level and the persistence of income. When the persistence coefficient is homogeneous across individuals, father's education is positive and significant in affecting the level of income, however it loses its significance when heterogeneity is introduced in the persistence coefficient. Poverty rate in childhood neighborhood affects the level of income negatively and significantly, but not the persistence. The average value of persistence is about 0.26, but when I disaggregate it by income levels, I find that poorer members of the income distribution have a higher persistence of income (about 0.34, compared to around 0.25 of those in the top 50% of the income distribution). This shows that the poor take a longer time to recover from a negative shock when compared to the rich. Also, because of heterogeneity of persistence by income group, the long-run coefficients are also different for different income group. The poor have a higher magnitude of long-run coefficients than the rich, implying that the poor are more susceptible to changes in the macroeconomic conditions than the rich. It would have been more beneficial for the poor if they had a lower persistence of income. For example, I find that the long run coefficient of current unemployment rate for

individuals in the bottom 25% of the income distribution to be almost -4.00 while that for the for the top 25% is around -3.50. Thus, even if the poor and the rich receive the same negative macroeconomic shock, the effect on the poor is much higher and persistent than that on the rich. I also run a number of sensitivity tests to test the validity of my results, and I find that the result from the baseline case remains generally valid.

To check which variable has a large effect on individual income, I run a series of tests where I slightly change each of the childhood neighborhood variables while holding others constant at their original values, and then I calculate the long-run income for each person. Using this data, I calculate the social welfare function of Sen (1976) and compare it with the baseline case. The results do appear to be dependent on the current state of the economy. If the current economic condition is bad, then concentrating on improving education level and poverty rate of childhood neighborhood can help to improve social welfare. In a healthy current macroeconomy, improving neighborhood poverty rate and unemployment rate would have helped to improve social welfare. Even though the coefficients on father's education are insignificant, increasing father's education by one year can help to improve social welfare in the long run, no matter what the future state of the economy. Overall, the exercise shows that reducing poverty rate by one percentage point and increasing father’s education by one year can help to improve social welfare the most, thus showing that improving neighborhood conditions can help to increase income and welfare of the society in the long run.

2.2 Review of Literature

State and national-level macroeconomy, along with anti-poverty policies, can have a strong effect on a family's propensity and severity of poverty (Gunderson and Ziliak, 2004). Thus, economic intuition would suggest that local environment can have an impact on individual income and poverty; however, as noted by Lewis (1966), researchers have focused more on using individual traits to explain income and poverty rather than family or community factors (Bane and Ellwood, 1986; Hansen and Wahlberg, 2009; Stevens, 1999). Bane and Ellwood (1986) study poverty spells of individuals using PSID and find that poverty spells can be pretty long. Stevens (1999) look at multiple poverty spells (that is, moving in and out of poverty continuously) of individuals after controlling for individual characteristics and find that individuals can move repeatedly in and out of poverty, but the longer a person is in poverty, the harder it is for them to leave poverty. Casual observation can show that a high-school graduate may earn above the poverty line during periods of an economic expansion, but may slip into poverty during an economic contraction. Although individual characteristics did not change over time, prevailing economic conditions can cause this person to slip in and out of poverty, which can have an impact on the well-being of their offspring. Provided that individuals were perfectly mobile geographically, they could sort themselves among neighborhood that they prefer the most or that which offers the most opportunities (Tiebout, 1956). However, Aaronson (1998) notes that households rarely move their residence due to differential abilities in the children that they have; and even when a family moves to a different neighborhood, they usually move to a neighborhood that has similar characteristics as the one before (Page and Solon, 2003b). There is also evidence that even if the poor move out of a poor neighborhood, they are more likely to move to

another poor neighborhood (Quillian, 2003), so they are, in effect, stuck in poverty-prone neighborhoods even if they change their residence periodically. Consequently, geographic immobility of adults, or their migration between places with similar neighborhood characteristics, can cause their children be trapped in bad neighborhoods, which can potentially have lasting effects throughout their lives.

Durlauf (1996) illustrates through a theoretical model the importance of neighborhood conditions in perpetuating poverty across generations. In his (Durlauf, 1996) model, individuals initially pick the neighborhood they wish to live in and then they become geographically immobile. Each neighborhood has an income distribution, and they self-finance the education of their young inhabitants. Using an overlapping generations model, Durlauf (1996) shows that members living in a neighborhood with a more favorable distribution of income have a higher probability of receiving a larger productivity shock (thus showing role-model effects a neighborhood can have on its young). Hence, neighborhoods populated with high income earners get high productivity shocks and those populated with low income earners get low productivity shocks. As time passes, the income differential between members of a given neighborhood becomes zero, but the heterogeneity of productivity shocks received by each neighborhood ensure that income differential between neighborhoods increase over time. If average income in a neighborhood is less than the poverty threshold, the neighborhood can settle into a poverty trap. Thus, if people end up living in neighborhoods that have low or inferior quality of public goods, it can lead to generations of individuals who end up getting a lower quality of education and earn a lower level of income, which in turn, can perpetuate low income and poverty across generations. This model shows how education

of role-models can have an affect on individual outcomes. This notion is similar to what Wilson (1987) states - that young African-Americans living in poorer neighborhoods do not have 'role-models' that show them the viability of education and stability in one's life, which may cause them to reject higher education and social stability. Durlauf's model (1996) also shows that partial improvements of a neighborhood in a poverty trap may not bring the whole neighborhood out of a poverty trap – structural changes to the whole neighborhood, such as changes to the productivity shock of the neighborhood, is needed to bring it above the poverty trap.

There are also theories showing how neighborhood composition can affect individual outcomes. Coleman (1988) stresses the importance of social capital in determining behavior, human capital formation and other labor-market outcomes of an individual. Social capital is defined by its function – it consists of certain social structures which can influence the behavior of the individuals within those structures (Coleman, 1988). For example, people growing up in a town that specializes in the textile industry may find themselves working in that industry as adults because they may have a network of acquaintances in that industry. Thus a person growing up surrounded by negative social capital can have low aspirations which can affect their income potential. A related literature shows that impediments such as hassles in getting welfare and opening a bank account (indicating neighborhood quality) can discourage a poor person from using these services, which can make that person remain in poverty (Bertrand et al., 2004).

A number of papers provide empirical evidence of the effect of neighborhood quality on income, poverty and educational attainment, showing that income and/or racial segregation of neighborhood can have a lot of adverse effects on its residents (Aaronson,

1998; Brooks-Gunn et al., 1993; Datcher, 1982; Duncan, 1994; Ginther et al., 2000; Harding, 2003 to name a few). Neighborhood variables can have some strong effect on African-American men or on those who live in welfare-dependent neighborhoods (Corcoran et al., 1992). African-Americans living in poor neighborhoods are more likely to be poor and geographically immobile than whites living in poor neighborhoods (Quillian, 2003). There is evidence that community variables affect academic grades of African-Americans more than that of whites (Dornbusch et al., 1991). In particular, it has been estimated that 40 percent of the differences of income and education attainment between African-Americans and whites can be explained by the poorer neighborhood backgrounds of African-Americans (Datcher, 1982). Cutler and Glaeser (1997) also find that African-Americans living in segregated neighborhoods are more likely to have less schooling and income and more likely to be single-parents than those living in less-segregated neighborhoods. All these provide strong evidence indicating that negative neighborhood qualities in segregated neighborhoods can adversely affect its residents.

Neighborhood quality can affect psychological distress, educational expectations and attainment of the children growing there (Aaronson, 1998; Brooks-Gunn et al., 1993; Ceballo, et al., 2004; Chapman and Mimi, 2004; Datcher, 1982; Duncan, 1994; Harding, 2003; Mello and Swanson, 2007; Peeples and Loeber, 1994). Overall, these papers show that neighborhood quality can affect human capital accumulation of a person through channels such as role-model effect or school quality, which can in turn influence their earnings. Children growing up in affluent neighborhoods attain more education than those growing up in poorer neighborhoods (Duncan, 1994). Similar effect was also found by Brooks-Gunn et. al (1993). School quality, which can be a proxy of neighborhood

quality, can also affect returns to education of an individual (Altonji and Dunn, 1996a). Peeples and Loeber (1994) show that poor neighborhood conditions can increase delinquency rates among the boys living there. Harding (2003) looks at outcomes of two groups of 10-year old who grew up in two very different neighborhoods. Using different matching techniques, he (Harding, 2003) shows that children in the group that grew up in a higher-poverty neighborhood have a higher probability of dropping out of high-school and increased chances of teenage pregnancy than the "control group," thus showing the effects of neighborhood on human capital accumulation and teenage pregnancy. A similar effect was also shown by Aaronson (1998). Duncan (1994) and Brooks-Gunn et. al. (1993) find that the concentration of low-income households in a neighborhood do not necessarily make individual outcomes worse off, but affluent neighbors do have a large degree of positive spillovers (probably through role-model effects). Similarly, Cutler et al. (2008) show that when ethnic groups with very low education are segregated, it leads to worse outcomes among the residents there, like income. Elliott and Sims (2001) also note that Hispanics are more likely than African-Americans to use neighbors and/or co-workers to get jobs; but, this networking does not exist in very poor or in co-ethnic neighborhoods. These research show the effect of neighborhood income on networking potential on its residents. However, using data of sisters from the PSID, Plotnick and Hoffman (1999) find some neighborhood variables affect individual-level outcomes such as income and education attainment in a cross-section model, but those variables lose significance in a fixed-effects model. Thus, they caution researchers not to use cross-section data to analyze neighborhood effects when selection is not taken into account (Plotnick and Hoffman, 1999).

On the other hand, ethnically diverse cities may have problems, such as lower disbursement of funds for public goods, increased expenditure on police and more transfers per capita (Alesina et al., 1999). When African-American boys living in wealthier neighborhoods are compared to whites, the delinquency rates are similar between these two groups, but African-American boys in poorer neighborhoods have a higher rate of delinquency than whites (Peeples and Loeber, 1994). However, the preliminary investigation of the MTO (which, as an experiment moved some poor household to neighborhoods with less poverty and crime) did not yield any significant impact on the income of the heads of household, and academic achievement of their children (Sanbonmatsu et al., 2006, Katz et al., 2001). But the MTO did show that girls were less prone to crime and the heads of households had better mental health when compared to the control group (Katz et al., 2001; Kling et al., 2005). These studies imply that the relationship between neighborhood quality and income may not be evident in the short run and may manifest itself in the long-run.

The other strand of economics literature shows the impact of family characteristics on future income of a person (Altonji and Dunn, 2000; Becker and Tomes, 1986), while some believe that family characteristics affect adult income more than neighborhood effects (Page and Solon, 2003a; Solon et al., 2000). Following the model of Becker and Tomes (1986), the intergenerational correlation of income literature shows that family variables have a bigger effect on income than community variables. Page and Solon (2003a) shows that the correlation of education among female siblings is much higher than that of neighborhood girls, while Solon et al. (2000) says that correlation of education amongst neighborhood children is very low. Empirically, it has been calculated

that correlation of income between fathers and sons is around 0.4 or more (Corcoran et al., 1992; Lee and Solon, 2009; Mazumder, 2005; Solon, 1992; Zimmerman, 1992). Such a high correlation of intergenerational income imply that income mobility in the US is not very high. There is evidence that intergenerational mobility of education is very low (Bauer and Ripahahn, 2007). Besides, children born in poor families are more likely to have low birth weights, diminished health, learning disabilities, emotional problems and unfavorable future health and economic outcomes (Brooks-Gunn and Duncan, 1997; Currie, 2009). For example, a 10 percent higher income of families can lead to 0.2-2 percent higher years of schooling completed by the children (Brooks-Gunn, Duncan, 1997). These imply that low income of parents, and not just childhood neighborhood characteristics, can affect future outcomes of a child.

2.3 The Model and Estimation

Using the model proposed by Durlauf (1996) as a reference, I model earned individual income as an autoregressive process with the coefficient on the lagged dependent variable a correlated random coefficient (Altonji and Dunn, 1996b; Heckman and Vytlacil, 1998)[1]:

$$Y_{it} = \alpha_i + Y_{it-1}\gamma_i + X'_{it}\theta + \varepsilon_{it} \qquad (1)$$

where Y_{it} is the log income-to-needs ratio of person i at time t. There is a total of n individuals and T time periods. Needs is the poverty line of a family adjusted to the size of the family. Any family earning below needs (that is, if the ratio of income to needs is less than or equal to 1) is said to be living in poverty. X_{it} is a kx1 vector containing

[1] Autoregressive income models have been studied in papers like Holtz-Eakin et al. (1988), Geweke and Keane (2000), Hu (2002) and Gervais and Klein (2010), but unlike the equation shown in (1), they treated the coefficient on the lagged dependent variable as homogeneous across individuals.

different individual characteristics (age, education) and the macroeconomic aggregates of the county where the adult individual is currently residing (crime rate, median income, poverty rate, unemployment rate). α_i is the individual-specific, time-invariant, unobserved heterogeneity. γ_i is the correlated random coefficient on the lagged dependent variable and it is heterogeneous across individuals. ε_{it} is the iid error term.

The coefficient γ_i measures the persistence of income. A higher value of γ_i implies income stability for person i, whether the person is rich or poor. For a richer individual, a high income stability is a good thing but may not be so good for a poor individual. A high persistence of income, together with low income, can make a person be stuck in a low-income trap. It also makes recovery from a negative shock longer. In this model, I assume that each individual has a different value of γ_i, and it is affected by childhood neighborhood and family characteristics (the persistent component of the equation). Thus, I parameterize it in the following way:

$$\gamma_i = \gamma_0 + F_i'\tau + N_i'\mu + \xi_i \qquad (2)$$

where γ_0 is a constant, *F* is a wx1 vector of family characteristics of individual *i* (such as, education level of parents, race, length of spell of poverty during childhood), *N* is a *px1* vector of average childhood neighborhood characteristics (poverty rate, proportion of high-school and above graduates, unemployment rate) and ξ_i is a individual-specific and time-invariant shock that affects γ_i but is uncorrelated with other variables in the model. This implies that $E(\xi_i|F_i, N_i, X_{it}, Y_{it-1}) = 0$. Like the coefficient γ_i, α_i is assumed to be a correlated random coefficient and is affected by childhood neighborhood and family characteristics. Plotnick and Hoffman (1999) stresses the importance of including individual-specific, time-invariant heterogeneity to the model. Following Mundlak

(1978), α_i is parameterized to be of the following form (the level component of the equation):

$$\alpha_i = \alpha_0 + F_i'\omega + N_i'\varrho + \upsilon_i \quad (3)$$

where the vectors F and N are defined the same way as in equation (2) and υ_i is the error term and $E(\upsilon_i|F_i, N_i, X_{it}, Y_{it-1}) = 0$. Plugging equations (2) and (3) into equation (1) gives the following equation:

$$Y_{it} = \alpha_0 + F_i'\omega + N_i'\varrho + Y_{it-1} \cdot (\gamma_0 + F_i'\tau + N_i'\mu) + X_{it}'\theta + Y_{it-1} \cdot \xi_i + \upsilon_i + \varepsilon_{it} \quad (4)$$

where $Y_{it-1} \cdot (\gamma_0 + F_i'\tau + N_i'\mu)$ is the dot product between $\gamma_0 + F_i'\tau + N_i'\mu$ and Y_{it-1}. In studying equation (4), I assume that the parents decide the neighborhood where to live which, according to Aaronson (1998), is not influenced by the abilities of their children. An individual cannot control for the variables in *N* and *F*. Thus, α_i and γ_i are set exogenously, and the variables in *F* and *N* are uncorrelated with ε_{it}. As an adult, the individual chooses the place where they want to live, whose macroeconomic characteristics (included in X_{it}) may be correlated with ε_{it}. In my estimation, I look at cases where these variables are both exogenous and predetermined respectively.

Previous research examining how childhood neighborhood conditions affect adult income studied the impact of vectors *F* and *N* on the level of income (α_i), but did not analyze income persistence to be a factor that explains adult income. By using equation (4), I can study how childhood neighborhood characteristics can both affect the level (through the coeffcients ω, ϱ) and persistence (through the coefficients $\tau,\ \mu$) of income. For example, assume that *F* is a *1*x*1* scalar. If $\omega > 0$ and $\tau > 0$, it would imply that *F* not only raises the level of current income, but also its persistence (by increasing the coefficient on the lagged dependent variable). In the long-run (where $Y_{it} = Y_{it-1}$), the

value of the coefficient on F is $\frac{\omega}{1-\gamma_i}$, which is higher if F is higher for person i. If, on the other hand $\omega < 0$ and $\tau < 0$, it would mean that F has a negative effect on the level of income and also reduces the persistence of income. A high value of F for person i would make their steady state income be low, and therefore, reducing F would help person i by increasing both their level and persistence of income. If ω and τ are of opposite signs, then the relative magnitude of ω and τ will determine the effect F has on the steady state level of Y.

Estimating the coefficients using a dynamic system generalized methods of moments (GMM) on panel data calls for taking first difference of the level equation. However, equation (4) has a number of time-invariant variables embedded in α_i, and first difference of equation (4) removes these time-invariant variables:

$$\Delta Y_{it} = \Delta Y_{it-1} \cdot (\gamma_0 + F_i'\tau + N_i'\mu) + \Delta X_{it}'\theta + \Delta(\xi_i \cdot Y_{it-1}) + \Delta\varepsilon_{it}. \qquad (5)$$

Equation (5) cannot estimate the coefficients ω and ϱ. Hausman and Taylor (1981) provide a method of estimating the coefficients of time-invariant variables using generalized least squares (GLS). Arellano and Bover (1995) improve on Hausman and Taylor (1981) by introducing generalized method of moments (GMM) to estimate the coefficients of the time-invariant variables; they use equation (5) and the time mean of equation (4) to construct the moment conditions. Blundell and Bond (1998) extend Arellano and Bover (1995) and suggest using both the level (equation 4) and the difference (equation 5) equations to construct the moment conditions. However, Blundell and Bond (1998) focus on estimating the coefficients of the time-varying variables only, and do not consider estimating the coefficients on the time-invariant variables. I use the correlated random effects estimation technique of Arellano and Bover (1995) and the

moment conditions specified in Blundell and Bond (1998) to estimate the coefficients in equation (4).

Equation (1) suggests that Y_{it-1} is correlated with ε_{it-1}, implying that $E(\Delta Y_{it-1}\Delta\varepsilon_{it}) \neq 0$. Therefore, Y_{it-1} cannot be used as an instrument for the difference equation $\Delta\varepsilon_{it}$. If *Y* is assumed to be predetermined, then Y_{it-b}, b>1 can be used as instruments for the difference equation since Y_{it-b} b>1 is uncorrelated with $\Delta\varepsilon_{it}$. Combining all these ideas, Blundell and Bond (1998) suggest using the following moment conditions for person i and time t:

$$E(\varepsilon_{it}z_{1it}) = 0 \tag{6}$$

$$E(\Delta\varepsilon_{it}z_{2it}) = 0 \tag{7}$$

where z_{1it} and z_{2it} are the vectors of instruments for person i at time t. z_{1it} is an 1xm vector that contains (i) the lagged first differences of Y ($\Delta Y_{it-1}, \Delta Y_{it-2}, \Delta Y_{it-3}, \ldots$), (ii) the first differences of explanatory variables in X ($\Delta X_{it}, \Delta X_{it-1}, \Delta X_{it-2}, \ldots$) and, (iii) the one period levels of variables *F* and *N* (since they are time-invariant for each individual, only values from one-period are used as instruments), while z_{2it} is a 1xm* vector and it contains (i) the current and lagged values of X ($X_{it}, X_{it-1}, X_{it-2}, \ldots$), (ii) the lagged values from period 2 and back of *Y* ($Y_{it-2}, Y_{it-3}, Y_{it-4}, \ldots$), and (iii) the one period levels of *F* and *N*. The moment conditions for person i can be written as:

$$E(z'_{1i}\varepsilon_i) = 0 \tag{8}$$

$$E(z'_{2i}\Delta\varepsilon_i) = 0 \tag{9}$$

where ε_i is a Tx1 vector of the error terms, and z_{1i} is a TxTm vector of instruments in block-diagonal form as shown below:

$$z_{1i} = \begin{bmatrix} z_{1i1} & 0 & 0 & \cdots & 0 \\ 0 & z_{1i2} & 0 & \cdots & 0 \\ 0 & 0 & z_{1i3} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & z_{1it} \end{bmatrix}. \tag{10}$$

So there are Tm moment equations generated by equation (8). z_{2i} is an TxTm* vector of instruments having a similar structure as z_{1i}, and similarly, there are Tm* moment equations generated by equation (9). The instrument matrix is of the following form:

$$Z_i = \begin{bmatrix} z_{2i} & 0 \\ 0 & z_{1i} \end{bmatrix}. \tag{11}$$

The term $\Delta(\xi_i \cdot Y_{it-1})$ is not included in the moment condition shown in equation (9). It is seen that $\Delta(\xi_i \cdot Y_{i-1}) = (\xi_i \otimes \Delta Y_{i,-1})$ for person i, where $Y_{i,-1}$ is the Tx1 matrix of the lagged dependent variable and $\otimes$ is the Kronecker product. Since first differencing removes the time-invariant part of the variable, and only keeps the random component in it, so, it can be assumed that $E\left(\xi_i \otimes \Delta Y_{i,-1}\right) = 0$. The term $\xi_i \cdot Y_{i,-1}$, which can also be written as $\xi_i \otimes Y_{i,-1}$, is not included in the moment condition shown in equation (8) because when this term is multiplied with the instrument matrix z_{1i}, and expectations taken, it becomes: $E\left[z'_{1i}\left(\xi_i \otimes Y_{i,-1}\right)\right] = E\left[\left(z'_{1i}\xi_i \otimes z'_{1i}Y_{i,-1}\right)\right]$. As said above, the instrument matrix z_{1i} contains first differences of variables as instruments, and therefore, those variables do not have any time-invariant component in them, making them uncorrelated with the error term ξ_i. In addition to that, the variables F and N in the instrument matrix z_{1i} are uncorrelated with ξ_i. Hence, the term $E[(z'_{1i}\xi_i \otimes z'_{1i}Y_{i-1})]$ becomes $E[(0 \otimes z'_{1i}Y_{i-1})] = 0$, showing that $\xi_i \otimes Y_{i-1}$ does not bias the results. Similarly, ν_i is not included in moment conditions (8) and (9) because it is uncorrelated with all the explanatory variables. Besides, Altonji and Dunn (1996b) say that correlated random

coefficients in their model do not have a large effect on the consistency of the coefficients. Following Arellano and Bover (1995), equations (8) and (9) can be used to calculate the first stage coefficients using the following equation:

$$\beta_1 = [\sum_n (W_i{}'Z_i)(\sum_n Z_i{}'Z_i)^{-1} \sum_n (Z_i{}'W_i)]^{-1} \sum_n (W_i{}'Z_i)(\sum_n Z_i{}'\, Z_i)^{-1} \sum_n (Z'_i Y_i) \quad (12)$$

where W is a $2T$x$(k+w+p+2)$ matrix, and $W = (0,0,0,\Delta Y_{-1}, \Delta Y_{-1}F',\ \Delta Y_{-1}N', \Delta X\backslash 1, F', N', Y_{-1}, Y_{-1}F',\ Y_{-1}N', X\ )$ (the matrix of the differenced variables have been placed on top of the matrix of level variables) for person i and $\beta_1 = (\alpha_0, \omega, \varrho, \gamma_0, \tau, \mu, \theta)'$. The estimate of the error term e is calculated from the first step and the weight matrix $Z'\hat{e}\hat{e}'Z$ then estimated. In the second step, the consistent and efficient estimate of the coefficients is calculated using the following equation[2]:

$$\beta_2 = [\sum_n (W_i{}'Z_i)(\sum_n Z_i{}'\hat{e}_i\hat{e}'_i Z_i)^{-1} \sum_n (Z_i{}'W_i)]^{-1} \sum_n (W_i{}'Z_i)(\sum_n Z_i{}'\, \hat{e}_i\hat{e}'_i Z_i)^{-1} \sum_n (Z'_i Y_i) \quad (13)$$

and the variance-covariance matrix of the coefficients is given by the following matrix:

$$Var(\beta_2) = [\sum_n (W_i{}'Z_i)(\sum_n Z_i{}'\hat{e}_i\hat{e}'_i Z_i)^{-1} \sum_n (Z_i{}'W_i)]^{-1} \quad (14)$$

Ziliak (1997) says that in small samples, the 2-step estimates may be biased because the error term from the first step may be correlated with the regressors. I therefore also do some one-step GMM in the robustness section to test the validity of my results.

2.4 Data

The Panel Study of Income Dynamics (PSID) is a longitudinal dataset that has been interviewing families since 1968. It also interviews offspring who left the original

[2] I estimated this model using the xtabond2 (Roodman, 2009) command of Stata and also using my codes that I wrote in mata and Stata

family unit of 1968 and formed their own families. The dataset has a unique option that allows parental data to be linked to their respective offspring. In addition to that, the PSID also has sensitive geocodes of an individual's place of residence, which can allow a researcher to identify what county and census tract[3] a person resides in each year. These geocodes allow the matching of census-tract level or county level aggregate data with the individual data files of the PSID. Attrition may seem to be an issue in a long panel like PSID. However, Fitzgerald (2011) investigates intergenerational relationships of different social and economic variables, and shows that attrition in the PSID does not have a substantial effect on the validity of the results obtained from analyzing it. Similarly, Ziliak and Kneiser (1998) have shown that attrition in the PSID does not significantly affect the results of the life-cycle labor supply model, conditional on differencing the fixed latent heterogeneity of the model.

I only use individuals who are members of the Survey Research Center (SRC) sample of the PSID. The SRC sample is the original random sample of households that the PSID surveyed in 1968, and it is representative of the US population in 1968. From the SRC subsample of the PSID, I collect data on working individuals over the age of 18, who are either head of the household or the wife of the head, and whose parents were interviewed by the PSID. The individual level data collected are income, year born, sex, race, education level completed, and place of residence during childhood and adulthood at the county and census-tract level. I only use data of the "children of the PSID" because the neighborhood where they spent their childhood has been recorded by the

[3] A census tract is defined by the Census Bureau as an area with a population between 2,500 to 8,000 individuals. (http://www.census.gov/geo/www/cen_tract.html)

PSID, and therefore, this data can be used to calculate the childhood neighborhood characteristics. In this paper, I treat childhood as the first 18 years of a person's life.

Some individuals had different sets of parents during childhood, as there are some individuals in the dataset who married and divorced more than once. The marriage file of 1985 in the PSID has a list of year of marriages and divorces for each individual. In cases where an individual had different sets of parents over time, I use the marriage file to calculate the average parental characteristics (education and years spent in poverty) when the individual was below the age of 19. I collect individual level data from 1974 to 2005. I do not use earlier and later years due insufficient individual and aggregate-level data. The PSID interviewed families every year till 1996 and then once in every two years from 1997 onwards, and so, I use annual data from 1974 till 1996 and then the bi-annual data from 1997 onwards.

The Census Bureau collects a number of macro-economic characteristics at the census-tract level in the US. I collect census-tract level data of the years 1970, 1980 and 1990 from the website of Inter-university Consortium for Political and Social Research (ICPSR), which is maintained by the University of Michigan[4]. I use census-tract level data on average family income, poverty rate, proportion of female-headed households, proportion of high-school graduates and above, and unemployment rate to measure the quality of childhood neighborhood. The Census Bureau collects different aggregate-level data at the census-tract level during each decennial census, but they did not collect any in between the decennial census years 1970 and 1980, and between 1980 and 1990. However, Page and Solon (2003b) shows that individuals do not usually move to neighborhoods with very different qualities, and so macroeconomic variables of their

[4] The web address is: http://www.icpsr.umich.edu/icpsrweb/ICPSR/

place of residence should not drastically change over time. Therefore, census-tract data for one of the years during childhood can be used as a proxy for neighborhood quality during other years of childhood. I use childhood census-tract data of 1970 for person i to proxy for their census-tract level data of years 1971 to 1974. Similarly, I use 1980 data to proxy for the years 1975 to 1984 and 1990 data to proxy those from 1986 to 1995. I then average census-tract data of each individual below the age of 19 to calculate their average childhood neighborhood characteristics. After that, I merge parents' and childhood neighborhood data with individual level data of PSID.

I use county-level variables instead of census-tract level data to capture current business cycle effects prevalent in the place where a person is residing as an adult. I obtain county-level aggregate data on crime rate, median income, poverty rate and unemployment rate for the years 1968 to 2005 from the ICPSR website and then merge them with the individual data of the PSID. I use these variables to control for the impact of current business cycle on adult income. The Census Bureau collects these data every 5 years, but for later years, it has been collecting some of these data annually. For the earlier years, I interpolate these variables to fill in the missing years and get a balanced panel of data for each county, before merging them with the individual-level data.

I convert all the dollar values to 2005 dollars and then take their natural logs. The dependent variable is the log of income-to-needs, with income being the total labor income earned by the individual in a given year, and needs being the family-adjusted poverty line of the individual's family. There are a few observations (less than 1 percent of the total sample) where income of a person is negative. I drop these values since log of a negative number is undefined. Some of the pooled summary statistics are presented in

Table 2.1. The childhood neighborhood variables are at the census tract level, while the current neighborhood variables are at the county level. There are a total of 2124 individuals in the dataset with a total of 16697 person-years of data. Half the sample is male, and about 89 percent is white. The average age is about 31 years and the individuals have about 14 years of schooling. Both the parents have about 13 years of schooling. The individuals grew up in neighborhoods that had about 70 percent high-school and above graduates, 5.5 percent unemployment rate and 10 percent poverty rate. However, the standard deviation of all these variables is pretty high, showing that there is a lot of variation among childhood neighborhood quality. As adults, they currently live in counties that have 11.5 percent poverty rate, a median income of around 50,000 dollars and about 5.6 percent unemployment rate.

2.5 Results

A. Baseline Model

Table 2.2 presents the model in the baseline case. The results were obtained by running a 2-step GMM following the methods of Arellano and Bover (1995) and Blundell and Bond (1998). The instrument matrix has all the instruments described above in the model section, but the lags of the time-varying variables go upto the 15th lag. I consider the time-varying variables as exogenous in this case. Although not reported, each regression controlled for a constant, the current macroeconomic characteristics of the place of residence of the individual (median income, poverty rate, unemployment rate crime rate), age of individual, age squared and education level. Model 2a estimates the income generation equation of the individuals while holding persistence coefficient constant across individuals. It shows that average value of γ across individuals is about

0.25. Males have a higher income than females, while childhood neighborhood poverty rate negatively affects current income. Father's education positively affects current income levels. One interesting variable is neighborhood unemployment rate, which is positive and significant. It is counterintuitive to think that higher unemployment rate in childhood neighborhood is associated with higher income today. It could also be that since unemployment rate does not capture underemployment and the discouraged workers, so individuals actually looking for work may provide incentives for the young to look for jobs when they become adults. Overall, model 2a shows that besides family characteristics, some childhood neighborhood characteristics affect the level of income.

Models 2b and 2c add heterogeneity to the persistent coefficient γ. The difference between model 2b and 2c is that in 2b, father's education is used as an indicator of overall education in the family, while in 2c, mother's education is used as the indicator. The results in 2b show that neighborhood and family variables do affect the persistence of income. The average value of estimated γ, which was obtained by calculating the value of each individual's γ and then averaging it, is estimated to be around 0.26. This value is not very different from the result in model 2a, but it has a lot more variation of persistence across individuals, as evidenced by a large value of standard deviation. Looking at the variables that affect the level of income, I find that similar to model 2a, model 2b shows that childhood neighborhood poverty rate has a negative coefficient (coefficient= -0.655), and males have higher level of income than females. However, father's education is no longer significant, and neighborhood highschool rate is positive and significant (coefficient= 0.267). Thus, adding heterogeneity in the persistence

coefficient makes father's education lose its significance[5]. Race and years spent in poverty during childhood are still not significant in model 2b. The Hansen's J test for models 2a-2c show that the instrument matrix for these models are generally valid.

Looking at the variables that affect the persistence of income, it is seen that males have a lower persistence of income than females (coefficient = -0.22), and higher proportion of highschool graduates and above lowers the value of persistence. Neighborhood unemployment rate is negative and significant, implying that a higher unemployment rate lowers the value of γ. Father's education, race and years spent in poverty during childhood do not affect the persistence of income. The chi-square test of no persistence (where all the coefficients affecting γ are equal to zero) is rejected at the five percent level, showing that persistence is important in determining income.

As a test, I replace father's education with mother's education to see if the results in the baseline case hold. The results, tabulated in Table 2c, indicate that the coefficient are similar in magnitude and significance in most cases. Neighborhood poverty rate affects the level of income negatively, highschool education affects it positively, and men earn a higher level of income than women. Looking at the persistence coefficient, it is seen that unemployment rate and education in neighborhood affect γ negatively. However, when mother's education is included, race becomes significant at the 10 percent level both at the level and the persistence of income. The average value of persistence is calculated to be 0.27, which is close to what was obtained from models 2a and 2b.

[5] As a test, I also estimated the model using longer lags (y_{t-5}) instead of y_{t-1}) as a dependent variable; however, that made the value of the lagged coefficient even smaller in magnitude

The results from Table 2.2 show that persistence is an important component in explaining income. Education level and unemployment rate affect the level and persistence of income, while neighborhood poverty rate affect the level of income. A higher education level helps to raise the level of income probably due to "role-model" effect, and it helps to lower persistence of income due to a networking effect. For example, if a person loses their job, a lower persistence of income indicates that they are able to quickly recover from their job loss. This may be because they are quick to get another job due to the network of educated individuals in the childhood neighborhood who can help them get another job relatively easily. Neighborhood poverty rate affects the level of income negatively, which probably shows negative role-model effects, where high poverty rate around a person influences their aspirations. Although, insignificant, neighborhood poverty rate negatively affects the persistence of income. Unemployment rate seems to positively affect the level of income and negatively affect the persistence of income. The result may seem odd at first, but this phenomenon was investigated and the results are explained later in the chapter. The overall effect of neighborhood unemployment rate cannot be ascertained, because it depends on the relative magnitude of the coefficients in the levels and persistence component of the equation. Later in the chapter, I find that lowering childhood neighborhood unemployment rate can increase income persistence, which can be a good thing when $X'_{it}\theta$ component of equation (1) (which includes the current macroeconomic characteristics of the adult individual) is high.

