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Health Endowment at Birth and Variation in Intergenerational Economic Mobility: Evidence From U.S. County Birth Cohorts

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Abstract

New estimates of intergenerational economic mobility reveal substantial variation in the spatial distribution of opportunity in the United States. Efforts to explain this variation in economic mobility have conspicuously omitted health despite it being a key pathway for the transmission of economic position across generations. We begin to fill this gap in the literature by examining the relationship between health endowment at birth and intergenerational economic mobility across county birth cohorts in the United States, drawing on estimates from two population-level data sets. Exploiting variation across counties and over time, we find a negative relationship between the incidence of low-weight births and the level of economic mobility as measured in adulthood for the county birth cohorts in our sample. Our results build on a large and growing literature detailing the role of early childhood health in the transmission of economic status across generations and suggest that the incidence of low-weight births is negatively associated with intergenerational economic mobility.

Keywords

Birth weight; Mobility; Inequality; Health

Introduction

New estimates of intergenerational economic mobility reveal substantial variation in the spatial distribution of economic opportunity in the United States (Chetty et al. 2014a, b). In Sussex County, New Jersey, 17.5 % of children born in 1980 to parents in the bottom quintile of the national income distribution reached the top quintile by adulthood. In Essex County, New Jersey, just a 45-min drive to the south, only 6.1 % of children born to parents in the bottom quintile had reached the top of the income distribution in adulthood (Chetty et al. 2014a, b). Moving from the bottom to the top quintile was almost three times as common in Sussex as in Essex County.

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Studies seeking to explain this geographic variation have looked at a range of social, institutional, and policy factors, including school quality, tax structures, government spending, income inequality, and even social capital (Chetty et al. 2014a, b; Behrman and Rosenzweig 1999; Solon 1992, 2002). Health has been conspicuously absent from these analyses despite a robust and growing literature detailing how health—particularly in early life—predicts life chances. To date, the question of whether geographic variation in infant health predicts variations in economic mobility has not been explored. In this study, we aim to answer this question and, in so doing, to explore how geographic variation in population health may be correlated with geographic variation in intergenerational economic mobility.

Low birth weight (LBW) is both *predicted by* an infant's parents' social position at birth and *predictive of* numerous developmental outcomes (Aizer and Currie 2014; Conley and Bennett 2000; Currie and Moretti 2007). Infants weighing less than 2,500g at birth perform worse on a variety of cognitive measures (Hack et al. 1995) and, as found in twin studies, LBW has causal effects on educational achievement and attainment (e.g., Figlio et al. 2013). Being born underweight casts a long shadow over the life course, increasing the odds of suffering from chronic conditions and reducing lifetime educational attainment and wages (Almond et al. 2005; Almond and Currie 2011; Black et al. 2007; Behrman and Rosenzweig 2004; Case et al. 2005; Conley and Bennett 2000; Conley et al. 2006). Moreover, low-weight births tend to reproduce existing inequalities because LBW is more common among African Americans and among parents with lower levels of education, income, or occupational status (Aber et al. 1997; Hughes and Simpson 1995; Kost and Lindeberg 2015).

As an indicator of disadvantage, as well as a potential pathway for the reproduction of inequality both within and between groups across generations, birth weight is an essential starting point for examining the relationship between health and intergenerational economic mobility. Determining whether and to what extent spatial and temporal variation in population health—in this instance, birth weight—correlates with variation in levels of economic mobility is critical to understanding the processes that condition both. As shown in Fig. 1, the percentage of low-weight births at the county level varies substantially across the United States, which may be associated with economic mobility.

In this study, we investigate the relationship between birth weight and intergenerational economic mobility by linking estimates drawn from two population-level data sets. First, we examine the degree to which the spatial distribution of low-weight births across counties corresponds to the distribution of economic mobility for a given birth cohort. Second, we examine whether within-county variation in the incidence of low-weight births across adjacent cohorts can account for the observed variation in economic mobility outcomes for the same cohorts within the same county. To answer these questions, we match county-by-birth cohort estimates of low-weight births generated from Vital Statistics data to county-by-birth cohort estimates of economic mobility generated by the Equality of Opportunity Project from linked parent-child data from the Internal Revenue Service (IRS). Estimates generated from these unique, population-level data sources enable us to analyze— for the first time—the extent to which variation in the incidence of low-weight births is associated with variation in economic mobility for a given birth cohort. Although we cannot establish a causal relationship between birth weight and mobility with these data, the fact that variation in within-county trends in birth weight predicts subsequent within-county trends in economic mobility does rule out a number of otherwise plausible explanations for the correlation. In so doing, this study highlights the need for incorporating measures of population health in future efforts to understand spatial and temporal variation in economic mobility outcomes.

Birth Weight and the Intergenerational Transmission of Economic Status

Socioeconomic status is a fundamental cause of health disparities, and infant birth weight is one mechanism through which the social becomes physical, linking SES and health. Birth weight both reflects existing social inequalities and reproduces them (Link and Phelan 1995; Phelan et al. 2010).

