An Assessment of Some Mechanisms Linking Economic Inequality and Infant Mortality

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Abstract

We use data from the 1985, 1987 and 1991 United States Vital Statistics Linked Infant Birth and Death Records to assess the effect of state-level economic inequality on an infant's probability of death. We find that economic inequality is associated with higher neonatal mortality even after we control mother's age and race and state characteristics that are likely to be associated with both inequality and infant death. Inequality is not associated with post-neonatal mortality. We assess three mechanisms that could link income inequality and infant deaths: non-linearity in the relationship between parental income and infant death, economic segregation, and state health care spending. Non-linearity in the relationship between family income and infant health accounts for little of the effect of inequality in infant death. However inequality is associated with greater economic segregation, which in turn is associated with a higher probability of infant death. This effect is partially offset by the fact that inequality is also associated with higher health care spending, which in turn is associated with lower death rates. The increase in economic segregation increases infant deaths more than the increase in health care spending reduces them, so the net effect of economic inequality is to increase infant deaths.

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A growing research literature estimates the effect of income inequality on health outcomes, including infant mortality. This research suggests that although there is a strong correlation between inequality and infant mortality, the effect usually disappears when other factors are controlled. However, changes in income inequality could set in motion a variety of social and political changes. Some of these could reduce infant mortality while others raise infant mortality. If these processes offset one another, we would see no net change in infant mortality. If changes in income inequality operate in this way, it may be possible to ameliorate the negative effects of a change in inequality while retaining the positive effects.

In this paper we estimate not only the net effect of economic inequality on infant death but also the effect of three mechanisms through which inequality can affect infant death. The first is non-linearity in the relationship between parental income and infant death. If an extra dollar of income reduces infant mortality among the poor more than among the rich, shifting income from the rich to the poor should lower the infant mortality rate. Secondly, previous research suggests that an increase in economic inequality results in an increase in economic segregation (Durlauf 1996, Mayer 2001). Economic segregation could affect infant mortality by altering the geographic distribution of physicians and medical facilities, the accessibility of medical care, and social networks that affect health practices. Third, previous research suggests that economic inequality may affect social welfare expenditures, including expenditures on health care (Alesina and Rodrik 1994, Perotti 1996). An increase in health care expenditure could in turn affect infant deaths. These political effects of inequality may be partly the result of segregation effects. We describe these mechanisms in more detail below. We also describe a fourth mechanism linking inequality to infant mortality, namely social comparisons, but our data do not allow a direct test of this hypothesis.

We estimate the effect of inequality on an infant's probability of death in the first year after birth. We also estimate the effect of inequality on neonatal deaths, which occur in the first 28 days after birth. About two-thirds of infant deaths occur in the first month, including almost all (98.4 percent) deaths related to low birth weight and to premature birth. Most deaths due to respiratory distress, maternal complications of pregnancy, intrauterine hypoxia and birth asphyxia as well as deaths due to complications of the placenta, umbilical cord or other membranes or to neonatal hemorrhage, also occur in the first month. We also estimate the effect of inequality on post-neonatal deaths, which occur between one month and one year after birth. Such deaths are more likely than neonatal deaths to be caused by accidents, Sudden Infant Death Syndrome, diseases of the circulatory system, and congenital malformations, deformations and chromosomal abnormalities (a third of which occur in the post-neonatal period) are also common causes of post-neonatal deaths.

Section 2 describes previous research that estimates the effect of inequality on infant death. Section 3 describes the possible links between inequality and infant deaths. Section 4 describes the data and models. Section 5 reports results, and Section 6 concludes.

II. Previous Research.

Table 1 shows previous estimates of the association between economic inequality and infant mortality. Nine studies use cross-sectional data. Seven of these nine use cross-national data and produce ten estimates, eight of which show that more unequal countries have higher infant mortality rates. Two (Pampel and Pillia 1986, Mellor and Milyo 2001) find that more unequal countries have lower infant mortality rates than countries with less inequality. The other cross-sectional studies (Kennedy et al. 1998, Meara 1999) use data on states in the United States. Both find a positive and statistically significant effect of inequality on infant death.

Cross-sectional studies have well-known and potentially serious limitations (Mellor and Milyo 2001, Fiscella and Franks 1997, Judge 1995). One limitation is omitted-variable bias. This is demonstrated in two of these studies. Mellor and Milyo (2001) find a positive and statistically significant effect of the Gini coefficient on infant mortality across forty-seven countries with no controls. But when they control GDP per capita the relationship becomes negative and statistically insignificant. When Judge, Mulligan and Benzeval (1998) add female labor force participation to their model the effect of inequality again declines and becomes statistically insignificant.

However, many of these studies also control factors that are likely to be the result of inequality. Judge, Mulligan, and Benzeval, for example, control health expenditure and social security transfers. Pampel and Pillai control government expenditure on medical care, public health and welfare programs. As we discuss below there is good reason to think that government spending is influenced by changes in inequality. If so controlling these variables will result in biased estimates of the effect of inequality.

If inequality affects infant mortality, we would expect it to change when the level of inequality in a country or state changes. Two studies in Table 1 estimate the effect of a change in inequality within countries, and one estimates the effect of a change in inequality within states in the United States. All three studies find that an increase in inequality is associated with a statistically insignificant decline in infant deaths. However, for reasons we discuss below, these models have potentially serious problems as well.

All the studies discussed so far use aggregate-level data. In principle, appropriately specified estimates based on aggregate data should produce the same results as appropriately specified estimates based on individual-level data. However, in practice it is difficult to model non-linear relationships at the aggregate level, and some potentially important characteristics of individuals may not be available at the aggregate-level. Only Meara (1999) uses individual-level data on infant deaths. She controls state median household income and the child's race and finds that the effect of inequality in the state on the probability of death is negative but statistically insignificant.

