The Impact of Rising Inequality on Health at Birth

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Abstract: The income distribution has widened significantly over the past 40 years, primarily due to skill biased technological change which has disproportionately raised the income of the most highly skilled. A major concern over rising inequality is its potential to reduce intergenerational mobility, leading to even greater inequality in the next generation. We estimate the impact of rising inequality over the period 1970-2000 on offspring health at birth, a measure of human capital that has been shown to be highly correlated with future education, IQ and income. We define inequality three ways: as a group-level measure (the Gini coefficient for each county), as an individual-level measure of relative deprivation and as an ordinal measure of rank. We find that including a modest set of controls reduces the negative relationship between aggregate measures of inequality and health, and limiting variation to changes in inequality over time within an area or instrumenting for inequality eliminates it completely. However, this null result likely reflects heterogeneity in the effect of rising inequality. When we estimate the impact of relative deprivation or rank on newborn health, we find negative and significant effects. Together these results suggest that increases in inequality in the current generation may lead to reduced intergenerational mobility and greater levels of inequality in the next generation.

I. Introduction

Income inequality has been on the rise in most industrialized nations since the 1970s. In the US, for example, the Gini coefficient increased steadily from .39 in 1970 to .47 by 2010. There has been considerable discussion of the causes of the rise in income inequality. Most research based on developed countries points to the increase in skill-biased technological change and globalization as the most important factors.[1]

In this paper we consider one potential consequence of rising inequality. Specifically, we estimate the impact of inequality on health at birth – a measure of the initial human capital of the next generation. We focus on health at birth for multiple reasons. First, newborn health is sensitive to changes in short term conditions (eg, Almond, 2006). This makes it easier to isolate the economic conditions affecting health. Second, health at birth has been shown to be an important determinant of long term outcomes such as educational attainment, IQ and earnings (Black, Devereaux and Salvanes, 2007). Third, individual-level data on birth outcomes has been collected and reported consistently at a local geographic level (county) for the period 1970-2010, allowing one to estimate the impact of increases in inequality and relative income at a local level on individual outcomes. Finally, by examining the impact of inequality on newborn health, we can learn not only about how inequality affects health, but how it might affect intergenerational mobility and inequality of the next generation.

In our estimates of the impact of rising inequality on health at birth, we define inequality in two ways. First, we define it as the Gini coefficient for the local area (state or county). This measure is common to all individuals in the area. Unlike much of the existing empirical work that relies on cross sectional variation, we utilize a 30 year panel of data which allow us to

[1] Between 1979 and 2002, the causal return to education increased by 40 percent (Deschenes, 2006).

include area fixed effects, thereby limiting variation to that within an area over time and reducing potential omitted variable bias. Another contribution is that we instrument for inequality (Boustan, Ferreira, Winkler and Zolt, 2012). The instrument allows us to isolate the change in the local income distribution that is driven by national shifts in the income distribution over time, not changes in the underlying composition of the area. More specifically, we construct an instrument for local, (state or county-level), distribution of income by holding local area income fixed at the 1970 distribution and match this initial distribution to national patterns in income growth for different points in the distribution of income.[2]

In initial results using aggregated data, we find a negative relationship between the Gini coefficient and newborn health (birth weight and an indicator for low birth weight). However, as we include even a parsimonious set of controls, the effect declines in magnitude and when we include area fixed effects thereby limiting variation to that within an area over time and/or instrument for the Gini, the estimated effect is neither large nor significant. When we repeat the analysis with individual level data that includes maternal income, we find the same pattern. This is consistent with either no causal effect of inequality on health, or significant heterogeneity in the effect that, in the aggregate, leads to no observed effect.

To help interpret this effect, we turn to two individual level measures of relative income. The first is the Yitzhaki measure of relative deprivation and it reflects the average distance

[2] For example, consider two counties, A and B. In 1970, county A had a disproportionate share of women in the bottom quartile of the (national) education distribution at the time, while county B had a disproportionate share of women in the top quartile of the (national) education distribution. By 1980, the distribution of education county A had changed so that it is more similar to the distribution of education in county B. However the instrument for the distribution of income in county A is calculated by holding the distribution of education fixed at the 1970 level and then predicting the income distribution based on national trends in income growth for the initial distribution of education.

between an individual's own income and the income of those above her. When we estimate the impact of relative deprivation on newborn health including own absolute income, area fixed effects and instrumenting for relative deprivation, we find that the one's relative deprivation is negatively related to newborn health. The second measure of relative income is an ordinal measure: rank based on the income of new mothers in the state. We find that conditional on absolute income, rank is related to newborn health and that the effect is non-linear (with greater effects for those at the bottom) and greater in areas characterized by larger income dispersion. These findings suggest that for the poor, rising inequality reduces the initial human capital of the next generation, thereby reducing intergenerational mobility for the most disadvantaged.

II. Background

A. Inequality and the Intergenerational Transmission of Economic Status

There is a considerable theoretical literature on the relationship between income inequality and intergenerational mobility, largely in the macroeconomics literature (see Piketty, 1998 for a review). In general, the research suggests that greater inequality should reduce intergenerational mobility and growth. There are a number of mechanisms. The first has to do with imperfect credit markets and investments in human capital. Galor and Moav(2004) posit that because of credit constraints, in an unequal society there will be suboptimal investment in the human capital of the next generation (see Burtless and Jenckes, 2003, for a more microeconomic perspective). Not only will this lead to greater inequality in the next generation, but also to reduced overall growth. A second potential mechanism relates to segregation. Durlauf (1996) argues that greater inequality will lead to greater segregation by income which will have the effect of reducing the human and social capital of the next generation. Finally, models of statistical discrimination can also explain how greater inequality in one generation will lead to reduced mobility and increased inequality in the next generation. In the presence of both inequality statistical discrimination, if employers discriminate in their hiring of the relatively disadvantaged, this will lead to reduced human capital investments among the discriminated group (the disadvantaged) and even greater inequality in the next generation (Arrow, 1973, Piketty, 1998).

While there is considerable theoretical work on this topic, the empirical work characterizing the relationship between inequality and intergenerational mobility is relatively under-developed. Corak (2012) shows that across OECD countries, there is a strong correlation between measures of inequality (the Gini) and intergenerational transmission of earnings. While the evidence he presents is suggestive, questions remain. First is the question of whether and to what extent this relationship exists at a more micro level. Second is the question of what underlies this relationship and whether it can be characterized as causal.

In this paper we attempt to shed greater light on this by estimating whether inequality affects the initial human capital of the next generation – thereby providing a mechanism by which inequality of one generation may lead to lower intergenerational mobility. We do so in the context of newborn health. While there does not yet appear to be any empirical analysis looking at this specific question, there is a substantial empirical literature looking at inequality and health more generally which we review below.

B. Inequality, Relative Income and Health

Inequality and relative income or relative deprivation are closely related but distinct concepts. Areas characterized by greater inequality have higher relative deprivation. However, inequality characterizes an entire group of individuals, whereas relative income or deprivation is specific to an individual within a group.

There are three reasons why inequality could be related to health. The first has to do with non-linearities in the production of health. If maternal income produces child health (see Case, Lubotsky and Paxson, 2002), but is marginally more productive at low levels of income than at high levels, then an increase in inequality would reduce average health. This could explain the link between income inequality and mortality that is observed in aggregate data at the country, state or metropolitan level. Miller (2002) presents evidence that non-linearities in the relationship between income and health can explain much of the observed relationship between the Gini and health in the context of adult mortality. We refer to this channel as an "indirect" effect.

The second has to do with relative status and the higher levels of psychological stress that characterize those who are relatively worse off than their peers. In this formulation, relative deprivation may be measured in terms of income, education, social or political status, all of which are correlated. Individuals who feel greater stress because of their lower status may be stressed and/or depressed and also more likely to engage in behaviors that negatively affect health (poor eating and exercise habits, smoking, etc). In previous work, Aizer, Stroud and Buka (2012) found that the stress hormone cortisol is higher in poor women and that higher levels of cortisol during the prenatal period is associated with worse outcomes for the offspring (lower IQ, worse health and less completed schooling). These data, however, did not allow for the examination of the direct role or impact of inequality on cortisol levels and offspring outcomes.