Parental SES is a strong predictor of infant birth weight (Aizer and Currie 2014; Brooks-Gunn and Duncan 1997; Currie 2009). The incidence of LBW among the most disadvantaged mothers is three times that among the most advantaged (Aizer and Currie 2014). Maternal disadvantage leads to low-weight infants through a variety of pathways, including lack of access to medical care, poor health behaviors, worse maternal health, and increased exposure to pollution (Aizer and Currie 2014; Currie 2011). Poor and minority women are also exposed to more sources of stress, such as domestic violence, which have been shown to negatively impact birth weight (Aizer 2011; Geronimus et al. 2006). Overall, African American mothers, single mothers, and those with lower levels of education are more likely to have a low-weight baby, indicating that low birth weight is socially structured and an indicator of disadvantage (Aber et al. 1997).

Yet, birth weight is more than just a marker of social disadvantage; it also serves to reproduce disadvantage across generations. A number of twin studies have found that even after taking account of parents' social and economic characteristics, birth weight has a lasting, independent effect on a child's health and cognitive development. These findings contribute to a large and growing literature spanning the social and medical sciences demonstrating that health endowment at birth is an important causal predictor of life chances. Using large-scale administrative data, Figlio et al. (2013) offered perhaps the most comprehensive study of the consequences of LBW for educational outcomes. Using twins fixed effects, the authors isolated the effect of birth weight on future outcomes from variation in-home or social contexts while also exploring the impact of school inputs. They found that the twin born at a higher birth weight has better cognitive skills as measured by test scores, an effect that remains constant across the first 13 years of life. Furthermore, they found that the greater the gap in birth weight between two twins, the larger the gap in test scores. However, as they noted, despite the significant effect of birth weight, social factors are more predictive of future outcomes: it is better to be the lighter child of a college-educated mother than the heavier child of a high school graduate. Using a similar identification strategy with twins, Black et al. (2007) found substantial, long-term effects of birth weight on IQ, earnings, and educational attainment. Studies examining the short-run health effects of LBW using twins fixed effects also demonstrated a significant effect on other important measures, such as post-neonatal mortality (Conley et al. 2006). Overall, these studies demonstrated a strong causal effect of birth weight on future outcomes given that they were uniquely able to control for all contextual and unobserved factors.

Although twin studies provide a useful analysis of causal effects, correlational studies demonstrate other association with LBW that might impact economic mobility prospects. Higher birth weight is associated with more years of schooling and greater human capital attainment (Royer 2009), while lower birth weight is associated with increased behavioral issues, such as ADHD, especially among boys (Gurevitz et al. 2014; Kelly et al. 2001). Evidence suggests that LBW exacerbates other negative social processes; the negative outcomes associated with being born to a low-income, less-educated, or minority mother are stronger for LBW children than for their regular-weight peers (Hack et al. 1995). Case et al. (2005) found a correlation between prenatal health and health in midlife, demonstrating that low-weight infants—particularly those born into impoverished families—experience worse health across the life span and have lower educational achievement. An important implication is that poor health early in life can impede educational attainment and thus is a pathway through which LBW affects future socioeconomic attainment. Boardman et al. (2002) suggested a heterogeneous effect of LBW: very LBW status has a large association with children’s outcomes, but moderate LBW has a small association when compared with mothers’ education or race. Importantly, the effect of birth outcomes remains constant over the life course, and social factors become more important in older children.

Despite evidence that birth weight has a direct effect on educational attainment and labor market outcomes—both key pathways of economic mobility—very little work has directly examined the link between birth weight and economic mobility outcomes. An important exception is Palloni’s (2006) research on health endowments and mobility. Examining small samples of men born in the UK in 1958, Palloni found a significant and substantial association between LBW and health status at age 7 and cognitive performance at age 11. Palloni ran simulation models to predict the impact of health on future outcomes, and his findings suggested that approximately 11 % of the variation in an adult’s economic status is associated with early health endowments. He further argued that improvements in child health could potentially equalize opportunities by improving the prospects for those at the bottom. Although Palloni’s study offers important insights into how birth weight may influence economic mobility, the sample used and the methodology employed limited the generalizability of his results.

Finally, our study builds on the literature in economics and sociology that emphasizes the importance of place in the process of economic mobility. Chetty et al. (2014a, b) demonstrated that geography and the characteristics of one’s county or commuting zone play an integral role in determining one’s chances of upward mobility beyond purely individual characteristics. Wilson (1987) demonstrated how disadvantage is compounded in communities of color, isolating them and inhibiting the process of upward mobility. Building on this work, Watson (2009) argued that inequality is associated with increasing segregation and isolation of minorities, while Sharkey (2013) argued that the transmission of disadvantage is tightly linked to the persistence of neighborhood inequality. Indeed, as Sharkey explained, the environment in which a child matures structures experiences and opportunities in ways that alter that child’s trajectories. Infant birth weight is one way in which the environment an individual grows up in is associated with, and potentially limits, future opportunities. Our study brings together the sociological literature that examines the importance of place and community with the public health and economics literature that grapples with child health and income mobility. In doing so, we shed new light on the transmission of disadvantage, providing a deeper understanding of the distribution of opportunity in America.

Research on the causes and consequences of LBW suggests that this measure of health endowment at birth may be a key pathway for the transmission of economic status across generations and within communities. However, to date, there has been no direct test of the link between birth weight and intergenerational economic mobility. Here, we analyze the extent to which county-by-birth-cohort variation in economic mobility outcomes in adulthood is associated with variation in health endowments at birth.