B. Long-run coefficients

I then calculate the long-run coefficients of the variables for the whole population, and also for people in each income group. In the long run, $E(y_t) = E(y_{t-1})$, and thus, the coefficients are equal to[6]:

$$LR = \frac{1}{n}\sum_i \frac{1}{1-\bar{\gamma}} \cdot [\omega', \varrho', \theta']' \tag{15}$$

where $\omega', \varrho', \theta'$ are the coefficients that are in the level component of equation (4), $\bar{\gamma}$ is the average value of the persistence coefficient and LR is the vector of the long-run coefficients. I use the results from model 2b to calculate the long run coefficients, and some of the results are tabulated in Table 2.3.

The average persistence of the total population is 0.2697. However, when I calculate the average value of persistence by income group, I find that richer individuals have a lower persistence of income. For example, for individuals whose lifetime earnings are in the top 50% of the income distribution, the persistence is about 0.25, while those in the bottom 50% have a persistence of about 0.28, a difference of about a little over 10%. The richer individuals are thus able to recover from a negative shock relatively quickly. Individuals earning at the bottom 25% of the income distribution have an even higher level of persistence (0.337). This indicates that the poorer segment of the population have a harder time recovering from a negative shock, which can be due to the poor role-models during childhood. If, on the other hand, the poor have a very low income, or live in

[6] The long run coefficients were also calculated using the following equation: $LR = \frac{1}{n}\sum_i \frac{1}{1-\gamma_i} \cdot [\omega', \varrho', \theta']'$, and the results obtained were similar.

counties that are economically depressed, then a high persistence makes them be stuck in a low-income trap, making it even more difficult for them to leave poverty.

Looking at the long-run coefficient of different income groups, I find that the magnitude of the coefficients is higher for the poor than for the rich. For example, the county median income of the current place of residence is calculated to be about 1.22 for the total sample, while it is 1.174 for the top 25% and 1.344 for the bottom 25% of the population. Similarly, the long run coefficient of county unemployment rate for the top 25% is -3.48 while it is -3.98 for those in the bottom 25%. Thus, if long-run unemployment rate increases in the county or economic growth is negative, it will have a more negative effect on the income of the poorer segment of the population than the richer segment. As an illustrative example, over the past few years, unemployment rates in the US have increased from 5 percent to about 9 percent, and have remained so[7]. This model suggests that the increase of unemployment rates by 4 percentage points will reduce the long run income of the top 25% by -3.48*0.04 = -0.1392 of log income, and that of the bottom 25% will be reduced by -3.98*0.04 = -0.1592 of log income. This suggests that the poor have a much higher fall of income than the rich. Since economic theory says that marginal utility of a dollar for the poor is much higher than that of the rich, a larger fall of income will make them worse off than the rich due to the same rise in unemployment rates.

Another interesting coefficient to note is the returns to schooling. From model 2b, I find that the coefficient on schooling is about 0.085, but disaggregating it by income groups show that the returns to schooling is much higher for the poorer segment of the

[7] Source: The Bureau of Labor Statistics: http://data.bls.gov/timeseries/LNS14000000

population. Thus an extra year of education would make returns to schooling higher for the poor than one year of schooling for the rich. It would be beneficial for the poor to get more schooling, but they may not be able to do so because of high costs of education that they may have.

As a test, I look at the time to recovery for different values of persistence coefficients and different state of the current economy, when hit by the same negative shock. The results are tabulated in Table 2.4. I look at three different cases of the economy – unfavorable ($X'_{it}\theta = 0.5$), average ($X'_{it}\theta = 1.0$) and very favorable ($X'_{it}\theta = 1.5$). These numbers are meant to serve as examples to see the speed of recovery at different levels of current macroeconomic situation. I look at how long does long-run get back to its original value (upto five decimal places) once it is hit by a one-time shock of -0.5 ($e_{it} = -0.5$). The results show that a value of lower persistence makes the speed of recovery faster. A favorable economy also ensures that the speed of recovery is faster, for a given value of persistence. This table shows that the poor take a longer time to recover from a shock than the rich (since the poor have a higher value of persistence). Also, if the poor live in counties that have unfavorable conditions, then it can take them even longer to recover from a negative shock. Table 2.4 shows the importance of looking at persistence to understand recovery of the poor.

C. Sensitivity Analysis

As a robustness check, I ran a number of regressions to test the validity of my results tabulated in Table 2.2. As a first test, I changed the instrument matrix by changing the number of lags of time-varying variables included as instruments. The results are

tabulated in Table 2.5. Model 5a has a larger instrument matrix; I use instruments upto the 20th lag of the time-varying variables. In model 5b, I reduce the number of lags of the time-varying variables to 10, while for model 5c, I reduce the lags further reduced to 5. Comparing the average value of γ across all these specifications, I find that the average value is around 0.26-0.27 with a standard deviation of around 0.14, which is pretty consistent with what was obtained in the baseline case. Neighborhood poverty rate has a negative and significant effect on the level of income, but only a negative (and not significant) effect on the persistence of income in all the three specifications. Neighborhood education level has a positive and significant effect on the level of income in models 5a and 5b, but not in 5c, and it has a negative effect on the value of γ in all three specifications. As seen in the baseline case, males have a higher level of income and lower level of persistence than females. Unemployment rate in the neighborhood continues to affect the level of income positively and the persistence of income negatively. Thus the overall effect cannot be determined by looking at the coefficients. Overall, it can be deduced that changing the lags in the instrument matrix does not affect the results obtained.

The time-varying variables used as instruments in Tables 2.2 and 2.5 were treated as exogenous, so as a further robustness test, I estimate the model by treating them as predetermined. Thus X_t is not used as an instrument in any of the regressions, but X_{t-1} and backwards are used as instruments. The results are tabulated in Table 2.6. Model 6a has the time-varying variables upto the 15th lag, model 6b has upto 10 lags, and model 6c has upto 5 lags used as instruments. The results are not so different from the baseline case.

The sign and significance of the coefficients remain the same. The average value of γ is also around 0.26.

As another test of robustness, I collapse the instrument matrix (they are not block-diagonal anymore) and run the GMM. The results are tabulated in Table 2.7. The magnitude and significance of the coefficients are a little different now. Neighborhood unemployment rate does not affect the value of γ anymore, but it still positively affects the level of income. Neighborhood poverty rate has a much more negative effect on the level of income, while neighborhood education level affect both the level and the persistence of income in model 7a and 7b. However, race is now a significant variable, it affects the level of income negatively and the persistence of income positively. The average value of γ is now in the range of 0.21 to 0.25, which is much lower than what was seen in the baseline case. The Hansen's J statistic is not rejected at the 10 percent level, indicating that the instrument matrices used are valid.

It may seem that the two-step estimates are biased because the error term from the first step may be correlated with the regressors (Ziliak, 1997). As a last test of robustness, I look at the one-step GMM results. The results are illustrated in Table 2.8. The average value of γ across the models is about 0.27, which is similar to what was seen in the baseline case. The sign and significance of most variables are the same, although neighborhood education level does not significantly affect the level of income anymore. Comparing the results of Table 2.8 with that of Table 2.2, I can say that the two-step estimates of the baseline model are similar in sign and value.

One problem noted in the baseline case illustrated in Table 2.2 was that neighborhood unemployment rate was positively related to the level of adult income. It may be that idleness, instead of unemployment rate in the neighborhood, may be a better measure of adult outcomes. Instead of using neighborhood unemployment rate as a dependent variable affecting α and γ, I use neighborhood idleness rate, which is one minus the sum of civilian employment rate and unemployment rate (1-civilian employment rate - unemployment rate). The results are tabulated in Table 2.9. Now, the idleness rate affects the level of income negatively, and the persistence of income positively, which implies that decreasing neighborhood idleness rate would increase level of income, and reduce persistence, which would help income generation in the long run. This is robust to changes in the instrument matrix. All the other variables remain the same, although father's education is now significant in the levels part of the equation. The average value of persistence is around 0.24, which is similar to what was seen in the previous cases.

Another variable that might affect individual outcomes is whether the child had different sets of parents over time, or the same set. A child growing up in families that experienced divorces and single-parenthood may affect individual outcomes. I thus add a dummy variable that indicates whether the child grew up in households with different sets of parents over time. The results are tabulated in Table 2.10. After controlling for other factors such as education of father, race, duration in poverty during childhood, the variable indicating changing family structure over time does not affect the level or the persistence of income in adult life.

The needs standard is constant for a given family size, so individual income-to-needs might differ if income of family members differ. For example, if the wife earns above the needs standard and the husband earns below it, then the individual income-to-needs will show the wife to be above poverty and the husband below poverty, even though family income is above needs. If the family size increases, the husband looks to be in deeper poverty than the wife, which may in turn not give the required results when I estimate the model. Therefore, as a robustness test, I change the dependent variable, from income-to-needs ratio to just log of real income of a person and run the regressions to see if the results are robust.
The results are tabulated in Table 2.11. The results are similar as seen before; however, neighborhood poverty rate does not significantly affect the level of income anymore when persistence is made heterogeneous in the model. High-school rate is positively affecting the level of income and negatively affecting the persistence of income. Unemployment rate still positively affects the level of income, as was seen in the baseline model. The average value of γ is around 0.22, which is slightly lower than what was seen in the base case.

I also tried adding in other childhood neighborhood variables (such as average family income in neighborhood during childhood, proportion of female headed household in the neighborhood during childhood) to the regression. While not reported here, I found those variables were not significant in explaining the level or persistence of income, and they did not affect the sign and significance of other variables.

Overall, the model indicates that neighborhood variables are important in determining the persistence and level of income. Poverty rate and education level in the childhood neighborhood have a big effect on both the level and the persistence of

income. This shows that there is some evidence of "role-model" effect. Individuals growing up in low poverty and highly educated neighborhoods have good role-models that they can look up to and aspire to become successful later in life. Conversely, a person growing up in a poor-quality neighborhood may not aspire to earn more because of a lack of role-models to look up to. The poor have a higher persistence of income than the richer segment of the society. If the poor live in depressed neighborhood, they can be trapped in a low-income trap, as seen in Table 4. From the next section, I find that reducing childhood neighborhood unemployment rate can be beneficial in states of the economy when $X'_{it}\theta$ if favorable. Looking at the effect of current macroeconomic variables on income from Table 2.3, I find that the long run coefficients are heterogeneous across income groups. In the next section I look at how current macroeconomic conditions affect the influence of childhood neighborhood variables on income.

2.6 Social Welfare Function

The model generally shows that there are a number of variables affecting both the level and persistence of income. However, it is difficult to find out with variable has the biggest influence among all the neighborhood variables. I use a social welfare function to study the impact of each variable on long-run income of a person. I assume that there is a social planner whose aim is to maximize social welfare function (SWF) using the coefficients of model 2b. In this exercise, I use the SWF proposed by Sen (1976):

$$SWF = \bar{y}(1 - G) \tag{16}$$

where $\bar{y}$ is the mean income in the population and G is the Gini coefficient. $G \in [0,1]$ measures inequality of income in a society. If $G=0$, it represents perfect equality of income (everyone earns the same amount of income) and as G increases, it represents a more unequal distribution of income. A higher value of SWF means that overall welfare of the society has increased, and SWF can increase if G decreases or if $\bar{y}$ increases, or both. One way to see if social welfare has improved is to compare the new SWF with some baseline SWF. For simplicity, I assume that the local macroeconomic conditions and other individual-level variables are held constant for all individuals, and so, the baseline natural log of long-run steady state income of person i is:

$$Y_i = \frac{\alpha_i + \kappa}{1 - \gamma_i} \tag{17}$$

where γ_i is the correlated random coefficient on the lagged dependent variable as shown in equation (2) while holding the shock $\xi_i = 0$, α_i is the person-specific time-invariant parameter, the same as shown in equation (3), and κ contains the rest of the time-varying and individual-level variables used as controls (current macroeconomic variables, age, sex, race and schooling). The value Y_i in equation (17) is in natural log form, and I use ln(Y) to calculate the mean income and Gini.

The baseline value is where all the childhood neighborhood and family variables (that affect γ and α) are held constant at their actual values. In the first case, I hold all other variables constant, and increase the variable percentage of high-school graduates in a neighborhood by 1 percentage point for individuals whose average earnings is at the bottom quartile of the steady state income distribution. Using the simulated data, I estimate the "new" long-run steady state income of individuals, and then calculate the

Gini, and the SWF. Consequently, I obtain simulated data by making each of the following changes sequentially for the same subgroup of population while holding all the other variables constant at the original levels: reduce unemployment rate by 1 percentage point, reduce poverty rate by 1 percentage point, increase father's education by 1 year and reduce years in poverty during childhood by 1 year. I calculate the Sen (1976) SWF using each set of these simulated data. I do this for two different values of κ, representing two different states of the economy - the average economic conditions and the more favorable economic conditions. In the first case, I assume that all the time-varying variables (current macroeconomic variables used as controls in the regression) are held at their average values, while the time-invariant variables are held constant at their actual values (schooling, sex, race). I also hold age to be less than or equal to 25 when calculating κ. In the second case, I hold age to be less than or equal to 25, but have other macroeconomic variables much more favorable than the average conditions. In this case too, I hold the time-invariant variables are held constant at their actual values. Thus, I am looking at the income distribution of the population when they are about to start employment (between the ages of 18 to 25) are currently living in similar counties. This way, I can look at how childhood neighborhood affects income level of a person who has just started working in the workforce, and thus, the effect of job experience has not manifested itself to a large extent yet. The results are shown in Table 2.9 (for the average macroeconomic conditions) and Table 2.10 (for the more favorable macroeconomic conditions).

Col (1) of Table 2.9 shows the baseline value. The SWF in bold indicate an improvement in the SWF. The results show that increasing the proportion of high-school

graduates and above in childhood neighborhood decreases Gini by about 0.1 percent and increases income by about 0.023 percent, which leads to an overall improvement of social welfare by about 0.05 percent. Reducing unemployment rate by 1 percentage point, on the other hand, leads to a fall in overall social welfare by 1.22 percent. Reducing poverty rate by one percentage point can lead to a fall in Gini by 0.84 percent when compared to the baseline case, while it increases average income by about 0.17 percent. This leads to an improvement of social welfare by 0.36%. Similarly, increasing father's education by one year leads to an improvement of welfare by 0.35%, and reducing duration of poverty during childhood by one year can help to increase welfare by 0.23%.

I do the same test where the macroeconomic conditions are more favorable, and the results are tabulated in Table 2.10. Now, education level in the neighborhood negatively affects the overall welfare, but reducing unemployment rate by one percentage point in the neighborhood has a positive effect on overall welfare, because of an increase in the persistence coefficient, which made the long-run effect of κ higher in magnitude. Now, the greatest improvement comes when father's education is increased by one year, followed by reducing poverty rate in the neighborhood by one percentage point. This exercise also shows that a growing macroeconomy greatly helps the poor, by increasing the value of κ.

A few things emerge from this exercise. It shows that improving childhood neighborhood quality of those who earn in the bottom of the income distribution can help to improve the long-run income, whatever the state of the current economy is. The effect may not be immediate, but the benefits of an improved neighborhood can manifest itself in the long run. As seen in Tables 2.9 and 2.10, different childhood neighborhood

variables affect the social welfare positively depending on the current state of the economy. If the social planner expects the economy to be weak, then improving education level and reducing poverty rate seem to provide good “role-model” effects for individuals which makes them cope with the bad economy in the future. If the economy is expected to be strong, the reducing neighborhood poverty rate, increasing father’s education and reducing unemployment rates seem to be providing good mechanisms to thrive in the future.

Combining results from Tables 2.9 and 2.10, I find that poverty rate and education level in the family are the most important when it comes to increasing income and social welfare, although the coefficient on father's education is insignificant. The result shows some evidence of the role of “role-models” during childhood in determining adult outcomes. The largest improvement is from the reduction of poverty rates in the neighborhood by one percentage point, followed by increasing father’s education by one year when the economy is expected to be weak in the future. Reducing childhood neighborhood unemployment rate does not have an effect on improving welfare of individuals if the current state of the economy is weak, but it does have a positive effect if the current state of the economy is strong. Another interesting variable to note is the reduction of duration of childhood poverty by one year. Although not as high as reducing childhood neighborhood poverty rates or increasing father’s education, reducing duration of childhood poverty increases social welfare no matter what the expectation of the future condition of the economy. Hence, it can be seen that although providing income support to families in poverty may not have an impact on their earnings capacity of the head (as

seen in the MTO), but it can help to increase income of the children when they become adults.

2.7 Conclusion

There is a number of research papers studying the role of childhood neighborhood conditions in explaining income and poverty in adulthood. Papers have shown that childhood neighborhood quality can affect education attainment, expectations, psychological distress and income of individuals. Another strand of literature shows that family characteristics affect incomes more than the childhood neighborhood characteristics. However, most research look into how childhood neighborhood characteristics affect the level of income only, and do not income the persistence of income as a component that can potentially affect current income.

In this chapter, I model income of a person as an autoregressive process where the coefficient on the lagged dependent variable is a correlated random coefficient. This coefficient is affected by different childhood neighborhood and family characteristics, which makes it heterogeneous across individuals. I apply the correlated random effects GMM estimator on the SRC portion of the PSID dataset. The PSID is a long panel that has been collecting data from a representative group of families since 1968. It also interviews individuals who left the original family unit of 1968 and formed their own families. This allows me to connect adult income and other individual characteristics with family characteristics. In addition to that, the PSID also have sensitive geocodes that tell a researcher where a person resides. The PSID geocodes provides information of the county and census-tract where each individual resides in. Using census-track level data

from the Decennial Censuses of 1970, 1980 and 1990, I calculate the average neighborhood characteristics where a person resides before they are 18. This provides a proxy of the neighborhood quality during childhood. I use county-level data as proxy for capturing business-cycles effect on adult income. Using all this data, I run GMM on 2124 individuals having 16697 person-years of data.

My results show that education level of neighborhood during childhood and poverty rate have a large influence on the level and persistence of income. Childhood neighborhood unemployment rate also affects the level and persistence of income, but the sign (positive and significant) is opposite of what one would expect in the levels part of the equation. However, I find that reducing childhood neighborhood unemployment rates when the future macroeconomy is more favorable can increase long-run income and increase social welfare function. The average persistence of income is about 0.26, but there is a great deal of heterogeneity among individuals (standard deviation is about 0.14), with the poor having a higher value of persistence than the rich. This makes the recovery time from a negative shock longer for those who have a higher value of income persistence. Because of heterogeneity of persistence, the long run effect of coefficients is also different for different segment of the population. The poor are more susceptible to changes in the macroeconomy than the rich. I run a number robustness tests to test the validity of the results and the results from the baseline case seem to be generally valid. I also find in the robustness tests that idleness rate, not unemployment rate, negatively affects the level of income.

As a further test, I run a series of experiments to see which childhood variables have the biggest impact on adult income of individuals. I find that reducing neighborhood

poverty rate of those earning in the bottom quartile of the income distribution and increasing their father's education by one year benefit the individuals the most (although the coefficients on father's education are no significant), no matter what the condition of the economy in their adult life. This provides evidence that improving childhood neighborhood characteristics can have a big effect on overall welfare of society in the long run. If family characteristics cannot be improved, then improving childhood neighborhood characteristics can help to increase adult income in the long run.

Table 2.1: Summary Statistics of Different Variables

Variable	Mean	Std. Dev.
Age of Individual	31.44	7.31
Education of Individual	13.72	2.05
Education of Father	12.82	3.63
Education of Mother	12.69	2.59
Income to Needs Ratio	9.80	80.94
Median Income of Current County of Residence[5]	47,477	10,461
Crime Rate per Person in the Current County of Residence	0.0281	0.0301
Poverty Rate of Neighborhood During Childhood	0.1023	0.0868
Poverty Rate of Current County of Residence	0.1145	0.0467
Proportion of Female Headed Household	0.1275	0.0803
Proportion White of Neighborhood During Childhood	0.8859	0.2098
Proportion with High-school Education and Above of Neighborhood During Childhood	0.6905	0.1558
Race of Individual	0.8625	0.3444
Sex of Individual	0.5094	0.5000
Total Population of Neighborhood During Childhood	5104.7	2066.85
Unemployment Rate of Neighborhood during Childhood	0.0555	0.0315
Unemployment Rate of Current County of Residence	0.0564	0.026
Years Spent in Poverty During Childhood	0.9826	2.5065

There are 2124 unique individuals and 16697 person-years of data. Childhood variables were averaged across individuals, while current macroeconomic aggregates were averaged across person years. [5]In 2005 dollars.

Table 2.2: Result of the Baseline Model with Exogenous Instruments.

	Model 2a	Model 2b	Model 2c
Variables Affecting Persistence			
LagY*Constant	0.2462**	0.7579**	0.7320**
	(0.027)	(0.164)	(0.171)
LagY*Sex		-0.2254**	-0.2234**
		(0.053)	(0.055)
LagY*Neigh Unemp. Pct		-1.9135**	-1.7187*
		(0.908)	(0.924)
LagY*Neigh. HS Educ		-0.5938**	-0.6344**
		(0.207)	(0.201)
LagY*Neigh Poverty Rate		-0.1567	-0.2437
		(0.376)	(0.367)
LagY*Father Educ		0.005	
		(0.006)	
LagY*Mother Educ			0.0076
			(0.008)
LagY*Race		0.1168	0.1370*
		(0.077)	(0.078)
LagY*Fam Yrs. In Poverty		-0.0061	-0.0068
		(0.010)	(0.010)
Variables Affecting Level			
Sex (1 – male, 0 – female)	0.5497**	0.6466**	0.6423**
	(0.033)	(0.048)	(0.048)
Neigh Unemp. Pct	1.5528**	2.8223**	2.8143**
	(0.571)	(0.735)	(0.752)
Neigh HS Educ	-0.109	0.2679*	0.3046*
	(0.124)	(0.163)	(0.170)
Neigh Poverty Rate	-0.7306**	-0.6556**	-0.6375**
	(0.279)	(0.265)	(0.271)
Father Educ	0.0075*	0.0058	
	(0.004)	(0.006)	
Mother Educ			0.0101
			(0.008)
Race (1 – white , 0 – black)	-0.0145	-0.0897	-0.1005*
	(0.0475)	(0.059)	(0.060)
Fam Yrs. In Poverty	-0.0095	-0.0084	-0.0101
	(0.008)	(0.008)	(0.008)
Hansen's test	1765.26	1565.82	1559.59
Degrees of freedom	(2207)	(2200)	(2200)
Chi2 Test of no persistence (df=8)		202.96	211.95
Average value of Gamma		0.2679	0.2678
Standard Deviation		(0.1425)	(0.1440)

Standard errors in parenthesis. The instrument matrix is block-diagonal with instrument going upto 15 lags. The regression controlled for age, age squared, education and current macroeconomic characteristics.

Table 2.3: The Short and Long-run Coefficients of Select Socioeconomic Variables

		Variables in Adulthood			Variables in Childhood	
Income Distribution	**Average Persistence**	**County Median Income**	**County Unemp. Rate**	**School**	**Neigh. Poverty Rate**	**Duration of Poverty**
		Short Run Coefficients				
		0.891**	-2.641**	0.062**	-0.6556**	-0.0084
		(0.144)	(0.623)	(0.007)	(0.265)	(0.008)
		Long-run Coefficients of Different Income Groups				
Total Sample	0. 2697	1.2200	-3.6160	0.0852	-0.8977	-0.0115
Top 25%	0.2410	1.1739	-3.4793	0.0819	-0.8638	-0.0111
Top 50%	0.2481	1.1850	-3.5122	0.0827	-0.8719	-0.0112
Bottom 75%	0. 2726	1.2249	-3.6305	0.0855	-0.9013	-0.0115
Bottom 50%	0..2835	1.2435	-3.6857	0.0868	-0.9150	-0.0117
Bottom 25%	0.3372	1.3443	-3.9843	0.0938	-0.9891	-0.0127

Note: Standard errors are in parenthesis

Table 2.4: Time to Recovery Under Different Persistence Level and Macroeconomic Conditions

	Economic Conditions		
Persistence	**Unfavorable**	**Average**	**Favorable**
0.21	9 years	8 years	7 years
0.25	11 years	10 years	10 years
0.30	11 years	11 years	10 years
0.35	14 years	13 years	13 years

Notes: Unfavorable condition is where $X'_{it}\theta = 0.5$, average conditions is where $X'_{it}\theta = 1$ and favorable is where $X'_{it}\theta = 1.5$. Time to recovery is when income returned to its original long-run level (the long-run income equaled to the original value at 5 decimal places) after receiving the initial shock at period 0. The shock equals to -0.5, and is the same for all conditions.

Table 2.5: Robustness Test of the Baseline Case Using Different Instrument Matrix

	Model 5a (20 Lags)	Model 5b (10 Lags)	Model 5c (5 Lags)
Variables Affecting Persistence			
LagY*Constant	0.7717**	0.7664**	0.8103**
	(0.162)	(0.170)	(0.180)
LagY*Sex	-0.2160**	-0.2228**	-0.2420**
	(0.052)	(0.056)	(0.058)
LagY*Neigh Unemp. Pct	-2.1175**	-1.9964**	-2.1267**
	(0.906)	(0.946)	(1.017)
LagY*Neigh. HS Educ	-0.6121**	-0.6091**	-0.5804**
	(0.203)	(0.213)	(0.225)
LagY*Neigh Poverty Rate	-0.1356	-0.1394	-0.1239
	(0.368)	(0.395)	(0.430)
LagY*Father Educ	0.0062	0.0054	0.0029
	(0.006)	(0.007)	(0.007)
LagY*Race	0.0977	0.118	0.0944
	(0.077)	(0.078)	(0.082)
LagY*Fam Yrs. In Poverty	-0.0061	-0.0067	-0.0026
	(0.010)	(0.011)	(0.011)
Variables Affecting Level			
Sex (1 – male, 0 – female)	0.6432**	0.6423**	0.6556**
	(0.047)	(0.049)	(0.050)
Neigh Unemp. Pct	2.9336**	2.8601**	2.8961**
	(0.743)	(0.753)	(0.773)
Neigh HS Educ	0.2790*	0.2747*	0.259
	(0.161)	(0.164)	(0.168)
Neigh Poverty Rate	-0.6728**	-0.6628**	-0.6616**
	(0.262)	(0.263)	(0.259)
Father Educ	0.0049	0.0055	0.007
	(0.006)	(0.006)	(0.006)
Race (1 – white , 0 – black)	-0.0806	-0.0895	-0.0783
	(0.059)	(0.059)	(0.060)
Fam Yrs. In Poverty	-0.0083	-0.0083	-0.0083
	(0.008)	(0.008)	(0.008)
Hansen's test	1573.21	1569.48	14009.15
Degrees of freedom	(2445)	(1830)	(1335)
Chi2 Test of no persistence (df=8)	192.85	194.81	201.48
Average value of Gamma	0.2660	0.2713	0.2719
Standard Deviation	(0.1405)	(0.1432)	(0.1476)

Standard errors in parenthesis. The instrument matrix is block-diagonal. The regression controlled for age, age squared, education and current macroeconomic characteristics.

Table 2.6: Robustness Test of the Baseline Case Using Predetermined Instrument Matrix

	Model 6a (15 Lags)	Model 6b (10 Lags)	Model 6c (5 Lags)
Variables Affecting Persistence			
LagY*Constant	0.7436**	0.7525**	0.8007**
	(0.165)	(0.171)	(0.181)
LagY*Sex	-0.2244**	-0.2222**	-0.2434**
	(0.053)	(0.055)	(0.058)
LagY*Neigh Unemp. Pct	-1.7928*	-1.8915**	-1.9714*
	(0.919)	(0.957)	(1.030)
LagY*Neigh. HS Educ	-0.5894**	-0.6048**	-0.5819**
	(0.204)	(0.210)	(0.222)
LagY*Neigh Poverty Rate	-0.2296	-0.2243	-0.2415
	(0.383)	(0.402)	(0.428)
LagY*Father Educ	0.0054	0.006	0.0034
	(0.006)	(0.007)	(0.007)
LagY*Race	0.1247	0.1248	0.1062
	(0.079)	(0.081)	(0.086)
LagY*Fam Yrs. In Poverty	-0.0055	-0.006	-0.0019
	(0.010)	(0.011)	(0.011)
Variables Affecting Level			
Sex (1 – male, 0 – female)	0.6418**	0.6383**	0.6526**
	(0.048)	(0.050)	(0.050)
Neigh Unemp. Pct	2.7789**	2.8558**	2.8816**
	(0.754)	(0.767)	(0.777)
Neigh HS Educ	0.2708*	0.2802*	0.2651
	(0.164)	(0.166)	(0.172)
Neigh Poverty Rate	-0.6317**	-0.6377**	-0.6248**
	(0.276)	(0.276)	(0.275)
Father Educ	0.0045	0.004	0.0057
	(0.006)	(0.006)	(0.006)
Race (1 – white , 0 – black)	-0.0909	-0.09	-0.0816
	(0.060)	(0.060)	(0.061)
Fam Yrs. In Poverty	-0.0097	-0.0097	-0.0097
	(0.008)	(0.008)	(0.008)
Hansen's test	1532.4	1524.72	1326.41
Degrees of freedom	(2096)	(1726)	(1231)
Chi2 Test of no persistence (df=8)	205.66	196.3	200.89
Average value of Gamma	0.2698	0.2720	0.2740
Standard Deviation	(0.1420)	(0.1430)	(0.1481)

Standard errors in parenthesis. The instrument matrix is block-diagonal. The regression controlled for age, age squared, education and current macroeconomic characteristics.

Table 2.7: Robustness Test of the Baseline Case Using Exogenous Collapsed Instrument Matrix

	Model 7a (15 Lags)	Model 7b (10 Lags)	Model 7c (5 Lags)
Variables Affecting Persistence			
LagY*Constant	0.6433	0.6873	0.4722
	(0.401)	(0.423)	(0.494)
LagY*Sex	-0.2730**	-0.2635**	-0.3603**
	(0.102)	(0.101)	(0.110)
LagY*Neigh Unemp. Pct	-3.4564	-3.6483	-5.4210*
	(2.226)	(2.333)	(2.951)
LagY*Neigh. HS Educ	-1.5105**	-1.2609**	-0.8191
	(0.542)	(0.502)	(0.638)
LagY*Neigh Poverty Rate	1.0721	1.0502	1.67
	(0.985)	(1.024)	(1.093)
LagY*Father Educ	0.0253	0.0177	0.0101
	(0.019)	(0.019)	(0.020)
LagY*Race	0.5746**	0.4761**	0.5815**
	(0.216)	(0.219)	(0.216)
LagY*Fam Yrs. In Poverty	0.0184	0.0096	0.0334
	(0.032)	(0.037)	(0.040)
Variables Affecting Level			
Sex (1 – male, 0 – female)	0.6491**	0.6411**	0.6883**
	(0.079)	(0.073)	(0.079)
Neigh Unemp. Pct	4.0202**	3.9216**	4.4097**
	(1.508)	(1.420)	(1.774)
Neigh HS Educ	1.1729**	0.8722**	0.6846
	(0.418)	(0.362)	(0.438)
Neigh Poverty Rate	-1.2732**	-1.3496**	-1.3199**
	(0.533)	(0.522)	(0.512)
Father Educ	-0.0084	-0.004	0.0026
	(0.016)	(0.015)	(0.015)
Race (1 – white , 0 – black)	-0.4255**	-0.3747**	-0.4100**
	(0.138)	(0.136)	(0.136)
Fam Yrs. In Poverty	-0.0278**	-0.0240**	-0.0275**
	(0.011)	(0.012)	(0.014)
Hansen's test	460.09	326.63	211.25
Degrees of freedom	(365)	(270)	(150)
Chi2 Test of no persistence (df=8)	101.40	111.66	111.37
Average value of Gamma	0.2167	0.2345	0.2577
Standard Deviation	(0.2954)	(0.2574)	(0.2994)

Standard errors in parenthesis. The instrument matrix is not block-diagonal. The regression controlled for age, age squared, education and current macroeconomic characteristics.

Table 2.8: Robustness Test of the Baseline Case Using Using One-step GMM with Exogenous Instrument Matrix

	Model 8a (15 Lags)	Model 8b (10 Lags)	Model 8c (5 Lags)
Variables Affecting Persistence			
LagY*Constant	0.7599**	0.7658**	0.8109**
	(0.164)	(0.170)	(0.180)
LagY*Sex	-0.2258**	-0.2228**	-0.2417**
	(0.053)	(0.056)	(0.058)
LagY*Neigh Unemp. Pct	-1.9192**	-1.9875**	-2.1307**
	(0.908)	(0.943)	(1.022)
LagY*Neigh. HS Educ	-0.5956**	-0.6092**	-0.5807**
	(0.207)	(0.213)	(0.225)
LagY*Neigh Poverty Rate	-0.16	-0.1413	-0.1261
	(0.376)	(0.396)	(0.429)
LagY*Father Educ	0.005	0.0054	0.0029
	(0.006)	(0.007)	(0.007)
LagY*Race	0.1169	0.1183	0.0943
	(0.077)	(0.079)	(0.082)
LagY*Fam Yrs. In Poverty	-0.0061	-0.0066	-0.0024
	(0.010)	(0.011)	(0.011)
Variables Affecting Level			
Sex (1 – male, 0 – female)	0.6464**	0.6427**	0.6553**
	(0.048)	(0.049)	(0.050)
Neigh Unemp. Pct	2.8057**	2.8476**	2.8970**
	(0.743)	(0.753)	(0.775)
Neigh HS Educ	0.2675	0.2761*	0.2586
	(0.163)	(0.165)	(0.168)
Neigh Poverty Rate	-0.6556**	-0.6616**	-0.6608**
	(0.265)	(0.264)	(0.260)
Father Educ	0.0058	0.0055	0.0071
	(0.006)	(0.006)	(0.006)
Race (1 – white , 0 – black)	-0.0904	-0.0902	-0.0783
	(0.059)	(0.059)	(0.060)
Fam Yrs. In Poverty	-0.0083	-0.0082	-0.0083
	(0.008)	(0.008)	(0.008)
Hansen's test	1565.82	1569.48	1409.15
Degrees of freedom	(2200)	(1830)	(1335)
Chi2 Test of no persistence (df=8)	202.50	194.70	200.14
Average value of Gamma	0.2694	0.2713	0.2720
Standard Deviation	(0.1429)	(0.1432)	(0.1475)

Standard errors in parenthesis. The instrument matrix is not block-diagonal. The regression controlled for age, age squared, education and current macroeconomic characteristics.