Another potentially important difference across these studies is that they consider different time periods. Rodger's (1973) data are from around 1965. Flegg's (1982) data are for 1968-72. Waldman's (1992) data are from 1960 and 1970. When Mellor and Milyo (2001) estimate the effect of the Gini coefficient on infant mortality across countries in 1960, 1970, 1980 and 1990, they find that the Gini coefficient has a statistically significant effect only in 1970.

Two studies estimate the effect of inequality on neonatal mortality. Pampel and Pillai (1986) find that the Gini coefficient has a large positive effect on the neonatal mortality rate across countries. This effect becomes much smaller and statistically insignificant when government expenditures on medical care are controlled. Meara (1999) in contrst finds a statistically insignificant effect of the Gini coefficient on a state's neonatal mortality rate. Pampel and Pillai (1986) also find that a country's Gini coefficient has a negative but statistically insignificant effect on post-neonatal mortality.

This research leaves considerable uncertainty about the effect of economic inequality on infant deaths. All studies find a positive correlation between infant mortality and economic inequality. But conclusions about the causal effect of inequality are sensitive to what else researchers control. Few studies consider the effect of inequality on neonatal mortality, and those that do are equivocal. In addition, inequality affects many aspects of society. Some of these changes could have a positive effect on infant death while others could have a negative effect. If positive and negative effects roughly cancel one another out, the net result would be an effect close to zero. Yet it would still be important to understand these mechanisms, because social policies might then be able to ameliorate the harmful effects of inequality.

III. Four Mechanisms

Before estimating the effect of economic inequality on infant deaths, we discuss four possible mechanisms through which this effect could occur. Understanding these mechanisms provides guidance about what to control in reduced-form estimates of the relationship between inequality and infant deaths.

Non-linear Income Effects. If the relationship between infant death and parental income is linear, an extra dollar will have the same effect on infant mortality regardless of whether it goes to the rich or to the poor. In this case taking a dollar from the rich and giving it to the poor will raise infant mortality among the rich and lower it among the poor by exactly equal amounts, leaving the mean unchanged. But if an extra dollar of income improves the health of low-income infants more than that of high-income infants, reducing income inequality while leaving the mean unchanged will reduce infant mortality. Some researchers (Fiscella and Franks 1997, Gravelle 1998) have argued that a nonlinear relationship between family income and health results in a spurious relationship between inequality and heath. However, such a nonlinear relationship means that a decline in economic inequality would improve population health. Thus we prefer to think of non-linearity in the relationship between family income and infant deaths as a possible mechanism through which inequality affects infant deaths rather than a specification error.

Segregation Effects. The effect of economic inequality is likely to depend to some extent on the geographic proximity of the rich to the poor. Indeed, this assumption is built into conventional measures of inequality, which describe the dispersion of income among all households in some geographic area, such as a nation, a state, or a neighborhood. Both theoretical (Durlauf 1996) and empirical research (Mayer 2001) suggest that economic inequality increases economic segregation. Research also suggests that higher levels of economic segregation are associated with higher levels of adult mortality (Waitzman and Smith 1998).[1]

Social Resources. The "neo-materialist" view of the relationship between inequality and health (Lynch et al., 2000) holds that inequality affects health and mortality mainly because it affects the level and distribution of material resources. According to this argument infant deaths could increase if an increase in inequality reduces state spending on medical care for the poor (or on other goods and services that affect mortality). Judge et al. (1998) find that national health care expenditures are associated with lower infant mortality rates across fifteen countries. Other research suggests that recent expansions in health insurance for pregnant women and their children reduced infant mortality largely by increasing access to medical care at delivery and during the neonatal period (Piper et al. 1990, Currie and Gruber 1997). Thus an increase in state spending on the poor is likely to reduce neonatal mortality more than overall infant mortality.

However, theory predicts that an increase in inequality could either raise or lower state spending for the poor, including spending for medical care. Most models of how governments spend revenue (Romer 1975, Roberts 1977, Meltzer and Richards 1981) assume that political competition makes the voter with the median income the decisive voter. As a result, the spending preferences of the median voter prevail. As inequality increases the median income falls relative to the mean income so the median voter feels poorer and will demand policies to reduce the income gap. A second argument that predicts increased redistribution when inequality rises is that as inequality increases the rich become increasingly fearful of the poor (Pivan and Cloward 1993, Gurr 1970). In order to forestall crime and civil disturbances, they will spend more to placate the poor. Medical care may be among such expenditures. But an increase in inequality could also reduce spending on the poor if disadvantaged voters become disillusioned or alienated and are less likely to vote as a result.[2]

[1] Research also suggests that racial segregation is assocaited with black infant mortality (Ellen 19xx). However, economic and racial segregation need not be highly correlated and in fact as economic inequality increased, economic segregation but not racial segregation increased.

[2] Moene and Wallerstein (2002) argue that when the median voter feels poorer, he will be more inclined to want to insure against future financial declines (or illness), but he will also want to pay less for such insurance. As the rich get richer they will pay a larger share of the taxes collected. The median voter will be more inclined to favor universal social programs as inequality increases because he will get these services at a lower cost. On the other

Under some circumstances, moreover, growing inequality will lead to a "mechanical" increase in re-distributive spending. If inequality increases while mean income stays the same, the poor almost always get poorer. The number of individuals and families that qualify for means-tested entitlement programs therefore tends to increase. Up until 1996, Medicaid was the main publicly supported health insurance program for low-income children. Children's eligibility for Medicaid was closely tied to their eligibility for the main cash transfer program, Aid to Families with Dependent Children. Expenditures on these programs usually increased when inequality increased.[3] This mechanical increase in government health care expenditures could result in better or worse health care. If the increase in spending is enough to keep pace with the increase in recipients, and if the health care of the new recipients under the government program is at least as good as the health care they had before inequality increased, average health care will not decline. If the government program provides new recipients worse health care than they had before the increase in inequality, average health care quality will decline, which could affect infant mortality.