Data and Analytic Strategy

Data

Our dependent variable is a measure of intergenerational economic mobility by county and year generated by the Equality of Opportunity Project. These authors linked federal income tax records of all children born between 1980 and 1991 to the tax records of their parents (or parent, if the child lives with only one parent) to generate county-level estimates of intergenerational economic mobility. They first ranked all children in a given birth cohort by income at age 26 and assigned them an income percentile in the national distribution from 1 to 100. They then ranked the parents of these children by their income when the child was aged 12–16 and assigned the parents an income percentile rank from 1 to 100. Their county-by-year mobility statistics are available online (equality-of-opportunity.org). They then fit a linear model, using data across the distribution, to generate a separate regression for each county cohort. Although the linearity assumption is strong, Chetty et al. (2014a, b) found that the relationship between mean child ranks and parent ranks is almost perfectly linear and highly robust to alternative specifications. Therefore, the slope and intercept generated by the predicted 25th and 75th percentiles provide a succinct summary of the conditional expectation of a child's rank given the parent's rank. Importantly, these values were generated from children observed across the income distribution: that is, they observed children at every percentile. Our interpolation is drawn from the same equation that Chetty et al. (2014a, b) used to generate the 25th and 75th percentile. (See Online Resource 1 for more information.) This method allowed them to generate a predicted value for children born to parents at any income level.

We then calculate the slope and the intercept of each line using the two data points so that we can determine the predicted income rank of any child given their parents income rank from the following equation:

$$P_{26} = B_0 + B_1 P_{16}, \quad (1)$$

where P_{26} is the child's income percentile at age 26, B_0 is the intercept, P_{16} is the parent's income percentile, and B_1 is the slope of the line predicting children's percentile rank at age 26 from their parent's income percentile. This slope is the intergenerational income rank elasticity. A higher slope indicates a higher correlation between parental and child income, implying less economic mobility across generations. This slope is our measure of what Chetty et al. (2014a) termed *relative mobility*, or the rank-rank slope.

We then estimate the mean child outcome for children with parents at the 10th, 25th, 50th, and 75th income percentile. This mean income rank then becomes the outcome for our main analyses. To generate this estimate at the 10th, 25th, 50th, and 75th income percentiles, we multiply the rank-rank slope by the parent's income percentile in the distribution, and then add the county-by-birth-cohort–specific intercept. This yields the estimated mean income rank of children born to parents in a given income percentile in a given county and year. The higher the expected mean income rank of children, the greater degree of *absolute upward mobility*. Chetty et al. (2014a) showed that the relationship is linear when using income ranks, although this does not mean that it is linear in dollars or logged dollars, which are the transformations used in most prior work.

These data are drawn from the "stayers" sample of children in the Chetty et al. data (2014a) to ensure that we are measuring the same children in the Chetty data sample as in Vital Statistics. We do not include those who moved out of their county because we want to align our populations as closely as possible to determine the economic trajectories of the children based on their birth weight. Of a total sample of approximately 41.4 million, there were 37.7 million stayers; thus, the movers that we exclude are a small part of the sample (see Online Resource 1 for more details). We also conducted a series of post-estimation sensitivity analyses demonstrating that our findings are robust to potential bias introduced by this selection.

Birth weight data are drawn from the Vital Statistics data accessed through the National Bureau of Economic Research (National Center for Health Statistics (1980–1986)). These data include information on virtually every birth in the United States, including information on birth weight, mother's education, race, and county of birth. We generate a measure of LBW by counting any child born weighing less than 2,500g as a LBW child. We then aggregate these numbers to generate the percentage of LBW babies born in each county in each year. Our data span seven birth cohorts (1980–1986), covering nearly every child born in the United States during that period.[1]

Our analytic sample consists of all counties for which Chetty and Hendren (2017) were able to generate estimates of intergenerational economic mobility. This yields a sample of 1,451 counties in the United States, including all the largest counties. Pooling data across seven birth cohorts from 1980 to 1986, the analytic sample comprises 9,416 county-years.

[1]For the 1980 and 1981 birth cohorts, some states reported data on a random draw of 50 % of all live births. Because there is no systematic difference in births reported, our estimated rates should be generally consistent with those estimated from the full universe of births, and findings are robust to the exclusion of the years for which we do not have the full population of births in all counties.

Table 1 shows that across counties and years, on average, 6.34 % of births are low weight. The mean intergenerational income percentile rank elasticity (relative mobility), or the correlation between parent and child income rank, is .27. We also see substantial regression to the mean across income percentiles. For example, children born in the 10th percentile of parental income ranks have, on average, a mean income rank of 41.68 in adulthood; children born in the 75th percentile achieve a mean income rank of only 58.90. Finally, the mean county population in our sample is approaching 200,000, allowing us to generate reliable birth statistics.

Analytic Strategy

To explore the relationship between variation in LBW and variation in levels of absolute economic mobility, we begin by estimating pooled cross-sectional ordinary least squares (OLS) models. We use four parental income percentiles: the children born to the 10th, 25th, 50th, and 75th percentiles. This allows us to look at the effect of LBW on mean child mobility outcomes conditional on having parents at different points the income distribution. We first estimate the bivariate relationship and then introduce our vector of county-level controls, interpolated from decennial census data. We then introduce county fixed effects, which allow us to net out all time-invariant characteristics of the county and calculate the average association of changes in birth weight with changes in mobility outcomes within counties. All models also include year fixed effects to net out national trends. Counties are weighted by the 1980–1982 birth cohort population estimates that Chetty and Hendren (2017) generated, the only year in which sample sizes are available. Weighting by population provides a least squares estimator that privileges the larger counties that are likely to have more precise estimates. Given that our dependent variables are an estimate, we would ideally be able to use the standard errors in our regression. These are not available, so weighting by population is our preferred correction because it privileges the observations that are drawn from larger samples. Later in this article, we describe a series of sensitivity analyses to test the robustness of our estimates. Standard errors are clustered at the county level to correct for serial correlation.