Table 2.9: Robustness Test of the Baseline Case Using Using Two-step GMM with Idleness Instead of Unemployment Rate and Exogenous Instrument Matrix

	Model 9a (15 Lags)	Model 9b (10 Lags)	Model 9c (5 Lags)
Variables Affecting Persistence			
LagY*Constant	1.9266**	2.0296**	2.0358**
	(0.398)	(0.409)	(0.426)
LagY*Sex	-0.2280**	-0.2280**	-0.2631**
	(0.054)	(0.055)	(0.057)
LagY*Neigh Idleness Pct	0.0182**	0.0195**	0.0205**
	(0.005)	(0.005)	(0.005)
LagY*Neigh. HS Educ	-0.3469	-0.2751	-0.1936
	(0.235)	(0.24)	(0.258)
LagY*Neigh Poverty Rate	-1.0968**	-1.1748**	-1.0416**
	(0.386)	(0.398)	(0.418)
LagY*Father Educ	0.0004	0.0006	-0.0023
	(0.006)	(0.006)	(0.006)
LagY*Race	0.0813	0.0714	0.0496
	(0.078)	(0.08)	(0.083)
LagY*Fam Yrs. In Poverty	-0.007	-0.0064	-0.0019
	(0.01)	(0.011)	(0.011)
Variables Affecting Level			
Sex (1 – male, 0 – female)	0.6469**	0.6446**	0.6673**
	(0.049)	(0.05)	(0.051)
Neigh Idleness Pct	-0.0105**	-0.0112**	-0.0115**
	(0.004)	(0.004)	(0.004)
Neigh HS Educ	0.067	0.0204	-0.0231
	(0.189)	(0.193)	(0.201)
Neigh Poverty Rate	-0.101	-0.0636	-0.1107
	(0.355)	(0.361)	(0.341)
Father Educ	0.0096*	0.0094*	0.0111**
	(0.005)	(0.005)	(0.005)
Race (1 – white , 0 – black)	-0.0789	-0.0725	-0.0585
	(0.059)	(0.059)	(0.059)
Fam Yrs. In Poverty	-0.0067	-0.0069	-0.0073
	(0.009)	(0.009)	(0.009)
Hansen's test	1768.88	1660.86	1456.44
Degrees of freedom	(2251)	(1881)	(1386)
Chi2 Test of no persistence (df=9)	210.34	204.55	216.69
Average value of Gamma	0.2375	0.2410	0.2415
Standard Deviation	(0.1770)	(0.1793)	(0.1894)

Standard errors in parenthesis. The instrument matrix is not block-diagonal. The regression controlled for average neighborhood family characteristics (both in level and persistent part of the equation), age, age squared, education and current macroeconomic characteristics.

Table 2.10: Robustness Test of the Baseline Case Using Using Two-step GMM with Changes in Family Structure Accounted For And Exogenous Instrument Matrix

	Model 10a (15 Lags)	Model 10b (10 Lags)	Model 10c (5 Lags)
Variables Affecting Persistence			
LagY*Constant	0.9403**	0.9699**	0.9318**
	(0.229)	(0.24)	(0.258)
LagY*Sex	-0.1980**	-0.1937**	-0.2216**
	(0.054)	(0.055)	(0.057)
LagY*Neigh Unemp. Pct	-1.7420*	-1.8848*	-2.0886**
	(0.956)	(0.981)	(1.013)
LagY*Neigh. HS Educ	-0.6583**	-0.6188**	-0.5878**
	(0.231)	(0.235)	(0.252)
LagY*Neigh Poverty Rate	-0.5503	-0.5904	-0.4525
	(0.39)	(0.406)	(0.437)
LagY*Father Educ	-0.0009	-0.0005	-0.0031
	(0.006)	(0.007)	(0.007)
LagY*Family Structure Change	0.0153	0.0258	0.0324
Dummy	(0.07)	(0.071)	(0.075)
LagY*Fam Yrs. In Poverty	-0.0099	-0.0096	-0.0039
	(0.01)	(0.01)	(0.01)
Variables Affecting Level			
Sex (1 – male, 0 – female)	0.6272**	0.6220**	0.6405**
	(0.049)	(0.05)	(0.05)
Neigh Unemploy. Pct	2.7805**	2.8816**	2.9417**
	(0.808)	(0.822)	(0.811)
Neigh HS Educ	0.2686	0.2417	0.2251
	(0.186)	(0.189)	(0.197)
Neigh Poverty Rate	-0.5430*	-0.5257	-0.5632*
	(0.323)	(0.329)	(0.308)
Father Educ	0.0107**	0.0104*	0.0119**
	(0.005)	(0.006)	(0.006)
Family Structure Change Dummy	0.0079	0.0017	-0.0046
	(0.053)	(0.054)	(0.054)
Fam Yrs. In Poverty	-0.0084	-0.0087	-0.0092
	(0.009)	(0.009)	(0.009)
Hansen's test	1768.88	1660.86	1456.44
Degrees of freedom	(2251)	(1881)	(1386)
Chi2 Test of no persistence (df=9)	210.34	204.55	216.69
Average value of Gamma	0.2375	0.2410	0.2415
Standard Deviation	(0.1770)	(0.1793)	(0.1894)

Standard errors in parenthesis. The instrument matrix is not block-diagonal. The regression controlled for average neighborhood family characteristics and race (both in level and persistent part of the equation), as well as age, age squared, education and current macroeconomic characteristics.

Table 2.11: Robustness Test of the Baseline Case Using Two-step GMM with ln(Income) as Dependent Variable and Exogenous Instrument Matrix

	Model 11a (All Lags)	Model 11b (15 Lags)	Model 11c (10 Lags)	Model 11d (5 Lags)
Variables Affecting Persistence				
LagY*Constant	0.1885**	0.7502**	0.7812**	0.7711**
	(0.029)	(0.231)	(0.240)	(0.256)
LagY*Sex		-0.1582**	-0.1518**	-0.1677**
		(0.051)	(0.053)	(0.056)
LagY*Neigh Unemp. Pct		-1.3714	-1.4697	-1.7717*
		(0.974)	(1.004)	(1.047)
LagY*Neigh. HS Educ		-0.5389**	-0.5163**	-0.5023*
		(0.239)	(0.245)	(0.262)
LagY*Neigh Poverty Rate		-0.6512	-0.7183*	-0.6483
		(0.421)	(0.429)	(0.460)
LagY*Father Educ		0.003	0.003	0.003
		(0.007)	(0.007)	(0.007)
LagY*Race		0.081	0.076	0.068
		(0.075)	(0.076)	(0.079)
LagY*Fam Yrs. In Poverty		0.0025	0.004	0.008
		(0.010)	(0.010)	(0.011)
Variables Affecting Level				
Sex (1 – male, 0 – female)	0.5821**	1.0558**	1.0321**	1.0822**
	-0.034	-0.176	-0.183	-0.19
Neigh Unemploy. Pct	1.5897**	6.1752*	6.5074**	7.4789**
	(0.565)	(3.188)	(3.287)	(3.408)
Neigh HS Educ	-0.1833	1.5689**	1.4921*	1.4503*
	(0.138)	(0.791)	(0.810)	(0.864)
Neigh Poverty Rate	-0.7127**	1.332	1.540	1.325
	(0.287)	(1.275)	(1.310)	(1.382)
Father Educ	0.0096**	0.0015	0.0014	0.0003
	(0.004)	(0.022)	(0.023)	(0.024)
Family Structure Change Dummy	-0.0135	-0.286	-0.2669	-0.2413
	(0.047)	(0.237)	(0.239)	(0.246)
Fam Yrs. In Poverty	-0.0027	-0.0115	-0.0162	-0.0277
	(0.008)	(0.030)	(0.031)	(0.032)
Hansen's test	1864.52	1741.09	1645.35	1432.32
Degrees of freedom	(2212)	(2251)	(1881)	(1386)
Chi2 Test of no persistence (df=8)		59.33	105.32	58.77
Average value of Gamma		0.2157	0.2201	0.2240
Standard Deviation		(0.1129)	(0.1120)	(0.1790)

Standard errors in parenthesis. The instrument matrix is not block-diagonal. The regression controlled for average neighborhood family characteristics and race (both in level and persistent part of the equation), as well as age, age squared, education and current macroeconomic characteristics.

Table 2.12: The Value of Sen (1976) Social Welfare Function Using Simulated Data When Economy is Weak

	Col (1)	Col (2)	Col (3)	Col (4)	Col (5)	Col (6)
	Baseline Value	**High-School Prop. Increased by 1 pct. pt**	**Unemp Rate Reduced by 1pct. pt**	**Poverty Rate Reduced by 1 pct pt**	**Father's education increased by 1 year**	**Duration of poverty reduced by 1 year**
Sen-measure Using Model 2b						
Mean Income	2.1835	2.1840	2.1714	2.1872	2.1872	2.1855
Gini	0.1903	0.1901	0.1957	0.1887	0.1888	0.1894
Sen Measure	1.7679	**1.7688**	1.7464	**1.7744**	**1.7742**	**1.7715**
Percentage Change of Mean Income from Baseline Value		0.023%	-0.5542%	0.1695%	0.1695%	0.0916%
Percentage Change of Gini from Baseline Value		-0.105%	2.8376%	-0.8408%	-0.7882%	-0.473%
Percentage Change of Welfare from Baseline Value		0.047%	-1.217%	0.3674%	0.3550%	0.2023%

*Number in bold indicates improvement in social welfare function when compared to the baseline model (col (1)). The coefficients in model 2b were used for the analysis. In calculating the long run effect, all the current macroeconomic variables were kept constant at their average; sex, race and education were taken at their actual values, and age was taken to be less than or equal to 25. The Sen measure is $\bar{y}(1-G)$ where $\bar{y}$ is the mean income and G is the Gini coefficient.

Table 2.13: The Value of Sen (1976) Social Welfare Function Using Simulated Data When Economy is Strong

	Col (1)	Col (2)	Col (3)	Col (4)	Col (5)	Col (6)
	Baseline Value	**High-School Prop. Increased by 1 pct. pt**	**Unemp Rate Reduced by 1pct. pt**	**Poverty Rate Reduced by 1 pct pt**	**Father's education increased by 1 year**	**Duration of poverty reduced by 1 year**
Sen-measure Using Model 2b						
Mean Income	9.2613	9.2437	9.2782	9.2813	9.2910	9.2810
Gini	0.1440	0.1457	0.1425	0.1421	0.1412	0.1421
Sen Measure	7.9276	7.8969	**7.9560**	**7.9624**	**7.9791**	**7.9621**
Percentage Change of Mean Income from Baseline Value		-0.190%	0.1824%	0.2160%	0.3207%	0.2127%
Percentage Change of Gini from Baseline Value		1.805%	-1.041%	-1.319%	-1.944%	-1.319%
Percentage Change of Welfare from Baseline Value		-0.388%	0.3580%	0.4384%	0.6488%	0.4351%

*Number in bold indicates improvement in social welfare function when compared to the baseline model (col (1)). The coefficients in model 2b were used for the analysis. In calculating the long run effect, all the current macroeconomic variables were kept constant at their average; sex, race and education were taken at their actual values, and age was taken to be less than or equal to 25. The Sen measure is $\bar{y}(1-G)$ where $\bar{y}$ is the mean income and G is the Gini coefficient

3 ON THE MEASUREMENT OF CHRONIC POVERTY

3.1 Introduction

Poverty measurement can be a challenging task for economists. As pointed out by Sen (1976), there are two problems in measuring the level and intensity of poverty - the first is identifying who is poor, and the second is finding out some method to aggregate poverty. The first problem is addressed by choosing a poverty line, denoted by z, so that anyone earning below z is said to be living in poverty. The second problem is solved by coming up with a mathematical function that satisfies different axioms of measuring poverty. Such a measure is collectively known as unidimensional measure, because they use one dimension, such as income or consumption, to determine whether a person is in poverty. Extending on that, economists have also developed chronic poverty measures to capture the incidence and severity of long-term poverty (Duclos et al, 2010; Foster, 2009; Gibson, 2001; Jalan and Ravallion, 1998). Economists have defined chronic poverty as long-term, or persistent poverty, and all these names have been used interchangeably. People in chronic poverty are said to be earning below the poverty line all the time, or for most of the time (Hulme and Shephard, 2003). However, it is difficult to measure whether the level of chronic poverty has changed over time using the prevailing chronic poverty measures. This paper introduces a new method to measure chronic poverty that treats income and poverty spells of a population as a bivariate distribution. This distribution can be used to identify those in chronic poverty and then measure each of their current poverty indexes. The aggregated poverty measure computed can be used to see if chronic poverty levels have changed over time, by using the method of stochastic

dominance (Davidson and Duclos, 2010). This can tell the policy-maker whether poverty reduction strategies undertaken to help the chronically poor have been effective or not.

The measurement of poverty literature has taken a multi-faceted approach. Poverty of a person is closely related to their capabilities. According to Sen, capabilities are the set of options or opportunities that are available for a person to achieve and what they value. Functionings, on the other hand, are the achievements that a person values to do. (Martinetti, 2006). According to Sen (1999), a person is in poverty if they have a restricted capabilities set. Throughout the years, many economists (Watts, 1968; Sen, 1976; Thon, 1979; Takayama, 1979; Blackorby and Donaldson, 1980; Clark, Hemming and Ulph, 1981; Chakravarty, 1983; and Foster, Greer and Thorbecke, 1984) have come up with different ways to measure uni-dimensional poverty using the poverty line, normally denoted by z. These poverty measures, however, may not capture the true condition of the poor, since they don't capture all the deprivations. Noting that a person in poverty may be deprived in multiple dimensions of well-being like income, food consumption, health and living conditions, some economists (Tsui, 2002; Bourguignon and Chakravarty, 2003; Alkire and Foster, 2011) came up with multi-dimensional poverty measures that aggregate different dimensions of well-being to measure the true extent of poverty. Multi-dimensioanal poverty measures try to provide a mathematical function of the deprivations in the capabilities set of a person. Some authors, such as Martinetti (2006) have tried to incorporate fuzzy sets in measuring poverty.

Other economists have noted that short- and long-term poverty can be very different in nature (Hulme and Shepherd, 2003; Sen 1981). For example, people who move in and out of poverty continuously may need income support during adverse times

to alleviate poverty. On the other hand, people suffering from long-term poverty may need structural changes to policy and support to eliminate poverty (Hulme and Shepherd, 2003). Long term poverty, persistent poverty or chronic poverty has been defined as poverty where a person has significant deprivation of capabilities for a number of years (Hulme and Shepherd, 2003). Besides income/consumption, time dimension is also added in this measure. The number of years in poverty can be arbitrary, but generally, if a person is poor for 5 or more years, then they are considered to be chronically poor. Chronic poverty is different from transient poverty in that it can have more severe and negative consequences on a person's well-being. The longer a person remains in poverty, the higher are the chances of other dimensions of well-being, such as consumption, health and asset accumulation, to be affected adversely, thus making it even harder for that person to exit poverty. However, it may be difficult for a researcher to measure variables of well-being such as health, consumption, income and education for a large sample of individuals, so identifying individuals who are trapped in poverty for long periods of time, and then comparing their level of income deprivation over time can give researchers some idea of the overall well-being of the chronically poor.

The poor are thus a heterogeneous group and different policy is needed to address poverty reduction in each group (Sen, 1981). However, poverty reduction policies tend to view the poor as one homogeneous group earning a low income, as evidenced from one of the Millennium Development Goals (decrease by half the proportion of people who earn less than a dollar a day)[8] (Hulme and Shepherd 2003). Such a policy is geared towards poverty reduction, rather than poverty alleviation. Therefore, a policymaker may

[8] http://www.un.org/millenniumgoals/poverty.shtml

have the incentive to help the near-poor first, rather than those in deep or severe poverty in order to get quick results. The chronically poor need different policy instruments, such as education, vocational training or micro-credit facilities to alleviate their poverty, while the transient poor may need instruments such as short-term income support during times of distress to alleviate their poverty. The chronically poor living in economically active areas would probably require only individual-level skills development, while those living in depressed areas needs policies that makes structural changes to the macroeconomy, besides individual-level skill-building. Therefore, it is important to treat chronic poverty separately from transient poverty and to see if their condition has improved over time, and to see if policies aimed at helping them are being effective. Building on this idea, it becomes important not only to identify the heterogeneity among the poor, but also use a better measurement technique to calculate and evaluate poverty among each of those groups.

In this paper, I devise a new measure of chronic poverty. I show here that improvements in poverty rate may not necessarily mean that the chronically poor got better off, which shows that it is important not to treat the poor as a homogeneous group. In this paper, I assume that a researcher has information about current level of income and the length of spell of poverty in prior years. A long panel is not needed to measure chronic poverty, a repeated cross-section that asks about current income and prior length of spell of poverty is needed to measure poverty rates. I treat current income and length of spell in poverty as the two dimensions in a bivariate distribution. Such duration-based approach has been introduced to measure other economic indices, such as unemployment rates (Shorrocks, 2009, Sengupta, 2009). I then measure chronic poverty of the

population by aggregating the poverty score of the people who are currently in poverty and who also spent a certain number of years in poverty (for example 3 consecutive years or more in the years prior to the current year). I show that this chronic poverty measure satisfies the axioms of poverty, as outlined by Zheng (1997). Unlike some of their other prevalent chronic poverty measures (Jalan and Ravallion, 1998; Foster, 2009, Duclos et al., 2010), my chronic poverty score is not dependent on previous poverty scores, and so, can be used to see if poverty rates have changed over time. I use the Panel Study of Income Dynamics (PSID) dataset to illustrate this measure empirically. The PSID is a rich panel dataset that contains information on a number of socio-economic variables or the interviewees. The results show that overall poverty in the US can fluctuate over time, but chronic poverty rates remain more-or-less, steady over the same period of time. Using the method of stochastic dominance as shown by Davidson and Duclos (2010), I show that there were years where overall income distribution of people in poverty improved, but those in chronic poverty deteriorated over the same period of time. The robustness checks also provide evidence of what was observed in the baseline case.

3.2 Review of Literature

Sen (1976) believes that the problem of identifying the poor can be solved by selecting the poverty line, and a person is poor if they earn below the poverty line. However, determining how to construct the poverty line can be an issue in its own right (Atkinson, 1987). The line can be an absolute measure, which is established by calculating the current price of a basket of goods that offer a minimum amount of well-being to a person; or it can be a relative measure that is dependent on what others in the society have (Hagenaars and de Vos, 1988). The United States follows the absolute measure of

determining the poverty line. This method, called the Orshansky method, computes the minimum food consumption requirement of a family and then multiplies that value by 3, because it was believed that an average family spends one-third of its income on food consumption (Ranney, 2008). However, a report by the National Academy of Sciences (Citro and Michael, 1995) has recommended certain variables to be included in determining the poverty line in the US. On the other hand, Britain uses a relative method to calculate the poverty line, and it is determined by taking 60% of the value of the median income of the population (Townsend, 2003).

Once the poverty line has been determined, the next step is to use some mathematical method to aggregate poverty score of the population, which is the second problem of measuring poverty as posed by Sen (1976). One of the more popular version of the poverty measure is the Foster, Greer and Thorbecke (1984) index, also known as the FGT index:

$$P_a(y;z) = \frac{1}{n}\sum_{i=1}^{n}\left(1-\frac{y_i}{z}\right)^{\alpha} \cdot I(y_i \le z) \qquad (1)$$

where z is the predetermined level of the poverty line, y_i is the income of individual/household i who is living in poverty, and n is the total number of people/households in the community. I() is an indicator function that is equal to 1 if $y_i \le z$, and 0 otherwise. α is a positive integer including zero {0,1,2,3…….} which gives different measures of poverty. When α=0, $P_\alpha(y;z)$ in equation (1) is known as the headcount ratio, and it measures the proportion of people living in poverty. When α=1, $P_\alpha(y;z)$ is the income gap ratio, and it measures the average normalized shortfall of

income of individuals/households earning less than the poverty line. When α=2, the measure is the squared-poverty gap. It measures the average normalized shortfall of income but puts more weight on poorer people in the community. Thus, when α=2, an improvement of income of the poorer people in poverty will show a higher improvement in the poverty index, when compared to a similar magnitude of improvement of income of a person in poverty whose income is much closer to the poverty line.

Foster and Shorrocks (1988) also shows that if the income of a population is treated as a continuous cumulative distribution F(s) with a pdf as f(s) where s is income, then the proportion of people living in poverty, or the headcount measure, is:

$$P_0(y,z) = F(z) \tag{2}$$

If the distribution is invertible, then Foster and Shorrocks (1988) show that the value $F^{-1}(p)$ (the inverse of the distribution) can be represented in the following way:

$$F^{-1}(p) = \inf\{s \geq 0 | F(s) \geq p\} \tag{3}$$

So, equation (3) basically shows the quantile at a certain value of p. Using the above definition, the FGT class of poverty measures can be calculated using the following method (Foster and Shorrocks, 1988):

$$P_\alpha(F;z) = \frac{1}{z^\alpha}\int_0^{F(z)}[z - F^{-1}(p)]^\alpha dp \tag{4}$$

with $\alpha \geq 0$. It can be seen that other poverty measures can be evaluated by treating income as a continuous distribution. For example, the Chakravarty (1983) index is:

$$P(y;z) = \frac{1}{n}\sum_{i=1}^{n}\left(1 - \left(\frac{y_i}{z}\right)^\epsilon\right) \cdot I(y_i \leq z) \tag{5}$$

where 0< ϵ <1. Following Foster and Shorrocks (1988), this measure can be written as:

$$P(F;z) = \frac{1}{z^\epsilon}\int_0^{F(z)}[z^\epsilon - (F^{-1}(p))^\epsilon]dp \tag{6}$$

However, economists noted that a person may not be deprived in one dimension, such as income, but may be deprived in other dimensions, such as health and consumption, which can have an impact in achieving all their functionings (Bourguignon and Chakravarty, 2003). For example, a person may have an income that is above the poverty line, but may have a bad health condition, which requires a lot of money for treatment. Consequently, the consumption of food and other goods may be lower than the minimum required level for this person. Multidimensional poverty measures thus have been developed to capture and measure the average shortcomings of different dimensions of a person, and hence, the average deprivation of a population can be measured. One example of a multidimensional measure is an FGT-type (1984) measure (Bourguignon and Chakravarty, 2003) (Alkire and Foster (2011) have a slightly different version):

$$P_\alpha(y,z) = \frac{1}{nJ}\sum_{i=1}^{n}\sum_{j=1}^{J}\left(1-\frac{y_{ij}}{z_j}\right)^{\alpha} \cdot I(y_{ij} \leq z_j) \tag{7}$$

where *n* is the total number of people in the economy, *J* is the total number of dimensions included in the measure (income, consumption, health measure, access to drinking water), y_{ij} is the amount of dimension j that person i has, and z_j is the threshold of dimension j. I() is an indicator function taking the value of 0 if $y_{ij} > z_j$, and 1 otherwise, for a certain value of *j* of person *i*. A person in chronic poverty may be deprived in a number of different dimensions of well-being. Chronic poverty has been defined as poverty where a person has significant deprivation of capabilities for a number of years (Hulme and Shephard, 2003). A panel dataset of income is needed to measure chronic poverty. Suppose that there is a total of T years of data. A general way to characterize chronic poverty using the FGT (1984) as mentioned in Duclos et al (2010) and Foster (2009) is the following equation:

$$P_\alpha(y,z) = \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}\left(1-\frac{y_{it}}{z_t}\right)^{\alpha} \cdot I(y_{ij} \leq z_j) \qquad (8)$$

Where n is the total number of people in the sample, y_{it} is the income of person i in time t who is below the poverty line, and z_t is the poverty line at time t, and α is a number greater than, or equal to 0. I() is the indicator function as defined above. The problem with this measure is that it does not take into account the length of spells of poverty. Foster (2009) referred this property as t*ime anonymity,* which means that the poverty measure does not change if vector x is obtained from vector y by a permutation of incomes across time. For example, it can be assumed that a person remaining in poverty for the last 3 consecutive years should have a higher severity of poverty than a person who is poor for 3 years, but not continuously. However, time anonymity treats both these cases as the same.

Jalan and Ravallion (1998) also came up with a chronic poverty measure which is similar to that shown in equation (1). They take the average income earned by each person across time, in the following way:

$$\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it} \qquad (9)$$

where $\bar{y}_i$ is the average income a person would have if the person faced no income shock during the time period. The chronically poor are the ones whose average income falls below the poverty line. The chronic poverty measure, according to Jalan and Ravallion is a modification of the FGT (1984) measure and can be represented in the following way:

$$P_\alpha(y,z) = \frac{1}{n}\sum_{i=1}^{n}\left(1-\frac{\bar{y}_i}{z}\right)^{\alpha} \cdot I(\bar{y}_i \leq \text{ z}) \qquad (10)$$

Where n is the number of people in the population, and the rest of the variables are the same as before. Recently, Duclos et al. (2010) also proposes a way of measuring chronic poverty using Jalan and Ravallion's (1998) measure as a starting point. They first propose the aggregate poverty gap for all individuals in poverty is given to be as follows:

$$\Gamma_\alpha(y_i, z) = \left(\frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}\left(1-\frac{y_{it}}{z}\right)^{\alpha}\right)^{\frac{1}{\alpha}} \cdot I(\overline{y_{it}} \leq \text{ z}) \tag{11}$$

The cost of having a fluctuating income stream, instead of a fixed income stream, for the whole population is given by:

$$C_\alpha(y_i, z) = \left(\frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}\left(1-\frac{y_{it}}{z}\right)^{\alpha}\right)^{\frac{1}{\alpha}} \cdot I(\overline{y_{it}} \leq \text{ z})$$

$$-\frac{1}{n}\sum_{i=1}^{n}\left(\sum_{t=1}^{T}\left(1-\frac{y_{it}}{z}\right)^{\alpha}\right)^{\frac{1}{\alpha}} \cdot I(\overline{y_{it}} \leq \text{ z}) \tag{12}$$

Using these measures, the authors conclude that the chronic poverty measure is:

$$\Gamma^*(y_i, z) = \Gamma_1(y_i, z) + C_\alpha(y_i, z) \tag{13}$$

It can be seen that the first term in the right hand side of equation (13) is the income gap ratio of all the people in poverty, and the second term is the cost, which is dependent on the value of α. The problem with these chronic poverty measures (Jalan and Ravallion, 1998, Foster, 2009, Duclos et al., 2010) is that they rely on using both the previous income stream and duration in poverty in determining the present value of poverty. While duration in poverty is an important indicator of chronic poverty, income level of previous years should not be a component in measuring the current level of poverty. The reason is that it becomes difficult to compare the welfare of people in chronic poverty changed over time. Another problem is that a long panel data is needed to assess chronic poverty levels, which may not be available, or may have to be constructed using repeated cross-section of data.

For example, assume that T is 10 years and a person is considered to be chronically poor if she spends more than 3 years in poverty. If the person was in poverty for 4 years in earlier periods, but not in later periods, then they should not be included in chronic poverty, but the poverty measure shown in (8) will include her in chronic poverty measure. Also, if the average income for this person is still below the poverty line, even though they has been out of poverty in recent years, the measures of Jalan and Ravallion (1998) and Duclos et al (2010) will still include them in chronic poverty measure, which may not be a good thing from a policy perspective. Similarly, if income in one year is very low, but remains high for the remaining years, it could be that the average income is less than the poverty line, so the person will be deemed to be in chronic poverty in Jalan and Ravallion (1998) and Duclos et al (2010) measures. It can be easily seen that a person may not be termed to be chronically poor when *T* is used, but may be chronically poor if a different time period *T'* is used, where *T'* is greater than *T*.

3.3 The Chronic Poverty Measure

I assume that the following is known about each person: (i) the income of the person in the current year (y), and (ii) the length of stay in poverty in prior years (t). The spell length can be continuous or discontinuous, depending on how a person wants to view chronic poverty. The variables y and t now can be viewed as a bivariate distribution following a technique similar to Foster and Shorrocks (1988). Therefore, in the continuous case, the pdf of the distribution can be as follows:

$$\mathrm{g}(y, t) \tag{14}$$

The cdf of the distribution can be G(y,t). G(0,0) = 0, since the probability of a person earning 0 and in poverty for 0 years can be assumed to be zero. It is seen that

G(Y,T)=1 where Y is the highest income in the distribution and T is the maximum length of stay in poverty. It is assumed that $y \in [0, Y]$ and $t \in [0, T]$, where Y is the highest income earned and T is the longest period a person can spend in poverty. The function G(y,t) is invertible. There is no prior assumption on the pdf. But it can be seen that

$$\int_0^T \mathrm{g}(y,t)dt = f(y) \tag{15}$$

and

$$\int_0^Y \mathrm{g}(y,t)ds = \gamma(t) \tag{16}$$

Equations (15) and (16) show the marginal distributions. So, f(y) is the distribution of people's income in a given year who have spent anytime from 0 to T years in poverty; hence it is the income distribution. Similarly $\gamma(t)$ is the distribution of time that the population has spent in poverty for all income levels. It can be seen that

$$P_0(y,z,w) = \int_0^z f(y)dy = \int_0^T \int_0^z g(y,t)dydt \tag{17}$$

Equation (17) is similar to the headcount measure, with the time dimension integrated out. Therefore, the measure in (17) shows that equation (4) with α=0, is just a partial measure of headcount, and (16) can encompass the measure shown in equation (4).

Let w be the cutoff value for chronic poverty. If a person is poor for less than w years, they are considered to be in transient poverty, and if they are poor for more than w years, then they are considered to be in chronic poverty. Therefore, the poverty measure now has two cutoff values – one is the poverty line, denoted by z, and the other is the chronic poverty line, denoted by w. The transient poverty measure is defined in the following way.

$$P_0(y,z,w) = \int_0^w \int_0^z g(y,t)dydt \tag{18}$$

where the headcount measure $P_0(y, z, w)$ is measuring the proportion of people in poverty today who were also poor for 0 to w years out of a possible of T consecutive years. The following equation then measures the proportion of people suffering from chronic poverty in the population:

$$P_0^c(y, z, w) = \int_w^T \int_0^z g(y, t) dy dt \tag{19}$$

Equation (19) therefore calculates the proportion of people who earn less than z and who have been poor for more than w years. A headcount measure similar to (19) can give some intuitive sense on the proportion of people living in poverty, but more information about the depth of people in chronic poverty may be desirable.

As an illustration, FGT (1984) will be used to aggregate poverty of individuals/households since it satisfies most of the axioms of a poverty measure as mentioned by Zheng (1997). Let:

$$C = \{i \in n | t \geq w \wedge y_i \leq z\} \tag{20}$$

$$U = \{i \in n | t < w \wedge y_i \leq z\} \tag{21}$$

where the set *C* in equation (20) identifies the individuals in chronic poverty in the population *n* (with current income below the poverty line and length of stay of poverty in prior years greater than *w*) and *U* in equation (21) identifies the set of individuals in transitory poverty. As can be seen, *C* and *U* are mutually exclusive and so, the set of all the people in poverty is the sum of C and U.

Assuming that G(y,t) is invertible, then, equation (17) can be written as:

$$P_0(y, z, w) = \int_0^T \int_0^z g(y, t) dy dt = G(z, T) \tag{22}$$

Then, equation 22 can be inverted in the following way (following the definition given in Foster and Shorrocks (1988)):

$$G_c{}^{-1}(p,T) = \inf\{y_i \geq 0 | G(y_i,T) = p \wedge i \subset C\} \tag{23}$$

Equation (23) thus selects the income level of those who are in the set of chronic poverty for a given value of p. Equation (23) gives the quantile for different values of p, for given values of T. Following Foster and Shorrocks (1988), the chronic poverty FGT measure can be written as shown (for a given value of z, w and T):

$$P_\alpha^c(s,w,T) = \frac{1}{z^\alpha}\int_0^{G(z,T)} \left(z - G_c{}^{-1}(p,T)\right)^\alpha dp \tag{24}$$

where $\alpha \geq 0$. For different values of α, equation (24) can show the headcount ratio, current income gap, squared income ratio, and other higher order poverty measures of people living in chronic poverty. The measure aggregates the current poverty value of people living in chronic poverty. In the discrete case, equation (24) can also be written as:

$$P_\alpha^c(s,w,T) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{z-y_i}{z}\right)^\alpha \cdot I(i \in C) \tag{25}$$

The poverty history of the population is taken to find out whose length of poverty falls into the chronic poverty criterion, and then, the current poverty measure of those people are calculated. In other words, it is the expectation of poverty of individuals who spent more than *w* years in poverty in previous years. A long panel is not needed to measure chronic poverty in this case. All that is needed is income earned today and the length of spell of poverty in prior years. So, a repeated cross section of individuals can also be used to chronic poverty, provided that they have these two information. Therefore, the chronic poverty index of people in chronic poverty can be measured for years i and i', where $i \neq i'$, and then the distributions can be compared to see which year has a higher incidence of chronic poverty, by using the method of stochastic dominance.

Since the set of people who are in chronic poverty and those who are in transitory poverty are mutually exclusive, the sum of poverty measure for transitory and chronic

poverty measures should equal to total poverty measure. It can be shown that the measure is additive, so total poverty is the sum of chronic and transitory poverty:

$$\frac{1}{z^{\alpha}}\int_0^{G(z,T)}\left(z-G^{-1}(p,T)\right)^{\alpha}dp=\frac{1}{z^{\alpha}}\int_0^{G(z,T)}\left(z-{G_c}^{-1}(p,T)\right)^{\alpha}dp$$
$$+\frac{1}{z^{\alpha}}\int_0^{G(z,T)}\left(z-{G_U}^{-1}(p,T)\right)^{\alpha}dp \quad (26)$$

which implies that:

$$P_{\alpha}\ (s,w,T)=P_{\alpha}^{c}(s,w,T)+P_{\alpha}^{T}(s,w,T) \quad (27)$$

Where ${G_U}^{-1}(p,T)=\inf\{y_i\geq 0|G(y_i,T)=p\wedge i\subset U\}$ and so it selects those who are in transitory poverty. It can be shown that this chronic poverty measrue can satisfy the different axioms of poverty, as illustrated below. These axioms are listed and explained in Zheng (1997):

Focus Axiom: This axiom states that the poverty of the poor only should be measured. This poverty measure only focuses on people who are in poverty for long periods of time, and thus, the focus axiom is satisfied.