What little empirical research exists on the relationship between inequality and health care expenditures, suggests that an increase in economic inequality increases support for re-distributive policies at the national level (Perotti 1996, Alesina and Rodrik 1994) and for spending on medical care in particular (Kaplan et al. 1996. Mayer 2001).

Relative Deprivation and Gratification. Social comparison theory assumes that individuals evaluate themselves relative to others. Relative deprivation theory is a special case of social comparison theory, which claims that people mainly compare themselves to others who are more advantaged than themselves and pay less attention to those who are less advantaged (Merton and Kitt 1950, Davis 1959, Runciman 1966, Williams 1975).[4] Comparisons with others

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hand, the median voter will not want to pay for services that he will never use. Thus his support for services targeted to the very poor is likely to decline. This argument predicts an increase in spending on universal or near-near universal health insurance but not on health insurance targeted to the very poor. How this would effect infant mortality is not known.

[3] On average state and local taxes are slightly progressive. Given a progressive tax rate, anything that makes the rich richer would increase the revenue available to pay for health care. Of course, over the long run voters could decide to change tax policy, increasing or decreasing tax progressivity.

[4] An important distinction is between individual relative deprivation in which an individual compares his or her personal situation to the situation of other individuals, and group relative deprivation in which a person compares his or her relevant group's situation with the situation of another group. Growing inequality can affect both sorts of relative deprivation, but we mainly emphasize individual comparisons not group comparisons. Individual

who are more advantaged make individuals feel relatively deprived. As inequality increases, the opportunity for negative social comparisons increases because the distance between the rich and poor increases. Researchers interested in adult health and mortality have argued that inequality worsens adult health through social comparison (Marmot et al. 1991). For example, Wilkinson (1996) argues that income inequality affects health because ranking low in the social hierarchy produces negative emotions such as shame and distrust that lead to worse health via neuro-endocrine mechanisms and stress-induced behaviors such as smoking, excessive drinking, taking dangerous drugs, and other risky activities.

Relative deprivation theory assumes that individuals largely ignore others who are worse off than themselves. When people do compare themselves to others who are worse off, sociologists assume that they experience what they call "relative gratification" (Davis 1959). If individuals mostly compared themselves to the poorest people in society rather than to the richest, increases in inequality would make most people feel better, because the distance between themselves and the bottom would grow. If people mostly compare themselves to some real or imagined national average, increases in inequality will make the rich feel richer and the poor feel poorer. How this would affect the mean level of subjective well-being would depend on the functional form of the relationship between income differences and subjective well-being, which is unknown.

The remainder of this paper assesses some of these possibilities empirically, although we will not be able to provide direct tests of the relative deprivation hypothesis.

IV. Data and Methods.

We use the United States Vital Statistics Linked Birth and Infant Death Records (LBID) to measure a child's chance of dying in the first year or the first month after birth. The LBID links all birth certificates for infants born in a given year with the death records for those infants who die before their first birthday. We use data on births in 1985, 1987 and 1991. We use these years partly because the data are collected in a consistent way during this period (but not before or after) and partly because inequality rose over this period.

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comparisons are more likely to lead to isolation and stress while group comparisons are more likely to lead to collective action (Gurr 1970, Smith, Spears and Hamstra 1999). Stress is more relevant for birth outcomes.

Our sample covers about 12 million births and 120,000 deaths. To make the data more manageable we include all deaths but only a random 10 percent sub-sample of infants who survived. The appendix explains the sampling strategy. Once we omit cases with missing data, the sample includes 2,294,088 births. These occurred in 150 state-year clusters and our standard errors are corrected for this clustering. We also weight our analyses to account for our sampling design.

Level of Aggregation. Economic inequality may have different effects at different levels of geographic aggregation (neighborhoods, municipalities, counties, states). Theory provides little guidance as to which geographic unit is most likely to be relevant for infant mortality. Theories about social comparisons are ambiguous about the most relevant geographic unit because it is not clear how individuals select the people to whom they compare themselves. Theories about how changes in income inequality affect taxpayers' inclination to fund health care imply, in contrast, that political jurisdictions such as nations or states should be the relevant units.

This paper investigates the impact of state-level inequality. Several studies find that inequality across states is associated with adult mortality (c.f. Kaplan et al. 1996, Kawachi, Kennedy and Lochner 1997, Kawachi et al. 1997, Kawachi and Kennedy 1997). Two studies have also found an association between state-level inequality in the United States and infant mortality (Mellor and Milyo 2001, Meara 1999).

We also assess the effect of economic segregation between census tracts in states. Wilkinson (1997), Kennedy et al. (1998) and Soobadeer and LeClere (1999) argue that levels of aggregation below the state are too homogenous to observe a significant association between inequality and health. This claim assumes that families are highly segregated by income within states. However, as we show below this is not the case. Because states vary greatly in the degree to which they are economically segregated, we can determine whether infants born in states with a high degree of inequality within neighborhoods are more or less likely to die than infants born in states with a low level of inequality within neighborhoods.

The Measure of Inequality. We use the Gini coefficient for household income as our measure of inequality mainly because of its familiarity.[5] Of the seventeen estimates in Table 1, thirteen use the Gini coefficient as a measure of inequality. Previous research (Kawachi and Kennedy 1997) suggests that the correlation between adult mortality and the Gini coefficient was similar to the correlation between adult mortality and five other commonly used measures of inequality. This is because the inequality measures are themselves highly correlated. When we estimated the sensitivity of our estimates to alternative measures of inequality we found essentially the same results regardless of the inequality measure that we used.[6] Therefore we report only results using the Gini coefficient, which allows us to compare our results to earlier studies of the relationship between income inequality and infant mortality.