We estimate the following:

$$(Y_{pct}) = \beta_c + \beta_t + \beta(\%LowWeightBirths_{ct}) + \beta\mathbf{X}_{ct} + \varepsilon_{ct},$$

where Y_{pct} is the measure of income rank at age 26 of children born to parents in percentile p, in county c and year t. Separate models are estimated for each income percentile. Fully adjusted models include county β_c and year β_t fixed effects, as well as a vector of time-varying county-level covariates, including proportion of the population with less than high school, some college, and a four-year college degree; proportion black; proportion below the poverty line; and proportion of single-parent households. These data are drawn from 1980 and 1990 U.S. Census files. We use linear interpolation to generate approximate estimates for intercensal years. All data are at the county level.

Results

Table 2 presents models analyzing the relationship between relative mobility and low-weight births. Estimates from our cross-sectional Models 1 and 2 reveal a positive association between the incidence of low-weight births and the correlation between the income ranks of parents and children: higher incidences of low-weight births is associated with lower intergenerational economic mobility. Point estimates from the fully adjusted model indicate that a one-percentage point increase in low-weight births is associated with a 0.4 percentage point increase in the correlation of the income ranks of children and their parents. This model suggests that a county with a 10 % incidence of low-weight births would have a rank-rank slope 2.0 points higher than a county in which the incidence of low-weight births was 5 %, indicating a higher correlation between parent and child income (and lower economic mobility overall).

Models 3 and 4 present results from fixed-effects models estimating the association between low-weight births and relative mobility, allowing us to examine whether within-county variation in the incidence of low-weight births over time is correlated with part of the observed variation in mobility outcomes across birth cohorts from the same county. The introduction of county fixed effects reduces the size of the coefficient on birth weight considerably, demonstrating that much of the association is due to unobserved county characteristics. Nevertheless, the association remains statistically significant in the fully adjusted model. The large difference in the size of the coefficient indicates that the association is much smaller when we examine only within-county change over time. This finding suggests that the within-county changes in the incidence of low-weight births across birth cohorts is predictive of within-county differences in the mobility outcomes for adjacent birth cohorts measured 26 years later, although the association is small given the size of the coefficients. Point estimates from the fully adjusted model indicate that a 1 percentage point increase in low-weight births is associated with a 0.1 percentage point increase in the correlation of the income ranks of children and their parents. This model suggests that a county with a 10 % incidence of low-weight births would have a rank-rank slope one-half percentage point higher than a county in which the incidence of low-weight births was 5 %, indicating a higher correlation between parent and child income (and lower economic mobility overall).

Table 3 presents models analyzing the county-by-cohort average mobility outcomes for children born to parents at the 10th, 25th, 50th, and 75th income percentiles, respectively. Columns 1, 3, 5, and 7 show the bivariate relationship between birth weight and mean income percentile rank. Columns 2, 4, 6, and 8 add county-level covariates. These models show a consistent, negative, and statistically significant relationship between the incidence of low-weight births and the mobility outcomes of these birth cohorts. Regardless of where one starts in the income distribution, absolute upward mobility is lower in counties where LBW is more common. The fully adjusted model for children with parents at the 10th percentile of income (Model 2) suggests that a 1 percentage point increase in the incidence of low-weight births across counties is associated with a 0.39 percentage point reduction in children's mean income percentile at age 26.

Across all 9,416 county birth cohorts in the sample, children raised in families at the 10th percentile, on average, move up to the 39.7th income percentile at age 26. Therefore, a child born to parents in the 10th income percentile from a county with 9 % low-weight births would have a predicted mean income rank 2.34 percentage points lower than a child born to parents of the same income rank with 3 % low-weight births.

Notably, the point estimate on the percentage of low-weight births is largest when we predict mobility outcomes for children born to families at the 10th percentile and attenuates as we move up the income distribution. This finding suggests that the mobility prospects of children from low-income families across counties may be more associated with the incidence of low-weight births relative to those from higher-income families.

To confirm the disparate effect of low-weight births on children of parents in high-versus low-income quintiles, we estimate a separate model using parental income rank as a predictor of child income rank and then interact the percentage of low-weight births in a county with parental income. The interaction is statistically significant and is illustrated in Fig. 2, verifying that the association of low-weight births with our outcome differs across parental income percentiles. Figure 2 shows that at low rates of low-weight births, predicted outcomes for children from various income brackets exhibit a much smaller variance than at higher levels of low-weight births. As the incidence of low-weight births increases, the predicted outcomes of children born to parents in the 10th percentile decline significantly, while those born to parents at the 75th percentile decline far less. Thus, not only does the proportion of low-weight births correlate with overall levels of economic mobility, but also the association is strongest at the bottom of the income distribution.

Overall, the cross-sectional models demonstrate that for children born in the 1980s, the distribution of intergenerational economic mobility maps closely on to the distribution of the infant birth weight. Although strongly suggestive, these cross-sectional models cannot effectively rule out the possibility that the observed relationship between birth weight and mobility is actually due to some unobserved—or unaccounted for—county-level factor.