Much of the evidence regarding a causal impact of social status on health is drawn from research on primates (Sapolsky et al, 1997; Cohen et al, 1997). In this work, researchers have documented a strong relationship between social status within a group and health outcomes. This relationship has been found to persist even after experimental manipulation of a primate's rank or status within a group, something that is impossible to do with humans.

A third and final reason why inequality and health might be related are the externalities associated with having richer neighbors. Depending on the nature of the externality, however, having wealthy neighbors could be either beneficial or harmful to the less wealthy. Examples of a positive externality include an increase in the availability of certain medical services that have high fixed costs and as a result only locate in counties with high average levels of income (assuming the services are normal goods). As a result, relatively poor individuals in the same county benefit from the increased availability of this service. A second example of a positive externality might be reductions in pollution - a public good that is also a normal good. An example of a negative externality is when an increase in average income in an area is associated with an increase in private expenditures on health and offsetting reduction in public expenditures on health, making the relatively poor worse off. Another potential negative externality would be an increase in segregation in unequal areas that can negatively affect access to goods and services and social capital among the poor (Durlauf, 1996).[3]

Of the three potential mechanisms by which inequality might be associated with health, the first is relevant only in the context of aggregate data. Because we have individual data that

[3] The policy implications of the first and the last two mechanisms differ. With respect to the first mechanism (heterogeneity and non-linearities in the production of health), increasing the wealth of the wealthiest individuals would not affect health. In contrast, for the latter two mechanisms, it would.

can be aggregated, we can explore the extent to which non-linearities in the production of health can explain the relationship between the Gini and average health observed in aggregate data.

With respect to the other two mechanisms, stress and externalities, we will be able to shed some light on the relative importance of the latter by examining how inequality affects behavior (investments), pollution levels (a public good), NICU availability (a service with high fixed costs) and segregation of the poor in separate hospitals.

C. Previous Evidence on Inequality, Relative Income and Health

The first evidence of a relationship between inequality and health was presented by Rodgers in 1979 who conducted cross-country analyses of the relationship between Gini coefficients, GNP and multiple measures of health (infant mortality, life expectancy of birth) and found a strong relationship between both income and inequality and health. Kennedy (1996) provided evidence of a strong relationship between mortality and inequality across the 50 US states. Since then, many others have conducted within country, cross-area analyses of the relationship between inequality and health. These studies have been reviewed elsewhere (Subramanian and Kawachi, 2004). In sum, evidence of a relationship between inequality and health is not conclusive but the estimated effects are strongest in the US and other more unequal countries, though there are also US based studies that find no relationship between inequality and health.

Nearly all of the existing analyses are based on cross sectional comparisons of adult mortality, which may be subject to considerable omitted variable bias. Indeed, Deaton and Lubotsky (2002) show that for the cross-state and cross-MSA level analyses for the US, once one controls for the share of the local area that is black, the negative relationship between inequality and average mortality disappears. This is due to the fact that inequality is higher in areas with a large share black and so is mortality (for both blacks and whites), though for reasons unknown. As such, the share black is an important omitted variable in analyses of the relationship between inequality and average health.

There is less work examining the impact of relative deprivation. Evans and Eibner (2005) estimate the impact of relative deprivation on mortality from cardio-vascular disease using NHIS survey data linked with mortality data from the period 1988-1991. They define a reference group as those of the same race, age and education class in one's own state of residence. They find that relative deprivation is predictive of higher mortality, worse self-reported death, higher BMI and riskier behavior, controlling for own income.

Miller and Paxson (2006) also estimate the impact of relative income on mortality in an effort to explain black-white differentials in mortality. Specifically, they assess the extent to which blacks' lower relative income can explain their higher rates of mortality. Using mortality data at the county level and census data on income at the puma (county-group) level, they find that within a county, the average income of blacks affects the black mortality rate, but that the average income of whites in the county also affects the black mortality rate. In fact, for black men, an increase in the average income of white residents of the same county increases the black mortality rate by about half as much as a similar-size decrease in black income.

II. Empirical Strategy and Data

A. Empirical Strategy

Our analysis consists of two parts. In the first we estimate the impact of the Gini on newborn health (birth weight, low birth weight). We define one's reference group (the population over which we construct the Gini) multiple ways: all households in the state, all new mothers in the state, all households in the county and all new mothers in the county. We begin with the most parsimonious regression based on aggregate data, add more controls and finally instrument for the Gini. The IV strategy exploits the variation in the growth of the Gini over this period that derives from differences in the initial (1970) distribution of income in a local area and national trends in income growth or returns to skill over this period. Specifically, to construct the instrument we follow Boustan et al (2012) and hold the income distribution of the county (or state) fixed at its 1970 level and predict changes in the distribution of income based on the initial income distribution in 1970 and national trends in income growth over this period. In this way, to borrow the language of Boustan et al (2012), we construct a "synthetic" version of the income distribution in each area that is not a function of the changing composition of the area. Note that we do not have an instrument for individual income. While this is consistent with existing empirical work on the topic (which doesn't instrument for inequality either), we are considering ways to instrument for individual income as well.

We follow the aggregate analysis with an analysis of the impact of the Gini on newborn health using individual level data for 1970-1990 that include state identifiers (note: when we get the non-public NSFG data we will also conduct county level analyses). Controlling for individual income does not change any of the results.

The focus of the second part of the paper is an exploration of whether the above null effects may mask heterogeneity in the effect of inequality on health. To do so, we focus on the relationship between relative income and health using individual level data. We hypothesize that relative income may matter, with those at the top of the distribution benefitting and those at the bottom suffering. To estimate this we construct measures of relative deprivation (YRD) initially developed by Runciman (1966) and refined by Yitzhaki (1979). The deprivation measure is:

$$YRD_i = \frac{1}{N}\sum_j (Y_j - Y_i) \quad \forall \ Y_j > Y_i$$

Intuitively this measure captures the average distance between an individual's own income and that of everybody with higher income in the state. N in the above equation is everyone in the state (not just all those with higher income). This implicitly assigns all those with lower income a distance of zero. This results in a measure that reflects not only average distance to those above, but also the number of people above. In other words, dividing by N adjusts the measure so that it also reflects the probability of comparing one's income to those above. The YRD is an individual measure but very much related to the Gini, as the average YRD in a society is equal to μ*Gini (Yitzhaki, 1979). However, we slightly modify the above measure by dividing by the average income in the state so that it is no longer sensitive to the scale of the reference group income, as suggested by Deaton.

Finally, we develop a measure of relative income that is an individual's rank. This is an ordinal measure that does not depend on the amount inequality. To understand whether the degree or amount of distance between an individual and others in her group matters, we estimate whether the impact of rank varies with the degree of income dispersion. A negative relationship between rank and low birth weight suggests that ordinal rank or status matters. If the effect of rank on newborn health increases in more disperse or unequal societies, that would suggest that ordinal rank matters but so too does the amount or size of the distance.

Below we describe the data used for the analysis.