We use Census data to calculate the Gini coefficient for household income in each of the fifty states in 1980 and 1990. (See the Appendix.) For most analyses we lag the Gini coefficient one year prior to the year of the birth. Thus we measure inequality in 1984, 1986, and 1990. We use linear interpolation to approximate the Gini coefficient for each state in 1984 and 1986.[7] We lag the Gini coefficient because the level of inequality at conception and during the pregnancy is likely to be more important than the level of inequality at the time of birth. Arguably inequality at even earlier periods is more important than the level of inequality at birth. We experimented with other lags and report these results below. Over the years for which we measure infant deaths the mean Gini coefficient across states was .381 with a standard deviation of .019.[8] This and the means for all other variables that we use in our analysis are reported in the Appendix.

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[5] The Gini coefficient is the proportion of the total area below the 45 degree line that lies above the Lorenz curve, which plots the cumulative percentage of households against the cumulative percentage of income received by them. See Atkinson (1970, 1983) for a discussion of statistical differences among inequality measures.

[6] In our data the correlation between a state's Gini coefficient and two other commonly used measures of economic inequality (the standard deviation of log income, and the ratio of the ninetieth to the tenth percentile) are between 0.925 and 0.963. The correlation between inequality in the top half of a state's income distribution (the 90-50 ratio) and inequality in the bottom half of its distribution (its 50-10 ratio) is 0.721. The correlation between each of these alternative measures of state income inequality with individual's infant mortality is negative but small (none differs from zero by more than .061).

[7] During the early 1980s the increase in inequality was nearly linear. Any deviation from the linear trend is a source of measurement error in the inequality measure and thus it probably biases the coefficient of the Gini coefficient towards zero.

[8] Because of our sampling framework, this mean and all the others reported in Appendix Table 1 implicitly weights states by the number of births.

Control Variables. In principle we can estimate the effect of inequality (Gini) in state *s* on an infant *i*'s probability of death (D) by estimating:

$$D_{is} = \beta_g \, Gini_s + \varepsilon_i$$

where ε is an error term. However, states vary in many ways besides their level of economic inequality. Some of these differences are likely to be associated with both economic inequality and infant death. Our goal is to estimate what would happen to infant mortality as a result of an exogenous change in economic inequality. Such a change might be a consequence of national changes in the organization of work, in the value of various skills, in political and social factors influencing wage inequality, or in the effectiveness of the welfare state in creating a safety net for those with no earnings. How a state responds to such national changes is likely to depend on the skill distribution in the state, the available mechanisms for increasing high-premium skills, the generosity of the state's social programs, the "culture" of the state, and many other factors. To estimate the effect of an exogenous change in inequality, one must control all the exogenous determinants of inequality that also affect birth outcomes.

To control potentially relevant omitted variables, we first include dummy variables for each of the nine census divisions in which a birth occurred. These dummy variables control characteristics of the census division that remain unchanged over the period of observation. Because there are nine divisions, each typically include five or six states. An alternative strategy is to control state dummy variables. Such a model would be equivalent to estimating the within-state effect of a change in inequality. This strategy has the advantage of controlling all invariant characteristics of states. However, it has three important disadvantages. First, it increases the relative importance of measurement error in independent variables measured at the state level, including the measure of inequality, which would downwardly bias the estimated effects. Second, if the lag structure of the model is not correctly specified, this model can again result in downwardly biased estimates of the effects of inequality. Third, including state dummy variables greatly reduces the degrees of freedom available to estimate the model, which in turn increases the standard errors of the estimates. If divisions capture all relevant unobserved variables, using state fixed effects would needlessly raise the standard errors. Thus while we test the sensitivity of the model to inclusion of state rather than division fixed effects, we emphasize results that include division fixed effects.

We include year fixed effects to account for the secular decline in infant mortality. With both division and year fixed effects, variation in inequality derives from a combination of changes in inequality within states over time and differences in equality among states in the same division.

We also control a set of arguably exogenous state-level determinants of inequality that can change over time. These include the state's racial and ethnic mix and mean household income.[9] The correlation between mean household income and the Gini coefficient was -0.425 in 1980 and –0.559 in 1990, so omitting this variable could be a serious source of bias.[10] We also control mother's age and marital status as well as the race of the child.

With these controls our basic equation for estimating the effect of inequality on an infant's probability of death is thus:

$$D_{isy} = \beta_g Gini_{sy} + b_{\mathbf{s}} \boldsymbol{S}_{\mathbf{sy}} + \beta_b F_i + \gamma_y + \gamma_d + \varepsilon_{isy}$$

where **S** is the set of exogenous state characteristics, F is a set of family background characteristics, γ_y is a set of year dummy variables and γ_d is a set of dummy variables denoting the census division in which the child was born.

Mechanisms. We estimate the importance of three mechanisms: the nonlinear relationship between family income and infant death, economic segregation, and state health care spending. We discuss the estimation strategy for determining the importance of these mechanisms below.

V. Results

The Overall Effect of Inequality. Table 2 shows the effect of the state Gini coefficient on an infant's probability of death within a year after birth, within the first 28 days after birth, and between 28 days and one year after birth. The numbers in the cells are partial derivatives from a probit model. They indicate marginal effects assessed at the mean of all the independent

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[9] In principle inequality could affect the racial composition of the state as well as vice versa. But in practice inequality cannot have much effect on a state's racial composition, because the inter-year correlations for both percent black and percent Hispanic are about .98.

[10] This negative correlation could reflect a negative effect of inequality on mean income rather than the other way around. Empirical research on the relationship between economic inequality and economic growth at the national level is inconclusive (Forbes 2002). Because inequality and mean income are correlated, and because it seems likely that state income levels affect inequality more than vice versa in the US, we control state mean income.

variables. The numbers in parentheses are *z*-statistics, which have been corrected to account for clustering of births within states.