To better isolate the correlation between the incidence of low-weight births and absolute mobility outcomes, we again estimate models that include county fixed effects, presented in Table 4. These fixed-effects models net out the effects of all time-invariant characteristics of a county, allowing us to estimate how within-county changes across adjacent birth cohorts in the incidence of low-weight births is correlated with economic mobility measured 26 years later. Again, we see a dramatic decline in the magnitude of the coefficient in the fixed-effects models, suggesting that unmeasured county-level characteristics are partially driving this correlation, but it remains statistically significant. In this case, a child born to parents in the 10th income percentile from a county with 15 % low-weight births would have a predicted mean income rank one-half percentage point lower than a child born to parents of the same income rank with 5 % low-weight births. In isolating variation within the counties over time, the fixed-effects model specification (which includes a host of covariates in an attempt to rule out other theoretical pathways) provides more convincing evidence that the incidence of low-weight births can help us to account for the observed variation in mobility outcomes across cohorts.

Sensitivity Analyses

Although generated using population-level data, our measures of intergenerational economic mobility are estimates, and no standard errors were reported to accompany these estimates. In our main models, we weight by population to provide a weighted least squares estimator, placing more weight on observations generated from larger samples and are thus more precisely estimated observations. Nevertheless, we also conducted two additional analyses to examine the sensitivity of our findings to varying degrees of uncertainty around our mobility estimates: simulating potential standard errors and adding uncertainty to our estimates.

First, we simulated a new data set by pooling our longitudinal data by county. Using these pooled data, we created a distribution of six data points for every county, one from every year. We then generated a measure of variance and a standard error from each of those distributions. We estimated our regressions again using the inverse of the variance in slope estimates by county across time to weight our observations. Our coefficients and their significance remained virtually unchanged (results available upon request).

We next conducted a sensitivity test to ascertain how much uncertainty there would have to be in our estimates of child rank in adulthood to invalidate our results. Given that our outcome is an estimate, we wanted to know how much imprecision we could introduce before our model would no longer be significant. Again, Chetty et al. (2014a) expressed confidence in these estimates given their use of administrative records. Yet, it is instructive to ask how robust our observed relationship between birth weight and mobility is to increased uncertainty in the mobility estimates. In other words, how noisy do the mobility estimates need to be for our observed association to be invalid? We addressed this question by conducting a series of simulations. The first simulation added a random draw from a distribution with a variance of 0.3, or 1 % of the mean of our data, to our mobility outcome. We then reestimated our model including this degree of uncertainty; our results were substantively unchanged. We then conducted the same simulation three additional times, adding a random draw from a distribution with a variance of 5 %, 10 %, and 15 % of our sample mean. Only adding a random draw from a distribution with a range of 15 % of the mean rendered our key results insignificant. Thus, a substantial amount of uncertainty would have to have been introduced in the estimation procedure used by Chetty and Hendren (2017) for our results to be invalid; we see this as unlikely given their use of data that were nearly population level.

Furthermore, the observed coefficient on birth weight may be sensitive to model specification and the selection of other covariates. We therefore performed an extreme bounds analysis, investigating the instability and variability of the coefficient on LBW when examining all possible combinations and subsets of the other independent variables. These results are reassuring: our predictor of interest—proportion of low-weight births—was very stable and never crossed 0 (see Figs. S1 and S2, Online Resource 1).

We also examined whether and to what extent our findings might be driven by spatial correlation. Given that the spatial effects are likely caused by stable characteristics of the observed units that do not change over the short time span of our study, our fixed-effects models likely account for this spatial variation. Fixed effects effectively eliminate clustering if the fixed effects for adjacent counties are fairly similar: their correlation would be reflected in the covariance matrix of the coefficients. This potential threat is greater in our cross-sectional models. Preliminary analyses of the residuals from our cross-sectional analysis did indeed suggest potential spatial correlation across counties. We therefore reestimated our models with a correction for spatially clustered standard errors. Notably, the coefficient on our predictor of interest did not change substantially after accounting for the spatial correlation of the error terms, and our analyses indicate that no additional spatial correlation remained after the correction (results available upon request).

Finally, the aforementioned analyses examined the relationship between birth weight and mobility for county birth cohorts using estimates drawn from all persons included in vital statistics and IRS tax data. However, previous research has indicated that infants born to black mothers are significantly more likely than their white counterparts to be underweight. It is possible that highly segregated areas of concentrated minority poverty are driving the association between birth weight to upward mobility—as measured by educational attainment and labor market outcomes— is more difficult for blacks than whites, all else being equal. Therefore, it is possible that the relationship that we observe between birth weight and mobility is spurious to the racial composition of counties across space and over time. Unfortunately, we are unable to disentangle mobility rates by race using the IRS data available from Chetty and Hendren (2017) because income tax returns do not identify taxpayer's race, and no race-specific mobility estimates to date have been generated using these data. As one check that our findings are not confounded by changes in local area racial composition, we reestimated our models using a measure of the incidence of low-weight births constructed from all births to white mothers only. Using the incidence of low-weight births to white mothers yielded substantively similar results (see Online Resource 1). We therefore feel confident that the observed association between birth weight and economic mobility is not being driven by the changing distribution of black births across space and time.

Extensions

Given the level of aggregation of our data, it is difficult to test specific pathways through which birth weight is likely to impact mobility. However, these data do permit us to explore how LBW is moderated by other contextual factors at the county level.