B. Data and Construction of Key Measures

1. Data on birth outcomes and maternal characteristics

The data on newborn health (birth weight and low birth weight) come from vital statistics birth records for the period 1970-2000. (The data will be updated to 2010 shortly). These data include the education, age, race and marital status of the mother and father as well as county-identifiers for counties with a population of at least 100,000. [4]

The most notable absence from these data is information on maternal income. We are in the process of applying for National Survey of Family Growth (NSFG) data that include birth outcomes, maternal characteristics including income, and county of residence, but we do not yet have the data. As a substitute, for the present analysis we use three alternative datasets: the 1969 and 1980 National Natality Surveys and the 1988/1991 National Maternal and Infant Health Survey. These datasets include information on birth outcomes and maternal characteristic for quasi-randomly selected live births from the vital statistics registries and also include information on family income ascertained through follow-up surveys of the mothers. They include only state of residence, not county and the 1988/1991 data only include low birth weight, not the continuous measure of birth weight. We use these data for the analysis of the impact of the Gini holding individual income constant and also for the relative deprivation analysis. The years do not match perfectly with the census data, introducing some measurement error into the measure of inequality which may result in some attenuation bias. Moreover, the income was collected in categories. As a result, we assign an income equal to the median of each category to

[4] Data on smoking was not collected until 1990 and data on Hispanic origin was not collected until 1980, though prior to 1980, there were few births to Hispanic women and in 2000 paternal education was not collected.

all mothers. The data were not perfectly randomly collected and the survey weights provided were used for the analysis.

For the analyses, we include two sets of controls. The first are derived from census data and characterize the population in the area (eg, share black, share poor, share elderly, average and median income), and the second are derived from the birth outcomes dataset and characterize the population of mothers (marital status, age, education, race, etc). The former are included as averages for the area, the latter are included either as averages for the area (for the aggregate analysis) or as individual characteristics (for the individual analysis).

2. Constructing the Gini coefficient and the instruments

We construct Gini coefficients for each state and county in 1970, 1980, 1990, and 2000 using data from the decennial census data for 1970, 1980, 1990 and 2000. In addition to constructing the Gini by state and by county, we also construct the Gini over all households in the area and over all households with a mother and child less than 5 years old (new mothers). We do so to investigate whether and to what extend the selection of a more similar reference group based not just on geographic proximity, but also on personal characteristics, matters.

Finally, to calculate an instrument for the Gini, we construct a Gini based on a "synthetic cohort." To do so we hold constant the area's distribution of income at its 1970 level and predict changes in the distribution of income based on national trends in income growth over this period (Boustan et al, 2012). This synthetic Gini captures the change in inequality driven by changes in national trends in income growth, not changes in the underlying characteristics or composition of the area. We use this second measure as an instrument for the Gini. Figure 1 illustrates a strong relationship between the Gini and the synthetic Gini measured at the level of the county. The first stage estimates can be found in the Appendix Tables.

3. Changes in the Production of Health as a Result of Inequality

In order to assess the extent to which inequality may change either the way that care is delivered or the provision of public goods that might directly affect outcomes, we collected data on hospital adoption of technology related to newborn care, the degree of segregation of low income patients in different hospitals, and a public good that has been shown to affect the production of newborn health (pollution). Our measure of technology adoption is the number of NICU beds per 1000 births in each county and year from annual AHA survey data. The measure of segregation is a dissimilarity index (that ranges from 0 to 1) and is also constructed from hospital data that includes the share of all admissions to a given hospital (with at least 10 births per year) that are Medicaid admissions (from 1980 on).[5] Based on this we can calculate for each county of residence the degree to which Medicaid patients tend to be treated in the same hospitals as the private pay patients. Note that counties with only 1 hospital will be perfectly integrated. Moreover, mothers need not have delivered in a hospital within their county and if they did not, then this measure of segregation will be mis-measured.

Finally, we are collecting local pollution levels (from the EPA) at the county level. We have focused specifically on those measures of pollution that are most amenable to changes in public policy. (note: we only have the EPA data for 1990 and 2000 and are awaiting the data for 1970 and 1980).

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[5] Actually these data are not available until 1981, but we assume levels in 1980 are similar.

III. Results

A. Changes in the Gini Over time

Table 1 shows only descriptive statistics for the distribution of the Gini coefficient across counties and over time. The main thing to note from the table is the considerable variation both over time and across counties within each year in the Gini coefficient.

We try to estimate the extent to which certain characteristics of the county in 1970 are associated with or predictive of greater increases in the Gini. For this analysis (based only on county level data for 1970 and 2000) we regress the change in the Gini on the following characteristics of the county as measured in 1970; size (population), share black, share Hispanic, share elserly, share poor and the average income of the county.

We find that all of these characteristics are predictive of changes in the Gini over time. Counties that are larger, have a greater share of Blacks and Hispanics are more likely to see increases in the Gini over time (Table 2). This is not surprising given that wages grew less fast for this population. The share elderly is negatively associated with changes in the Gini. Regarding income in 1970, higher average income and lower poverty are associated with widening inequality, consistent with an increase in inequality being driven by increases in income at the top of the distribution. In columns 2 and 3, we also include measures of the average health at birth in the county in 1970. Counties with worse newborn health in 1970 witness greater increases in inequality over time.

B. The Impact of the Gini on Health at Birth

In Figure 1, we present scatter plots at the level of the county of the relationship between average birth weight and the Gini – we do this separately by year because there are considerable differences by year. In 1970, the relationship between the Gini and average birth weight is quite small, but each decade becomes increasingly large and negative. Below we examine whether this relationship remains once we include adequate controls for potential confounders in a regression analysis.

Analysis Based on Aggregate Natality Data

Our first analysis using the same empirical strategy as existing work (looking at mortality) that is based on aggregated data. To do so, we present OLS estimates of the following equation based on the individual level data that is aggregated up to the level of the state-year or county-year (area indexed by c):

$$\text{Newborn Health}_{ct} = \beta_0 + \beta_1\text{Income}_{ct} + \beta_2\text{Gini}_{ct} + \beta_3 X_{ct} + \beta_4 G_{ct} + \gamma_t + \gamma_c + \varepsilon$$

Newborn health is measured as either continuous birth weight in grams or the share born below low birth weight (<2500 grams). X_{ct} is a vector of maternal controls including the average age and marital status, average years of schooling of the mother and father, and race. G_{ct} is vector of area-level (state or county, depending on the specification) controls from the census (population size, share black, share Hispanic, poverty rate, mean income, median income and share over 65), following Boustan et al (2012). We include year FE in all specifications and area FE in some.

We present OLS estimates of the above equation (Table 3) but in the first column, include only the Gini coefficient and year fixed effects, no other controls. We then include increasingly more controls until we have included all controls indicated above. In column 1, we see a negative and significant relationship between the Gini and average birth weight in the county: a 0.10 increase in the Gini is associated with a decline in average birth weight of 134 grams. In column 2 we include controls for the average state characteristics from the census, but not income, and the results fall by almost two thirds, adding income (column 3) reduces the effect further still and it is no longer significantly different from zero. The effect of income on newborn health is positive and quadratic and the consistent with Miller (2002) we find that the concavity can explain some of the relationship between inequality and health, but not most. Adding controls for average maternal characteristics results in a positive but insignificant relationship between the Gini and birth weight (column 4). In column 5 we include all controls and state fixed effects and the estimated effect is no longer significant and the point estimate positive in sign. In the last column we include state fixed effects and instrument for the Gini and the results remain small and insignificant, suggesting that once we adequately control or account for underlying characteristics of areas with high rates of inequality, there is no longer a negative relationship between the Gini and newborn health.

In the second panel of the table (panel B), we calculate the Gini over all mothers in the state and the same pattern emerges: a large negative relationship when no controls are included but as increasingly more controls are included, the impact of the Gini on birth weight is small and no longer significantly different from zero. In panel C of Table 3, we calculate the Gini over all households in the county. These estimates are more robust than those for the state-level Gini. The estimate falls to -635 but remains significant when we include the full set of controls (excluding the fixed effect). However, after including county FE (column 5) or instrumenting for the Gini (column 6) the estimated relationship between the Gini and newborn health is neither large nor significant.

The last panel of the table (panel D) presents estimates based on a Gini calculated over all new mothers in the county. The results are smaller than those based on all households in the county (panel C) and approach zero as more controls are included.