Replication Invariance: If everyone's income, including the poverty line, is increased by the same proportion, then the poverty rate should not change, according to this axiom. It is seen that the FGT (1984) measure satisfies the replication axiom, and thus, this chronic poverty measure also satisfies replication invariance. Also, it is seen that if everyone's duration in poverty is increased by the same proportion, including the chronic poverty cutoff value, then chronic poverty rate will not change. The replication invariance axiom, thus is satisfied.

Continuity: The function g(y,t) and G(y,t) are considered to be a continuous distribution, which means that if y is changed slightly, g(y,t) and G(y,t) do not become undefined. Also, small changes in z should not make the poverty measure undefined. So, small

changes in income or time in poverty should not make the whole poverty measure undefined.

Symmetry: A permutation of the pair (s,t) does not change the poverty measure. That is, if person A has (s,t) and B has (s', t') pair, then giving A (s', t') and B (s,t) will not make the poverty measure any different. This ensures that the names and location of individuals should not affect the poverty measure. In this chronic poverty measure, it is seen that switching income-duration in poverty pair among people does not affect the chronic poverty rate.

Monotonicity: This axiom states that poverty rate should decrease if income of a poor person increases, or the number of poor decreases. Other than the headcount measure, it can be seen that marginally reducing income of the chronically poor individual should increase the poverty rate, while increasing the income of the chronically poor should reduce the poverty measure. This is because the derivative of the poverty measures (other than the headcount measure) with respect to income is generally less than or equal to zero.

Sub-group Consistency: This axiom states that if income of the poor of one group falls, while that of another group stays the same, then the overall poverty rate should rise. According to equation (26), total poverty is the sum of chronic and transitory poverty in the economy. Thus, if chronic poverty decreases while transient poverty remains the same, then total poverty should decrease.

The chronic poverty measure can be further disaggregated by years in poverty, such as poverty score of people who spend exactly 6 years in poverty, poverty score of people who spend exactly 7 years in poverty, and so on. From equation (26), it can be

seen that if the condition of the people who are in poverty for exactly 7 years improves, while the rest stay the same, then poverty rate decreases, and this is due to the fact that the FGT (1984) measure is a sub-group consistent poverty measure.

Decomposability: This axiom states that the weighted average of poverty score of two groups, A and B, should equal to the poverty score of C, where C=A+B. Using the FGT (1984) measure to calculate chronic poverty should ensure that the measure is decomposable, because FGT (1984) is a decomposable poverty measure. Thus, measuring chronic poverty rates of different locations separately and then aggregating them together should give the same results if chronic poverty rates of all the locations were measured together.

Transfer: This axiom states that when some income is transferred from a 'richer' poor individual to a 'poorer' poor individual, then the aggregate poverty measure should decrease. The transfer axiom is not satisfied when $\alpha=0$ or when $\alpha=1$. However, it is seen from equation (24) that if some income is transferred from one person in poverty to a person who has a lower income, then poverty rate should decrease if α is greater than or equal to 2, regardless of the chronic poverty status of the person.

In addition to the axioms illustrated in Zheng (1997), Foster (2009) adds a few more axioms that a chronic poverty measure should satisfy:

Time Focus: If the non-poverty income of a chronically poor person increases, then poverty index does not change. So, the measure should only focus on those those periods where a person is poor, not those periods when the person is above the poverty line. In this measure, time is only used to identify the poor, and not included to measure poverty. So, income in previous periods does not affect the current index of poverty. If income in

non-poverty years of the chronically poor is increased, it will not affect the duration of poverty of that individual, and thus it will not change the current measure of poverty when using this measure. Therefore, the measure satisfies time focus axiom.

Time Monotonicity: If x is obtained from y after decreasing the duration of poverty suffered by a poor person, then the poverty measure will decrease. If the spell of poverty decreases below the critical value for a certain person, then the person will not be chronically poor. The number of chronically poor will decrease and hence, the chronic poverty level decreases. However, if the spell length decreases, but is not below the critical value (with current income being the same), then the chronic poverty index will not change. If the spell length is increased, then some in transient poverty may be moved to chronic poverty, and hence the chronic poverty rate can increase. Thus, in the measure introduced in the measure, the time monotonicity depends on the choice of w.

Time Anonymity: The poverty measure does not change if x is obtained from y by a permutation of incomes across time. However, this measure does not necessarily satisfy time anonymity. If a person suffering from three consecutive years in poverty is considered to be chronically poor, then a permutation of incomes of this person can make them not chronically poor.

In all, the chronic poverty measure satisfies all the axioms of a poverty measure, and can be used to measure poverty among the chronic poverty measure.

3.4 Empirical Illustration

The PSID dataset contains a rich database of information on families and their offspring from 1968 till date. This dataset has information on different socio-economic variables from the families. For calculating chronic poverty in the case where the

individuals are interviewed every year, only income of current and previous years of each individual or family is needed. The PSID has information on total income earned by each family each year and the needs standard of each family. The needs standard specifies the minimum amount of income needed for a family to have a specified standard of living. A family earning less than the needs standard, therefore, is said to be in poverty. The duration spend in poverty in prior years is calculated by summing the number of years the income of a family was below the poverty line. Table 3.1 shows the total proportion of individuals in poverty and in chronic poverty. Here, chronic poverty has been defined as a household spending four consecutive years in poverty in the previous four years. It also shows the income gap poverty measure (α=1 in equation (1)) of the poor and the chronically poor (equation (25)). The t-test of equal means tests whether average poverty in year t is different from that in year t-5. It is seen that total and chronic poverty fell from 1970 till 1975. There isn't a significant change in total poverty for each of the five year interval between 1975 and 1995. The poverty headcount fell between 1995 and 2000. The income gap, similarly, fell between 1970 and 1975 and between 1980 and 1985, but rose between 1990 and 1995, indicating the condition of those who were poor deteriorated from 1990 to 1995. The income gap measure fell from 1995 to 2005, showing that, on an average, the poor were getting better off during that 10 year period.

The changes in poverty are also illustrated graphically in figures 3.1 and 3.2. Figure 3.1 measures the proportion of the households in poverty and chronic poverty. It shows that although total headcount poverty fluctuates a lot in the US from the 1970s till date, the proportion of chronically poor remains more or less the same proportion over time. Therefore, it can be seen that most of the entry into poverty and exit is by people

who are in transient poverty, and not by those in chronic poverty. Chronic poverty rates did decrease during the economic expansion of the late 1990s, but it increased again in the 2000s. This indicates that continued economic growth can help the chronically to exit poverty. The average poverty gap (α=1) measure illustrated in figure 3.2 for both households in poverty and in chronic poverty also shows the same picture. The average poverty gap of total poverty fluctuates more over time than that of those in chronic poverty. However, the poverty gap measure of the chronically poor fell in the late 1990s which indicates that there was an improvement of income of the chronically poor. However, average poverty gap of rose again in 2000s, showing that their conditions worsened.

The poverty measure gives us an average value of chronic poverty across individuals, therefore, if the measure decreases while the variance increases, then it means that some people are worse-off than before. Therefore, looking at the average may not tell a researcher the change in overall condition of the poor. In order to get a better picture of the improvement of families in poverty over time, I use the method of stochastic dominance (Davidson and Duclos, 2010) in the next section.

3.5 Comparing Poverty Across Time

Figure 3.1 shows that people in chronic poverty may not be able to exit poverty quickly. It may need some time to bring the chronically poor out of poverty, and so, studying their distribution of income can tell researchers if their welfare is changing over time. Foster and Shorrocks (1988) show that if income distribution X stochastically dominates Y, then poverty level in X is less than that in Y. This step is important because it can tell a policy-maker whether a poverty alleviation strategy has been effective.

Therefore, instead of looking at average poverty measure from one year to the next, it would be more appropriate to look at the distribution of income of the chronically poor to see if their condition has improved. Davidson and Duclos (2000) provide a way to use stochastic dominance to measure if poverty improved over time. Let $D_j^1(x) = F_j(x)$, where $j = \{A, B\}$ and F(x) is the cumulative distribution of x. Then,

$$D_j^s = \int_0^x D_j^{s-1}(y)dy \tag{28}$$

As shown by Davidson and Duclos (2000), the above equation can be written as the following for FGT (1984):

$$D_j^s(x) = \frac{1}{(s-1)!}\int_0^x (x - y_i)^{s-1} dF(y) \tag{29}$$

where $x \in [0, z]$ and it is increased incremently to get a different value of $D_j^s(x)$. This implies that for a given year, in the discrete case:

$$D_j^s(x) = \frac{1}{N(s-1)!}\sum_{i=1}^{N}(x - y_i)^{s-1} \cdot I(y_i \leq x) \tag{30}$$

$D_B^s(x)$ stochastically dominates $D_A^s(x)$ at order s if $D_A^s(x) \geq D_B^s(x)$ for all *x*. Since we are interested in looking at the income distribution of the chronically poor, so, the above equation is modified and written in the following way:

$$D_j^s(x) = \frac{1}{N(s-1)!}\sum_{i=1}^{N}(x - y_i)^{s-1} \cdot I(y_i \leq x) \cdot I(i \in C) \tag{31}$$

Where the definition of I() and C remains as before. The value of $D_j^s(x)$ at different levels of *x* (holding w constant) can be calculated and then be used to study stochastic dominance; and using the stochastic dominance measure shown above together with the chronic poverty measure introduced in the paper, the following proposition can be made:

Proposition 1: Stochastic dominance of income distribution of those people in poverty does not necessarily imply stochastic dominance of income distribution of those in chronic poverty during the same time period, and vice versa.

Proof: The case of first order stochastic dominance is proved first. Let there be two time periods, A and B. Suppose that the income distribution of all people in poverty in year B first order stochastically dominates that of year A. This implies that for all x:

$$D_A^1(x) \geq D_B^1(x) \tag{32}$$

Where:

$$D_j^1(x) = \frac{1}{N*0!}\sum_{i=1}^{N}(x - y_i)^0 \cdot I(y_i \leq x) \tag{33}$$

Let the set of people in poverty be P_j, where $j = \{A,B\}$. Let the corresponding people in chronic poverty be represented by C_j, $j = \{A,B\}$. It is seen that:$C_j \in P_j$, $j = \{A,B\}$. Let the stochastic dominance equation for the people in chronic poverty be the following:

$$E_j^1(x) = \frac{1}{N*0!}\sum_{i=1}^{N}(x - y_i)^0 \cdot I(y_i \leq x) \cdot I(i \in C) \tag{34}$$

Since $C_j \in P_j$, it can be seen that for each value of x,

$$E_j^1(x) \leq D_j^1(x) \tag{35}$$

The above equation implies, for each value of x, the proportion of individual in chronic poverty is less than that of total poverty. Even though $D_A^s(x) \geq D_B^s(x)$, nothing can be assumed about the relationship between $E_A^1(x)$ and $E_B^1(x)$, because any of the following equation can be true and still hold the assumptions made above true:

$$D_A^s(x) \geq E_A^1(x) \geq D_B^s(x) \geq E_B^1(x) \tag{36}$$

$$D_A^s(x) \geq D_B^s(x) \geq E_A^1(x) \geq E_B^1(x) \tag{37}$$

$$D_A^s(x) \geq D_B^s(x) \geq E_B^1(x) \geq E_A^1(x) \tag{38}$$

Similarly, it is seen that if $E_A^1(x) \geq E_B^1(x)$, it does not necessarily imply the stochastic dominance of $D_A^1(x)$ over $D_B^1(x)$.

The above arguments can also be made for any s>1. Hence the stochastic dominance of any order of poverty does not necessarily imply stochastic dominance of chronic poverty from one year to the next, and vice versa.

Table 3.2 calculates the first order stochastic dominance of total poverty for different years, while table 3.3 does that for the second order stochastic dominance of total poverty. It is difficult to see if one year dominates the other year from these numbers, so graphs have been drawn using these numbers. Figures 3.3 and 3.4 show the first and second order stochastic dominance of total poverty respectively. If line A is below line B, then line A stochastically dominates line B and the income distribution of line A is better than that of line B.

Figure 3.3 shows that the income distribution of the poor in 1980 first order stochastically dominates (FOSD) 1985, implying that the poor were worse off in 1985 than in 1980. Similarly, it is seen that 1990 FOSD 1985, 1990 FOSD 1995, 2000 FOSD 1995 and 2005 FOSD 2000. The second order stochastic dominance of figure 3.4 shows similar results. The graphs in figure 3.3 show that the condition of the poor worsened between 1980 and 1985. They got better off between 1985 to 1990, and then again between 1995 to 2005. Figure 3.4 shows a similar result, since first order stochastic dominance indicate second order stochastic dominance.

Table 3.4 shows the results of first order stochastic dominance of chronic poverty, while figure 3.5 graphically illustrates the results shown in table 3.4. In this case, chronic poverty is defined as a person in poverty for 3 consecutive years in the years prior to the

current year. Figure 3.5 shows that income distribution of the chronically poor in 1980 does not FOSD 1975. This implies that the condition of the poor improved between 1970 and 1975, but remained unchanged between 1975 and 1980. It seems that 1980 FOSD 1985, showing that the distribution of income worsened for the chronically poor during this time. Income distribution got better in 1990 compared to 1985, which is similar to what was seen in figure 3.3. However, it remained the same between 1990 and 1995, before getting much better in 2000. However, it is seen that the income distribution worsened in 2005 when compared to 2000, indicating that the chronically poor are getting worse off even though figure 3.3 showed that the overall condition of the poor improved between the years 2000 and 2005.

Table 3.5 shows the results of second order stochastic dominance of chronic poverty while, figure 3.6 graphically illustrates the results. Figure 6 shows similar results as that seen in figure 3.5 (since FOSD implies SOSD), although it shows that 1990 second order stochastically dominates (SOSD) 1995, thus implying that income distribution worsened in 1995 when compared to 1990. Looking at the stochastic dominance graphs and the average chronic poverty measures of table 3.1, it is seen that stochastic dominance provides a better picture on the income distribution of the chronically poor, and shows whether the condition of the chronically poor changed over time.

An interesting thing to note is that the income distribution of total poverty got better in 2005 when compared to that of 2000 (as shown in figures 3.3 and 3.4), but income distribution of the chronically poor deteriorated during the same time period (as shown in figures 3.5 and 3.6). This empirical example clearly illustrates what was being

shown in the proposition above – that stochastic dominance of income of poverty (or lack thereof) does not imply that everyone in poverty got better off.

As a robustness check, the definition of chronic poverty was changed to a person who lives in poverty for 4 or more years and then the test of stochastic dominance was done. The result for first order and second order stochastic dominance are shown in tables 3.6 and 3.7 respectively and the graphs for the first and second order dominance are shown in figures 3.7 and 3.8. The graphs show a similar result as those obtained from analyzing figures 5 and 6, thus affirming that changes in total poverty does not necessarily imply chances in chronic poverty.

3.6 Further Extension

This poverty measure can be extended to be included in a multi-dimensional framework. The number of dimensions a person is poor in can be collected and then it can be used to measure the multi-dimensional chronic poverty level of a community.

$$P_\alpha(y,z) = \frac{1}{NJ}\sum_{i=1}^{n}\sum_{j=1}^{J}\left(1-\frac{y_{ij}}{z_j}\right)^{\alpha} \cdot I(T_{ij} > \overline{T_j}) \cdot I(\, y_{ij} \leq z_t) \qquad (39)$$

Where T_{ij} is the length of time a person i has been deprived in dimension j, and the other notations are the same as described above. If T_{ij} is greater than the threshold of chronic poverty $\overline{T_j}$, then the person is chronically poor in that dimension and that dimension is included in the chronic poverty measure. $\overline{T_j}$ can be made to vary across dimensions; for example if a person has health problem for at least a year can be considered to be in chronic poverty, but if a person earns below the poverty line for more than 3 years, then they can be considered to be chronically poor in the income dimension.

This equation, therefore measures the current level of multidimensional poverty amongst the chronically poor in a community.

A thorough investigation of chronic multi-dimensional poverty of the poor in developing countries can provide a better picture of the long-term deprivation of the poor, instead of just getting a snapshot of the condition of the poor for one period only. It can also provide information on the dimensions of well-being that needs to be improved to make the poor better off.

3.7 Conclusion

Researchers have used different ways to measure poverty in a society. Some economists have recognized that chronic poverty need to be studied separately from total poverty, and a number of methods have been devised to aggregate chronic poverty. Chronic poverty has been defined as a person experiencing long spells of poverty. The actual definition of what is long term poverty may vary, but anyone suffering for five or more years of poverty is termed to be chronically poor. It can be detrimental to the well-being of a person because living in poverty for extended periods of time can cause other dimensions of well-being to deteriorate. Researchers have proposed different methods to measure chronic poverty; however, they cannot be used to evaluate whether chronic poverty rates have changed over time. I devise a method to measure chronic poverty where the information needed to aggregate chronic poverty is current income level and the length of spell of poverty in previous years. A long panel may not be necessary to measure chronic poverty rates; a repeated cross-section panel which has information on current income and length of spells of poverty in prior years is needed to measure chronic

poverty rates. Using this information, I show that a chronic poverty measure can be computed that can be compared across time to see if chronic poverty has improved over time.

I use the PSID dataset to show empirically how to measure chronic poverty using the method introduced in this paper. The exercise shows that both the headcount and the income gap measure of total poverty fluctuate over time but chronic poverty headcount and income gap measure is steady. I then use the method of stochastic dominance to see whether overall welfare of the poor and chronically poor improved over time. My results show that overall welfare of the poor has changed over time. However, the analysis also show that even though poverty rates may have improved over time, chronic poverty rates may not change, or may even deteriorate over time, as seen in the years 2000 to 2005. This illustrates the importance of measuring chronic poverty rates separately from overall poverty to see if the overall well-being of people in chronic poverty have changed over time.

Extending this chronic poverty measure in a multi-dimensional poverty framework can help researchers examine the extent of long-term deprivation of different dimensions in the society. It can also help to measure the whether overall multi-dimensional poverty has improved over time by using the method of stochastic dominance.

Table 3.1: Headcount and income gap measures of total poverty and chronic poverty*

Year	Observation	Headcount	T-test	Income gap	T-test
Total Poverty					
1975	3173	0.1018		0.0732	
		(0.3024)		(0.2194)	
1980	3506	0.0916	-1.4126	0.0644	-1.5765
		(0.2884)		(0.2379)	
1985	3649	0.0924	0.1166	0.0594	-0.8189
		(0.2895)		(0.2776)	
1990	3848	0.0826	-1.4870	0.0540	-0.8614
		(0.2753)		(0.2641)	
1995	4395	0.0833	0.1045	0.0488	-0.8371
		(0.2763)		(0.3037)	
2000	5080	0.0661	-3.1532*	0.0373	-1.8161
		(0.2485)		(0.3120)	
2005	4931	0.0554	-2.2589*	0.0366	-0.1181
		(0.2287)		(0.2437)	
Chronic Poverty					
1975	3173	0.0293		0.0202	
		(0.1687)		(0.2096)	
1980	3506	0.0154	-3.8147*	0.0095	-2.0273*
		(0.1231)		(0.2224)	
1985	3649	0.0332	4.9041*	0.0209	1.9850*
		(0.1791)		(0.2628)	
1990	3848	0.0281	-1.2783	0.0191	-0.3139
		(0.1652)		(0.2324)	
1995	4395	0.0212	-2.0103*	0.0122	-1.1809
		(0.1439)		(0.2961)	
2000	5080	0.0093	-4.6647*	0.0065	-1.0829
		(0.0957)		(0.2010)	
2005	4931	0.0241	5.8011*	0.0146	1.7505
		(0.1535)		(0.2603)	

*Standard errors in parenthesis. The t-test is the test of equal means between the current and the previous year. Asterisks indicate significance at 5% significance level. Chronic poverty is defined as a person remaining in poverty for three consecutive years

Table 3.2: First Order Stochastic dominance of poverty of different years*

	1975	1980	1985	1990	1995	2000	2005
0.1*Z	0.0009	0.0031	0.0047	0.0049	0.0100	0.0077	0.0006
	(0.0307)	(0.0559)	(0.0681)	(0.0701)	(0.0996)	(0.0873)	(0.0247)
0.2*Z	0.0025	0.0054	0.0090	0.0073	0.0125	0.0120	0.0043
	(0.0502)	(0.0734)	(0.0947)	(0.0850)	(0.1112)	(0.1089)	(0.0651)
0.3*Z	0.0050	0.0074	0.0156	0.0096	0.0155	0.0159	0.0055
	(0.0708)	(0.0858)	(0.1240)	(0.0976)	(0.1234)	(0.1253)	(0.0738)
0.4*Z	0.0113	0.0097	0.0197	0.0140	0.0216	0.0207	0.0079
	(0.1059)	(0.0980)	(0.1391)	(0.1176)	(0.1454)	(0.1423)	(0.0886)
0.5*Z	0.0180	0.0160	0.0244	0.0195	0.0291	0.0246	0.0136
	(0.1328)	(0.1254)	(0.1543)	(0.1383)	(0.1682)	(0.1549)	(0.1158)
0.6*Z	0.0274	0.0248	0.0343	0.0268	0.0385	0.0303	0.0207
	(0.1633)	(0.1556)	(0.1819)	(0.1614)	(0.1923)	(0.1715)	(0.1423)
0.7*Z	0.0388	0.0359	0.0436	0.0398	0.0487	0.0398	0.0270
	(0.1931)	(0.1862)	(0.2042)	(0.1954)	(0.2152)	(0.1954)	(0.1620)
0.8*Z	0.0552	0.0539	0.0589	0.0533	0.0567	0.0472	0.0361
	(0.2283)	(0.2259)	(0.2355)	(0.2246)	(0.2312)	(0.2122)	(0.1866)
0.9*Z	0.0769	0.0710	0.0740	0.0683	0.0676	0.0561	0.0452
	(0.2665)	(0.2569)	(0.2618)	(0.2524)	(0.2510)	(0.2301)	(0.2078)
Z	0.1018	0.0916	0.0924	0.0826	0.0833	0.0661	0.0554
	(0.3024)	(0.2884)	(0.2896)	(0.2754)	(0.2763)	(0.2486)	(0.2287)

*Standard errors in parenthesis. Poverty is defined as a family earning less than the poverty line z.

Table 3.3: Second Order Stochastic Dominance of Poverty of Different Years

	1975	1980	1985	1990	1995	2000	2005
0.1*Z	0.0009	0.0023	0.0041	0.0044	0.0078	0.0065	0.0003
	(0.0303)	(0.0463)	(0.0616)	(0.0635)	(0.0843)	(0.0780)	(0.0157)
0.2*Z	0.0013	0.0034	0.0058	0.0053	0.0097	0.0085	0.0015
	(0.0324)	(0.0524)	(0.0685)	(0.0682)	(0.0917)	(0.0846)	(0.0282)
0.3*Z	0.0020	0.0043	0.0077	0.0062	0.0112	0.0103	0.0027
	(0.0370)	(0.0582)	(0.0761)	(0.0726)	(0.0974)	(0.0915)	(0.0396)
0.4*Z	0.0033	0.0054	0.0100	0.0077	0.0129	0.0123	0.0037
	(0.0437)	(0.0633)	(0.0843)	(0.0772)	(0.1025)	(0.0979)	(0.0477)
0.5*Z	0.0057	0.0067	0.0124	0.0095	0.0155	0.0143	0.0050
	(0.0532)	(0.0686)	(0.0922)	(0.0828)	(0.1082)	(0.1041)	(0.0547)
0.6*Z	0.0085	0.0090	0.0151	0.0118	0.0185	0.0165	0.0069
	(0.0639)	(0.0749)	(0.0999)	(0.0891)	(0.1146)	(0.1100)	(0.0621)
0.7*Z	0.0118	0.0119	0.0184	0.0148	0.0221	0.0191	0.0093
	(0.0749)	(0.0826)	(0.1078)	(0.0961)	(0.1217)	(0.1160)	(0.0702)
0.8*Z	0.0162	0.0159	0.0225	0.0187	0.0259	0.0221	0.0122
	(0.0861)	(0.0912)	(0.1159)	(0.1040)	(0.1291)	(0.1221)	(0.0788)
0.9*Z	0.0218	0.0212	0.0273	0.0234	0.0299	0.0253	0.0153
	(0.0978)	(0.1011)	(0.1244)	(0.1127)	(0.1367)	(0.1285)	(0.0876)
Z	0.0286	0.0272	0.0330	0.0286	0.0345	0.0289	0.0188
	(0.1100)	(0.1118)	(0.1333)	(0.1219)	(0.1442)	(0.1349)	(0.0964)

*Standard errors in parenthesis. Poverty is defined as a family earning less than the poverty line z.

Table 3.4: First Stochastic dominance of Chronic Poverty of Different Years*

	1975	1980	1985	1990	1995	2000	2005
0.1*Z	0.0000	0.0003	0.0005	0.0005	0.0018	0.0002	0.0002
	(0.0000)	(0.0169)	(0.0234)	(0.0228)	(0.0426)	(0.0140)	(0.0142)
0.2*Z	0.0003	0.0006	0.0022	0.0010	0.0023	0.0002	0.0006
	(0.0178)	(0.0239)	(0.0468)	(0.0322)	(0.0477)	(0.0140)	(0.0247)
0.3*Z	0.0009	0.0014	0.0052	0.0016	0.0027	0.0002	0.0006
	(0.0307)	(0.0377)	(0.0720)	(0.0395)	(0.0522)	(0.0140)	(0.0247)
0.4*Z	0.0019	0.0020	0.0071	0.0023	0.0050	0.0002	0.0012
	(0.0435)	(0.0446)	(0.0841)	(0.0483)	(0.0706)	(0.0140)	(0.0349)
0.5*Z	0.0041	0.0034	0.0090	0.0039	0.0061	0.0004	0.0024
	(0.0639)	(0.0584)	(0.0947)	(0.0623)	(0.0781)	(0.0198)	(0.0493)
0.6*Z	0.0063	0.0048	0.0110	0.0070	0.0080	0.0018	0.0037
	(0.0792)	(0.0695)	(0.1041)	(0.0835)	(0.0889)	(0.0421)	(0.0603)
0.7*Z	0.0091	0.0066	0.0137	0.0109	0.0096	0.0030	0.0043
	(0.0952)	(0.0807)	(0.1163)	(0.1039)	(0.0973)	(0.0543)	(0.0651)
0.8*Z	0.0123	0.0086	0.0200	0.0148	0.0116	0.0039	0.0065
	(0.1102)	(0.0921)	(0.1400)	(0.1208)	(0.1071)	(0.0626)	(0.0803)
0.9*Z	0.0173	0.0108	0.0238	0.0192	0.0141	0.0049	0.0089
	(0.1305)	(0.1036)	(0.1526)	(0.1374)	(0.1179)	(0.0700)	(0.0940)
Z	0.0221	0.0117	0.0282	0.0223	0.0162	0.0059	0.0107
	(0.1469)	(0.1075)	(0.1656)	(0.1478)	(0.1261)	(0.0766)	(0.1031)

*Standard errors in parenthesis. Chronic poverty is defined as a person remaining in poverty for three consecutive years, not including the current year

Table 3.5: Second Order Stochastic Dominance of Chronic Poverty of Different Years*

	1975	1980	1985	1990	1995	2000	2005
0.1*Z	0.0000	0.0000	0.0002	0.0005	0.0013	0.0002	0.0001
	(0.0000)	(0.0026)	(0.0090)	(0.0228)	(0.0333)	(0.0140)	(0.0066)
0.2*Z	0.0000	0.0003	0.0010	0.0006	0.0017	0.0002	0.0003
	(0.0003)	(0.0114)	(0.0222)	(0.0234)	(0.0381)	(0.0140)	(0.0124)
0.3*Z	0.0002	0.0005	0.0018	0.0009	0.0020	0.0002	0.0004
	(0.0080)	(0.0164)	(0.0314)	(0.0257)	(0.0412)	(0.0140)	(0.0158)
0.4*Z	0.0005	0.0008	0.0028	0.0011	0.0024	0.0002	0.0005
	(0.0141)	(0.0211)	(0.0396)	(0.0283)	(0.0438)	(0.0140)	(0.0179)
0.5*Z	0.0010	0.0011	0.0038	0.0015	0.0031	0.0002	0.0007
	(0.0199)	(0.0250)	(0.0469)	(0.0314)	(0.0471)	(0.0141)	(0.0204)
0.6*Z	0.0017	0.0016	0.0048	0.0021	0.0037	0.0003	0.0011
	(0.0263)	(0.0290)	(0.0533)	(0.0352)	(0.0508)	(0.0147)	(0.0236)
0.7*Z	0.0025	0.0022	0.0059	0.0031	0.0045	0.0006	0.0015
	(0.0326)	(0.0335)	(0.0592)	(0.0399)	(0.0546)	(0.0167)	(0.0273)
0.8*Z	0.0035	0.0029	0.0072	0.0043	0.0053	0.0009	0.0019
	(0.0389)	(0.0382)	(0.0647)	(0.0455)	(0.0585)	(0.0198)	(0.0311)
0.9*Z	0.0049	0.0037	0.0088	0.0057	0.0061	0.0013	0.0026
	(0.0453)	(0.0428)	(0.0704)	(0.0516)	(0.0623)	(0.0234)	(0.0351)
Z	0.0064	0.0044	0.0106	0.0072	0.0070	0.0018	0.0033
	(0.0521)	(0.0474)	(0.0762)	(0.0579)	(0.0662)	(0.0272)	(0.0395)

*Standard errors in parenthesis. Chronic poverty is defined as a person remaining in poverty for three consecutive years, not including the current year.