The first row of Table 2 shows that with no controls, being born in a state with a high level of inequality is associated with a significantly greater probability of death than being born in a state with less inequality. This model suggests that increasing the Gini coefficient by about one standard deviation (.02) increases the mean probability of infant death by $.02(.058) \approx .0012$ or about 10.9 percent of the observed mean (.011). The second column in Table 2 shows that the effect of a .02 increase in the Gini coefficient raises neonatal deaths by .02(.040) = .0008 or 11.4 percent of the observed mean (.007). The last column shows that this same increase in the Gini coefficient is associated with an increase in the probability of post-neonatal deaths of .02(.018) = .0004 or 10percent of the mean probability of post-neonatal death (.004).

Model 2 includes dummy variables for census divisions, year, and the other state characteristics described above. With these controls the effect of inequality on the probability of death within a year is smaller but it remains statistically significant. With these controls the effect of the Gini coefficient on the probability of neonatal death is also smaller but statistically significant, but the effect of the Gini coefficient on post-neonatal death is nearly zero.

Model 3 controls mother's age and the race of the child. Controlling these factors modestly reduces the effect of the Gini coefficient on infant death and on neonatal death. Other maternal characteristics are likely to be correlated with mothers' age and race. So these results do not suggest that variation in maternal characteristics across states is likely to be a large source of bias in the estimated effect of inequality. Model 3 is arguably the reduced form estimate of the effect of inequality. It shows that inequality has a small and marginally statistically significant effect on an infant's probability of death in the first year but a nontrivial and statistically significant effect on an infant's probability of death in the first month after birth. These results suggests that a one standard deviation rise in the Gini coefficient increases the probability of neonatal death by .02(.014) = .0028, which is 4 percent of the observed probability of neonatal death. The Gini coefficient has a very small effect on the probability of post-neonatal death. Combining neonatal and post-neonatal deaths to get the effect of inequality on the overall infant mortality rate may obscure an important cost of inequality, namely its effect on neonatal mortality.

Mechanisms. Looking at the overall effect of inequality without understanding the mechanisms through which it operates may also be misleading.

Nonlinear Effects of Family Income. The LIBD data do not include information on family income so we cannot directly test the hypothesis that the effect of inequality is due to the nonlinear relationship between parental income and infant death. As an alternative we estimate whether the effect of inequality is greater in poor than in rich states. Given the same level of inequality, the poor will usually be poorer in a state with a low average income compared to a state with a high average income.[11] If inequality mainly affects infant deaths due to a nonlinear relationship between family income and infant death, its effect should be greater in poorer states.

The range of average incomes across states is considerable. In 1989 the most affluent state was Connecticut with a median household income of $41,721 (in 1989 dollars). The poorest state was Mississippi with a median household income of $20,136. The median income in Mississippi was thus about half that in Connecticut (Statistical Abstract of the United States, 1993, Table 719).[12] But it also costs more to live in Connecticut than in Mississippi. The United States does not produce state cost of living indexes, but housing costs account for about a third of family expenditure (Statistical Abstract of the United States, 2000 Table 732) and vary across states more than most other expenditures.[13] Thus housing costs are a fairly good indicator of living costs. To try to take into account variation in the cost of living, we control state mean housing costs. Mean housing cost is the weighted average of both owner cost (mortgage, taxes, and utilities) and renter costs (rent and utilities).

To see if inequality has a greater effect in low-income than in high-income states, we re-estimated Model 3 in Table 2 controlling housing costs and including the interaction between the Gini coefficient and mean state income. Table 3 shows that this interaction term is positive and

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[11] Given the same Gini coefficient the poor will be poorer in states with a low average income than in states with a higher average income unless the Lorenze curves for the states cross.

[12] State rankings on income are fairly consistent over time. Connecticut, New Hampshire, Maryland, Alaska and Hawaii are always among the most affluent states while southern states are always among the poorest.

[13] For example, in 1998 average consumer unit expenditures were highest in the west and lowest in the south. The average food expenditure in the south was 86.3 percent of the average food expenditure in the west. But average expenditure on rent in the south was only 61.2 percent of the average expenditure on rent in the west. Average expenditures for an owned home in the south were 65.8 percent of the expenditure for an owned home in the west. Expenditures for apparel and services, transportation, and other categories varied much less across regions than even the expenditures for food.

statistically significant for the probability of death in the first year after birth. The effect of both state mean income and the Gini coefficient is negative and statistically significant. These results therefore suggest that the positive relationship between inequality and an infant's probability of death is greater in high-income than in low-income states. This is the opposite of what we would expect if the relationship between family income and infant death were non-linear. The same is true for neonatal and post-neonatal deaths.

If the effect of family income were nonlinear we might also expect the effect of educational attainment to be non-linear. Thus a second test of the hypothesis that the effect of inequality is due to the non-linear relationship between income and mortality is to re-estimate Model 2 in Table 2 controlling both mother's education and mother's education squared. When we do this the effect of the Gini coefficient hardly changes.[14]

Although these results provide no support for the hypothesis that non-linearity in the relationship between family income and infant death results in inequality increasing infant deaths, it also does not disprove it. However, if this non-linearity results in inequality increasing infant deaths, other factors must out-weigh that effect.

Economic segregation. Model 4 in Table 2 controls the level of economic segregation in a state in order to assess the hypothesis that inequality affects infant deaths by increasing economic segregation. Economic segregation is the proportion of the total variance in income in a state that is between rather than within census tracts. The appendix explains the construction of this variable. An increase in economic inequality is associated with an increase in economic segregation (Mayer 2001). Adding segregation to the model reduces the effect of inequality on both overall infant deaths and on neonatal deaths to nearly zero. This is because, as Model 1 in Table 4 shows, living in a state with a high level of economic segregation is associated with a higher probability of infant death than living in a less economically segregated state. A one standard deviation (.10) increase in economic segregation in a state is associated with a .006(.10) = .0006 increase in the probability of infant death, which is 5.5 percent of the mean probability of infant death. This same increase in economic segregation is associated with a .004 (.10) = .0004 increase in neonatal deaths, which is 5.7 percent of the mean probability of neonatal death.