We re-estimate the equation for a different but related outcome: the share of babies born low birth weight. We do this for two reasons. First, it is arguably the lower tail of births that is most likely to be affected by an increase in inequality. Second, the individual level data that we use has only an indicator for low birth weight, so we present these results in order to compare estimates across aggregate and individual level data. The estimates (Table 4) are very similar to those for birth weight. When few controls are included, the relationship is strong but as more controls are included, the estimated effect falls until, with the inclusion of fixed effects or instrumenting for the Gini, the point estimate becomes small and insignificantly different from zero. It is also the case that the estimated effects seem slightly larger and more robust in the county-level regressions and that changing the reference group to mothers results in, if anything, slightly smaller effects. The latter might be attributable to increased measurement error in the construction of the Gini over a subset of the population, or that the relevant reference group is the entire community, not just those most similar to oneself.

Analysis Based on Individual Data

We follow the analysis based on aggregate data with one based on individual level data (approximate years 1970-1990) that allows us to control for an individual mother's income in the analysis. The results are very similar to those based on the aggregate data. When no controls are included, the relationship between the Gini and the probability of low birth weight is strong and significant, but it disappears quickly once even parsimonious set of controls are included (Table 5).

Inequality and the Production of Health Care

Finally, we estimate whether income inequality affects the way that health is produced. Specifically, we look at the relationship between income inequality measured at the county level over all households and technology adoption (the number of NICU beds per 1000 births in a county) as well as the extent to which poor mothers (proxied by Medicaid) are segregated in different hospitals within the county.

We find no effect of the Gini on the adoption of technology (Table 6). In the FE setting there seems to be some evidence that segregation increases in more unequal counties (and the effect is sizeable), but once we instrument for the Gini, the effect is no longer positive or significant. Note: we have pollution data for 1990 and 2000 but are awaiting the data from 1970 and 1980. When we get them, we'll estimate whether inequality and pollution are related.

How should we interpret these results? One possibility is that any observed relationship between rising inequality in income as measured by the Gini and health is purely correlation. Another possibility is that the effect is heterogeneous, with positive effects for some and negative effects for others, leading to overall null effects. Below we consider the latter interpretation by estimating whether two measures of relative income affect newborn health.

C. Relative Deprivation and Newborn Health

Our estimates of the impact of relative deprivation (the YRD) on newborn health using individual level data are presented in Table 7. The specification includes all controls previously included as well as state and year fixed effects. The results in column 1 suggests that conditional on absolute level of income, relative deprivation matters: if the average difference between one's income and those above increases by an amount equal to half the mean income of the area (a large increase), the probability of a LBW birth increases by 3.5 percentage point (slightly more than half, relative to the mean probability of LBW in these data). These results hold when we instrument for relative deprivation (column 2) using a measure of relative deprivation based on the synthetic distribution of income, as described previously. Note that in these regressions, income (which enters as a quadratic) is no longer a significant predictor of LBW, largely because of its negative collinearity with relative deprivation once state FE are included.

It is also the case that when we include a measure of relative advantage (not shown), there is no significant effect on the probability of a LBW birth. This suggests that the distance between a mother and those with income below her is not a predictor of LBW. The interpretation of this lack of symmetry is not straightforward. It could reflect the fact that marginal relative improvements at the bottom have a much bigger effect than similar improvements at the top. Alternatively, it could be due to the fact that LBW is less common among higher income women (those with high relative advantage) or that the measure of relative advantage is small (on average, half the size of the relative disadvantage measure) in this sample of young women who tend to be located closer to the bottom of the distribution than the top.

D. Rank and Newborn Health

Finally, we explore the extent to which rank within a reference group matters. Rank (which ranges from 0, lowest rank, to 1, highest rank) differs from relative deprivation because it is an ordinal measure that reflects one's relative position, but not the distance between one and one's neighbors. The estimates of the impact of "social status" in animal studies involve manipulation of an ordinal measure of rank.

The results suggest that rank is negatively correlated with the probability of a LBW birth: moving from the bottom to the bottom quarter (25^{th} percentile) reduces the probability of a LBW birth by 15 percent (Table 8, column 1). Moreover, the effects are non-linear: moving from the middle to the top quarter (75^{th} percentile) reduces the probability of a LBW birth by 11 percent.

To understand whether not only rank but also the degree or amount of distance between an individual and others in her group matters, we estimate whether rank matters more in areas (states) with greater income dispersion (as measured by the standard deviation of income based on census data). If the effect of rank increases in more disparate (higher variance) societies, this would be consistent with the amount or size of the relative deprivation mattering. For this analysis we construct two measures of variance. The first is the variance based on the reported income distribution by state from census data, the second is the variance based on the synthetic distribution of income as described previously which we use as an instrument for the first measure of variance.

The results of stratifying the sample by the level of variance (low is equivalent to below the median, high to above the median), show that rank matters in high variance areas but not in low variance areas (columns 2-3 of Table 8). In fact, the effect of rank double in high variance areas, while the effect of rank falls to zero in low variance areas. When we stratify by rank as predicted by the synthetic distribution of income, the results are largely unchanged (columns 4-5 of Table 8). We should note that interpretation of these effects is not straight forward. While they could represent true effects, the results could also simply be an artifact of the outcome (low birth weight) which disproportionately affects those at the bottom. We can assess this once we get the NSFG data which contains some continuous measures of newborn health.

IV. Conclusions

These results are still very preliminary and will be updated with data from the NSFG that contains measures of maternal income and county identifiers as well as measures of maternal prenatal investment. However, there appear to be two preliminary findings. First, aggregate measures of inequality (the Gini) are not predictive of worse newborn health in either aggregate or individual level data once one includes controls for area characteristics that might be correlated with health. Second, once one uses measures of deprivation that are specific to an individual, there does appear to be a negative relationship between relative position (relative deprivation or ordinal rank) and newborn health. Moreover, these effects are not linear or symmetric: those at the bottom of the distribution suffer more from a decline in relative position than those closer to the top.

These two findings do not appear to be wholly consistent. If the effect of rank matters more for those of the lowest rank in high variance areas, this would suggest that rising inequality would result in worse average health, contrary to what we found in the first part of the analysis. What can explain this? One possibility is that the Gini is too crude a measure – not only does it not capture heterogeneous effects within an area across individuals, but the effect may also vary with the degree of inequality (ie, only sufficiently high levels.) In future work, we hope to explore this seeming inconsistency. We also hope to estimate models that are based on more general measures of socio-economic status and consider plausibly exogenous variation in measures of own income.

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Table 1: The Gini Over Time and Across Counties

	1970	1980	1990	2000
Average	0.323	0.342	0.378	0.404
Standard Deviation	0.034	0.027	0.032	0.032
10th percentile	0.281	0.314	0.341	0.366
25th percentile	0.302	0.323	0.356	0.384
median	0.318	0.339	0.374	0.400
75th percentile	0.342	0.360	0.401	0.424
90th percentile	0.370	0.376	0.419	0.446

Table 2: Predicting Changes in the Gini Over Time (2000-1970) from 1970 Characteristics

	(1)	(2)	(3)
County population	93.19***	93.80***	93.38***
	[30.62]	[30.64]	[30.59]
Share black	10.61***	10.09***	10.38***
	[1.331]	[1.403]	[1.362]
Share Hispanic	11.93***	11.78***	11.92***
	[1.535]	[1.557]	[1.540]
Share over 65	-11.47***	-11.48***	-11.42***
	[2.153]	[2.223]	[2.202]
Poverty rate	-43.40***	-42.92***	-43.29***
	[3.191]	[3.185]	[3.189]
Median family income	-0.101**	-0.101**	-0.0992**
	[0.0432]	[0.0434]	[0.0436]
25th percentile family income	-0.000138***	-0.000137***	-0.000138***
	[4.40e-05]	[4.36e-05]	[4.39e-05]
75th percentile family income	9.30e-05***	9.34e-05***	9.22e-05***
	[1.57e-05]	[1.57e-05]	[1.59e-05]
Mean birth weight		-0.00152*	
		[0.000854]	
Share low birth weight			2.819
			[2.213]
Constant	11.62***	16.57***	11.40***
	[0.681]	[2.845]	[0.702]
Observations	421	420	420
R-squared	0.658	0.661	0.659