Table 3.6: First Order Stochastic Dominance of Chronic Poverty of Different Years*

	1975	1980	1985	1990	1995	2000	2005
0.1*Z	0.0003	0.0003	0.0005	0.0008	0.0025	0.0002	0.0006
	(0.0178)	(0.0169)	(0.0234)	(0.0279)	(0.0500)	(0.0140)	(0.0247)
0.2*Z	0.0006	0.0006	0.0025	0.0013	0.0030	0.0002	0.0030
	(0.0251)	(0.0239)	(0.0496)	(0.0360)	(0.0543)	(0.0140)	(0.0551)
0.3*Z	0.0013	0.0020	0.0063	0.0023	0.0034	0.0004	0.0032
	(0.0355)	(0.0446)	(0.0792)	(0.0483)	(0.0583)	(0.0198)	(0.0569)
0.4*Z	0.0028	0.0026	0.0082	0.0034	0.0059	0.0004	0.0051
	(0.0532)	(0.0506)	(0.0903)	(0.0580)	(0.0767)	(0.0198)	(0.0710)
0.5*Z	0.0060	0.0043	0.0101	0.0055	0.0077	0.0012	0.0083
	(0.0772)	(0.0653)	(0.1002)	(0.0737)	(0.0876)	(0.0344)	(0.0908)
0.6*Z	0.0091	0.0074	0.0129	0.0086	0.0100	0.0028	0.0116
	(0.0952)	(0.0858)	(0.1128)	(0.0922)	(0.0996)	(0.0524)	(0.1069)
0.7*Z	0.0136	0.0091	0.0159	0.0130	0.0123	0.0045	0.0134
	(0.1156)	(0.0951)	(0.1251)	(0.1133)	(0.1102)	(0.0671)	(0.1149)
0.8*Z	0.0183	0.0117	0.0230	0.0177	0.0148	0.0061	0.0168
	(0.1340)	(0.1075)	(0.1500)	(0.1318)	(0.1207)	(0.0779)	(0.1287)
0.9*Z	0.0236	0.0145	0.0280	0.0234	0.0180	0.0075	0.0209
	(0.1519)	(0.1197)	(0.1649)	(0.1512)	(0.1329)	(0.0862)	(0.1430)
Z	0.0293	0.0154	0.0332	0.0281	0.0212	0.0093	0.0241
	(0.1687)	(0.1232)	(0.1791)	(0.1652)	(0.1439)	(0.0958)	(0.1535)

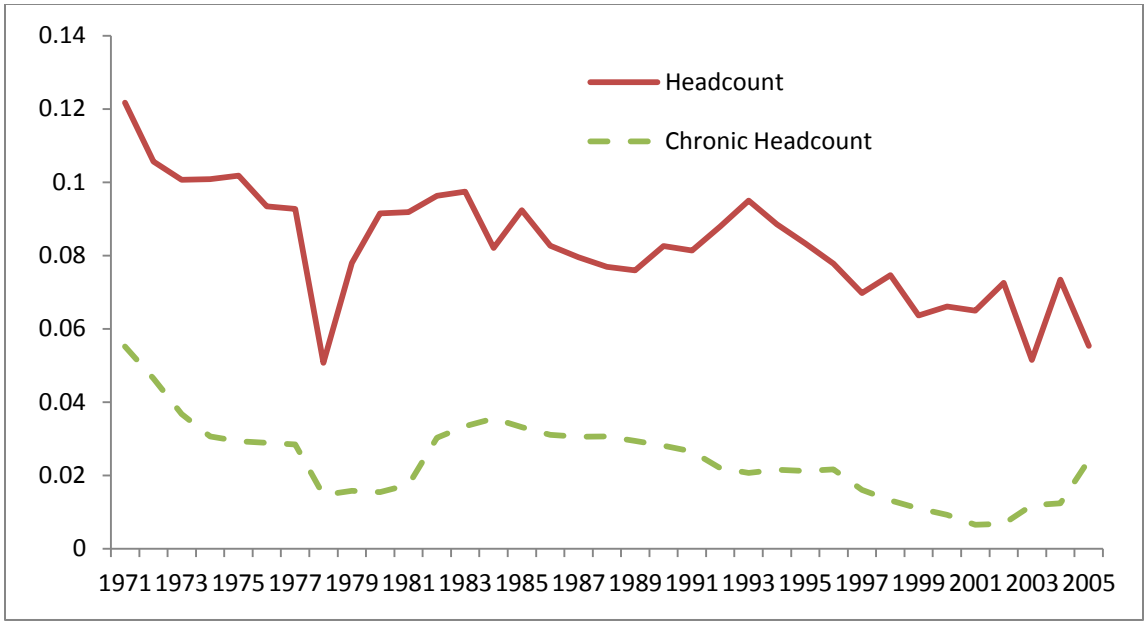
*Standard errors in parenthesis. Chronic poverty in this case is defined as a person remaining in poverty for four consecutive years, not including the current year

Table 3.7: Second Order Stochastic dominance of Chronic Poverty of Different Years*

	1975	1980	1985	1990	1995	2000	2005
0.1*Z	0.0003	0.0000	0.0002	0.0008	0.0020	0.0002	0.0003
	(0.0170)	(0.0026)	(0.0090)	(0.0279)	(0.0420)	(0.0140)	(0.0157)
0.2*Z	0.0003	0.0003	0.0011	0.0009	0.0024	0.0002	0.0011
	(0.0174)	(0.0114)	(0.0230)	(0.0284)	(0.0460)	(0.0140)	(0.0242)
0.3*Z	0.0005	0.0006	0.0020	0.0011	0.0027	0.0002	0.0018
	(0.0192)	(0.0166)	(0.0328)	(0.0303)	(0.0486)	(0.0144)	(0.0329)
0.4*Z	0.0009	0.0010	0.0032	0.0016	0.0031	0.0003	0.0024
	(0.0229)	(0.0226)	(0.0419)	(0.0335)	(0.0509)	(0.0152)	(0.0389)
0.5*Z	0.0017	0.0014	0.0044	0.0022	0.0039	0.0004	0.0032
	(0.0281)	(0.0274)	(0.0499)	(0.0373)	(0.0540)	(0.0162)	(0.0443)
0.6*Z	0.0026	0.0021	0.0055	0.0030	0.0047	0.0006	0.0043
	(0.0346)	(0.0323)	(0.0569)	(0.0418)	(0.0577)	(0.0183)	(0.0500)
0.7*Z	0.0038	0.0030	0.0068	0.0040	0.0057	0.0010	0.0054
	(0.0414)	(0.0381)	(0.0632)	(0.0468)	(0.0618)	(0.0214)	(0.0558)
0.8*Z	0.0052	0.0039	0.0083	0.0054	0.0067	0.0016	0.0067
	(0.0485)	(0.0438)	(0.0692)	(0.0526)	(0.0660)	(0.0255)	(0.0615)
0.9*Z	0.0071	0.0050	0.0102	0.0071	0.0078	0.0021	0.0080
	(0.0559)	(0.0494)	(0.0754)	(0.0589)	(0.0702)	(0.0300)	(0.0671)
Z	0.0091	0.0059	0.0123	0.0090	0.0090	0.0028	0.0095
	(0.0635)	(0.0548)	(0.0817)	(0.0656)	(0.0745)	(0.0345)	(0.0726)

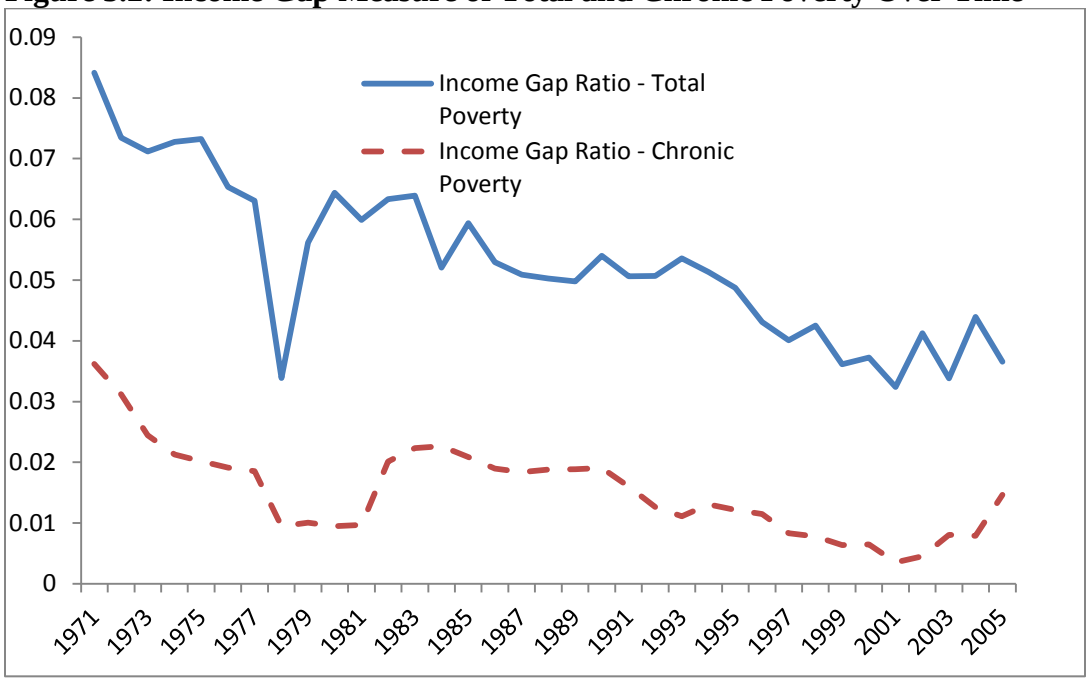
*Standard errors in parenthesis. Chronic poverty in this case is defined as a person remaining in poverty for four consecutive years, not including the current year

Figure 3.1: Headcount Poverty Measure of Total and Chronic Poverty Over Time*



* Chronic poverty in this case is defined as a person remaining in poverty for four consecutive years, including current year

Figure 3.2: Income Gap Measure of Total and Chronic Poverty Over Time



* Chronic poverty in this case is defined as a person remaining in poverty for four consecutive years, including current year

Figure 3.3: Illustrating First Order Stochastic Dominance of Total Poverty

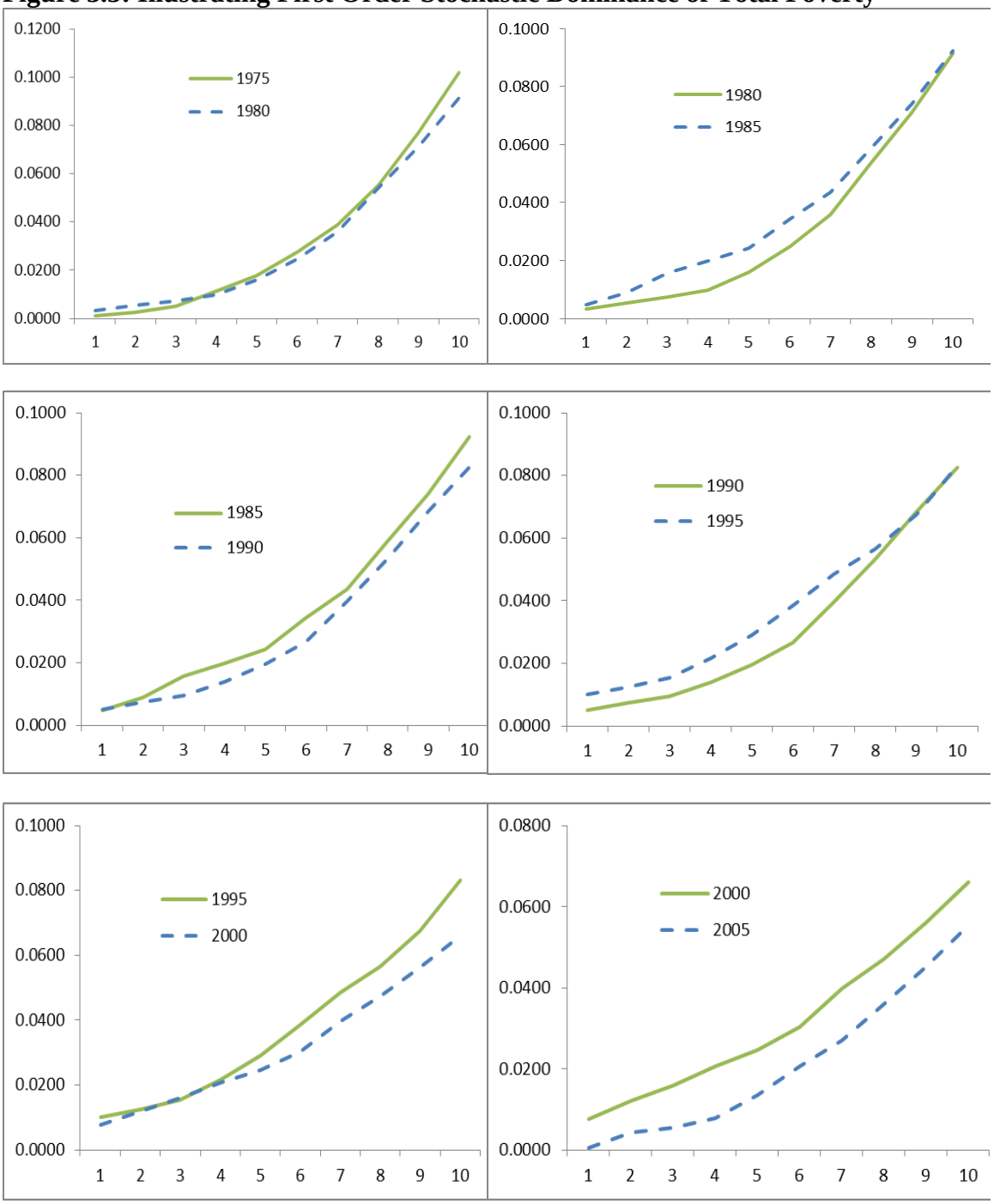


Figure 3.4: Illustrating Second Order Stochastic Dominance of Total Poverty

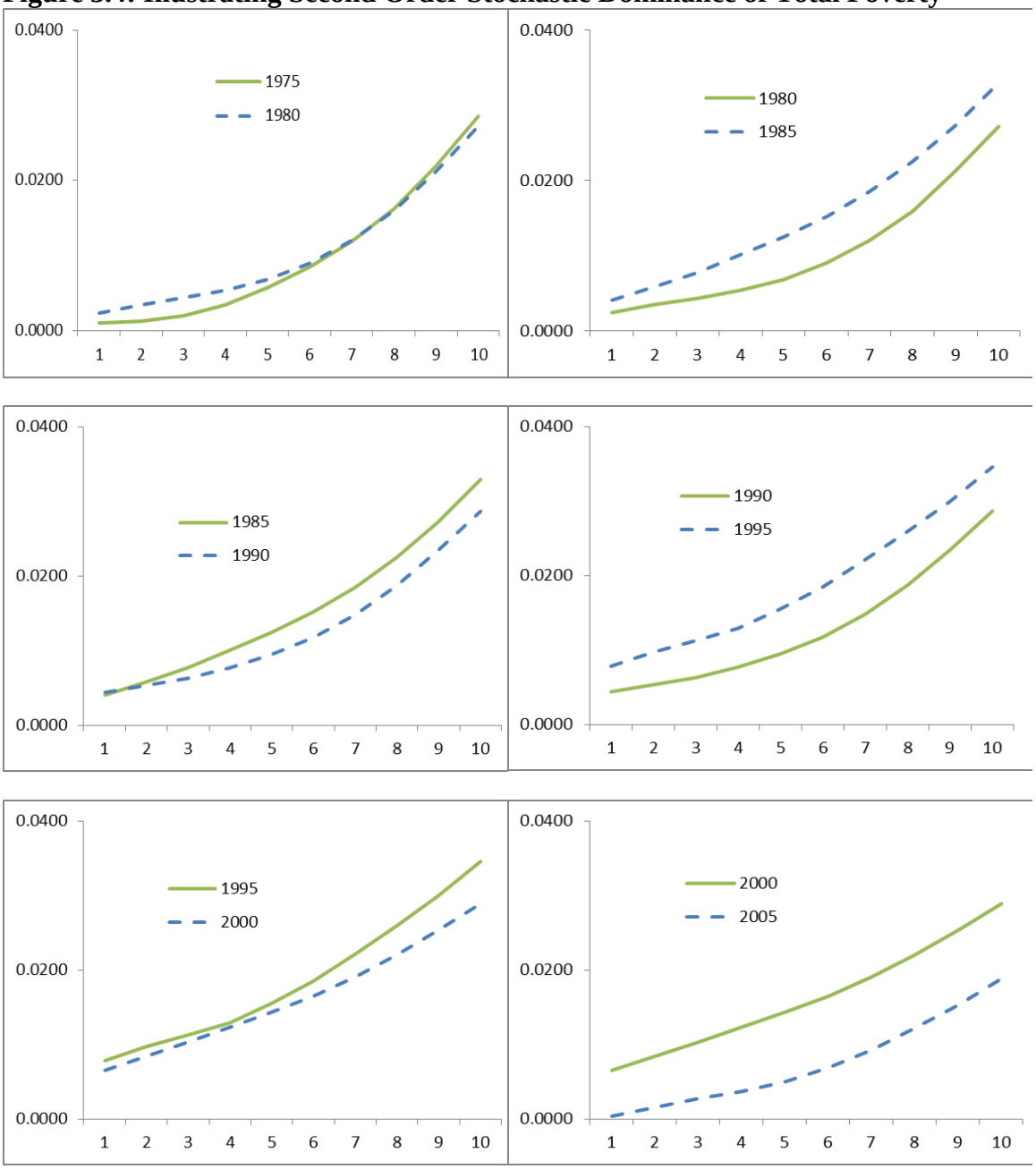


Figure 3.5: Illustrating First Order Stochastic Dominance of Chronic Poverty (3 Continuous Years in Poverty Prior to the Current Year)

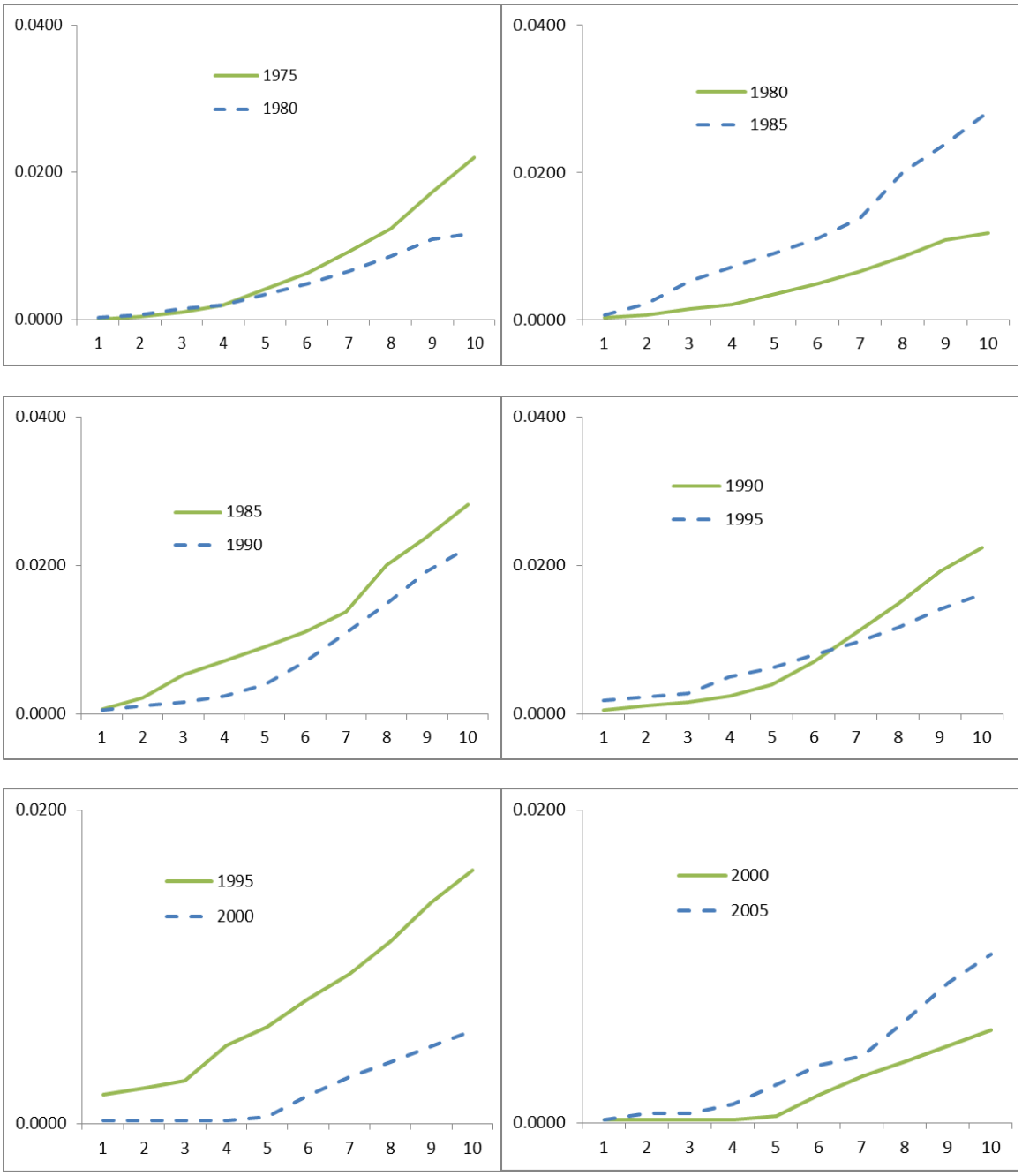


Figure 3.6: Illustrating Second Order Stochastic Dominance of Chronic Poverty (3 Continuous Years in Poverty Prior to the Current Year)

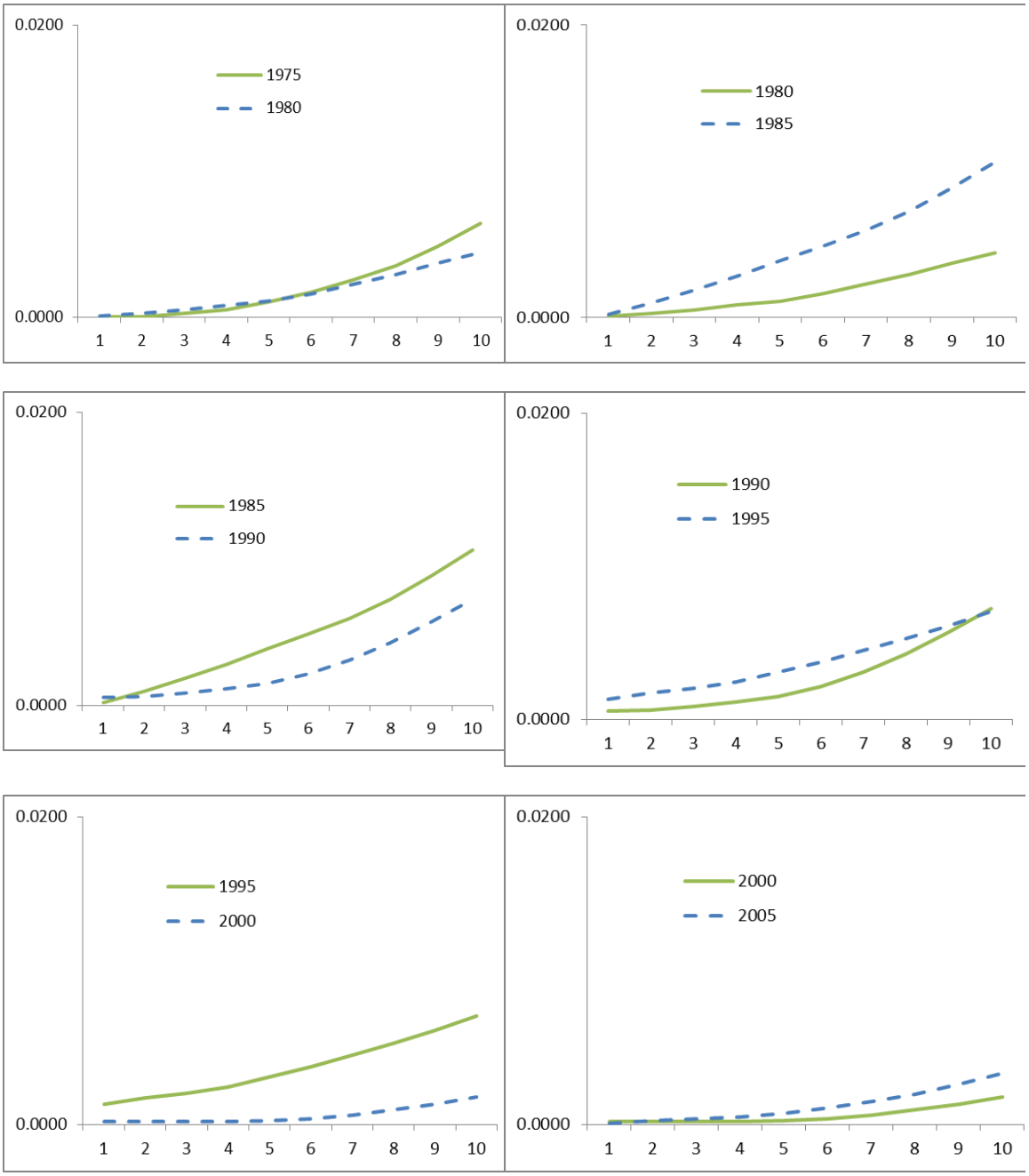


Figure 3.7: Illustrating First Order Stochastic Dominance of Chronic Poverty (4 Continuous Years in Poverty Prior to the Current Year)

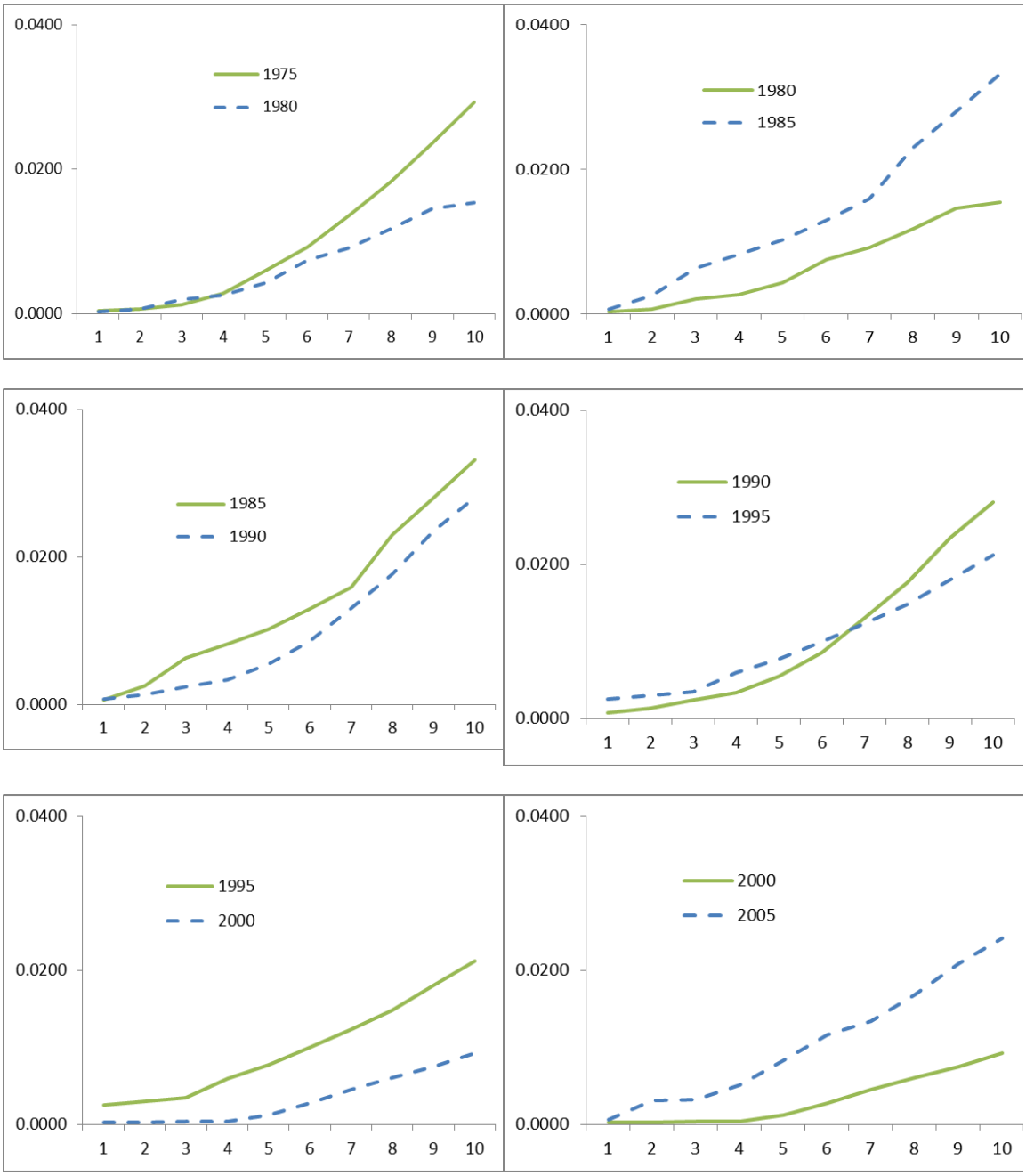
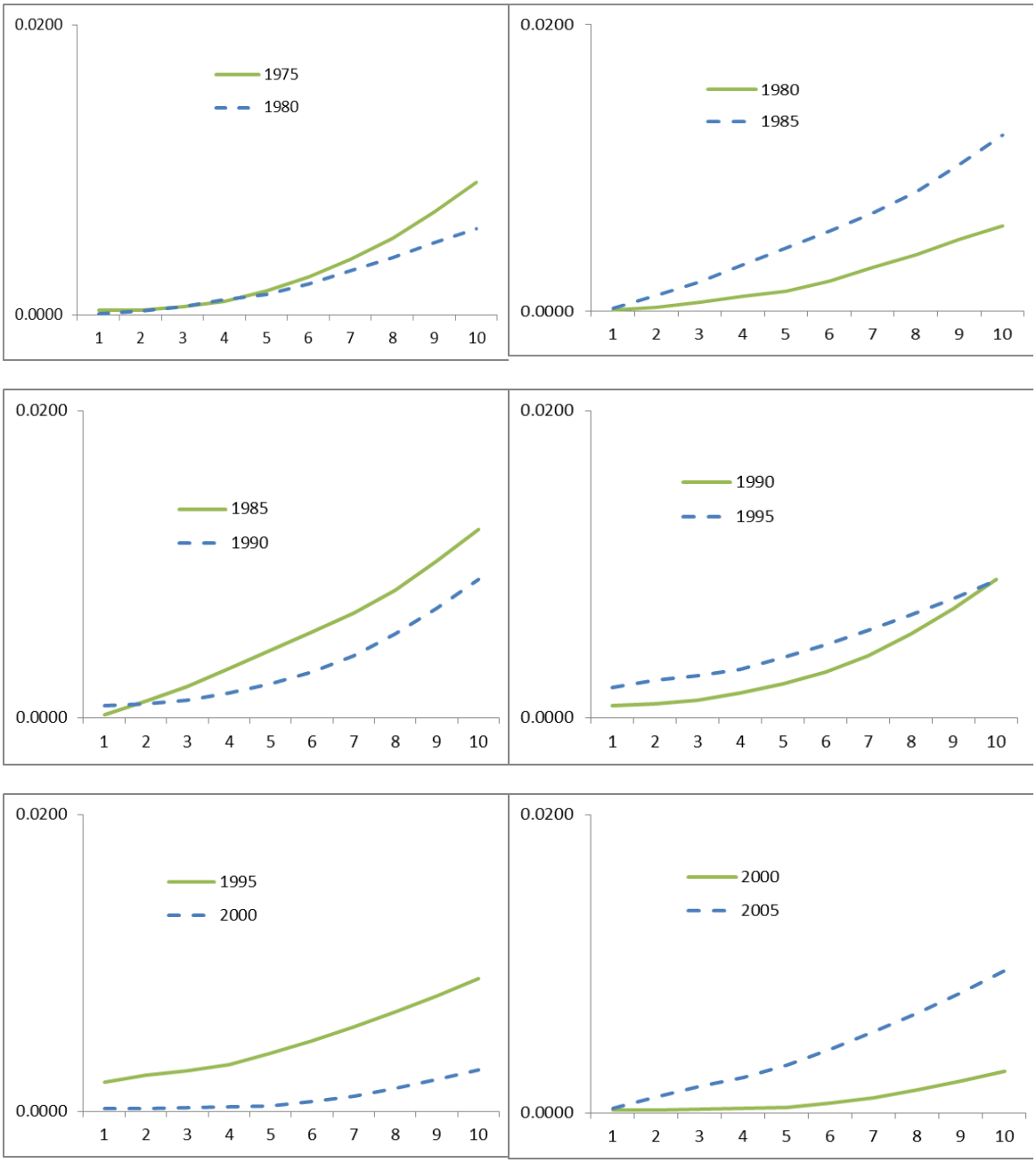


Figure 3.8: Illustrating Second Order Stochastic Dominance of Chronic Poverty (4 Continuous Years in Poverty Prior to the Current Year)



4 ON PERSISTENT POVERTY IN A RICH COUNTRY

4.1 Introduction

There is a continued interest in identifying the factors that determine growth and prosperity within a country and across countries. A number of papers have investigated income, growth and convergence rates of countries and have found different factors such as human capital, policy choices, culture and geography to be reasons key to growth and development (Easterly and Levine, 2001; Grief, 1994; Hall and Jones, 1999; Mankiw, Romer and Weil; 1992, Rappaport and Sachs, 2003 to name a few). However, labor and capital mobility between countries may be limited due to various reasons. As a result, returns to labor and capital may not be equalized across countries, which can have an impact on the growth of capital-scarce or labor-scarce countries. Similarly, these returns may not be fully realized by a country due to cultural, religious and geographical obstacles, which can also affect growth and convergence rates. Besides, there hasn't been a rigorous study on how historical cultural and geographic factors affect current level of income and growth. In this paper, I study growth rates at the county level in the United States to see how income and convergence rates differ in regions that have free movement of labor and capital between them and broadly similar policy choices. I look at how current and historical factors affect current levels of growth in a county, and explain why some counties remained poor for such long periods of time. Finally, I use the results to analyze whether factor endowment or production technology affects growth and development of a county.

The United States is a successful story in poverty reduction, and it has been able to reduce poverty rates substantially over the past 40 years. From the data collected from the Census Bureau and USDA, I find that the proportion of people in poverty fell from around 20 percent to about 11 percent between the years 1960 to 2000. In the 1960s, there were large parts of the US where poverty rates were well over 50%, as shown in figure 4.1. The poverty rate, or the headcount ratio, is defined as the proportion of people earning below the official poverty line of the US[9]. From the 1960s onwards, poverty rates declined drastically mainly due to expansion of income transfers under the Great Society Program of President Johnson's administration and due to strong economic growth in the US as a whole. Figures 4.2 to 4.5 shows how poverty rates changed in the US between the years 1970 to 2000. The maps show that poverty generally decreased throughout the US during this time period. However in 2000, there are still some counties where poverty rates are over 20 percent. These counties have had high and persistent poverty rates for the past 40 years. Counties with poverty rates of 20 percent or more for long periods of time are referred as "persistently-poor" by the USDA, and so, I use this cut-off to identify counties that are persistently-poor[10]. I call these persistently poor counties "poor counties" and the rest of the counties "non-poor counties." Figure 4.6 illustrates the location of the counties that have poverty rates of over 20 percent for the four decades starting from 1960. Income transfers and economic growth could not reduce poverty rates of these counties to below 20 percent. These counties are not uniformly distributed in the US – rather, they are concentrated in the Appalachian region, the "Black Belt" region in the Carolinas and Alabama, the counties around the Mississippi

[9] Poverty line in the US is determined using the Orshanksy method. It is calculated by measuring the minimum amount to purchase a basket of goods, and then multiplying that amount by 3 (Fisher, 1997)
[10] "County Types" 1997 http://www.ers.usda.gov/publications/aib710/aib710l.htm

Delta, the counties bordering Mexico and the counties in the western part of the country that have Native American reservations. Thus, studying factor endowment and production technology differences of these poor regions and the rest of the non-poor regions of the US can help explain the important factors affecting growth and prosperity. There is some research in sociology postulating that historical culture and institutions of the South and Appalachia contributed to the persistence of poverty there (Engerman, 1966, Fogel and Engerman, 1974, Billings, 1974, Duncan, 1999). However, very little econometric research has been done to study why all these counties have such high poverty rates in an otherwise wealthy country. A growth model can thus be used to explain whether counties remain persistently poor because of differences in factor accumulation, or due to differences in production technologies.

Although most of the literature on growth explains differences in growth rates across a cross-section of countries (Mankiw, Romer, Weil, 1992, Acemoglu, Johnson and Robinson, 2005), there is some research on growth rates at the state-level in the US (Barro and Sala-i-Martin, 1992, Evans and Karras, 1996), and at the county level (Rappaport and Sachs, 2003, Clifton and Romero-Barrutieta, 2006, Higgins, Levy and Young, 2006). Higgins, et al. (2006) studies county-level growth rates of the US, but did not investigate the persistence of income and how historical institutions and culture affects current level of income and growth. Clifton and Romero-Barrutieta (2003) look at how land tenure in 1910 (an indicator of institutions) affects poverty of Appalachian counties today, but did not study the whole of the US or look at growth in Appalachian counties. Rappaport and Sachs (2003) looks at population changes in US counties and how the population is moving more towards the coastal regions of the US. However,

none of the papers studied the persistence of income in US counties and how historical cultural and geographic factors affect current level of income and growth across counties.

In this paper, I collect data on US counties from 1960 to 2000 and their corresponding historic data on church attendance, urbanity, illiteracy rate, land tenure and geography from the late 1800s. About 800 counties did not exist back in 1890s, so I study the growth rates of those counties which existed back in the late 1800s.I follow the dynamic panel growth model from Islam (1995) to estimate the model. I parameterize the total factor productivity of each county using historical culture, human capital, institution and geographic variables. I then apply the correlated random effects GMM estimator (Arellano and Bover, 1995) to estimate the coefficients on the time-invariant and the time-varying variables. I run regressions on the pooled sample, and also on the poor and non-poor subsample of counties. Using the estimated coefficients, I explain whether the difference between poor and non-poor counties in the US is due to (1) differences in factor endowments, or (2) differences in returns to human and physical capital. I also change the definition of persistently-poor counties and run a series of robustness tests to test the validity of the results. The results indicate that both current and past levels of human capital accumulation (past human capital proxied by illiteracy rates in 1890) are important determinants of current county income. Although poor and non-poor counties have different production technologies, I find that most of the difference in income is due to the difference in factor accumulation. A number of sensitivity analyses also suggest that the findings are true. However, I do not find past culture, institutions and geography have much of an influence explaining difference in income between the poor and non-poor counties, although some of their coefficients are significant in the growth model.