To further understand the relationship between our predictors and contextual factors, we estimated models with interaction terms between our measure of mobility and a range of county-specific covariates, including percentage living in poverty, percentage of households headed by a single parent, and percentage black. Results from these analyses are illustrated in Fig. 3 and in Figs. S3 and S4 in Online Resource 1.

Child mean income rank at low levels of poverty, for example, are often not statistically different from each other; at high levels of poverty, though, high rates of LBW are associated with lower mean child income ranks. Thus, the estimated association between birth weight and mobility is larger in more impoverished areas. Similarly, the association of LBW with mobility is greater in areas with high percentages of blacks. The figure illustrating the effect of single parenthood offers a slightly different picture, but it still agrees with the general finding that LBW has a stronger negative correlation with our outcomes in more disadvantaged areas.[2]

Limitations

As we note throughout our study, the ecological nature of our birth weight and mobility estimates limits our analyses in several key ways. First, despite the highly suggestive evidence from the fixed-effects models, the use of county-level estimates makes it difficult to isolate a causal effect on the incidence of low-weight births on the level of intergenerational economic mobility. Second, the use of ecological data makes it difficult to test the individual pathways through which the literature suggests birth weight may influence mobility. Finally, the nature of these data makes it difficult to test for heterogeneous effects by population: for example, testing how the relationship between low-weight births and economic mobility may operate differently for males and females or blacks and whites.

The intergenerational mobility estimates generated by Chetty et al. (2014a) are the first reliable measures of mobility rates across U.S. localities estimated from population-level administrative data. Indeed, the subnational variation in mobility rates revealed in these estimates provides social scientists with a new and rich data source to examine the correlates of mobility and potentially even the consequences of growing up in a low-versus high-mobility environment. At the same time, these mobility estimates present clear limitations to researchers beyond their ecological nature. One limitation is the timing of the measurement of parental and child income. As we note in Online Resource 1, parental income is measured when the child is between 12 and 16 years of age; it is therefore possible that a child's birth weight—or any early-life condition—may influence parental income. Having a LBW child could decrease parental income if it is accompanied by developmental issues that may in turn influence parental labor force attachment (Kuhlthau and Perrin 2001; Newacheck et al. 2004). At the same time, the costs associated with caring for a child with developmental difficulties may induce parents to work more. Regardless of the direction of the association, the proportion of low-weight babies who will go on to have significant developmental difficulties is relatively small (Hack et al. 1995) and thus is unlikely to significantly influence parental labor market attachment at the aggregate level. Although we do not believe that the potential endogeneity of parental income to child health undermines the current analyses, future work must consider the temporal ordering of the health and income measures.

[2]These results are consistent with recent studies at the individual level showing heterogeneous parental response to the birth weight of their infant, with consequences for future outcomes. Although we cannot test these mechanisms without longitudinal data on individuals, recent research shows that better-educated parents devote more time, and more educationally oriented time, to lower birth weight children. Conversely, less-educated mothers adopt the opposite strategy, investing more time in their heavier children (reinforcing behavior). Therefore, families redistribute resources in response to their child's birth weight in ways that can either offset or accentuate the effects of low birth weight. Crucially, compensatory investments by better educated mothers lead their children to catch up, leaving low-income, LBW children even further behind (Hsin 2012; Leigh and Liu 2016; Restrepo 2016).

Conclusion

Our analyses demonstrate that the county-level incidence of low-weight births for a given birth cohort is highly associated with that birth cohort's economic mobility outcomes as measured in adulthood nearly three decades later. This study echoes a growing literature documenting the lasting effects of early-life health on later educational and labor market outcomes. These findings suggest that interventions aimed at improving health endowments at birth—both directly through prenatal care and other health-based interventions and indirectly by addressing the social and economic causes of LBW (such as material deprivation)—may help level the playing field and make children's economic position in adulthood less dependent on that of their parents while improving the health of communities. Notably, this study also underscores the important and thus far underexamined role of population health in accounting for spatial and temporal variation in economic mobility and economic opportunity more broadly, particularly the mechanisms linking individual outcomes to aggregate outcomes. Health is a key pathway for the transmission of (dis)advantage across generations. Future studies should work to further disentangle the bidirectional relationship between health and economic outcomes to determine whether and to what extent investments in health may serve to reduce the determinative power of a parent's economic position on their children's economic outcomes and thereby promote economic opportunity.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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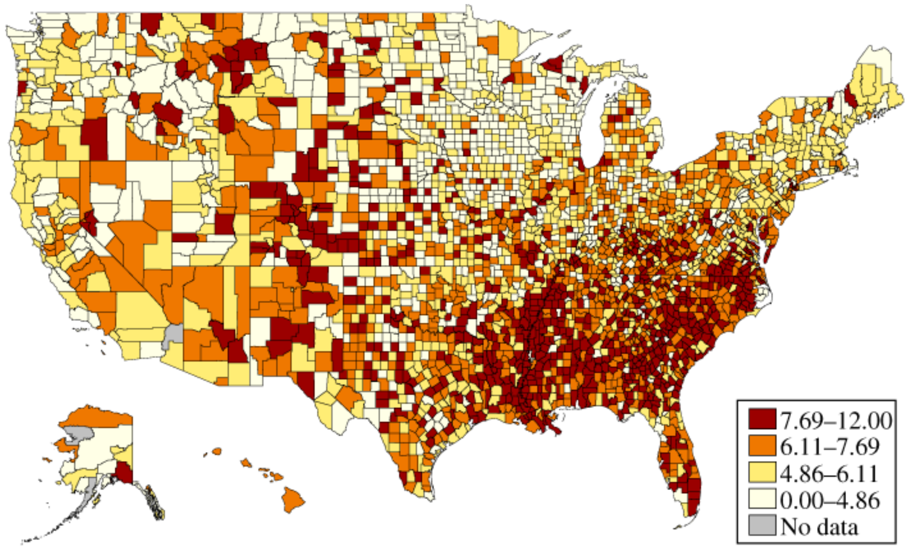