Table 3: Inequality and Newborn Health (Birth Weight) Aggregate Data

Panel A: Gini over all households in state	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FE	(6) IV-FE
Gini Coefficient	-1,345***	-425.2**	-175.1	35.67	478.3*	-56.2
	[199.9]	[194.0]	[188.2]	[209.2]	[271.9]	[75.41]
Mean income			6.862***	5.143	5.120**	-8.316
			[2.207]	[3.111]	[2.329]	[183.2]
Mean income squared			-0.0375**	-0.0340	-0.0434**	0.468
			[0.0190]	[0.0253]	[0.0186]	[6.695]
County population/10,000		1,841***	1,020**	860.8**	5,221*	-111
		[446.6]	[455.1]	[355.5]	[3,054]	[1.526e+06]
Share black		-285.7***	-295.9***	-14.84	-184.4	-776
		[37.12]	[34.25]	[73.45]	[173.3]	[101,395]
Share Hispanic		-263.7***	-270.7***	-407.7***	-129.9	7,993
		[50.60]	[46.11]	[57.36]	[141.5]	[108,216]
Share over 65		75.02	124.1	11.85	-519.1	19,095
		[166.8]	[152.5]	[157.3]	[358.3]	[258,858]
Share poor		292.4***	323.0***	229.6***	186.5**	4,338
		[57.99]	[53.35]	[64.26]	[79.28]	[56,301]
Maternal age				23.93	16.02	162.4
				[17.61]	[12.71]	[1,699]
Over 35				69.56	334.9	1,078
				[423.9]	[256.0]	[18,485]
Married				62.28	-15.33	3,587
				[97.06]	[107.4]	[49,320]
Marital status missing				-37.70**	-2.012	-1,249
				[18.58]	[21.32]	[16,744]
Maternal education				-37.57**	3.774	-113.0
				[14.88]	[15.36]	[1,344]
Black				-285.4***	-410.2**	8,865
				[94.80]	[175.3]	[123,158]
Hispanic				52.72***	42.40**	153.9
				[15.67]	[19.59]	[1,538]
Asian				-183.3***	60.41	-9,034
				[16.87]	[223.0]	[120,870]
Year 1970	-130.0***	-110.4***	95.24*	10.30	99.01	-2,699
	[13.99]	[12.70]	[48.58]	[72.20]	[70.76]	[37,900]
Year 1980	-48.82***	-19.80	131.5***	67.48	153.7***	-2,806
	[13.67]	[12.38]	[34.70]	[57.18]	[51.68]	[39,839]
Year 1990	-24.51**	-8.290	59.62***	13.82	78.60***	-2,217
	[11.85]	[10.56]	[15.81]	[32.30]	[29.06]	[30,683]
Constant	3,959***	3,546***	3,173***	3,026***	2,551***	21,472
	[91.35]	[83.47]	[114.5]	[261.9]	[316.1]	[255,245]
Observations	192	192	192	149	149	136
R-squared	0.412	0.605	0.664	0.759	0.943	

Panel B: Gini calculated over mothers in state	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FE	(6) IV-FE
Gini Coefficient	-832.3***	-263.1	-249.8	-338.6**	38.83	77.79
	[127.1]	[170.2]	[163.2]	[140.0]	[169.7]	[205.9]
Mean maternal income			7.094***	3.411	5.183**	4.773
			[2.165]	[3.020]	[2.378]	[5.332]
Mean maternal income squared			-0.0390**	-0.0219	-0.0404**	-0.0315
			[0.0187]	[0.0248]	[0.0189]	[0.0508]
Observations	192	192	192	149	149	136
R-squared	0.399	0.603	0.669	0.769	0.941	

Panel C: Gini calculated over all in county	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FE	(6) IV-FE
Gini Coefficient	-1,018***	-361.9***	-417.5***	-635.9***	-50.31	25.13
	[80.15]	[131.0]	[122.9]	[130.4]	[232.0]	[648.3]
Mean income			0.00487	0.00635	-0.000426	-0.000133
			[0.0169]	[0.0178]	[0.0263]	[0.0264]
Mean income squared			1.06e-05	1.50e-05	2.38e-05	2.35e-05
			[9.73e-06]	[1.11e-05]	[1.99e-05]	[2.00e-05]
Observations	1,780	1,780	1,392	1,079	1,079	1,079
R-squared	0.291	0.395	0.422	0.503	0.839	

Panel D: Gini calculated over all mothers in county	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FE	(6) IV
Gini Coefficient	-469.6***	-89.39**	-90.09**	-107.2***	5.830	225.3
	[41.72]	[37.96]	[38.11]	[38.52]	[41.65]	[584.2]
Mean maternal income			863.3**	-159.1	684.0	941.8
			[396.2]	[409.2]	[514.5]	[713.0]
Mean maternal income squared			-1,895	2,596	-3,187	-3,738
			[2,338]	[2,505]	[3,169]	[4,113]
Observations	1,392	1,392	1,392	1,079	1,079	430
R-squared	0.212	0.416	0.422	0.489	0.838	0.520

Table 4: Inequality and Newborn Health (Low Birth Weight) Aggregate Data

Panel A: Gini calculated over all households in state	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FE	(6) IV-FE
Gini coefficient	0.410***	0.254***	0.165**	0.0268	-0.101	3.519
	[0.0626]	[0.0698]	[0.0670]	[0.0654]	[0.0969]	[48.80]
Mean income			-0.00250***	-0.00296***	-0.00205**	-0.000662
			[0.000726]	[0.000802]	[0.000830]	[0.0119]
Mean income squared			1.61e-05**	2.27e-05***	1.86e-05***	-1.94e-05
			[6.24e-06]	[6.91e-06]	[6.61e-06]	[0.000433]
County population/10,000		-0.352***	-0.0927	-0.0573	-0.355	7.910
		[0.124]	[0.115]	[0.0793]	[1.088]	[98.72]
Share black		0.0685***	0.0724***	-0.00925	0.0708	0.568
		[0.00992]	[0.00929]	[0.0196]	[0.0617]	[6.559]
Share Hispanic		0.0114	0.0135	0.0436***	-0.0142	-0.532
		[0.0140]	[0.0122]	[0.0119]	[0.0504]	[7.000]
Share over 65		-0.0851*	-0.1000**	-0.0649	-0.231*	-1.502
		[0.0468]	[0.0471]	[0.0406]	[0.128]	[16.74]
Share poor		-0.0959***	-0.103***	-0.116***	-0.124***	-0.364
		[0.0277]	[0.0217]	[0.0167]	[0.0282]	[3.642]
Maternal age				-0.00424	0.000791	-0.0185
				[0.00431]	[0.00453]	[0.110]
Over 35				-0.0352	-0.160*	-0.0204
				[0.114]	[0.0912]	[1.196]
Married				-0.0418*	-0.0754*	-0.257
				[0.0222]	[0.0383]	[3.190]
Marital status missing				0.0102***	0.0132*	0.0883
				[0.00372]	[0.00759]	[1.083]
Maternal education				0.00512	0.00497	0.0189
				[0.00357]	[0.00547]	[0.0869]
Black				0.0867***	0.177***	-0.437
				[0.0243]	[0.0624]	[7.967]
Hispanic				-0.0144***	-0.00990	-0.0169
				[0.00323]	[0.00698]	[0.0995]
Asian				0.0374***	0.000831	0.553
				[0.0106]	[0.0794]	[7.819]
Year 1970	0.0304***	0.0253***	-0.0426***	-0.0390**	-0.00613	0.160
	[0.00362]	[0.00371]	[0.0159]	[0.0182]	[0.0252]	[2.452]
Year 1980	0.0156***	0.00911***	-0.0397***	-0.0387***	-0.0205	0.161
	[0.00342]	[0.00340]	[0.0111]	[0.0139]	[0.0184]	[2.577]
Year 1990	0.0103***	0.00772**	-0.0130***	-0.00675	-0.00146	0.143
	[0.00314]	[0.00309]	[0.00445]	[0.00706]	[0.0104]	[1.985]
Constant	-0.122***	-0.0386	0.0890**	0.222***	0.149	-0.944
	[0.0281]	[0.0284]	[0.0418]	[0.0758]	[0.113]	[16.51]
Observations	192	192	192	149	149	136
R-squared	0.361	0.570	0.649	0.775	0.897	