[14] The coefficient for the Gini coefficient is .012 (z= 1.44) for infant death in the first year, .012 (z=1.86) for neonatal mortality and, -.001 (z=-.25) for post neonatal mortality.

These results imply that had economic inequality not increased economic segregation, it would have had little effect on infant deaths. Put another way, the main negative effect of inequality on an infant's chances of surviving is due to the fact that inequality increased economic segregation (and its correlates).

State Spending. Our measure of state spending on health care is mainly the state's contribution to Medicaid but it also includes state spending on health care not associated with Medicaid, such as state contributions to health clinics. Appendix 1 describes this variable in detail. Inequality is positively associated with state spending on health care.[15] Because expenditures on health care could vary with the cost of living in the state, this model also controls housing costs. Model 5 in Table 2 shows that adding these variables increases the effect of the Gini coefficient on the probability of death in the first month as well as the probability of death in the first year. This is because, as the second column in Table 4 shows, state health care expenditures are associated with a decrease in the probability of neonatal deaths and hence deaths in the first year. This suggests that had inequality not increased spending on health care it would have increased infant deaths significantly, mainly by increasing neonatal deaths. This is consistent with research showing that Medicaid reduces neonatal mortality more than post-neonatal mortality (Currie and Gruber 1997).

When states increase expenditures on health care, this can be because they cover more families or because they spend more per covered family. During the period when these data were collected, all AFDC recipients were eligible for Medicaid, which was the main state health care expenditure. If inequality reduced infant deaths mainly by increasing the number of Medicaid recipients, controlling the number of recipients would increase the harmful effects of inequality. Model 6 in Table 2 shows that the effect of inequality increases slightly when we include the proportion of state residents receiving AFDC, suggesting that the harmful effects of inequality may have been avoided partly by a "mechanical" increase in Medicaid recipients. The last row in Table 4 shows that the effect of health care expenditure on neonatal deaths hardly changes when the proportion of AFDC residents is controlled. This result suggests that the

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[15] Using state level data from 1970 to 1990 the coefficient predicting per capita health care spending (in constant 1998 dollars) is 3087.52 (t= 3.26) in a model that controls state fixed effects, state mean income, percent of state residents who are black, percent of state residents who are white and year. This implies an increase in state spending equal to about a fifth of the mean level of state spending for a .02 increase in the Gini coefficient.

reduction in infant death due to health care spending is mainly due to additional spending per recipient.

Inequality increases economic segregation, which increases infant deaths. But inequality also increases state spending on health care, which reduces infant deaths. These two factors (and any uncontrolled correlates) account for much of the effect of inequality on infant deaths. Inequality has very little effect on post-neonatal deaths, which leads to speculation that it affects birth weight and pre-term births, which account for a large proportion of neonatal deaths. This is a useful topic for future research.

Sensitivity Test. When we estimate model 3 in Table 2 (the reduced form model) but substitute state dummy variables for census division dummy variables, the estimated effect of inequality on infant deaths and on post-neonatal deaths increases, but the z-statistics are much smaller so the effect of inequality is statistically insignificant. (The coefficients are .024 for infant death, .009 for neonatal death and .018 for post-neonatal death. The z-statistics are 1.10, .05, and 1.70 respectively.) There is no way to determine which model provides the best estimate, but all the point estimates are positive, suggesting the economic inequality increases infant deaths.

Inequality may not have an immediate effect on infant deaths. Depending on the mechanism, it could take several years for a change in inequality to affect infant deaths. Both changes in state health care spending and changes in residential segregation are likely to lag changes in the distribution of income. Ideally we would like to use a lag structure based on a theory of how inequality operates. But no such theory exists. To experiment with the lags, we estimated Model 3 in Table 2 but added a measure of state inequality five years before a birth. In the models predicting both the probability of death within a year of birth and the probability of post-neonatal death, the coefficient for current inequality is greater than the coefficient for inequality five years earlier, but the difference is small and neither coefficient is statistically significant. Nor is the difference between the coefficients. However, in the model predicting neonatal deaths, the coefficient for current inequality (b= .046, t= 2.59) is greater than the coefficient for inequality five years age (b= -.039, t= 1.93) suggesting that the level of inequality near the child's birth is what matters.

VI. Conclusion

Infants born in states with high levels of inequality have a greater chance of dying in the first year than infants born in states with lower levels of inequality. Controlling a state's racial and ethnic composition, age composition, mean income, and census division, as well as the mothers' age and race, reduces the estimated effect of inequality but it remains marginally significant. Inequality increases economic segregation, which increases infant death. Inequality also increases state spending on health care, which reduces infant death. However, the net effect of the change is to increase infant deaths. If a transfer of health care services is equivalent to a transfer of income, the fact that an increase in spending on health care for the poor reduces infant deaths is equivalent to saying that a reduction in inequality reduces infant deaths.

Appendix

State-level variables.

Most of the state-level variables used in this paper come from the 1980 and 1990 Public Use Microdata Sample (PUMS) of the U.S. Census 5 percent samples.

Household Income was computed by summing the components of income for each person in a household within a state. Using components of income rather than the variable for total household income increases the detail available at the upper tail of the distribution by avoiding Census Bureau top-coding of total income. To reduce problems of comparability over time that arise from changes in the Census Bureau's top-codes for income components, we created uniform income components and top-codes for all years. Variables are top-coded by reassigning values above the lowest 99th percentile of positive values among the years to the median of all values across years that lie above that lowest 99th percentile. The same was done for negative values using the highest 1st percentile as the cutoff. I sum the resulting components to get household income. All measures of income are adjusted to 1998 dollars using the CPI-U-X1. We use this income measure to calculate state-level measures of income and income inequality. Persons in group quarters were excluded from all calculations.