Fig. 1.
Incidence of low-weight births, by county

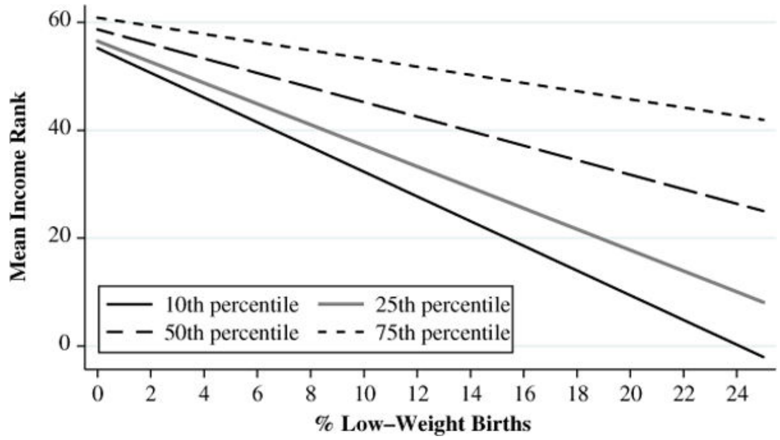

Fig. 2.

Effect of low-weight births on estimated mean income rank for children in a given income percentile

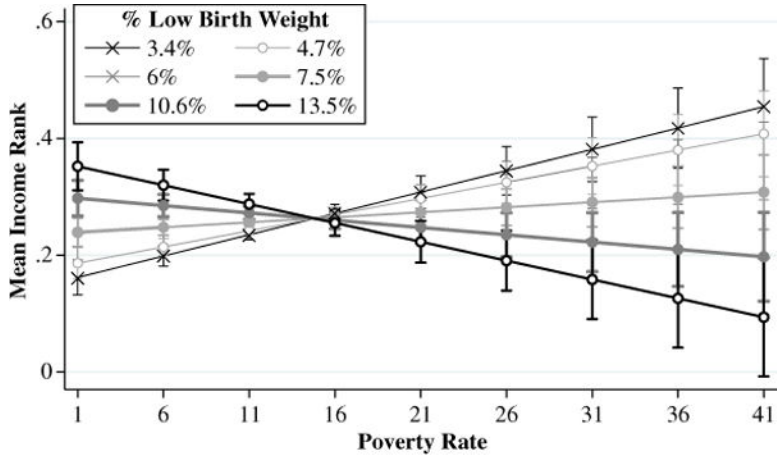

Fig. 3.
County-level mean predicted income rank by low birth weight and poverty

Table 1

Means for key independent and dependent variables (standard deviations in parentheses)

	Mean	1 %	99 %
Proportion Low-Weight Births	0.063 (0.027)	0	.136
Mean Income Rank at Age 26 of Children With Parents at 10th Percentile of Parental Income	41.683 (6.033)	28.905	57.526
Mean Income Rank at 25th Percentile of Parental Income	45.657 (5.110)	34.784	59.307
Mean Income Rank at 50th Percentile of Parental Income	52.280 (3.986)	43.299	62.535
Mean Income Rank at 75th Percentile of Parental Income	58.903 (3.778)	50.162	68.268
Slope (intergenerational income percentile rank elasticity)	0.265 (0.083)	0.077	0.460
County Population	188,059.6 (423,760)	24,849	1,623,018

Table 2

Ordinary least squares models of relative mobility (rank-rank slope) on incidence of low-weight births

	Rank-Rank Slope (1)	**Rank-Rank Slope + Controls (2)**	**Rank-Rank Slope (3)**	**Rank-Rank Slope + Controls (4)**
Low-Weight Births (%)	0.019 *** (0.002)	0.004 *** (0.001)	0.001 (0.000)	0.001 * (0.000)
Total Population (log)		0.011 *** (0.003)		−0.039 (0.045)
Population Density (log)		0.005 * (0.002)		0.002 (0.042)
Black (%)		0.001 ** (0.000)		−0.005 *** (0.001)
Latino (%)		−0.001 ** (0.000)		−0.004 * (0.002)
Single-Parent Households (%)		0.002 (0.002)		−0.004 (0.004)
College Graduate (%)		−0.000 (0.001)		−0.003 *** (0.001)
Less Than High School (%)		0.001 (0.001)		−0.005 *** (0.001)
Some College (%)		−0.002 ** (0.001)		−0.0019 (0.000)
Unemployed (%)		−0.003 ** (0.001)		−0.001 (0.002)
Labor Force Population		0.000 (0.000)		−0.000 (0.002)
Total Household Income (log)		−0.000 (0.000)		0.000 (0.000)
Poverty Rate		0.002 (0.001)		0.009 *** (0.002)
Foreign-born (%)		−0.006 *** (0.001)		0.005 ** (0.002)
Median Household Income (log)		0.005 (0.017)		0.116 ** (0.044)
County Fixed Effects	No	No	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Number of Observations	9,409	9,409	9,409	9,409
R^2	.196	.591	.024	.054

Notes: Robust standard errors, clustered at the county level, are shown in parentheses. All models include year fixed effects.