4.2 Review of Literature

Papers such as Mankiw, et al (1992), Barro (1991) and many others try to explain differences in growth rates across countries through factor accumulation using a cross-section of countries. Barro (1991) finds that initial education level has a positive influence on growth in subsequent years, while initial GDP per capita had a negative influence, showing that initial human capital is an important factor in explaining growth. Mankiw et al. (1992) also find that education level is an important factor contributing to growth. Looking at growth rates of cities in the US, Glaeser et al (1995) also find that initial education level is an important variable that can affect growth of cities. These papers emphasize the role of factor accumulation in explaining growth. Extending on these growth models, Islam (1995) uses a panel data of countries to explain differences in growth rates across countries. Islam (1995) also says that the country fixed effects can be a proxy for total factor productivity, and can be used for further analysis. This idea has also been advocated by Durlauf et al. (2005) and Durlauf and Quah (1999), which says that this total factor productivity can be important in analyzing the reasons behind permanent differences in income between countries. However, it may be more beneficial to study differences of growth rates between different regions within a country because labor and capital are freely mobile within a country, and institutions and rule of law are also fairly similar across a given country. This can explain how technology and factor endowments affect income within a country, *ceteris paribus*.

There is a strand in growth literature that emphasizes the importance of institutions on growth, and sometimes implying that these factors explain more of the difference in growth rates between countries than factor accumulation (Easterly and

Levine 2001; Acemoglu et al. 2005). Fogel and Engerman (1974) and Ransom and Sutch (2001) emphasized the role of institutions on economic development in the southern part of the US following the Civil War, while some sociologists such as Duncan (1999) and Billings and Blee (2000) argue that persistent poverty in counties in the Appalachian region and the Mississippi Delta of the US can be explained by the historic social and economic institutions of those regions. Those regions gave most of the land rights to a select group of individuals instead of taking a more egalitarian approach, which negatively affected income in later years (Duncan, 1999; Billings and Blee, 2000). In another example, resettlement of Native Americans in the 19th Century sometimes placed them from regions in the south and east of the country to arid regions in the central Plains (Barrington 1999), which may explain the high poverty rates in those areas. Acemoglu et al (2005) study the rise of Western Europe in the 1500s till the 1800s and show that opening up Atlantic trade routes helped Western European countries to grow. Increased profits helped those countries to improve political institutions and property rights by reducing the absolute power of the monarchy. These institutional changes further helped to spur growth in those countries (Acemoglu et al, 2005). Easterly and Levine (2001) have said that most of the difference in growth between countries is explained by total factor productivity, and national policies have a strong effect on growth. A similar conclusion has been found by Hall and Jones (1999). These studies show that factor accumulation only does not lead to long-term growth and prosperity; productivity and institutions play a big role in the growth and development of a country.

Culture prevalent in a region or a county can also explain differences in growth and income (Banfield 1970; Billings 1974; Murray 1984; Grief 1994). Max Weber

posited a theory that northern Europe is richer than southern Europe mainly because of the prevalence of Protestantism (and Calvinism in particular) in northern Europe and Catholicism in southern Europe. Research by Barro and McCleary (2003) and Cavalcanti, Parente, and Zhao (2007) do provide some evidence supporting Weber's theory across countries. Barro and McCleary (2003) finds that belief in heaven and hell positively affects growth while religious service attendance negatively affects growth. Cavalcanti, Parente, and Zhao (2007) study Weber's thesis in a general equilibrium framework and find that it explains differences in development between northern and southern Europe, but it does not explain the differences in development between Europe and Latin America.

Geography, proxied by variation of terrain and temperature has also been included in the growth regression to explain differences in income (Gallup, Sachs, and Mellinger 1999; Acemoglu, et al. 2005; Iyigun 2005; Rappaport and Sachs 2003; Rappaport 2007; Eller 2008). Gallup, Sachs, and Mellinger (1999) show that geography can affect economic policy and certain geographic regions, such as those located far from coastal areas, do not help to promote growth. Rappaport (2007) find that the US population has been moving to regions with nicer weather and it is being driven by higher income of the migrants who value nicer weather more. Iyigun (2005) finds that human capital accumulation is higher in geographically favorable areas because chances of survival of individuals are higher in those areas. Longer life expectancy also leads to more human capital accumulation, according to Oster et al. (2012). Consequently, higher education levels of the population helps to sustain economic growth in those areas, according to Iyugun (2005). The US does have huge variation of terrain and temperature across

counties, and these factors may contribute to differences in income levels and growth rates across this vast country.

There is some research that attempts to explain income differences within US states and counties. Higgins et al (2006) calculates income convergence rates between counties using a panel data from 1970 to 2000 and find that the convergence rates range from 6 to 8 percent amongst the counties. They also show that growth rates of southern counties converge at a faster rate than the richer counties of New England. Barro and Sala-i-Martin (1992) also find some evidence of convergence between the richer and poorer states of the US. Bauer et al. (2006) find that the knowledge stock in a US state has a big impact on its income levels. However, they do not look at how historical variables affect current growth rates. Clifton and Romero-Barrutieta (2006) shows that geography and land tenure of 1910 both negatively affects current levels of poverty in counties, concluding that Appalachia is not poor because it is mountainous, but because it had unfavorable institutions in the past (Clifton and Romero-Barrutieta, 2006). However, Clifton and Romero-Barrutieta (2006) only look at how past institutions affect poverty rates, and do not study how they affect current growth rates of counties. Rappaport and Sachs (2003) show that the US is mainly a coastal nation because counties closer to water-bodies are more densely populated than those that are in the interior of the US, and these coastal counties are more productive and have a higher quality of life than the non-coastal counties.

4.3 The Model and Estimation

Most papers on growth use a variation of the Solow (1957) model to estimate the growth model. For example, Mankiw et al. (1992) use a Solow growth model that is a variation of the Cobb-Douglas production function with a constant returns to scale:

$$Y_t = K_t{}^{\alpha} H_t{}^{\gamma} [A_t L_t]^{1-\alpha-\gamma} \tag{1}$$

Where Y is the aggregate level of output, K is the level of physical capital in the economy, H is the level of human capital in the economy, L is the labor force, and A is the level of technology that is assumed to grow at an exogenous rate of g. It is also referred to as productivity of a country. Traditionally, this kind of a model is estimated using data from a cross section of countries, assuming identical production functions, population and technological growth rates across economies. Under these assumptions, and after controlling for rates of population growth and savings, growth papers have assumed that an initially poor economy "converges" to the same steady state as an initially richer economy. This test of "conditional convergence" has received wide support in the empirical literature. Islam (1995) introduces the use of panel data in analyzing growth. This approach allows for the estimation of different initial *levels* of technology across economies. Thus A_t is allowed to vary across countries. The model specification in a panel data setting is as follows (Islam, 1995; Durlauf et al., 2005):

$$y_{it} = (1+\beta) y_{it-1} + X_{it}\varphi + \varepsilon_{it} \tag{2}$$

where y_{it} is the log of real income per capita for county *i* (=1,...,N) in year *t* (=1,...,T); y_{it-1} is the lag of the dependent variable; and X_{it} are time-varying rates of factor accumulation (new capital investment, population growth rate, school enrollment rates);

and $\varepsilon_{it} = \mu_i + \delta_t + \xi_{it}$ is a compound error term that is a function of unobserved, permanent differences across counties in productivity that do not vary over time (μ_i), a time-varying but common across county macroeconomic shock (δ_t), and an iid error term (ξ_{it}). The parameter identifying the speed of convergence is β.

In the growth literature, μ_i is an indicator of "productivity" or "technology" in a country, and can be explained by historical institutions, cultures, and other factors. By construction, μ_i is correlated with y_{it-1}, and is also likely correlated with the X_{it}. A standard approach used by researchers is to treat this unobserved heterogeneity as a nuisance parameter and apply first differences to remove it from the model. This way, the unbiased estimates of the coefficients β and φ can be obtained. However, first differencing the country fixed effect makes us lose valuable information, since Durlauf and Quah (1999) say that μ_i can be used to explain permanent differences in income between. Instead of removing if from the model, I assume that μ_i is affected by historical factors of a community and then parameterize this initial productivity (μ_i) by adopting a correlated random effects framework of Hausman and Taylor (1981):

$$\mu_i = Z_i\theta + \psi_i \tag{3}$$

where Z_i are observed time-invariant factors that may affect initial productivity such as land tenure, church share, weather, and initial human capital endowments, and ψ_i is an error term. Substituting this into equation (2) yields:

$$y_{it} = (1+\beta)y_{it-1} + X_{it}\varphi + Z_i\theta + \psi_i + \delta_t + \xi_{it} \tag{4}$$

where $E[Z_i\psi_i] = 0$ and $E[y_{it-1}\psi_i] \neq 0$ and $E[X_{it}\psi_i] \neq 0$. Equation (3) can be written concisely in the following way:

$$y_i = d_i\Lambda + \upsilon_i \tag{5}$$

where y_i is the $T \times 1$ vector of log income per capita for county i, $d_i = [y_{i,-1}, X_i, \iota_T Z_i']$ is the $T \times (1 + G + P)$ matrix of independent variables that includes both the past and present variables for county i, and ι_T is a $T \times 1$ vector of ones, $\Lambda = [(1 + \beta), \varphi, \theta]$ is a $(1 + G + P) \times 1$ vector of coefficients to be estimated by GMM, and $\upsilon_i = \iota_T\psi_i + \delta_t + \xi_i$. For consistent estimates of Λ I construct a nonsingular transformation, C, and a matrix of instruments, M_i, such that the moment conditions $E[M_i' C\upsilon_i] = 0$ are satisfied. I follow the method specified in Arellano and Bover (1995) to create M_i, and C. The correlated random effects GMM estimator of Arellano and Bover (1995) allows the estimation of the coefficients on both the time-varying and time-invariant regressors. Arellano and Bover (1995) assume $C = \begin{bmatrix} K \\ \iota_T'/T \end{bmatrix}$ where K is a $(T - 1) \times T$ matrix containing the first difference operator and ι_T'/T converts a variable into its time mean. The matrix K eliminates ψ_i from the first (T-1) rows, which allows the identification of the coefficients on time-varying regressors (y_{it-1}, X_{it}). The term ι_T'/T creates an equation in levels (i.e., 'between-groups'), and it allows the identification of coefficients on time-invariant regressors Z_i.

For the instruments, Arellano and Bover suggest a block-diagonal instrument matrix of the form g_i , where g_i is the instrument matrix for county i consisting of two-period lagged levels of the dependent variable along with the lagged values of X's, and Z's from d_i. The shape of the matrix for county i, thus is as follows:

$$g_i = \begin{bmatrix} 0 & 0 & 0 & & X_{it-1} & 0 & 0 & & 0 \\ y_{it-2} & 0 & 0 & & 0 & X_{it-1} & X_{it-2} & & 0 \\ 0 & y_{it-2} & y_{it-3} & \cdots & 0 & 0 & 0 & \cdots & 0 \\ & \vdots & & & & \vdots & & & \vdots \\ & 0 & & & & 0 & & & Z_i \end{bmatrix} \tag{6}$$

y_{it-1} cannot be used as an instrument for the first difference equation because $e_{i,-1}$is in the error term of the first difference equation, and $E(y_{i,-1}e_{i,-1}) \neq 0$. Thus, $y_{it-n}, n > 1$ can be used as valid instruments. Moreover, assuming that the X_{it} in equation (4) are predetermined, which for variables such as capital and labor force seems reasonable, then lags of X_{it} should be used as instruments instead of contemporaneous X_{it} in order to maintain consistency of the estimated coefficients. g_i also contains the time-invariant Z's, which drop out due to first differencing in the first (T-1) rows of equation (5) but they can be used as instruments for themselves in the level equation in time T. Stacking the observations across all i, the GMM estimator in Arellano and Bover (1995) is given as:

$$\widehat{\Lambda} = [d'\bar{C}'M\left(M'\bar{C}\widehat{\Omega}\bar{C}'M\right)^{-1}M'\bar{C}d]^{-1}d'\bar{C}'M(M'\bar{C}\widehat{\Omega}\bar{C}'M)^{-1}M'\bar{C}y, \tag{7}$$

where $\bar{C} = I_N \otimes C$, I_N is an $N \times N$ identity matrix, $M = I_N \otimes g_i$and $\widehat{\Omega}$ is a conformable matrix. In the 2-step GMM estimator, $\widehat{\Omega}$ is the identity matrix in the first step. The square of the residuals from the first step are used to fill in the principal diagonal of $\widehat{\Omega}$ for the second step, while the off-diagonal entries are kept as zero, and then equation (7) is estimated again. However, as shown by Ziliak (1997), a two step GMM may produce biased coefficients when sample size is finite. Thus, I use the one-step GMM estimator to obtain the coefficients. The one-step GMM estimator replaces $\bar{C}\widehat{\Omega}\bar{C}'$ with $J = I_N \otimes j$, where $j = \begin{pmatrix} j_d & 0 \\ 0 & j_l \end{pmatrix}$ with j_d a $(T-1) \times (T-1)$ matrix with 2s on the diagonal and -1

on the off-diagonal accounting for the first difference transform, and j_l is equal to the identity matrix (see Arellano and Bond 1991). In this setting, $j_l = 1$.

The model in equation (4) assumes that both the poor and non-poor counties have the same production technology, but different initial endowments that is embedded in μ_i. To see if the poor and non-poor counties have different technologies, I divide the total sample into poor and non-poor subsamples and then apply the correlated random effects GMM estimator in (6) to the each of these poor counties ($\widehat{\Lambda}^P$) and non-poor counties ($\widehat{\Lambda}^N$). I then conduct a Wald test to see if the estimated coefficients between these two counties are statistically different using the formula:

$$Wald = \left(\widehat{\Lambda}^P - \widehat{\Lambda}^N\right)'\left[Var\left(\widehat{\Lambda}^P\right) + Var\left(\widehat{\Lambda}^N\right)\right]^{-1}\left(\widehat{\Lambda}^P - \widehat{\Lambda}^N\right) \qquad (8)$$

The Wald test statistic is distributed asymptotially chi-square with degrees of freedom equal to the dimension of the coefficient Λ. This statistic helps to explain whether production technology between the poor and non-poor counties are statistically different from one another.

As a further exercise, I examine whether the difference in income between poor and non-poor counties is due to differences in technology or due to differences in endowments of factors. For this, I utilize a decomposition technique called the Oaxaca decomposition (Oaxaca and Ransom 1994). This method has been used extensively in labor economics to study gender or race wage gap (for example, Cotton, 1988). Intuitively, if there were no difference in production functions between poor and non-poor counties, the production function would be characterized by the pooled model in equation (5), implying that differences in income between poor and non-poor counties

would be solely due to differences in factor shares and initial endowments of culture, institutions, human capital, and geography. If production functions do differ due to significantly different coefficients in $\widehat{\Lambda}^P$ and $\widehat{\Lambda}^N$, then the differences in income would be a function both of different factors and different production functions. The Oaxaca Decomposition is implemented using the following equation :

$$\bar{\hat{y}}^P - \bar{\hat{y}}^N = \left(\bar{d}^P - \bar{d}^N\right)\widehat{\Lambda} + \bar{d}^P\left(\widehat{\Lambda}^P - \widehat{\Lambda}\right) + \bar{d}^N(\widehat{\Lambda} - \widehat{\Lambda}^N) \tag{8}$$

where the left hand side is the predicted difference in mean log income per capita between poor and non-poor counties, the first term on the right hand side reflects differences in income that is due to differences in factor shares and initial productivity endowments, the second term reflects the differences in aggregate production functions (differences in parameter estimates) between the poor counties and the pooled counties, and the third term is differences in aggregate production functions between the pooled counties and the non-poor counties.

4.4 Data

I collect county-level socio-economic data from various agencies of the US government. Some of the county-level data collected are income, population, civilian labor, private capital expenditure, persons living in poverty, number of high-school and above degree holders, number of African-Americans, land tenure, religiosity, geography and institutions. A summary of variable definitions and their measurement units is shown in Table 4.1.

The contemporaneous county-level variables were collected from the 1960, 1970, 1980, 1990 and 2000 Decennial Censuses. The USA Counties Basic Information

database of the Census Bureau provides information on many of the variables from the 1980-2000 Census[11]. Included in this database are county per capita income (average income earned by the residents of the county), the total population of the county, civilian labor force residing in the county (defined as the number of people over the age of 16 in the county who are not employed in the armed forces and are not institutionalized), number of people living in urban areas in the county (defined later in this section), number of African-Americans living in each county, persons living under the poverty-level in the county according to the official poverty definition of the US, and the proportion of residents residing in the county who are over the age of 25 and have at least a high school degree. The corresponding variables for the years 1960 and 1970 were collected from the County and City Data Book of the Census (1962, 1972 and 1977), which are available on the website of ICPSR (Inter-University Consortium for Political and Social Research). This site is maintained by the University of Michigan[12].

I obtain private capital expenditure in the manufacturing sector (measured in millions of US dollars) of each county for the years 1960, 1970 and 1980 from the County and City Data Books of various years (obtained from ICPSR website). Private capital expenditure is defined as either a permanent addition or a major change made by a manufacturing firm and/or the addition or replacement of any machinery or equipment in the plant (and whose depreciation account was maintained). The data for 1990 and the definition of capital expenditures are obtained from the 1992 Census of Manufactures

[11] These data are publicly available from the URL: http://www.census.gov/support/DataDownload.htm.

[12] These data can be obtained from: http://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/2896/system

Report on each county[13]. The 1990 data are in pdf format, and thus a pdf-to-Excel converter was used to convert the data from pdf to Excel, and then exported to Stata, the statistical software I used to analyze data. Private capital expenditure data for the year 2000 was obtained from US Counties Basic Information database. The data from 1960 to 1990 were converted to real 2000 dollars using the personal consumption expenditure deflator from the Bureau of Economic Analysis (BEA).

Data on the standard deviation of elevation of each county was obtained from Rappaport and Sachs[14] (March, 2003). Elevation of a county (in feet) measures how high the land is from sea-level. This data measures how varied the terrain of a county is. The higher the standard deviation, the more extreme the terrain of the county; the lower the standard deviation, the terrain is more or less constant

As explained before, historical data of variables that proxies institution and culture are used to parameterize the productivity (μ_i) of a county. Some of the data used to proxy μ_i are percentage of foreign-born living in a county, land tenure of a county, number of county residents living in urban areas (areas that have been legally incorporated as cities, towns or boroughs[15]) and number of illiterate people in a county (number of people living in the county who cannot read or write), and they were collected from the 1890 and 1900 Census Database, which can also be obtained from the website of ICPSR.

The raw data obtained was then aggregated together to create data that can be used in my analysis. Religious data on total church attendance and followers of different

[13] The Census of Manufactures can be obtained from: http://www.census.gov/prod/1/manmin/92area/92manufa.htm.
[14] This data was provided by Jordan Rappaport of the Federal Reserve Bank of Kansas City, and I am thankful to him for providing me with this data
[15] Source: http://www.census.gov/population/www/documentation/twps0027/twps0027.html

denominations, namely Baptists, Calvinists and Catholics, were obtained from the 1890 Census of Religious Bodies. In this paper, the Baptist denomination includes Regular (North, South and Colored), Freewill, General, Primitive and Old Two-Seed denominations. The Calvinists denomination includes Welsh Calvinist, Presbyterian (Northern and Southern), Cumberland Presbyterian (Regular and Colored), United Presbyterian, US Reformed Church and American Reformed Church Organizations. All these historical and religious data can be obtained from the ICPSR database [16].

The growth rate of labor force is defined as the percentage change of civilian labor force in a country from one decade to the next. To construct this variable for 1960 I obtained the county-level civilian labor force population from the 1950 Census to construct the 1950-1960 change.

Historical temperature and precipitation data were obtained from the website of the National Oceanic and Atmospheric Administration (NOAA)[17]. However, this data indicated temperature and precipitation by regions in each state, and not by county (there are about 200 regions in the country). The NOAA did provide a map that indicated which counties belonged to which region in a state[18]. This data was coded by hand and then the file was merged to the main dataset to get the historical temperature of counties.

The percentage foreign-born in 1890 is defined as the proportion of people living in a county who were not born in the United States. Land tenure is defined as the total area farmed by owners in a given county, divided by the total amount of farmland in the county. This number was not given explicitly; what was given was the number of farm

[16] Census of Religion can be obtained from http://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/2896/system
[17] http://www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp
[18] http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/regional_monitoring/CLIM_DIVS/states_counties_climate-divisions.shtml

owners who farmed 0-9 acres of farmland, 10-19 acres, 20-49 acres, 50-99 acres, 100-499 acres, 500-999 acres and 1000+ acres. The mid-point of each segment was multiplied by their respected number of farm owners (for 1000+ acres of farm segment, the number of farmers was multiplied by 1000 to estimate the total number of farmland owned by farmers farming 1000+ acres) and then they were added together to get the total acres of farmland farmed by owners.

Over time, the Census Bureau changed the definition of what constitutes as an urban area. In 2000, an urban area was defined as a core census block groups or census block that had at least 1000 persons per square mile and the surrounding census blocks that have a population density of at least 500 persons per square mile[19]. Thus, a city with a population density of at least 1000 people per square mile and the surrounding suburbs with at least 500 people per square mile would be considered to be an urban area. For the years 1960, 1970, 1980 and 1990, the definition of an urban area was less stringent; any area that was one of the Census designated places with more than 2500 people, or was incorporated in an urban area was considered to be an urban area[20]. Therefore, for those areas, people living in a city or a town with at least 2500 people or, living in an area that was historically considered to be urban would be considered to be living in an urban area.

A number of counties changed their area and many new counties formed over time. Large counties were split to form new counties and some counties were merged together to form a new county. For example, Manitou County in Michigan does not exist anymore and was merged with other neighboring counties[21]. Also, some states such as

[19] "Census 2000 Urban and Rural Classification" http://www.census.gov/geo/www/ua/ua_2k.html
[20] http://www.census.gov/population/censusdata/urdef.txt
[21] http://en.wikipedia.org/wiki/Manitou_County,_Michigan

Oklahoma, Hawaii and Alaska were not even declared as states in the 1890s. These redrawing of county boundaries posed a problem because different social indicators data (such as population, number of people illiterate in the county, land tenure) changed whenever county boundaries were changed. Thus, I used only counties whose shape remained the same from the years 1890 onwards. Data on whether county boundaries have changed over time were obtained from the website of Newberry Library (http://www.newberry.org). The library has electronic files of state maps from different periods that show how the counties in each state evolved over time. The maps for the year 1890 were compared with those of current day (which are also available in the website of Newberry Library[22]) to see which counties did not change their shape between 1890 and present day. The counties whose shape remained constant were identified and then this data was merged to the rest of the data. The final number of counties having all the information is 2,400, where 2,166 counties were classified as non-poor counties and 234 counties were classified as persistently-poor counties (that is, counties with more than 20 percent headcount poverty rates from 1960 till 2000).

Table 4.2 shows some summary statistics of the non-poor and poor counties for the years 1960 and 2000 and pooled 1960 to 2000. The summary statistics show that the average income gap between the poor and non-poor counties increased from about 3,000 dollars to about 5,000 dollars between 1960 to 2000. Average population of the poor counties remained the same, while that of non-poor counties increased by almost 35,000 during the same time period. In all time periods, the fraction in labor force, fraction high school graduate and above, capital expenditure, and urban share are much higher for the

[22] http://publications.newberry.org/ahcbp/

non-poor counties than the poor counties. The proportion black is much higher for poor counties than for non-poor counties. The summary statistics show that economic variables for the poor counties are much lower than those for the non-poor counties, and this difference is increasing over time.

Table 4.3 lists the summary statistics of the counties that were not included in the analysis because they did not exist back in 1890. The t-test of equal means compares the equality of these variables between counties included (illustrated in Table 4.2) and those excluded from the analysis. The t-values show that the non-poor counties included in the study are better off than those not included in the analysis. Also, the poor counties included in the analysis are worse off compared to the poor counties not included in the analysis. Thus, the means of these excluded counties are generally in between those included in the analysis. Since the excluded counties are not outliers, not including them should not affect the general results of this paper. .

Table 4.4 summarizes some of the historical variables for the poor and non-poor counties. Institution, as proxied by land tenure, is not significantly different between the poor and non-poor counties. The proportion of individuals who attended church services is also pretty similar, although a higher proportion who churched were Baptists in the poor counties. The poorer counties were much warmer (60 F as opposed to 52.9 F for the non-poor counties), and had slightly higher precipitation levels and are less mountainous. The non-poor counties were much more urbanized in 1890 than the poor counties, while the proportion foreign born was much higher for non-poor counties (9.4%) than for poor counties (2.6%). Illiteracy rate, measured by the proportion of individuals who cannot

read or write, was much higher for poor counties (36%) than for non-poor counties (11%).

Table 4.4 thus shows that poor counties were disadvantaged when it came to historical urban share and human capital. Other than that, variables measuring institutions and culture were not so different between these two sets of counties. To give an idea how historical variables may affect current poor/non-poor status, I run a linear probability model, where the dependent variable equals 1 if the county is poor and 0 if the county is non-poor. The results are tabulated in Table 4.5. The first column does not control for culture and agglomeration, and it shows that geography affects current poverty status more than institutions. Warmer and wetter counties have a higher probability of being poor, while mountainous counties are less likely to be poor. Column (2) adds variables that measures culture and agglomeration and it shows that a higher urban share in 1890 reduces the likelihood of a county being poor today. The higher the illiteracy rate, the higher is the likelihood of a county being poor. Also, the higher the church share, the lower is the likelihood that a county is poor. Column (3) disaggregates church share by denomination and shows that the higher the share of Baptists and Calvinists, the lower is the likelihood of a county being poor. When illiteracy rate is removed from the model, land tenure becomes significant, as seen in columns (5) and (6). A higher land tenure reduces the likelihood for a county to be poor. Warmer counties are more likely to be poor and more urban counties are less likely to be poor. One interesting thing to note is that once human capital is removed from column (5), Baptist share become positive and significant, while Calvin share becomes negative and significant, showing that a higher proportion of Baptists historically can make a county poor today, while a higher

proportion of Calvinists reduces the likelihood of a county to be poor, which may give some support to Weber's theory. However, when columns (3) and (5) are compared, it is clearly seen that human capital is much more important than culture in determining the persistence of poverty in county. This is further analyzed in the next section.

4.5 Results

A. Pooled Model

Column 1 of Table 4.6 reports the results of the one-step GMM run on the pooled sample (12,000 county-year observations). The variables are of the form $\begin{bmatrix} K \\ \iota_T'/T \end{bmatrix} * D$ where K is a $(T-1) \times T$ matrix containing the first difference operator, ι_T'/T converts a variable into its time mean where ι_T' is a vector of 1's as described above in the model section, and D can be y, X or Z. The instrument matrix is block diagonal, as shown in equation (5) with (t-2) to (t-4) lagged values of y_{it}, (t-1) to (t-4) lagged levels of the time-varying variables (X_{it}) and levels of the time-invariant variables (Z_i) used as instruments. The results in column (1) broadly indicate that both present and past levels of human capital accumulation have important effects on current income levels. For example, a one percentage point increase in the fraction of high-school graduates implies an increase in income levels of 7.4 percent, while a one percentage point decrease in 1900 illiteracy rates implies a 4.3 percent increase in income. Other variables such as current urban agglomeration and labor force growth are also positively correlated with income. Black share is positive and statistically significant. Institutions and culture do not significantly affect present value of income, however, the variables proxying for geography do affect current income. For example, a more mountainous region has a higher level of income while warmer counties have a lower level of income. Counties with higher precipitation

are generally richer. This could be because warmer climates have more infectious diseases, like cholera and malaria, which lowered life expectancy in the 1890s, thus affecting human capital accumulation, as pointed out by Iyigun (2005).

Following Islam (1995), the convergence rate for the pooled model is calculated by: $Convergence = -1 \times \log(\hat{\beta})\,/time$, where *time* (10 years in our case) the interval of data measurement and $\hat{\beta}$ is the coefficient on the lagged dependent variable. The estimated convergence rate is around 10 percent, which is within the range of estimates found in previous research at various levels of aggregation (e.g., Islam 1995 at the cross-country level; Higgins et al 2006 at the county level). However, as shown in the last panel of the table, Hansen's J test indicates that the model's over-identifying restrictions are rejected. To address this problem, I change the shape of the instrument matrix in several ways, as discussed later in the chapter.

B. Poor versus Non-poor Aggregate Production Technologies

Next, I look at whether production technologies between poor and non-poor counties are significantly different. Columns (2) and (3) show the result of the poor and non-poor subsamples respectively. Looking at column (2), one can see that current stock of human capital has an important effect on income, and so does labor force growth. However, proxies for geography, culture or institutions do not affect the current level of income of poor counties. Looking at column (3), it is seen that most of the coefficients are close to what was estimated in the pooled model in column (1). This is because about 90 percent of the counties are non-poor in the pooled sample. Geography and past and present levels of human capital have a big effect on income for non-poor counties, but culture and institutions do not. The convergence rates of both poor and non-poor counties

are around 10 percent. The Wald test rejects the null that the coefficients of columns (2) and (3) are equal, thus indicating different aggregate production technologies used by poor and non-poor counties.

C. Poor/Non-Poor Decomposition

Table 4.7 presents the result of Oaxaca-Blinder decomposition between the poor and non-poor counties to explain the reasons behind their income difference. I used the coefficients from Table 4.5 to do the decomposition. The result shows that about 80 percent of the difference can be attributed to differences in endowments between poor and non-poor counties, while about 20 percent is due to differences in coefficients (difference in technologies). Among the factor endowments, past and present levels of human capital explain about 70 percent of the difference in endowments, while current urban share explain about 20 percent of the difference in endowments. This exercise shows the importance of human capital in growth and prosperity. Counties with initially low levels of human capital are more likely to have low income today; however, increasing current level of human capital can help to close some of the income gap. Other variables, such as those measuring culture, geography and institutions do not explain much of the income difference between the poor and non-poor counties.

D. Further Regressions

The J-test statistic of columns (1) and (3) show that the models are overidentified. In Table 4.8, I change the instrument matrix by restricting the number of lags of X_{it} included as instruments. I only use upto the second lag of X_{it} as instruments. The instrument is still block diagonal. The result is very similar to what was observed in Table 4.6. The convergence rates for poor and non-poor counties is around 10 percent,

while the Wald test still reject the null that the coefficients are equal. The decomposition results in Table 4.9 also show that about 80 percent of the difference in income is due to factor endowments, and almost 70 of the difference in endowment is due to past and present stock of human capital. However, the J-test statistic is still rejected for the pooled and the non-poor regression.

In Table 4.10, I further restrict the instrument matrix by making the instrument matrix not block diagonal. The instrument matrix has only (t-2) lag of *Y* as instrument, (t-1) and (t-2) lagged levels of the time-varying variables, and the level of time-invariant variables as instruments. The pooled result in column (1) show that past and present stock of human capital is no longer significant in explaining income. Urban share positively affects growth, and temperature and precipitation affect current levels of income. The convergence rate is much lower (at 6.5 percent) than what was seen in the previous results. In column (2) current human capital stock is significant in affecting income of the poor counties, but other present and past endowments do not seem to affect income levels significantly. The convergence rate of poor counties is around 10 percent.

Column (3) shows capital investment is important to growth. As seen in column (1), current and past stock of human capital do not affect current level of income. Average temperature negatively affects income in non-poor counties. The decomposition exercise of Table 4.11 shows that endowments are still important in explaining most of the difference in income between the poor and non-poor counties. However, the effect of human capital is much lower now, past and present stock of human capital explains about 30 percent of the difference in income due to factor endowments.

As a final test, I drop using lagged values of y as instruments and only use X's as instruments. The results are tabulated in Table 4.12. The coefficients are similar in magnitude and sign as seen in previous cases; although capital is negative, but insignificant in the pooled and non-poor case. However, the J-statistic remains high and it is rejected in the pooled and non-poor cases. The Hansen's test is rejected no matter what the shape of the instrument matrix.

E. Two-step GMM Results

I also run some two-step GMM to see if the results from the one-step GMM remain consistent. Table 4.14 shows the result of two-step GMM where the instrument matrix is the same as that used in Table 4.6. To recap, the instrument matrix is block diagonal, as shown in equation (5) with (t-2) to (t-4) lagged values of y_{it}, (t-1) to (t-4) lagged levels of the time-varying variables (X_{it}) and levels of the time-invariant variables (Z_i) used as instruments. Across the columns, it is seen that capital expenditure is negatively significant for pooled sample and non-poor subsample, which runs counter-intuitive to what is suggested in the literature. Capital expenditure is also negative in Table 4.16 where a more restricted, block-diagonal instrument matrix is used as weights. It could be because the first-stage residuals are correlated with the regressors, as pointed out by Ziliak (1997). The decomposition exercise in Tables 4.13 and 4.15 show that current human capital is an important factor explaining differences in income.

In Table 4.18, I use a non-block diagonal matrix to estimate the coefficients, similar to the one used in Table 4.10. Now capital spending is positive and significant, but current stock of human capital is only significant in the case of the poor counties. The convergence rates of pooled and non-poor counties is much lower, and the decomposition

exercise of Table 4.19 show that historical human capital stock does not explain much of the difference between income of these two subsample of counties.

These two-step GMM do not provide consistent estimates when the instrument matrix is changed. Therefore, the validity of these results comes to question. Thus, I draw conclusion from the one-step analysis only.