Percent African American and Percent Hispanic were computed for each state by summing the number of state residents who reported their race as black or ethnicity as Hispanic and dividing by the state population.

Age composition includes two variables, one for the percent of state residents who are less than eighteen years old and the other for state residents who are greater than 65 years old.

Housing Costs include mortgage payments, taxes and utilities for owners and rent and utilities for renters.

Economic Segregation. Economic segregation is measured as the percent of the total income variance in a state that is between census tracts. Suppose we divide a geographic area such as a state (or metropolitan area or country) into mutually exclusive geographic areas such as neighborhoods. We can then decompose the total variance of household income in the state (σ_{ts}^2) into two additive components: a between-neighborhood component (σ_{bn}^2) and a within-neighborhood component (σ_{wn}^2). This yields the identity:

$$\sigma_{ts}^2 = \sigma_{bn}^2 + \sigma_{wn}^2 \qquad (1)$$

The ratio of the between-neighborhood variance to the total variance ($\sigma_{bn}^2/\sigma_{ts}^2$) is a measure of economic segregation (Farley 1977, Jargowsky 1996). In the absence of economic segregation, all neighborhoods will have the same mean income and $\sigma_{bn}^2/\sigma_{ts}^2 = 0$. With complete economic segregation, there is no income variation within neighborhoods and $\sigma_{bn}^2/\sigma_{ts}^2 = 1$.

To estimate the level of segregation in a state we begin with the variance of total household income in a state calculated from the PUMS data described above. Next we compute the mean household income of each census tract in the state using data from the STF5 files by dividing the aggregate household income of the tract by the number of households in the tract. We weight mean tract income by the number of households in the tract and calculate the variance of mean tract income. This is the *between tract variance of income*. The *within-tract variance of income* is the total variance of income less the between tract variance. The measure of segregation is the percent of the total variance in the state that is between census tracts.

Not all the geographic areas of states are grouped into census tracts. The number of census tracts changed over time both because new tracts were created and because the boundaries of old tracts changed. The number of tracts increased from 41,925 in 1980 to 48,187 in 1990. We use all the tract data available in a year, rather than using a consistent definition of tracts. We do this because the growth in census tracts reflects growth in and concentration of population. We estimate the mean income for the state population not living in census tracts and treat that area like a "super census tract." That is, for the purpose of computing the between tract variance of income we treat the weighted mean of the untracted area as a census tract. This allows the within and the between tract variance of income to exactly sum to the total variance of income for the state. Because we implicitly weight by state population (since higher population states have more births), states with a higher proportion of their residence living in census tracts get greater weights than states with a smaller number of residents living in census tracts.

Health care expenditures include state payments to private vendors for physician and other professional medical or dental services, private hospital care, long-term health care, ambulatory care and so forth. It includes direct payments to vendors under Medicaid, general relief, public assistance, and other welfare programs. Data are from the U.S. Census Bureau Annual Survey of Government Finances. Expenditures are adjusted to 1998 dollars using the CPI-U and have been divided by the total state population to get annual per capita expenditures.

Maternal and child characteristics

Mother's age and the child's race are taken from the linked infant birth and death records.

Sampling Strategy

In order to make estimation of the models manageable, the following sampling strategy was employed. We first selected all birth records ending in a death within one year. We then selected a random sample of 10 percent of births that did not end in a death in each state and year. We then weight this sample up by a factor of ten when we estimate the overall effect of economic inequality. Standard errors are computed on the number of cases in the sample and not the weighted sample size.

Table A1, Means and Standard Deviations of Variables Used in the Analysis

Variable	Mean	Standard Deviation
Probability of death within one year after birth	.011	.102
Probability of death within one month after birth	.007	.081
Probability of death between one month and one year after birth	.004	.062
Mother's age	26.076	5.612
State proportion African American mothers	.20	0.40
Gini coefficient	0.38	.019
State mean income/10,000	4.622064	.629525
State percent black	11.694	7.861
State percent Hispanic	6.672	7.921
State per capita expenditure on health care/1,000	.032557	.0117
Economic segregation	.291	.10
Mean housing cost	.08076	.01653
Proportion state residents receiving AFDC	.045	..0152
Percent less than 18 years old	26.136	2.222
Percent greater than 65 years old	12.333	2.027

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Table 1, Previous Research on the Effect of Inequality on Infant Mortality

Author	**Data and time period**	**Models, controls**	**Results (mean [sd] of inequality measure)**
Cross-national, cross-sectional			
Rodgers (1973) Estimate 1	51 countries around 1965	Various functional forms of mean income	β_g = 112.5* - 64.1
Estimate 2	"less developed countries" (N not given)	Same	β_g= 61.3 (mean not given)
Flegg (1982)	47 under-developed countries most between 1965-1975 Mean IMR=107.1	Mean income, female literacy rate, nurses, physicians per 10,000	$\beta\log_g$= .654*
Pampel and Pillai (1986)	18 advanced industrial market economies, 1950 to 1975, N=108	GNP per capita, unemployment rate, literacy, fertility, government expenditure on medical, public health and welfare programs, ethnic and language diversity, teen births, female tertiary school enrollment, physicians, hospital beds and nurses per 1,000	β_g = -7.98 (38.3 [3.4])
Waldman (1992) Estimate 1	57 country and year (1960, 1970) data points Mean IMR = 74.0, SD = 56.9	Income of poorest 20%, female literacy, #doctors and # nurses per capita, %urban, continent	As income of richest 5% increases IMR increases β_r= 1.96* (24.38 [8.28])
Estimate 2	41 developing country data points (1960 and 1970) Mean IMR =94.4, SD = 54.6	Same	β_r = 2.09* (27.02 [8.03])
Wennemo (1993)	9 developed countries, LIS data 1950 to 1985, N=136	GDP per capita, Gini is bases on after-tax and after transfer income per capita	β_g = 33.86* (no means given)
Judge, Mulligan and Benzeval (1998)	15 OECD countries, 10 for two years	Year, GDP per capita, health expenditure, social security transfers, female labor force participation	β percent of income going to poorest 60% = -.024, becomes small and insignificant when female labor supply is controlled
Mellor and Milyo (2001) Estimate 1	47 countries, 1990, Mean IMR = 48.1	GDP per capita, secondary school enrollment	β_g = 1.688* with no controls; with controls β_g = -.818* (38.9 [9.25])
Estimate 2	12 OECD countries, 1990, Mean IMR = 38.7	same plus year	β_g = -.007 with no controls, positive and insignificant with controls