Panel B: Gini calculated over all mothers in state	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FE	(6) IV-FE
Gini coefficient	0.210***	0.0866*	0.0738	0.0245	-0.103*	0.868
	[0.0348]	[0.0476]	[0.0462]	[0.0341]	[0.0586]	[1.473]
Mean maternal income			-0.00308***	-0.00295***	-0.00215**	0.000557
			[0.000680]	[0.000793]	[0.000821]	[0.00381]
Mean maternal income squared			2.11e-05***	2.27e-05***	1.92e-05***	-8.14e-06
			[5.86e-06]	[6.81e-06]	[6.54e-06]	[3.63e-05]
Observations	192	192	192	149	149	136
R-squared	0.269	0.534	0.640	0.775	0.899	

Panel C: Gini calculated over all households in county	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FE	(6) IV-FE
Gini coefficient	0.248***	0.125***	0.152***	0.180***	-0.0752	0.0362
	[0.0298]	[0.0485]	[0.0423]	[0.0452]	[0.0767]	[0.215]
Mean income			8.87e-07	2.58e-07	1.11e-07	5.44e-07
			[5.24e-06]	[5.67e-06]	[8.69e-06]	[8.74e-06]
Mean income squared			-3.10e-09	-2.63e-09	-3.04e-09	-3.49e-09
			[3.54e-09]	[3.67e-09]	[6.57e-09]	[6.63e-09]
Observations	1,780	1,780	1,392	1,079	1,079	1,079
R-squared	0.160	0.262	0.316	0.401	0.776	

Panel D: Gini Calculated over all mothers in county	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FE	(6) IV
Gini coefficient	0.124***	0.0369***	0.0377***	0.0436***	0.00825	0.229
	[0.0123]	[0.0115]	[0.0116]	[0.0123]	[0.0137]	[0.192]
Mean maternal income			-0.0684	0.0585	-0.0931	-0.157
			[0.127]	[0.137]	[0.170]	[0.234]
Mean maternal income squared			-0.215	-0.878	0.268	0.614
			[0.791]	[0.869]	[1.045]	[1.352]
Observations	1,392	1,392	1,392	1,079	1,079	430
R-squared	0.134	0.311	0.313	0.396	0.776	0.319

Table 5: Inequality and Newborn Health (Low Birth Weight) Individual Data

Panel A: Gini cacluated over all households in state	(1) OLS	(2) OLS	(3) OLS	(4) FE	(5) IV	(6) FE IV
Gini Coefficient	0.45	0.092	0.084	0.112	-0.078	-1.22
	[0.161]**	[0.164]	[0.171]	[0.468]	[0.350]	[1.623]
Family income, real, $1000			0	0	0	0
			[0.000]**	[0.000]**	[0.000]**	[0.000]**
Family income squared			0	0	0	0
			[0.000]	[0.000]	[0.000]	[0.000]
Maternal age		-0.016	-0.019	-0.018	-0.019	-0.019
		[0.005]**	[0.005]**	[0.005]**	[0.005]**	[0.006]**
Maternal age squared		0	0	0	0	0
		[0.000]**	[0.000]**	[0.000]**	[0.000]**	[0.000]**
Mother Black		0.058	0.039	0.036	0.04	0.037
		[0.007]**	[0.008]**	[0.008]**	[0.008]**	[0.008]**
Mother Asian		-0.003	0.003	0.009	-0.001	0.005
		[0.018]	[0.020]	[0.020]	[0.020]	[0.020]
Mother Hispanic		-0.014	-0.008	-0.005	-0.008	-0.007
		[0.013]	[0.013]	[0.014]	[0.013]	[0.014]
Maternal education in years		-0.009	-0.007	-0.007	-0.007	-0.007
		[0.001]**	[0.001]**	[0.001]**	[0.001]**	[0.001]**
Male		-0.025	-0.02	-0.02	-0.02	-0.02
		[0.006]**	[0.006]**	[0.006]**	[0.006]**	[0.006]**
year = 1990	0.173	0.173	0.171	0.17	0.175	0.198
	[0.009]**	[0.009]**	[0.010]**	[0.013]**	[0.012]**	[0.035]**
year = 1980	0.104	0.114	0.095	0.095	0.096	0.096
	[0.008]**	[0.008]**	[0.008]**	[0.008]**	[0.008]**	[0.008]**
Constant	-0.107	0.345	0.361	0.347	0.443	0.913
	[0.067]	[0.098]**	[0.103]**	[0.208]	[0.165]**	[0.678]
Observations	19142	19016	16047	16047	15820	15820
R-squared	0.03	0.04	0.04	0.04	0.04	

Panel B: Gini calcualted over mothers in state	(1) OLS	(3) OLS	(4) OLS	(5) FE	(6) IV	(7) FE IV
Gini Coefficient	0.267**	0.0570	0.0420	-0.000337	-0.0656	-2.368
	[0.113]	[0.115]	[0.122]	[0.303]	[0.234]	[8.722]
Constant	-0.00645	0.365***	0.383***	0.394***	0.431***	1.170
	[0.0369]	[0.0782]	[0.0837]	[0.122]	[0.106]	[2.810]
Observations	19,142	19,016	16,047	16,047	15,820	15,820
R-squared	0.027	0.035	0.037	0.039	0.038	

Standard errors in brackets
* significant at 5%; ** significant at 1%

Table 6: Inequality, Technology Adoption and Segregation

	NICU beds per birth		Segregation	
	FE	IV-FE	FE	IV-FE
Gini Coefficient	0.44	2.372	0.786*	-1.49
	[0.908]	[2.604]	[0.448]	[1.560]
Constant	28.22***	25.68***	7.399***	10.39**
	[6.030]	[7.018]	[2.428]	[4.204]
Observations	1,256	1,256	1,256	1,256
R-squared	0.733		0.634	

Includes all controls listed in last column of Table 3, Panel A and county fixed effcts

Table 7: Relative Deprivation and Newborn Health (Low Birth Weight) Individual Data

	FE	IV
Relative Deprivation divided by Mean Income (Deaton)	0.0692**	0.0725*
	[0.0326]	[0.0375]
Family income, real, $10000	0.00548	0.00585
	[0.00346]	[0.00405]
Family income squared	-1.43e-08	-1.52e-08
	[9.29e-09]	[1.06e-08]
Maternal age	0.000617	0.000617
	[0.000446]	[0.000446]
Married	-0.0305***	-0.0305***
	[0.00679]	[0.00679]
Maternal education in years	0.00596*	0.00600*
	[0.00340]	[0.00339]
Maternal education squared	-0.000323**	-0.000325**
	[0.000139]	[0.000139]
Mother Black	0.0504***	0.0503***
	[0.00650]	[0.00650]
Mother Hispanic	-0.00206	-0.00202
	[0.00574]	[0.00574]
State Population/100000	-0.000317	-0.000318
	[0.000293]	[0.000293]
Share black in state	-0.520	-0.516
	[0.517]	[0.517]
Share hispanic in state	0.200	0.203
	[0.290]	[0.292]
Share over 65 in state	0.602	0.608
	[0.552]	[0.549]
Poverty rate	0.304	0.308
	[0.228]	[0.229]
Median family income,	-0.00495	-0.00493
	[0.00549]	[0.00549]
Mean state income	3.97e-06	3.95e-06
	[4.55e-06]	[4.56e-06]
Year 1980	-0.00892	-0.00788
	[0.0189]	[0.0198]
Year 1988	-0.0220	-0.0211
	[0.0372]	[0.0375]
Constant	-0.0385	0.00883
	[0.111]	[0.156]
Observations	16,250	16,250
R-squared	0.015	0.015