F. Disaggregating Church Share

I also do a GMM where I disaggregate church share by the following denominations – Catholic, Baptist and Calvinist. The linear probability model in Table 4.5 showed that in the absence of human capital variable, Baptist and Calvin share affected the likelihood of a county to be poor. Instead of just looking at church share as a proxy for culture, I disaggregate it by denominations and then run the one-step GMM using the instrument matrix similar to the one used in Table 4.6. As a recap, the instrument matrix is block diagonal, as shown in equation 4.5 with (t-2) to (t-4) lagged values of y_{it}, (t-1) to (t-4) lagged levels of the time-varying variables (X_{it}) and levels of the time-invariant variables (Z_i) used as instruments. The results are tabulated in Table 4.20. The rest of the coefficients remain similar in sign and magnitude. Only in the pooled sample (column (1)) and the non-poor subsample (column (3)) is Baptist share having a positive effect on income. The share of Catholics and Calvins do not affect income of any of the samples, although the sign for Calvin is positive in the pooled and non-poor subsamples and negative for the poor subsample. The decomposition shown in Table 4.21 still show that past and present stock of human capital explains much of the difference in income between poor and non-poor counties (close to 75 percent of the

difference in endowment is due to these two factors). Culture, on the other hand, explains only about 4 percent of the difference in income between the poor and non-poor counties.

4.6 Sensitivity Analysis

A. Changing the Definition of a Poor County

In this section I test the validity of the results obtained from the one-step GMM estimation by changing the definition of poor and non-poor counties. I only report the results of the decompositions in Table 4.22. Column (1) defines persistently poor county the same way as before, (a poverty rate over 20% in each decennial Census between 1960 and 2000), but use only non-urban, non-poor counties as the comparison group.[23] In Column (2), I only compare poor and non-poor counties of states that have poor counties (states with no poor counties are removed from this analysis. There are 26 states with no poor counties). Column (3) excludes the persistently poor counties that are primarily *colonias* or Native American reservations (that is, the persistently poor counties included here are only from Appalachia, the "Black Belt," and the Mississippi Delta).[24] In Column (4), the definition of a poor county is relaxed and any county that has poverty rates of over 20 percent in three of the five Census years is considered to be a poor county. Finally, in Column (5), I define a poor county as one that has at least 30% (rather than 20%) poverty rate in each decennial Census between 1960 and 2000. In all of the estimations, the instrument matrix is block diagonal, consisting of (t-2), (t-3), and (t-4)

[23] I use the Beale system of 1974 developed by the US Department of Agriculture (also known as the Rural-Urban Continuum Codes) to define whether a county is urban or rural. If a county has a Beale score of less than or equal to 5, it is considered as an urban county; a score of higher than 5 is considered to be a rural county.

[24] Technically, we exclude states between the Mississippi Delta and the Pacific Coast states. The non-poor sample includes counties from these states.

lags of log income per capita and (t-1) through (t-4) lagged levels of the time-varying variables and the level of time-invariant variables.

Across these columns, it is seen that the gap of log income between the poor and non-poor counties ranges from -0.32 to -0.48, while factor endowments explain about 80 percent of the gap. Technology, on the other hand, explain about 20 percent of the difference in income. These results are consistent with the results obtained from the decomposition of the one-step GMM estimates. Human capital stock remains an important factor in explaining income gap - past human capital explains around 23 to 38 percent of the difference in endowment, while contemporaneous human capital explains between 36 and 42 percent of this gap. Together, these two factors explain well over half the difference in factor endowments between poor and non-poor counties. Culture and institutions respectively explain less than one percent of the difference in endowments, while geography explain about 2 to 10 percent of the difference in endowment. This shows that past and present human capital stock explain most of the variation of income between poor and non-poor counties.

B. Decomposition by Region

As a further decomposition, I compare production technology and endowments of poor and non-poor counties of specific regions of the US, namely – the Appalachian region (the states of Kentucky, Tennessee and West Virginia), the Black Belt region (Alabama, Georgia, North Carolina and South Carolina), the Mississippi Delta region (Arkansas, Louisiana, Missouri and Mississippi), and the colonias and western counties of the US (Arizona, Colorado, New Mexico, North Dakota, Montana, South Dakota, Texas and Utah). I run separate regressions for the poor and non-poor counties in each of

these respective regions and then do the Oaxaca Decomposition. This way, I can study the differences of income of poor/non-poor counties in regions that have similar geography and culture. The results of the decomposition are tabulated in Table 4.23.

The decomposition of poor/non-poor counties in the Appalachian region show that most of the difference in income is due to factor endowments and very little is due to the differences in technology, as seen in the baseline result. Current level of human capital account for about half the difference in factor endowments, while urban share accounts for about 13 percent of this difference. Interestingly, historical factors do not account for much of the difference in current income; culture and institutions account for about 2.5 percent respectively, while geography accounts for 1.3 percent of the differences in current income, which goes counter to what Duncan (1999) and Billings and Blee (2000) hypothesized.

When looking at the Black Belt region, I find that historical human capital accumulation account for almost 45 percent for the current differences in endowment share. Current level of human capital account for about 15 percent of the differences between income. This shows that the Black Belt remained poor because of the difference in past and present level of human capital accumulation.

In the Mississippi delta, all the difference in income between poor and non-poor counties is due to factor endowment, and there is no difference in technology between poor and non-poor counties. About 3.4 percent of the difference in endowments can be accounted because of differences in historical human capital accumulation and almost 30 percent is due to current levels of human capital accumulation. Differences in urban share account for 13 percent of the differences in endowments.

The western counties also show that all the differences in income can be explained by differences in endowments between the poor and non-poor counties. About 6.5 percent is due to historical human capital accumulation and about 3.5 percent is due to culture and institutions respectively. Geography of the region accounts for about 16 percent of the difference in income. As seen in the other regions, current levels of human capital account for a large part of the differences in income between poor and non-poor counties. In the western counties, current human capital account for almost 40 percent of the differences in current level of income between poor and non-poor counties.

Thus, the following can be summarized about the reason why these regions are poorer from the rest of the US. Current and past levels of human capital accumulation play a huge role in explaining the differences in income between the poor and non-poor counties. Historical culture and institutions do not have much of an influence in explaining current differences in income. Thus increasing the present level of human capital stock of poor counties can help to reduce the income gap between the poor and non-poor counties by a large extent.

4.7 Conclusion

The United States has been successful in reducing poverty rates across the country between the years 1960 to 2000. However, there are still a number of counties where poverty rates remain high and persistent. Most of the previous literature on the topic of growth explained differences in income between countries; however, casual observation shows that there is much variation in policy and restrictions to movement of labor and capital across countries, which may not explain the persistence of poverty in certain regions, if policy is not controlled for. In this chapter, I try to find the reasons why certain

counties remained poor for such a long period of time in an otherwise wealthy nation, where national policies are broadly consistent and there is free movement of labor and capital across the country. I look at whether current and historical factor endowments, or differences in technology are the reasons behind the persistence of poverty in some of these counties.

I divide the sample of US counties into poor and non-poor counties, according to the definition provided by the US Department of Agriculture. I run a correlated random effects one-step GMM estimator to obtain coefficients of the pooled, poor and non-poor subsamples of the counties. The results generally show that present and past stock of human capital have a big effect on income of a county, whether they are poor or non-poor. The Wald test of equal coefficients between the poor and non-poor coefficients generally rejects the null, stating that the poor and non-poor counties use different production technologies. Historical geography variables seem to have an important effect, indicating that wetter and warmer counties are generally poorer. This could be because wetter and warmer regions generally have a high prevalence of different infectious diseases, which could have affected the life expectancy and thus human capital accumulation of a person in the late 1800s. Consequently, income of those counties became generally lower than colder, drier counties. Variables measuring culture and institutions, however do not significantly affect income in either poor and non-poor counties.

I also run some decomposition exercises to understand whether it is the difference in factor endowments or the difference in technology that explains the difference in income between these two sets of counties. Most of the difference in income

can be attributed to differences in factor endowments (around 80 percent). Out of that, almost 70 percent of the difference in endowment is due to differences in past and present levels of human capital accumulation, according to the baseline model. Other changes in the specification also show that human capital has a high effect on income. Culture, geography and institutions do not explain much of the difference in income between these two set of counties. These results are generally robust to different changes of: (1) the instrument matrix, (2) the definition of a poor/non-poor counties and (3) decomposition by regions.

Thus this chapter can conclude that human capital accumulation is importnat to growth and prosperity in US counties. Culture, geography and institutions do not have a big effect in explaining current levels of income in a county. Counties that are currently poor had low levels of human capital accumulation in the past, which explains current income differences. This shows the importance of human capital not only at the present level, but also past levels of human capital are important in explaining growth and income differences across the poor and non-poor counties.

Table 4.1: Description of Variables Used in the Regressions

Variable	Description	Measurement Units
Per Capita Income ($)	Average income earned by the residents of the county	In dollar amounts; values from 1960 to 1990 have been converted to 2000 dollars using the personal consumption expenditure deflator from the Bureau of Economic Analysis (BEA)
Population	Total number of people living within the boundary of a county	In absolute value
Fraction in Labor Force	The number of people over the age of 16 in the county who are not employed in the armed forces and are not institutionalized, divided by the population of the county.	Between 0 and 1
Growth in Labor Force	The increase in civilian labor force in a country from one decade to the next	Between 0 and 1
Fraction High School Graduate	The number of residents over the age of 25 with at least a high school degree in the county, divided by the population of the county	Between 0 and 1
Capital Expenditure	A permanent addition or a major change made by a manufacturing firm and/or the addition or	In millions of dollars, and the values have been

Table 4.1 Continued

	replacement of any machinery or equipment in the plant (and whose depreciation account was maintained).	converted to real 2000 dollars using the personal consumption expenditure deflator from the Bureau of Economic Analysis
Fraction Living in Urban Area	The number of residents living in an urban area as defined by the Census, divided by the total population	Between 0 and 1
Fraction Black	The number of African-Americans living in a county, divided by the total population	Between 0 and 1
Land Tenure in 1890	The total area of farmland farmed by their respective owners in the year 1890, divided by the total area under cultivation in a county in 1890	Between 0 and 1
Share Churched in 1890	The total number of people who attended church services in 1890, divided by the total number of people living in the county in 1890	Between 0 and 1
Share Baptist in 1890	The total number of people in a county who identify themselves as Baptists (Regular (North, South and Colored), Freewill, General, Primitive and Old Two-Seed denominations) in 1890,	Between 0 and 1

Table 4.1 Continued

	divided by 1890 total population	
Share Calvinist in 1890	The total number of people in a county who identify themselves as Calvinists (Welsh Calvinist, Presbyterian (Northern and Southern), Cumberland Presbyterian (Regular and Colored), United Presbyterian, US Reformed Church and American Reformed Church Organizations) in 1890, divided by the total population in 1890	Between 0 and 1
Share Catholic in 1890	The total number of people in a county who identify themselves as Catholics in 1890, divided by the total population in 1890	Between 0 and 1
Average Temperature 1895	The average monthly temperature of a county for the years 1895 to 1905	In Fahrenheit
Average Precipitation 1985	The average monthly precipitation of a county for the years 1895 to 1905	In inches
Std Dev to area	The standard deviation of elevation of a county divided by area of that county	In feet per square mile

Table 4.1 Continued

Urban Share in 1890	The number of residents living in an urban area as defined by the Census, divided by the total population in 1890	Between 0 and 1
Share Foreign Born in 1900	The number of residents living in the county who were not born in the United States in 1890, divided by the total population	Between 0 and 1
Illiteracy Rate in 1900	The number of people who cannot read or write in a county in 1890, divided by the total number of people living in the given county in 1890	Between 0 and 1

Table 4.2: Summary Statistics of Social Indicators for Counties by Persistent Poverty Status

	Not Poor		Poor	
	Mean	Standard Deviation	Mean	Standard Deviation
Pooled 1960-2000 Census Data				
Per Capita Income ($)	12,436	4,952	8,451	3,585
Population	83,741	261,370	21,749	39,192
Fraction in Labor Force	0.423	0.065	0.349	0.057
Growth in Labor Force	0.161	0.235	0.036	0.211
Fraction High School Graduate	0.579	0.190	0.409	0.173
Capital Expenditure ($millions)	38.916	155.244	4.718	18.158
Fraction Living in Urban Area	0.373	0.287	0.217	0.235
Fraction Black	0.068	0.114	0.288	0.254
1960 Census Data				
Per Capita Income ($)	6,864	1,872	4,074	1,192
Population	66,094	229,251	21,424	41,972
Fraction in Labor Force	0.360	0.036	0.300	0.042
Growth in Labor Force	0.053	0.224	-0.166	0.136
Fraction High School Graduate	0.355	0.103	0.212	0.064
Capital Expenditure ($millions)	17.221	80.589	1.117	3.324
Fraction Living in Urban Area	0.330	0.277	0.182	0.215
Fraction Black	0.073	0.128	0.307	0.267
2000 Census Data				
Per Capita Income ($)	18,664	3,695	13,399	1,896
Population	100,491	322,866	21,865	35,766
Fraction in Labor Force	0.482	0.046	0.394	0.040
Growth in Labor Force	0.142	0.152	0.056	0.108
Fraction High School Graduate	0.790	0.073	0.636	0.065
Capital Expenditure ($millions)	43.997	180.537	4.892	16.898
Fraction Living in Urban Area	0.410	0.301	0.241	0.241
Fraction Black	0.064	0.105	0.283	0.283
Observations	10,830		1,170	
Number of Counties	2,166		234	

Notes: "Poor" counties have poverty rates of at least 20% in 1960, 1970, 1980, 1990, and 2000. "Not poor" are all others. Per capita income and capital expenditures are in real 2000 dollars, based on the personal consumption expenditure deflator.

Table 4.3: Summary Statistics of Social Indicators for Counties that did not Exist in 1890, by Persistent Poverty Status

	Not Poor			Poor		
	Mean	Std. Dev.	T-test of Eq. Means	Mean	Std. Dev.	T-test of Eq. Means
Pooled 1960-2000 Census Data						
Per Capita Income ($)	12,163.3	4,738.7	2.64*	8,659.4	3,205.7	-2.94*
Population	67,360	200,199	3.55*	33,774	68,148	-8.79*
Fraction in Labor Force	0.415	0.066	5.64*	0.362	0.057	-10.58*
Growth in Labor Force	0.208	0.509	-4.66*	0.107	0.244	-13.85*
Fraction High School Graduate	0.600	0.185	-5.23*	0.457	0.174	-12.81*
Capital Expenditure ($millions)	19.895	77.248	9.02*	7.519	23.841	-5.69*
Fraction Living in Urban Area	0.393	0.330	-2.88*	0.326	0.260	-19.81*
Fraction Black	0.085	0.135	-6.01*	0.190	0.215	20.36*
1960 Census Data						
Per Capita Income ($)	7,006.4	1,925.0	-1.54	4,593.6	1,355.9	-18.19*
Population	47,594	157,189	2.20*	26,316	41,044	-5.50*
Fraction in Labor Force	0.356	0.045	1.91	0.314	0.051	-13.16*
Growth in Labor Force	0.127	0.566	-2.97*	-0.051	0.281	-20.61*
Fraction High School Graduate	0.380	0.112	-4.70*	0.254	0.081	-25.00*
Capital Expenditure ($millions)	6.421	29.743	5.01*	1.180	2.764	-1.013
Fraction Living in Urban Area	0.352	0.318	-1.47	0.281	0.259	-18.30*
Fraction Black	0.095	0.148	-3.16*	0.202	0.224	20.88*
2000 Census Data						
Per Capita Income ($)	17,696.9	4,206.98	4.88*	12,777.4	1,940.0	14.93*
Population	91,714	253,952	0.677	44,418	97,928	-11.74*
Fraction in Labor Force	0.466	0.051	6.63*	0.400	0.040	-6.96*
Growth in Labor Force	0.166	0.208	-2.51*	0.107	0.127	-19.16*
Fraction High School Graduate	0.790	0.078	0.00	0.660	0.081	-14.26
Capital Expenditure ($millions)	20.914	70.255	4.68*	10.764	34.152	-8.65*
Fraction Living in Urban Area	0.436	0.334	-1.64	0.345	0.268	-18.35*
Fraction Black	0.083	0.132	-3.10*	0.190	0.220	18.44*
Observations	2685			475		
Number of Counties	537			95		

Notes: "Poor" counties have poverty rates of at least 20% in 1960, 1970, 1980, 1990, and 2000. "Not poor" are all others. Per capita income and capital expenditures are in real 2000 dollars, based on the personal consumption expenditure deflator. The t-test of equal means tests the equality of means of variables listed in Table 4.3 with those listed in Table 4.2. * indicate significance at 5 percent.

Table 4.4: Summary Statistics of Historical Indicators for Counties by Persistent Poverty Status

	Not Persistently Poor		Persistently Poor	
	Mean	Standard Dev.	Mean	Standard Dev.
Institutions				
Land Tenure in 1890	0.798	0.115	0.769	0.143
Culture				
Share Churched in 1890	0.293	0.118	0.309	0.148
Share Baptist in 1890	0.065	0.081	0.135	0.097
Share Calvinist in 1890	0.019	0.022	0.009	0.015
Share Catholic in 1890	0.058	0.086	0.034	0.123
Geography				
Average Temperature	52.90	7.405	60.27	6.037
Average Precipitation	3.089	0.910	3.611	0.721
Std Dev of Elevation	0.089	0.129	0.064	0.076
Human Capital/Agglomeration				
Urban Share in 1890	0.129	0.211	0.026	0.107
Share Foreign Born in 1900	0.094	0.103	0.023	0.072
Illiteracy Rate in 1900	0.112	0.135	0.360	0.217
Number of Counties	2,166		234	

Notes: "Persistently poor" counties have poverty rates of at least 20% in 1960, 1970, 1980, 1990, and 2000. "Not persistently poor" are all others. The historic Census data include only counties without redefined borders between the relevant year (1890, 1900) and 1960. See the Data Appendix for detailed variable definitions.

Table 4.5: Linear Probability Estimates of the Probability of Being Poor

Variables	(1)	(2)	(3)	(4)	(5)
Land Tenure in 1890	-0.072	0.049	0.041	-0.138**	-0.193**
	(0.057)	(0.054)	(0.055)	(0.063)	(0.063)
Average Temperature	0.010**	-0.0001	0.0002	0.009**	0.007**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Average Precipitation	0.011*	-0.027**	-0.025**	0.015**	0.007
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)
Std. Dev of Elevation	-0.072**	-0.028	-0.016	-0.053*	-0.048*
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Share Foreign-born in 1900		-0.053	-0.118	0.094	-0.011
		(0.078)	(0.092)	(0.081)	(0.097)
Urban Share 1890		-0.057**	-0.067**	-0.175**	-0.147**
		(0.021)	(0.022)	(0.023)	(0.024)
Illiteracy Rate 1900		0.921**	0.913**		
		(0.063)	(0.071)		
Church Share 1890		-0.181**		0.027	
		(0.057)		(0.063)	
Baptist Share 1890			-0.254**		0.340**
			(0.119)		(0.117)
Calvin Share 1890			-0.557**		-1.414**
			(0.263)		(0.296)
Catholic Share 1890			-0.017		0.189*
			(0.106)		(0.113)
Constant	-0.422**	0.094	0.057	-0.355**	-0.164**
	(0.063)	(0.077)	(0.077)	(0.074)	(0.078)
Adjusted R^2	0.085	0.220	0.219	0.097	0.117
Number of Counties	2,400	2,400	2,400	2,400	2,400

Notes: Standard errors are in parentheses. The dependent variable is a binary variable equal to one for counties that are persistently poor between 1960 and 2000 and zero otherwise. * indicates significance at the 10% while ** indicate significance level at the 5%.

Table 4.6: One-step GMM Estimates of Pooled, Poor and Non-Poor Counties

	(1) Pooled Model	(2) Poor Counties	(3) Non-Poor Counties
Current Factors			
Lag Income per Capita	0.3757**	0.3673**	0.3731**
	(0.0267)	(0.0834)	(0.0292)
Fraction High School	0.7424**	1.0445**	0.7047**
	(0.0728)	(0.3134)	(0.0791)
Capital Spending (x1,000,000)	3.7949	253.82	20.98
	(41.77)	(378.66)	(40.39)
Labor Force Growth	0.1350**	0.1704**	0.1346**
	(0.0166)	(0.0405)	(0.0177)
Urban Share	0.4346**	0.0708	0.4459**
	(0.0600)	(0.1422)	(0.0621)
Black Share	0.5594**	0.0417	0.5039**
	(0.1379)	(0.3934)	(0.1285)
Human Capital/Agglomeration			
Illiteracy Rate 1900	-0.4272**	-0.1708	-0.2653**
	(0.1035)	(0.2517)	(0.0896)
Proportion Foreign Born 1900	-0.0942**	-0.0382	-0.06758
	(0.0465)	(0.2954)	(0.04687)
Urban Share 1890	-0.3402**	-0.0825	-0.3480**
	(0.0512)	(0.12892)	(0.0517)
Culture			
Proportion Churched 1890	0.0346	-0.0119	0.0284
	(0.0278)	(0.0976)	(0.0306)
Institutions			
Land Tenure 1890	0.0448	-0.0825	0.0029
	(0.0337)	(0.0990)	(0.0329)
Geography			
Standard Dev. to Area	0.1756**	0.0881	0.1610**
	(0.0273)	(0.2463)	(0.0257)
Average Temperature 1895	-0.3486**	0.1310	-0.3725**
(x100)	(0.0807)	(0.3144)	(0.0809)
Average Precipitation 1895	0.0322**	0.0511**	0.0251**
	(0.0051)	(0.0198)	(0.0050)
	5.4397**	5.2170**	5.5422**
Constant	(0.2012)	(0.5748)	(0.2162)
Convergence Rate	0.09788	0.10014	0.09857
Hansen's J (df., p-value)	378.918	33.757	380.471
	[50, 0.000]	[50, 0.962]	[50, 0.000]
Wald Test of Equal Coef. (df., pvalue)			197.97
			[17, 0.000]

Notes: Robust standard errors are reported in parentheses. The number of county-years in the pooled model is 12280, in the persistently poor model, it is 1170 and in the non-poor model, it is 10830. Each model controls for time effects. The p-value for the chi-square distribution is reported in square brackets. The instrument matrix is block diagonal and consists of (t-2), (t-3) and (t-4) lag of log income, and (t-1), (t-2), (t-3) and (t-4) lagged levels of the time-varying variables, and the levels of time-invariant variables. ** indicate significance at 5% level

Table 4.7 Decomposition Using Coefficients From Table 4.6

Poor - Non-Poor Decomposition	
Present Predicted Gap	-0.3979
Proportion Difference due to	
Factor Endowments	0.8088
Poor Coefficients	0.1707
Non-Poor Coefficients	0.0204
Of Factor Endowments Share, Proportion due to:	
Historical Factors	
Human Capital	0.3109
Agglomeration	-0.1068
Culture	-0.0017
Institutions	0.0044
Geography	0.0419
Current Factors	
Lag Log Income	0.4815
Human Capital	0.3997
Capital	0.0004
Labor Force Growth	0.0404
Urban Share	0.2027
Black Share	-0.3737

Table 4.8: One-step GMM Estimates of Pooled, Poor and Non-Poor Counties

	(1) Pooled Model	(2) Poor Counties	(3) Non-Poor Counties
Current Factors			
Lag Income per Capita	0.3753**	0.3908**	0.3648**
	(0.0267)	(0.0916)	(0.0281)
Fraction High School	0.7321**	0.9834**	0.7105**
	(0.0723)	(0.3363)	(0.0767)
Capital Spending	8.263	329.6	25.54
(x1,000,000)	(45.46)	(397.8)	(44.27)
Labor Force Growth	0.1404**	0.1697**	0.1400**
	(0.0174)	(0.0416)	(0.0186)
Urban Share	0.4744**	0.0747	0.4995**
	(0.0667)	(0.1593)	(0.0696)
Black Share	0.5242**	0.2025	0.4356**
	(0.1351)	(0.4236)	(0.1264)
Human Capital/Agglomeration			
Illiteracy Rate 1900	-0.3943**	-0.2653	-0.2153**
	(0.1021)	(0.2716)	(0.0892)
Proportion Foreign Born 1900	-0.1132**	0.0498	-0.0893
	(0.0498)	(0.3069)	(0.0510)
Urban Share 1890	-0.3692**	-0.1079	-0.3842**
	(0.0559)	(0.1401)	(0.0572)
Culture			
Proportion Churched 1890	0.0306	-0.0445	0.0239
	(0.0288)	(0.1049)	(0.0325)
Institutions			
Land Tenure 1890	0.0499	-0.04432	0.00676
	(0.0348)	(0.10501)	(0.03486)
Geography			
Standard Dev. to Area	0.1757**	0.17644	0.1618**
	(0.0279)	(0.2639)	(0.0269)
Average Temperature 1895	-0.3996**	0.0649	-0.4280**
(x100)	(0.0904)	(0.3693)	(0.0922)
Average Precipitation 1895	0.0321**	0.0467**	0.0251**
	(0.0053)	(0.0202)	(0.0054)
	5.4629**	5.0559**	5.6269**
Constant	(0.2027)	(0.6341)	(0.2111)
Convergence Rate	0.09798	0.09396	0.10083
Hansen's J (df., p-value)	345.151	24.297	334.774
	[35, 0.000]	[35, 0.912]	[35, 0.000]
Wald Test of Equal Coef. (df.,			184.395
pvalue)			[17, 0.000]

Notes: Robust standard errors are reported in parentheses. The number of county-years in the pooled model is 12280, in the poor model, it is 1170 and in the non-poor model, it is 10830. Each model controls for time effects. The instrument matrix is block diagonal and consists of (t-2), (t-3) and (t-4) lag of log income, and (t-1) and (t-2) lagged levels of the time-varying variables, and the levels of time-invariant variables. ** indicate significance at 5%

Table 4.9: Decomposition Using Coefficients From Table 4.8

Poor - Non-Poor Decomposition	
Present Predicted Gap	-0.3992
Proportion Difference due to	
Factor Endowments	0.8161
Poor Coefficients	0.1643
Non-Poor Coefficients	0.0195
Of Factor Endowments Share, Proportion due to:	
Historical Factors	
Human Capital	0.2779
Agglomeration	-0.1145
Culture	-0.0015
Institutions	0.0049
Geography	0.0532
Current Factors	
Lag Log Income	0.4752
Human Capital	0.3894
Capital	0.0009
Labor Force Growth	0.0415
Urban Share	0.2186
Black Share	-0.3459

Table 4.10: One-step GMM Estimates with Restricted Instrument Set

	(1) Pooled Model	(2) Poor Counties	(3) Non-Poor Counties
Current Factors			
Lag Income per Capita	0.5219**	0.3413**	0.5061**
	(0.0796)	(0.1269)	(0.0966)
Fraction High School	0.2196	1.30260	0.21092
	(0.2070)	(0.49997)	(0.23652)
Capital Spending (x1,000,000)	751.23**	509.23	807.42**
	(172.68)	(494.37)	(175.57)
Labor Force Growth	0.2107**	0.1249**	0.2146**
	(0.0282)	(0.0559)	(0.0289)
Urban Share	0.2605	0.0727	0.2901**
	(0.1365)	(0.1991)	(0.1301)
Black Share	0.38869	0.76800	0.32361
	(0.35024)	(0.54709)	(0.34207)
Human Capital/Agglomeration			
Illiteracy Rate 1900	-0.2909**	-0.6589	-0.1646**
	(0.2378)	(0.3621)	(0.2176)
Proportion Foreign Born 1900	-0.1850**	0.4940	-0.2182**
	(0.0729)	(0.4061)	(0.0826)
Urban Share 1890	-0.3774**	-0.2235	-0.4126**
	(0.1151)	(0.2007)	(0.1110)
Culture			
Proportion Churched 1890	0.0131	-0.1935	-0.0004
	(0.0295)	(0.1464)	(0.0317)
Institutions			
Land Tenure 1890	0.0076	0.0595	-0.0069
	(0.0766)	(0.1449)	(0.0708)
Geography			
Standard Dev. to Area	0.0929	0.5848	0.0893**
	(0.0481)	(0.3669)	(0.0419)
Average Temperature 1895	-0.6746**	-0.0152	-0.7792**
(x100)	(0.1366)	(0.5210)	(0.1425)
Average Precipitation 1895	0.0199**	0.0467	0.0161
	(0.0079)	(0.0249)	(0.0087)
Constant	4.7065**	5.3094**	4.9288**
	(0.5892)	(0.8373)	(0.7208)
Convergence Rate	0.065	0.107	0.068
Hansen's J (df., p-value)	30.53	1.43	23.73
	[5, 0.000]	[5, 0.920]]	[5, 0.000]]
Wald Test of Equal Coef.			140.642
			[17, 0.000]

Notes: Robust standard errors are reported in parentheses. The number of county-years in the pooled model is 12,000 (1,170 persistently poor and 10,830 non-poor). Each model controls for time effects. The instrument matrix is not block diagonal and consists of the (t-2) lag of log income, and (t-1) and (t-2) lagged levels of the time-varying variables, and the levels of time-invariant variables. ** indicate significance at 5% level

Table 4.11: Decomposition Using Coefficients From Table 4.10

Predicted Gap in Current Income	-0.4351
Proportion Difference due to	
Factor Endowments	0.7398
Coefficients	0.2407
	0.0194
Of Factor Endowments Share, Proportion due to:	
Historical Factors	
Human Capital	0.1858
Agglomeration	-0.1185
Culture	-0.0006
Institutions	0.0007
Geography	0.1301
Current Factors	
Lagged Log Income	0.6688
Human Capital	0.1182
Capital	0.0904
Labor Force Growth	0.0631
Urban Share	0.1215
Black Share	-0.2596

Table 4.12: One-step GMM Estimates with Instrument Set Without Lagged Values of Y

	(1) Pooled Model	(2) Poor Counties	(3) Non-Poor Counties
Current Factors			
Lag Income per Capita	0.3175**	0.3802**	0.2755**
	(0.0321)	(0.0889)	(0.0365)
Fraction High School	0.9287**	1.0056**	1.0079**
	(0.0918)	(0.3398)	(0.1000)
Capital Spending (x1,000,000)	-37.1900	237.4700	-36.5040
	(42.4700)	(381.2800)	(41.7220)
Labor Force Growth	0.1163**	0.1697**	0.1039**
	(0.0183)	(0.0532)	(0.0192)
Urban Share	0.4541**	0.1076	0.4799**
	(0.0544)	(0.1512)	(0.0565)
Black Share	0.4898**	0.0114	0.4293**
	(0.1244)	(0.4108)	(0.1154)
Human Capital/Agglomeration	-0.3765**	-0.1466	-0.2025**
Illiteracy Rate 1900	(0.0919)	(0.2694)	(0.0793)
Proportion Foreign Born 1900	-0.0898**	-0.0706	-0.0559
	(0.0405)	(0.3146)	(0.0416)
Urban Share 1890	-0.3398**	-0.1041	-0.3527**
	(0.0454)	(0.1473)	(0.0455)
Culture			
Proportion Churched 1890	0.0422**	-0.0009	0.0422
	(0.0209)	(0.1112)	(0.0224)
Institutions	0.0402**	-0.0795	-0.0034
Land Tenure 1890	(0.0296)	(0.1152)	(0.0285)
Geography			
Standard Dev. to Area	0.1840**	0.0740	0.1781**
	(0.0228)	(0.2823)	(0.0214)
Average Temperature 1895 (x100)	-0.2781**	0.0705	-0.2632**
	(0.0884)	(0.3237)	(0.0896)
Average Precipitation 1895	0.0356**	0.0534**	0.0301**
	(0.0037)	(0.0222)	(0.0037)
Constant	5.8081**	5.1388**	6.1688**
	(0.2323)	(0.6190)	(0.2649)
Convergence Rate	0.1147	0.0967	0.1289
Hansen's J (df., p-value)	291.1971	28.542	269.317
	[44, 0.000]	[44, 0.9656]	[44, 0.000]
Wald Test of Equal Coef.			197.076
			[17, 0.000]

Notes: Robust standard errors are reported in parentheses. The number of county-years in the pooled model is 12,000 (1,170 persistently poor and 10,830 non-poor). Each model controls for time effects. The instrument matrix is not block diagonal and consists of (t-1), (t-2), (t-3) and (t-4) lagged levels of the time-varying variables, and the levels of time-invariant variables. ** indicate significance at 5% level

Table 4.13: Decomposition Using Coefficients From Table 4.12

Predicted Gap in Current Income	-0.3915
Proportion Difference due to	
Factor Endowments	0.8308
Coefficients	0.1692
Of Factor Endowments Share, Proportion due to:	
Historical Factors	
Human Capital	0.2697
Agglomeration	-0.1056
Culture	-0.0020
Institutions	0.0039
Geography	0.0274
Current Factors	
Lagged Log Income	0.4026
Human Capital	0.4947
Capital	-0.0044
Labor Force Growth	0.0345
Urban Share	0.2096
Black Share	-0.3238

Table 4.14: Two-Step GMM Estimates of Pooled, Poor and Non-Poor Counties

	(1) Pooled Model	(2) Poor Counties	(3) Non-Poor Counties
Current Factors			
Lag Income per Capita	0.2474**	0.2572**	0.2228**
	(0.0208)	(0.0566)	(0.0223)
Fraction High School	1.0785**	1.3380**	1.1054**
	(0.0562)	(0.2027)	(0.0595)
Capital Spending	-66.13**	424.43**	-58.92**
(x1,000,000)	(18.75)	(206.13)	(18.86)
Labor Force Growth	0.1450**	0.1923**	0.1391**
	(0.0145)	(0.0337)	(0.0151)
Urban Share	0.2339**	0.1011	0.2699**
	(0.0486)	(0.1003)	(0.0505)
Black Share	-0.0216	-0.4838	0.0108
	(0.1236)	(0.2707)	(0.1165)
Human Capital/Agglomeration			
Illiteracy Rate 1900	-0.0576	-0.0560	0.0263
	(0.0936)	(0.0929)	(0.0825)
Proportion Foreign Born 1900	0.0257	0.0849	0.0559
	(0.0435)	(0.0709)	(0.0439)
Urban Share 1890	-0.0996**	-0.0560	-0.1328**
	(0.0426)	(0.0929)	(0.0431)
Culture			
Proportion Churched 1890	0.0738**	-0.0849	0.0706**
	(0.0274)	(0.0709)	(0.0302)
Institutions			
Land Tenure 1890	-0.0966**	0.0849	-0.1171**
	(0.0316)	(0.0709)	(0.0313)
Geography			
Standard Dev. to Area	0.1062**	-0.1815	0.1155**
	(0.0262)	(0.1715)	(0.0249)
Average Temperature 1895	0.0522	0.3018	0.0367
(x100)	(0.0805)	(0.2294)	(0.0836)
Average Precipitation 1895	0.0323**	0.0689**	0.0267**
	(0.0050)	(0.0166)	(0.0049)
Constant	6.3372**	6.007**	6.5691**
	(0.1593)	(0.3972)	(0.1697)
Convergence Rate	0.13968	0.13578	0.15012
Hansen's J (df., p-value)	543.400	49.8169	501.725
	[50, 0.000]	[50, 0.4807]]	[50, 0.000]]
Wald Test of Equal Coef.			240.749
			[17, 0.000]