Author	Data and time period	Models, controls	Results (mean [sd] of inequality measure)
Across U.S. States, Cross-sectional			
Kennedy et al. 1996a,b	States in 1990	Poverty rate, smoking	Robin Hood Index positive and significant
Meara (1999)	1990 Census data, US Vital Statistics IMR rate = .0086	State median family income, share of births by birth weight	β_g = .0447* (.432 [.026]) similar results with other measures of inequality
Change in Inequality within Countries			
Judge, Mulligan and Benzavel (1998)	15 LIS countries, 10 of these at 2 time periods	Year, GDP per capita, health expenditure, social security transfers, female labor force participation	Δ Gini negative and insignificant
Mellor and Milyo (2001) Estimate 1	30 countries, 1960, 1970, 1980, 1990, N=120, mean IMR =63.1, SD = 51.3	GDP per capita, secondary school enrollment, year	Δ Gini negative and insignificant for 10 and 20 year changes
Estimate 2	12 OECD countries 1960-90	Same	Δ Gini negative and insignificant for 10 and 20 year changes (40.5[9.67])
Change in Inequality within U.S. States			
Mellor and Milyo (2001)	48 continental states, 1950-1990, mean IMR= 19.6, SD=8.9	State median income, % with high school education, % with college education, % black, % urban, age composition of state	Δ Gini negative and insignificant for 10 and 20 year changes with controls (.376[.038])
Individual-level data			
Meara (1999)	1990 linked infant birth/death records, 1980 National Natality and Fetal Mortality Survey, 1988 National Maternal and Infant Health Survey, Mean IMR = 8.6	State median family income, log household income, mother is black	β_g is negative and insignificant. (43.2)

Notes: β_g is the OLS unstandardized coefficient for the Gini Coefficient. IMR is deaths per 1,000 live births
* indicates a statistically significant effect

Table 2, The Effect of the Gini Coefficient on Infant Death by the Timing of the Death

Model	Probability of Infant Death	Probability of Neonatal Death	Probability of Post-Neonatal Death
Model 1: No Controls	.058 (6.04)	.040 (5.65)	.018 (5.13)
Model 2: Controlling state mean income, % black, % Hispanic, age distribution, census divisions	.018 (2.00)	.016 (2.23)	.001 (0.35)
Model 3: Adding mother's age and race	.015 (1.94)	.014 (2.10)	.001 (0.26)
Model 4: Adding state economic segregation	.0015 (0.20)	.003 (0.47)	-.0019 (0.42)
Model 5: Adding state expenditure on health care, housing costs	.023 (2.26)	.022 (3.01)	.002 (0.30)
Model 6: Adding proportion of state residents receiving AFDC	.029 (2.97)	.024 (3.15)	.005 (0.99)
Mean			
Number of Observations	2, 294,088	2,294,088	2,294,088

Source: 1985, 1987, 1991 combined Linked Birth and Infant Death Records.
Notes: All models control the year of the birth. Coefficients are partial derivatives from a probit model. The absolute value of *z*-statistics are in parentheses and are corrected for clustering in states.

Table 3, Effect of the Gini coefficient on the probability of infant deaths by the timing of infant death and state mean income

Predictor	Probability of Infant Death	Probability of Neonatal Death	Probability of Post-Neonatal Death
Gini Coefficient	-0.099	-0.067	-0.028
	(2.48)	(2.08)	(2.12)
State Mean Income/10,000	-0.00873	-0.00608	-0.00244
	(2.52)	(2.17)	(2.33)
Gini*State Income	.0248291	.0176909	.0064318
	(2.57)	(2.23)	(2.40)

Source: 1985, 1987, 1991 combined Linked Birth and Infant Death Records.

Notes: All models control census division, year, percent black, percent Hispanic, age distribution in the state, housing costs, mom age and child race. Coefficients are partial derivatives from a probit model. The absolute value of z-statistics are in parentheses and are corrected for clustering in states.

Table 4, Effect of economic segregation and state health care expenditures on the probability of infant death

Predictor	Model 1	Model 2	Model 3
Infant Death			
Economic Segregation	0.0056	0.00323	0.00345
	(3.90)	(2.01)	(2.27)
Health care Expenditure/10,000		-0.0332	-0.0281
		(3.31)	(2.95)
Proportion of state residents receiving AFDC			-0.0179
			(2.65)
Neonatal Death			
Economic Segregation	0.00437	0.0023	0.00237
	(3.99)	(1.89)	(1.97)
Health care Expenditure/10,000		-0.0279	-0.0263
		(3.71)	(3.51)
Proportion of state residents receiving AFDC			-0.0058
			(1.14)
Post-Neonatal Death			
Economic Segregation	0.00122	0.000824	0.000980
	(1.85)	(1.14)	(1.53)
Health Care Expenditure/10,000		-0.00597	-0.00271
		(1.47)	(0.78)
Proportion of state residents receiving AFDC			-0.011
			(2.96)

Source: 1985, 1987, 1991 combined Linked Birth and Infant Death Records.

Notes: All models control the Gini coefficient, state mean income, age and racial composition of the state, mother's age, child's race. Models 2 and 3 also control state average housing costs. Cell entries are partial derivatives from a probit model. The absolute value of z-statistics are in parentheses and are corrected for clustering.