State FE also included
*** p<0.01, ** p<0.05, * p<0.1
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Relative Rank and Newborn Health (Low Birth Weight) Individual Data

	(1)	(2)	(3)	(4)	(5)
		Actual Variance		Predicted Variance	
	All	Low	High	Low	High
Rank among mothers in state	-0.0525*	-0.00309	-0.0986*	0.0157	-0.102*
	[0.0295]	[0.0275]	[0.0545]	[0.0223]	[0.0526]
Rank squared	0.0627**	0.0228	0.0997*	-0.00432	0.102*
	[0.0297]	[0.0337]	[0.0567]	[0.0259]	[0.0546]
Family income, real, $10000	-0.00229***	-0.00243	-0.00223*	-0.00105	-0.00215*
	[0.000887]	[0.00172]	[0.00120]	[0.00160]	[0.00114]
Maternal education in years	-0.00137	-0.00173*	-0.00112	-0.00224***	-0.000969
	[0.000854]	[0.000934]	[0.00140]	[0.000750]	[0.00133]
Maternal age	-0.0121***	-0.00865**	-0.0147**	-0.00784**	-0.0150***
	[0.00379]	[0.00440]	[0.00588]	[0.00346]	[0.00565]
Maternal age squared	).000222***	0.000170**	0.000260**	0.000152**	0.000271***
	[6.74e-05]	[8.03e-05]	[0.000103]	[6.21e-05]	[9.95e-05]
married	-0.0289***	-0.0377***	-0.0207**	-0.0554***	-0.0185**
	[0.00683]	[0.0103]	[0.00936]	[0.0138]	[0.00822]
Mother Black	0.0518***	0.0491***	0.0538***	0.0438***	0.0554***
	[0.00647]	[0.00763]	[0.0104]	[0.00701]	[0.00970]
Mother Asian	0.00472	0.00716	0.00169	0.00408	-0.00301
	[0.00844]	[0.00957]	[0.0139]	[0.00862]	[0.0156]
Mother Hispanic	-0.00249	-0.00248	-0.00118	-0.00324	-0.00545
	[0.00591]	[0.00669]	[0.0102]	[0.00720]	[0.00948]
year1990	-0.0187***	-0.0225	-0.0131*	0.00806	-0.0174***
	[0.00531]	[0.0147]	[0.00701]	[0.00530]	[0.00638]
year1980	-0.0243***	-0.0286**	-0.0336		
	[0.00497]	[0.0142]	[0.0237]		
Constant	0.293***	0.247***	0.330***	0.226***	0.329***
	[0.0516]	[0.0587]	[0.0818]	[0.0483]	[0.0772]
Observations	16,250	9,919	6,330	8,695	7,231
R-squared	0.016	0.016	0.021	0.013	0.018

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table A1: First Stage: Predicting the Gini Using Aggregate Data

	(1) OLS	(2) FE
Gini Coefficient, Predicted	0.376***	0.738***
	[0.0190]	[0.0779]
County population/10,000	0.561***	-1.810***
	[0.0726]	[0.474]
Share black in county	0.0502***	0.0619***
	[0.00852]	[0.0147]
Share Hispanic in county	0.0198***	0.0955***
	[0.00711]	[0.0163]
Share over 65 in county	0.0666***	0.0667**
	[0.0130]	[0.0303]
Share poor in county	0.296***	0.312***
	[0.0143]	[0.0196]
Maternal age	0.00130	-0.000938
	[0.000833]	[0.000902]
Over 35	0.102***	0.0477***
	[0.0197]	[0.0179]
Married	-0.00313	0.0152**
	[0.00736]	[0.00749]
Marital status missing	-0.000179	-0.00739***
	[0.00301]	[0.00222]
Maternal education	0.00112	0.00153
	[0.00108]	[0.00124]
Black	0.00380	0.0173**
	[0.00846]	[0.00845]
Hispanic	0.00212	-0.00785**
	[0.00415]	[0.00371]
Asian	0.0197***	0.0375*
	[0.00717]	[0.0209]
Mean income	-3.83e-06	-2.14e-06
	[4.26e-06]	[4.28e-06]
Mean income squared	-2.39e-09	2.35e-09
	[2.92e-09]	[3.24e-09]
Year 1970	-0.0313***	-0.0290***
	[0.00389]	[0.00608]
Year 1980	-0.0139***	-0.0135**
	[0.00379]	[0.00523]
Year 1990	-0.0107***	-0.0121***
	[0.00301]	[0.00308]
Constant	0.135***	0.0529
	[0.0173]	[0.0347]
Observations	1,079	1,079
R-squared	0.892	0.979

Gini calcluated over all household in county
FE refers to county FE.

Table A2: First Stage: Predicting the Gini Using Individual Data

	(1)	(2)	(3)	(4)
	Gini- All		Gini- Moms	
	OLS	FE	OLS	FE
Gini Coefficient, Predicted	0.190***	0.475***		
	[0.00267]	[0.0125]		
Gini Coefficient, Predicted			0.251***	0.0652***
			[0.00324]	[0.0147]
Maternal age	-0.000297	1.73e-05	0.000215	3.21e-05
	[0.000220]	[8.91e-05]	[0.000303]	[0.000142]
Mother Black	0.00594***	0.000189	0.00701***	0.000203
	[0.000318]	[0.000134]	[0.000437]	[0.000214]
Mother Asian	0.00453***	0.000433	0.00853***	0.000452
	[0.000793]	[0.000331]	[0.00109]	[0.000530]
Mother Hispanic	0.00621***	-0.000412*	0.00818***	-0.000666*
	[0.000535]	[0.000223]	[0.000736]	[0.000356]
Maternal Education	-0.000238**	-6.25e-06	-0.000248**	1.97e-05
	[5.71e-05]	[2.31e-05]	[7.85e-05]	[3.70e-05]
male	5.84e-05	0.000228**	-0.000279	5.65e-05
	[0.000240]	[9.69e-05]	[0.000330]	[0.000155]
Maternal age squared	6.40e-06	-1.00e-07	-1.72e-06	-4.86e-07
	[3.90e-06]	[1.57e-06]	[5.36e-06]	[2.52e-06]
Real Family Income	-2.68e-06	-6.49e-06***	1.43e-05***	-1.30e-05***
	[3.09e-06]	[1.26e-06]	[4.24e-06]	[2.01e-06]
year 1990	0.0165***	0.0106***	0.0567***	0.0846***
	[0.000361]	[0.000306]	[0.000563]	[0.00125]
year 1980	-0.000459	0.000950***	0.0218***	0.0345***
	[0.000326]	[0.000138]	[0.000463]	[0.000563]
Constant	0.344***	0.225***	0.240***	0.342***
	[0.00318]	[0.00515]	[0.00424]	[0.00499]
Observations	15,820	15,820	15,820	15,820
R-squared	0.489	0.917	0.733	0.941

Gini calculated over all households in
Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