Notes: Robust standard errors are reported in parentheses. The number of county-years in the pooled model is 12280, in the persistently poor model, it is 1170 and in the non-poor model, it is 10830. Each model controls for time effects. The p-value for the chi-square distribution is reported in square brackets. The instrument matrix is block diagonal and consists of (t-2), (t-3), (t-4) lag of log income, and (t-1) to (t-4) lagged levels of the time-varying variables, and the levels of time-invariant variables.** indicate significance at 5% level

Table 4.15: Decomposition Using Coefficients From Table 4.12

Poor - Non-Poor Decomposition	
Present Predicted Gap	-0.3909
Proportion Difference due to	
Factor Endowments	0.8292
Coefficients	0.1708
Of Factor Endowments Share, Proportion due to:	
Historical Factors	
Human Capital	0.0498
Agglomeration	-0.0310
Culture	-0.0036
Institutions	-0.0095
Geography	-0.0552
Current Factors	
Lag Log Income	0.4782
Human Capital	0.3970
Capital	0.0004
Labor Force Growth	0.0402
Urban Share	0.2014
Black Share	-0.3712

Table 4.16: Two-Step GMM Estimates of Pooled, Poor and Non-Poor Counties

	(1) Pooled Model	(2) Poor Counties	(3) Non-Poor Counties
Current Factors			
Lag Income per Capita	0.5189**	0.2706**	0.5220**
	(0.0567)	(0.1158)	(0.0663)
Fraction High School	0.1463	1.5187	0.1145
	(0.1623)	(0.4763)	(0.1758)
Capital Spending (x1,000,000)	884.91**	685.52**	870.20**
	(197.78)	(425.91)	(197.57)
Labor Force Growth	0.2432**	0.1256**	0.2429**
	(0.0257)	(0.0551)	(0.0260)
Urban Share	0.2529**	0.1919	0.2819**
	(0.0953)	(0.1843)	(0.0985)
Black Share	0.3632**	0.4924	0.3143
	(0.1792)	(0.5089)	(0.1670)
Human Capital/Agglomeration			
Illiteracy Rate 1900	-0.2788**	-0.5129	-0.1694
	(0.1290)	(0.3438)	(0.1139)
Proportion Foreign Born 1900	-0.2082**	0.3632	-0.2326**
	(0.0657)	(0.3930)	(0.0779)
Urban Share 1890	-0.3945**	-0.2235	-0.4166**
	(0.0809)	(0.1884)	(0.0849)
Culture			
Proportion Churched 1890	0.0064	-0.1469	-0.0072
	(0.0251)	(0.1414)	(0.0280)
Institutions			
Land Tenure 1890	-0.0020	-0.0095	-0.0117
	(0.0457)	(0.1353)	(0.0472)
Geography			
Standard Dev. to Area	0.0783**	0.4606	0.0777**
	(0.0333)	(0.3505)	(0.0333)
Average Temperature 1895	-0.7589**	0.0845	-0.8430**
(x100)	(0.1752)	(0.3834)	(0.1921)
Average Precipitation 1895	0.0179	0.0583**	0.0142
	(0.0179)	(0.0232)	(0.0086)
Constant	4.8387**	5.7994**	4.8882**
	(0.4042)	(0.7479)	(0.4861)
Convergence Rate	0.06559	0.13071	0.06500
Hansen's J (df., p-value)	20.658	2.6219	16.124
	[5, 0.000]	[5, 0.7580]]	[5, 0.006]]
Wald Test of Equal Coef.			153.594
			[17, 0.000]

Notes: Robust standard errors are reported in parentheses. The number of county-years in the pooled model is 12280, in the poor model, it is 1170 and in the non-poor model, it is 10830. Each model controls for time effects. The p-value for the chi-square distribution is reported in square brackets. The instrument matrix is not block diagonal and consists of (t-2) lag of log income, and (t-1) to (t-2) lagged levels of the time-varying variables, and the levels of time-invariant variables. ** indicate significance at the 5% level

Table 4.17: Decomposition Using Coefficients from Table 4.14

Poor - Non-Poor Decomposition	
Present Predicted Gap	-0.4429
Proportion Difference due to	
Factor Endowments	0.7245
Coefficients	0.2755
Of Factor Endowments Share, Proportion due to:	
Historical Factors	
Human Capital	0.1719
Agglomeration	-0.1242
Culture	-0.0003
Institutions	-0.0002
Geography	0.1520
Current Factors	
Lag Log Income	0.6709
Human Capital	0.1185
Capital	0.0906
Labor Force Growth	0.0633
Urban Share	0.1219
Black Share	-0.2604

Table 4.18: Two-Step GMM Estimates of Pooled, Poor and Non-Poor Counties

	(1) Pooled Model	(2) Poor Counties	(3) Non-Poor Counties
Current Factors			
Lag Income per Capita	0.2371**	0.3041**	0.2080**
	(0.0219)	(0.0637)	(0.0234)
Fraction High School	1.0901**	1.1674**	1.1295**
	(0.0591)	(0.2310)	(0.0623)
Capital Spending (x1,000,000)	-64.61**	533.74**	-56.11**
	(20.98)	(208.65)	(21.62)
Labor Force Growth	0.1505**	0.2029**	0.1434**
	(0.0152)	(0.0354)	(0.0159)
Urban Share	0.3339**	0.1469	0.3767**
	(0.0555)	(0.1226)	(0.0589)
Black Share	-0.3698**	-0.3491	-0.0002
	(0.1254)	(0.3148)	(0.1176)
Human Capital/Agglomeration			
Illiteracy Rate 1900	-0.0292	0.0576	0.0471
	(0.0953)	(0.2009)	(0.0841)
Proportion Foreign Born 1900	-0.0196	-0.2876	0.0102
	(0.0468)	(0.2368)	(0.0484)
Urban Share 1890	-0.1772**	-0.1009	-0.2160**
	(0.0468)	(0.1101)	(0.0497)
Culture			
Proportion Churched 1890	0.0646**	-0.0664	0.0610
	(0.0285)	(0.0800)	(0.0321)
Institutions			
Land Tenure 1890	-0.0739**	-0.1634	-0.0940**
	(0.0331)	(0.0861)	(0.0335)
Geography			
Standard Dev. to Area	0.1169**	-0.1224	0.1283**
	(0.0271)	(0.1969)	(0.0263)
Average Temperature 1895 (x100)	-0.0594	0.1501	-0.0759
	(0.0885)	(0.2643)	(0.0936)
Average Precipitation 1895	0.0332**	0.0643**	0.0278**
	(0.0052)	(0.0166)	(0.0053)
Constant	6.4386**	5.7222**	6.7019**
	(0.1682)	(0.4384)	(0.1792)
Convergence Rate	0.1439	0.13071	0.1569
Hansen's J (df., p-value)	501.457	32.955	464.259
	[35, 0.000]	[35, 0.5671]]	[35, 0.000]]
Wald Test of Equal Coef.			212.230
			[17, 0.000]

Notes: Robust standard errors are reported in parentheses. The number of county-years in the pooled model is 12280, in the persistently poor model, it is 1170 and in the non-poor model, it is 10830. Each model controls for time effects. The p-value for the chi-square distribution is reported in square brackets. The instrument matrix is block diagonal and consists of (t-2), (t-3) and (t-4) lag of log income, and (t-1) to (t-2) lagged levels of the time-varying variables, and the levels of time-invariant variables. ** indicate significance at 5% level

Table 4.19: Decomposition Using Coefficients from Table 4.18

Poor - Non-Poor Decomposition	
Present Predicted Gap	-0.3859
Proportion Difference due to	
Factor Endowments	0.8592
Coefficients	0.1407
Of Factor Endowments Share, Proportion due to:	
Historical Factors	
Human Capital	0.0179
Agglomeration	-0.0540
Culture	-0.0031
Institutions	-0.0071
Geography	-0.0296
Current Factors	
Lag Log Income	0.4669
Human Capital	0.3826
Capital	0.0009
Labor Force Growth	0.0408
Urban Share	0.2148
Black Share	-0.3399

Table 4.20: One-step Dynamic GMM Estimates of Pooled, Poor and Non-Poor Counties

	(1) Pooled Model	(2) Poor	(3) Non-Poor
Current Factors			
Lag Income per Capita	0.3664**	0.3673**	0.3620**
	(0.0281)	(0.0797)	(0.0311)
Fraction High School	0.7678**	1.044**	0.7349**
	(0.0773)	(0.3057)	(0.0813)
Capital Spending (x1,000,000)	1.776	253.82	18.34
	(42.30)	(378.67)	(41.06)
Labor Force Growth	0.1362**	0.1704**	0.1358**
	(0.0172)	(0.0511)	(0.0177)
Urban Share	0.4465**	0.0708	0.4599**
	(0.0528)	(0.1439)	(0.0548)
Black Share	0.5546**	0.0417	0.5049
	(0.12151)	(0.3984)	(0.1128)
Human Capital/Agglomeration			
Illiteracy Rate 1900	-0.4639**	-0.1765	-0.3181**
	(0.0879)	(0.2830)	(0.0749)
Proportion Foreign Born 1900	-0.0841**	0.0314	-0.0463
	(0.0420)	(0.2765)	(0.0421)
Urban Share 1890	-0.3468**	-0.0783	-0.3546
	(0.0434)	(0.1479)	(0.0430)
Culture			
Proportion Catholic 1890	0.0433	-0.0465	0.0195
	(0.0363)	(0.0798)	(0.0375)
Proportion Baptist 1890	0.2017**	0.1009	0.2198**
	(0.0446)	(0.1571)	(0.0482)
Proportion Calvin 1890	0.0142	-0.3751	0.0323
	(0.1196)	(0.7722)	(0.1206)
Institutions			
Land Tenure 1890	0.0363	-0.0799	-0.0015
	(0.0288)	(0.0983)	(0.0277)
Geography			
Standard Dev. to Area	0.1747	0.0917	0.1599**
	(0.0236)	(0.2656)	(0.0213)
Average Temperature 1895 (x100)	-0.3683**	0.0700	-0.3903**
	(0.0824)	(0.3102)	(0.0829)
Average Precipitation 1895	0.0303	0.0474**	0.0233**
	(0.0036)	(0.0203)	(0.0036)
Constant	5.5273**	5.2528**	5.636**
	(0.2111)	(0.5747)	(0.2338)
Convergence Rate	0.1007	0.10014	0.10159
Hansen's J (df., p-value)	376.116	33.755	374.82
	[50, 0.000]	[50, 0.9620]	[50, 0.000]]

Table 4.20 Continued

Wald Test of Equal Coef.	190.765
	[19, 0.000]

Notes: Robust standard errors are reported in parentheses. The number of county-years in the pooled model is 12280, in the persistently poor model, it is 1170 and in the non-poor model, it is 10830. Each model controls for time effects. The p-value for the chi-square distribution is reported in square brackets. The instrument matrix is block diagonal and consists of (t-2), (t-3) and (t-4) lag of log income, and (t-1), (t-2), (t-3) and (t-4) lagged levels of the time-varying variables, and the levels of time-invariant variables.

Table 4.21 Poor/Non-Poor Decomposition From Results of Table 4.20

Poor - Non-Poor Decomposition	
Present Predicted Gap	-0.3979
Proportion Difference due to	
Factor Endowments	0.8151
Coefficients	0.1848
Of Factor Endowments Share, Proportion due to:	
Historical Factors	
Human Capital	0.3401
Agglomeration	-0.1068
Culture	-0.0400
Institutions	0.0037
Geography	0.0476
Current Factors	
Lag Log Income	0.4671
Human Capital	0.4108
Capital	0.0002
Labor Force Growth	0.0400
Urban Share	0.2057
Black Share	-0.3684

Table 4.22: Decomposition Results from the Sensitivity Analysis

Poor - Non-Poor Decomposition

	Using Different Definitions to Define Persistently-Poor/Non-Poor Counties				
	(1)	(2)	(3)	(4)	(5)
Predicted Gap in Current Income	-0.379	-0.319	-0.410	-0.335	-0.477
Proportion Difference due to					
Factor Endowments	0.816	0.830	0.800	0.886	0.853
Coefficients	0.184	0.170	0.191	0.114	0.147
Of Factor Endowments Share, Proportion due to:					
Historical Factors					
Human Capital	0.231	0.308	0.260	0.233	0.377
Agglomeration	-0.107	-0.056	-0.107	-0.132	-0.067
Culture	-0.002	-0.00002	0.003	-0.001	0.001
Institutions	0.002	0.004	0.002	-0.002	0.011
Geography	0.032	-0.022	0.101	0.045	0.067
Current Factors					
Lag Log Income	0.468	0.520	0.476	0.443	0.512
Human Capital	0.421	0.398	0.379	0.383	0.362
Capital	-0.001	0.007	-0.003	0.001	0.0003
Labor Force Growth	0.036	0.041	0.046	0.036	0.038
Urban Share	0.189	0.116	0.218	0.259	0.113
Black Share	-0.268	-0.316	-0.376	-0.265	-0.415

Notes: Column (1) compares between persistently-poor counties with non-urban, non-poor counties, according to the Beale System. Column (2) removes all the counties located in states that do not have any persistently-poor counties within their borders. Column (3) keeps the non-poor set the same, but removes poor counties between Mississippi Delta and the western states of Washington, Oregon and California. Column (4) considers a county to be persistently poor if it has 20% or higher poverty rates for 30 out of 50 years. Column (5) considers a county to be persistently-poor if it has 30% or higher poverty rates for 50 years. The instrument matrix is block diagonal and consists of (t-2), (t-3) and (t-4) lags of log income, and (t-1), (t-2), (t-3) and (t-4) lagged levels of the time-varying variables, and the levels of time-invariant variables.

Table 4.23: Decomposition between Poor/Non-Poor Counties of Different Regions of the US

	Decomposition of Persistently-Poor/Non-Poor Counties of			
	Appalachia	**Black Belt**	**Mississippi Delta**	**Western Counties**
Predicted Gap in Current Income	-0.370	-0.270	-0.248	-0.334
Proportion Difference due to				
Factor Endowments	0.838	0.789	1.036	1.001
Coefficients	0.161	0.210	-0.036	-0.001
Of Factor Endowments Share, Proportion due to:				
Historical Factors				
Human Capital	-0.002	0.447	0.075	0.064
Agglomeration	-0.032	-0.005	-0.049	-0.044
Culture	0.023	0.008	-0.0002	0.035
Institutions	0.025	-0.027	-0.011	0.037
Geography	0.013	0.095	-0.012	0.161
Current Factors				
Lag Log Income	0.290	0.619	0.439	0.244
Human Capital	0.547	0.146	0.299	0.383
Capital	0.002	-0.006	0.024	0.006
Labor Force Growth	0.020	0.120	0.056	0.043
Urban Share	0.133	0.043	0.092	0.071
Black Share	-0.022	-0.442	0.134	-0.002

Notes: Appalachia compares between persistently-poor counties with non-poor counties of KY, TN and WV. Black Belt compares the poor and non-poor counties of AL, GA, NC and SC. Mississippi Delta compares the poor and non-poor counties AR, LA, MO and MS. Western counties compares the poor and non-poor counties AZ, TX, NM, ND, SD, MT, CO, UT. The instrument matrix is block diagonal and consists of (t-2), (t-3) and (t-4) lags of log income, and (t-1), (t-2), (t-3) and (t-4) lagged levels of the time-varying variables, and the levels of time-invariant variables.

Figure 4.1: Poverty Rates in the US in 1959

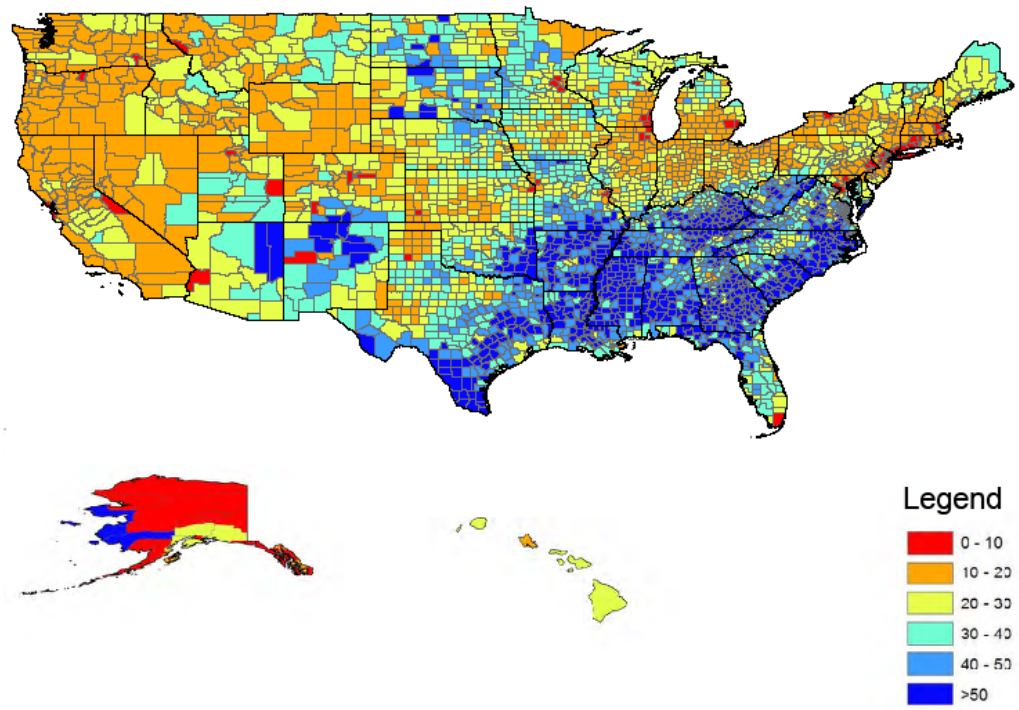


Figure 4.2: Poverty Rates in the US in 1969

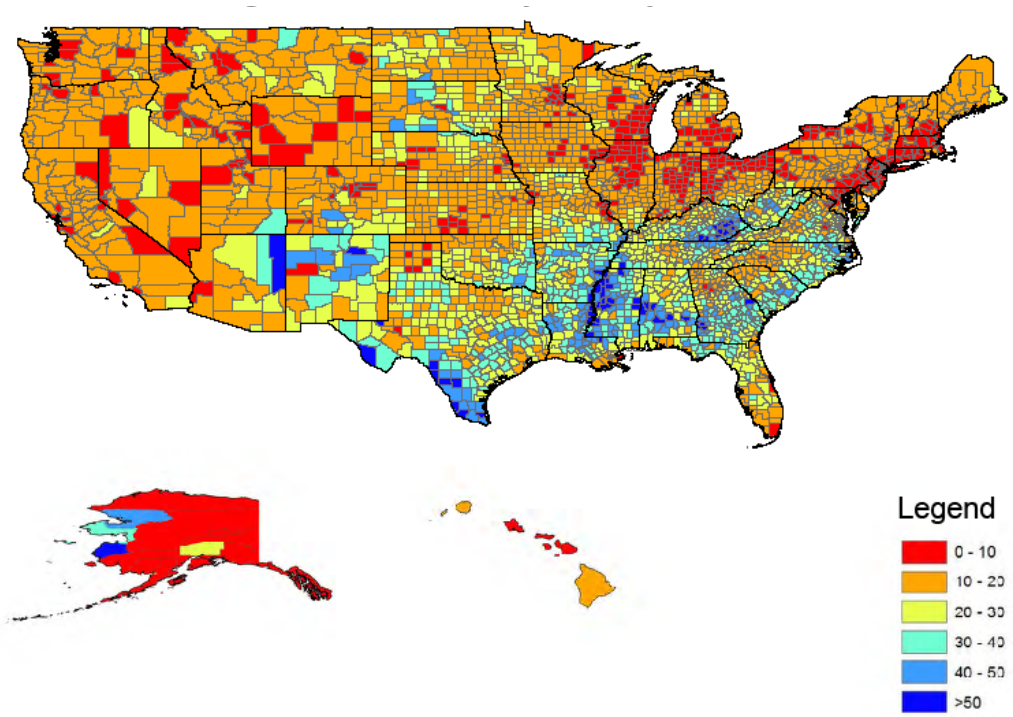


Figure 4.3: Poverty Rates in the US in 1979

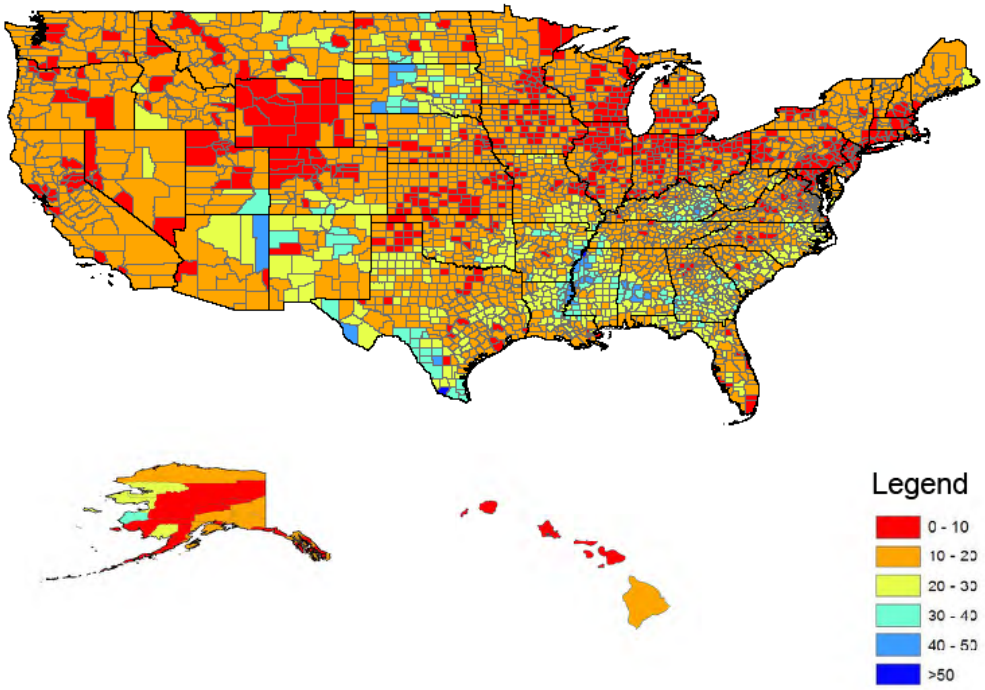


Figure 4.4: Poverty Rates in the US in 1989

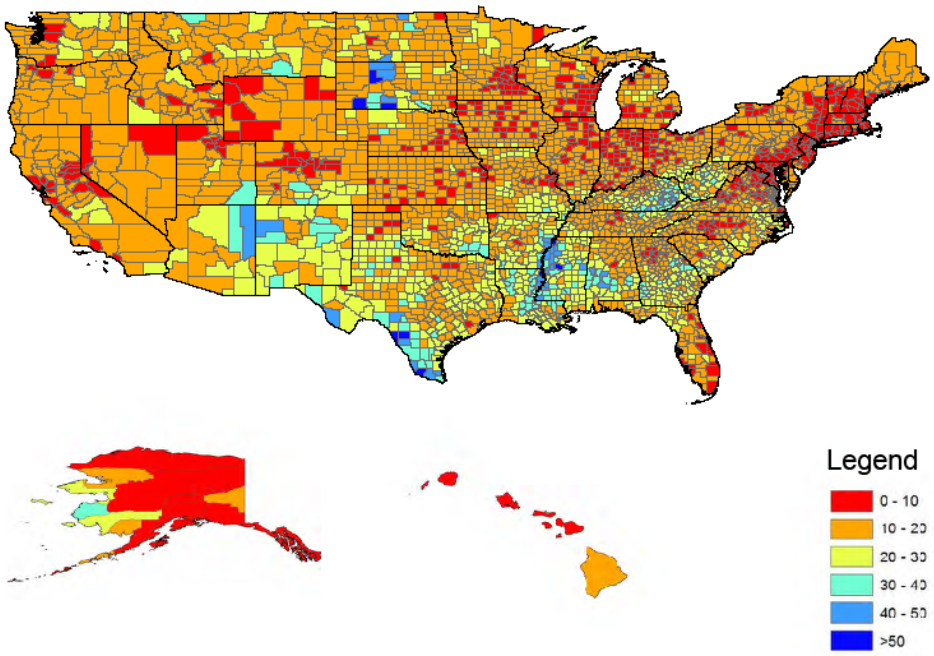


Figure 4.5: Poverty Rates in the US in 1999

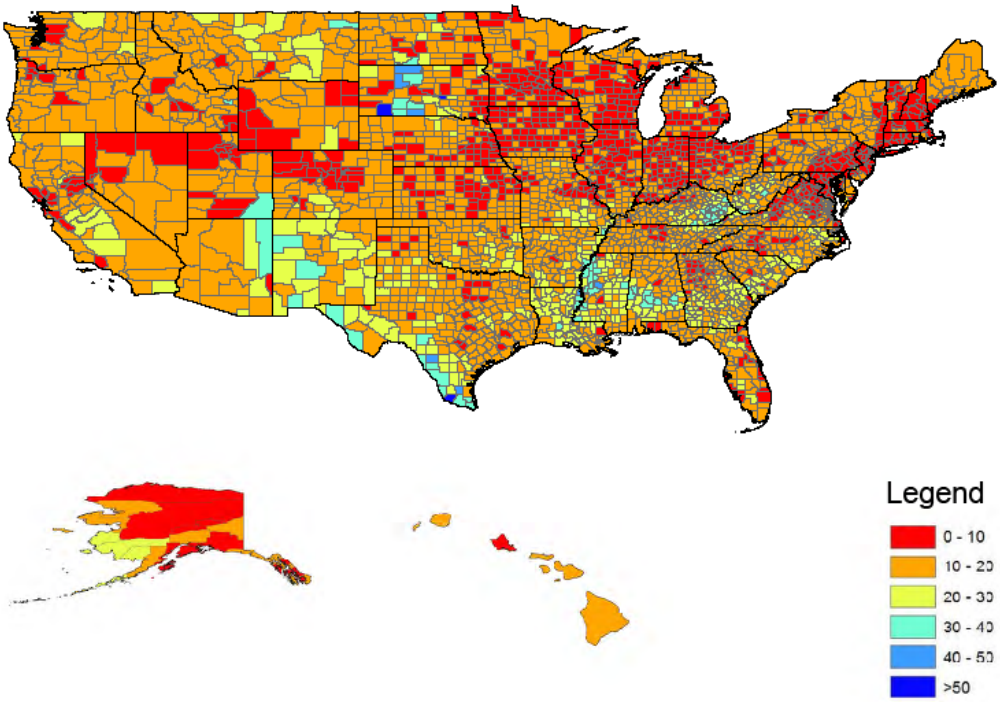
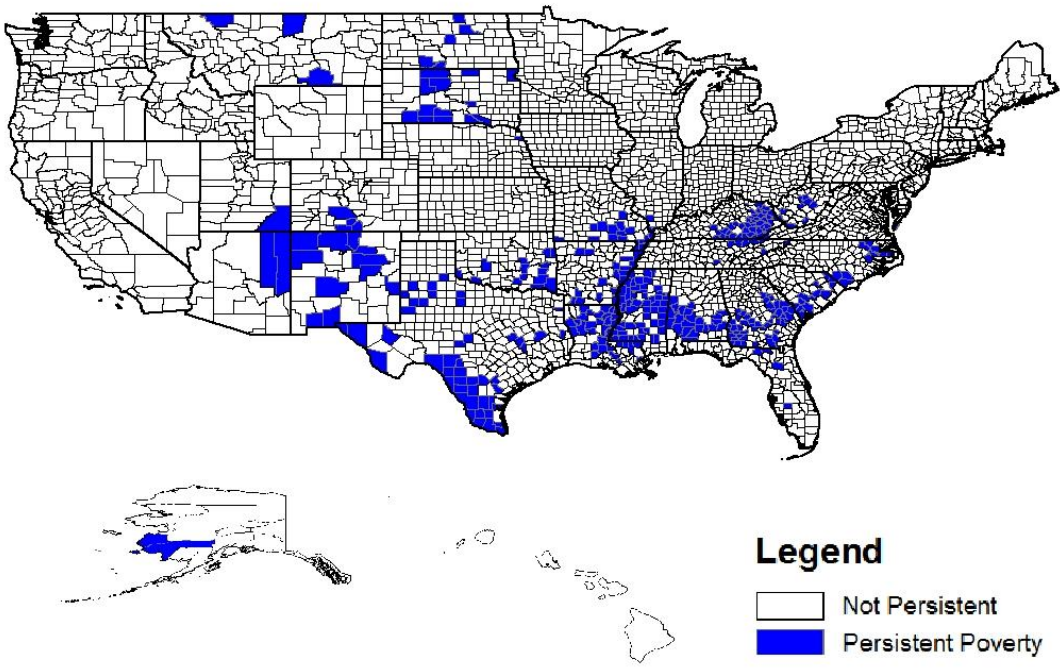


Figure 4.6: US Counties with Persistent Poverty from 1959-1999



5 CONCLUSION

The essays in my dissertation help to understand the underlying reasons behind low income and poverty among individuals and regions. These essays can also provide policymakers with some insight as to why certain individuals and regions remain persistently poor and what can be done to help them. The policymaker can also use the methods outlined in essay 3 to test if the well-being of long-term poor improved over time. Through essay 3, I provide a better way of measuring long-term poverty that can be used to show the improvements of well-being over time. This can especially aid policymakers to measure the effectiveness of an anti-poverty program aimed at helping the long-term poor. Essays 2 and 4 show the long-term consequences of historical variables on income. The second essay of my dissertation shows that childhood neighborhood conditions can affect adult income. This shows that "role-model" effects can have some long-run consequences and so, steps need to be taken to improve childhood neighborhood conditions. Essay 4 shows the importance of human capital in explaining growth in a US county. This essay provides evidence that even human capital from the 1890s can have a large effect in explaining the differences in income between a rich and a poor county. However, increasing the current stock of human capital can help to lower the gap between rich and poor counties. These two essays thus show that past variables do affect present-day outcomes, and although we cannot improve the past variables currently, we can take steps to improve the present conditions of these past variables to ensure that future earnings have increase.

These essays can be a stepping-stone to further research on the impact of initial conditions in explaining income. For example, one could study how migration of

workforce can affect income in a county, or how migration of an adult affects their income generation ability. One can also apply the model and estimation methods of essays 2 and 4 to countries other than the US to see if the results hold in those countries. Essay 2 can be replicated using the National Longitudinal Survey of Youth (NLSY) to see if the predictions hold for that panel of data. The methods of essay 4 can be applied to data such as local-government level data of European countries to see how historical variables affect growth of those regions. Essay 2 can be broadened to analyze multi-dimensional long-term poverty of a region and can be used to evaluate a program that has multiple outcomes. This measure can also be regressed using current variables to see what macroeconomic indicators affect the well-being of the long-term poor the most.

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Vita

T M Tonmoy Islam

Birthdate/Place: February 15, 1984, Mexico DF, Mexico

Education

Master of Arts, Economics, Vanderbilt University, Nashville, TN., May 2008

Bachelor of Arts, Magna Cum Laude, Economics and Business Administration,

Transylvania University, Lexington, KY, May 2006

Professional and Research Experience

Visiting Research Scholar, The George Washington University, Washing, DC, May, 2012-August,2012

Short-term Consultant, The World Bank, Washington, DC, May, 2012-July, 2012

Research Assistant, University of Kentucky Center for Poverty Research (UKCPR), May, 2009 – present

Instructor of Record, Economics and Business Statistics, University of Kentucky, Summer, 2010

Instructor of Record, Principles of Microeconomics, University of Kentucky, Summer, 2009

Research Assistant, National Bureau of Economic Research and Vanderbilt University, Summer, 2007 – Summer, 2008

Academic Awards and Honors

The 2011 Graduate Student Award, Southern Economic Association, November, 2011

Dissertation Year Fellowship, University of Kentucky, Summer, 2011 – Summer, 2012

Director's Research Assistantship Award, University of Kentucky, Fall, 2009 – Summer, 2011

Kentucky Opportunity Fellowship, University of Kentucky, Winter, 2009

Kentucky Graduate Scholarship, University Of Kentucky, Fall, 2008
Tuition Scholarship, Vanderbilt University, Fall, 2007 – Winter, 2008

University Fellowship Vanderbilt University, Fall, 2006 – Winter, 2007

David and Betty Jones Faculty Development Fund, Transylvania University, Summer, 2005

Morrison Scholarship, Transylvania University, Winter, 2003 – May, 2006

Publications

Ziliak, James P. (Research Assistance: Bradley Hardy, Charles Hokayem, and T M Tonmoy Islam). 2010. "Alternative Poverty Measures and the Geographic Distribution of Poverty in the United States," Report Prepared for the Office of the Assistant Secretary for Planning and Evaluation, U.S. Department of Health and Human Services.

Working Papers

Islam, T M Tonmoy, "Childhood Neighborhood Conditions and the Persistence of Adult Income," 2012

Islam, T M Tonmoy, "On the Measurement of Chronic Poverty," 2012

Islam, T M Tonmoy, Jenny Minier, James Ziliak "On Persistent Poverty in a Rich Nation," 2012

Islam, T M Tonmoy, James Ziliak **"**Program Evaluation Using Multidimensional Poverty Measures: Evidence from TUP," 2012

Berdiev, Aziz, Abdullah Al-Bahrani, T M Tonmoy Islam "The Impact of Remittance on the Banking Sector of Developing Countries," 2012