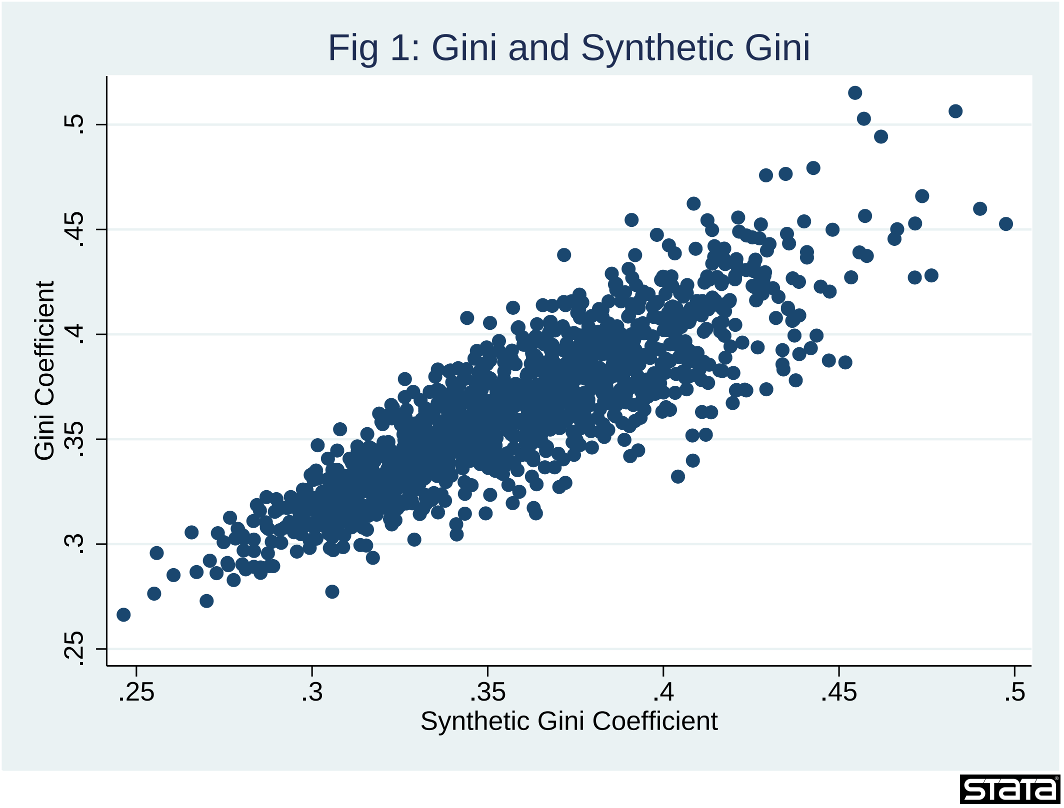

Fig 1: Gini and Synthetic Gini
Gini Coefficient
.25
.3
.35
.4
.45
.5
Synthetic Gini Coefficient
.25
.3
.35
.4
.45
.5

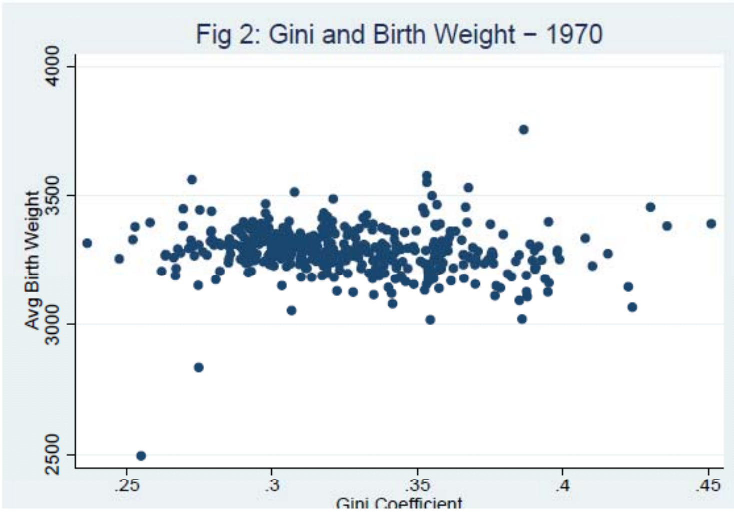
Fig 2: Gini and Birth Weight – 1970
Avg Birth Weight
2500
3000
3500
4000
.25
.3
.35
.4
.45
Gini Coefficient

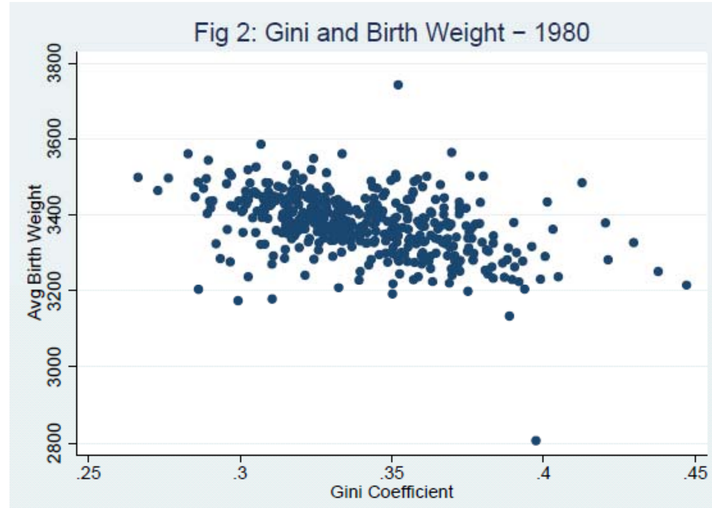
Fig 2: Gini and Birth Weight – 1980
Avg Birth Weight
2800
3000
3200
3400
3600
3800
.25
.3
.35
.4
.45
Gini Coefficient

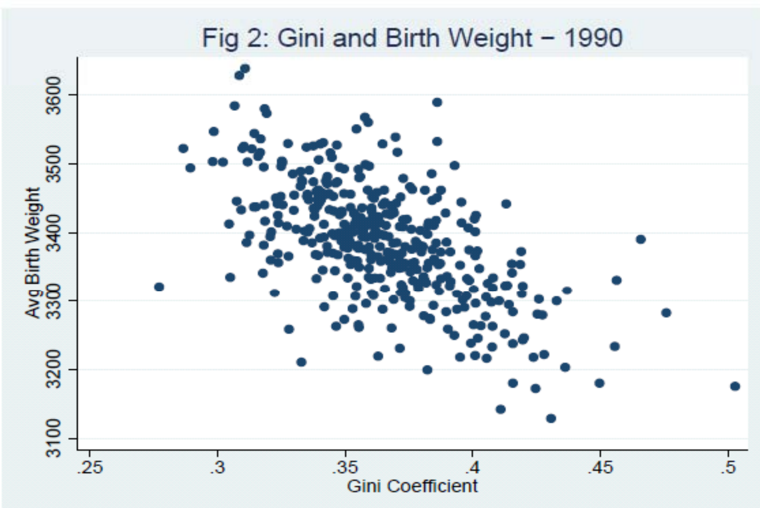
Fig 2: Gini and Birth Weight – 1990
Avg Birth Weight
3100
3200
3300
3400
3500
3600
.25
.3
.35
.4
.45
.5
Gini Coefficient

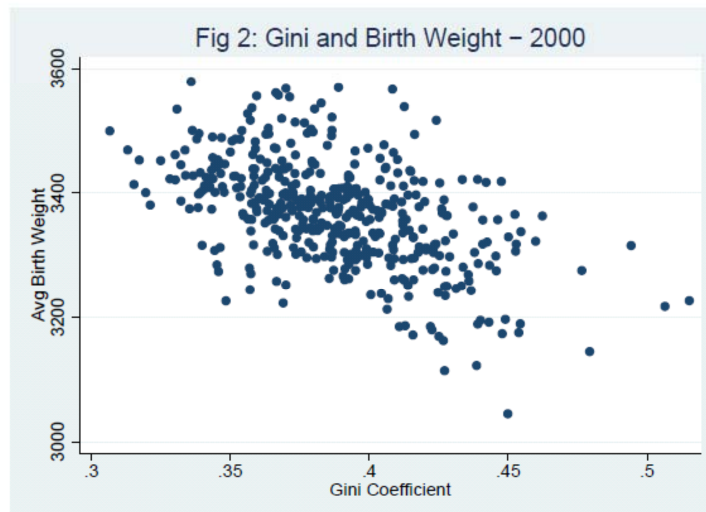
Fig 2: Gini and Birth Weight – 2000
Avg Birth Weight
3000
3200
3400
3600
.3
.35
.4
.45
.5
Gini Coefficient