* $p < .05$;

** $p < .01$;

*** $p < .001$

Table 3

Ordinary least squares models of economic mobility outcomes by income percentile on incidence of low-weight births

	10th Percentile (1)	10th + Controls (2)	25th Percentile (3)	25th + Controls (4)	50th Percentile (5)	50th + Controls (6)	75th Percentile (7)	75th +Controls (8)
Low-Weight Births (%)	−1.938***	−0.394***	−1.646***	−0.338***	−1.159***	−0.246***	−0.673***	−0.154**
	(0.210)	(0.086)	(0.179)	(0.076)	(0.132)	(0.063)	(0.099)	(0.055)
Total Population (log)		−1.191***		−1.025***		−0.748***		−0.471**
		(0.224)		(0.196)		(0.161)		(0.147)
Population Density (log)		−0.190		−0.114		0.013		0.139
		(0.163)		(0.142)		(0.115)		(0.108)
Black (%)		−0.129***		−0.112***		−0.082***		−0.053**
		(0.030)		(0.025)		(0.020)		(0.019)
Latino (%)		−0.015		−0.025		−0.040**		−0.056***
		(0.017)		(0.015)		(0.012)		(0.013)
Single-Parent Households (%)		−0.405**		−0.379**		−0.336**		−0.292**
		(0.156)		(0.135)		(0.105)		(0.090)
College Graduate (%)		−0.074		−0.079		−0.089*		−0.099*
		(0.054)		(0.049)		(0.043)		(0.043)
Less Than High School (%)		−0.167*		−0.149*		−0.119*		−0.089
		(0.068)		(0.062)		(0.055)		(0.053)
Some College (%)		−0.092		−0.116*		−0.156***		−0.196***
		(0.054)		(0.048)		(0.041)		(0.039)
Unemployed (%)		−0.163*		−0.205**		−0.274***		−0.343***
		(0.077)		(0.065)		(0.051)		(0.047)
Labor Force Population		0.011		0.015		0.022		0.029
		(0.032)		(0.029)		(0.026)		(0.026)
Total Household Income (log)		0.000		0.000*		0.000*		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Poverty Rate		0.050		0.076		0.119*		0.162**
		(0.064)		(0.056)		(0.049)		(0.052)
Foreign-bom (%)		0.339***		0.244***		0.087**		−0.070*
		(0.042)		(0.037)		(0.030)		(0.031)
Median Household Income (log)		4.482***		4.563***		4.699***		4.836***
		(1.297)		(1.171)		(1.060)		(1.105)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	No	No	No	No	No	No	No	No

	10th Percentile (1)	10th + Controls (2)	25th Percentile (3)	25th + Controls (4)	50th Percentile (5)	50th + Controls (6)	75th Percentile (7)	75th +Controls (8)
Number of Observations	9,409	9,409	9,409	9,409	9,409	9,409	9,409	9,409
R^2	.370	.624	.370	.622	.294	.602	.107	.561

Notes: Robust standard errors, clustered at the county level, are shown in parentheses. All models include year fixed effects.

* $p < .05$;

** $p < .01$;

*** $p < .001$

Table 4

Ordinary least squares models of economic mobility outcomes by income percentile on incidence of low-weight births, fixed effects

	10th Percentile (1)	10th +Controls (2)	25th Percentile (3)	25th +Controls (4)	50th Percentile (5)	50th + Controls (6)	75th Percentile (7)	75th + Controls (8)
Low-Weight Births (%)	−0.056* (0.023)	−0.058** (0.020)	−0.043* (0.018)	−0.044** (0.015)	−0.020 (0.012)	−0.021* (0.009)	0.002 (0.015)	0.003 (0.014)
Total Population (log)		−1.424 (2.219)		−2.014 (1.961)		−2.998 (2.019)		−3.981 (2.615)
Population Density (log))		−1.652 (1.692)		−1.620 (1.493)		−1.568 (1.704)		−1.515 (2.396)
Black (%		0.134 (0.079)		0.055 (0.066)		−0.077 (0.059)		−0.210** (0.073)
Latino (%)		0.324** (0.123)		0.270* (0.110)		0.179 (0.097)		0.089 (0.101)
Single-Parent Households (%)		0.428 (0.249)		0.361 (0.215)		0.250 (0.187)		0.138 (0.210)
College Graduate (%)		0.236*** (0.043)		0.190*** (0.036)		0.114 (0.030)		0.037 (0.032)
Less Than High School (%)		0.174*** (0.035)		0.102*** (0.030)		−0.016 (0.026)		−0.135*** (0.030)
Some College (%)		−0.027 (0.036)		−0.038 (0.031)		−0.057* (0.026)		−0.076** (0.027)
Unemployed (%)		0.532*** (0.100)		0.510*** (0.082)		0.474*** (0.063)		0.437*** (0.066)
Labor Force Population		0.108 (0.087)		0.103 (0.073)		0.095 (0.066)		0.087 (0.083)
Total Household Income (log)		0.000 (0.000)		0.000 (0.000)		0.000 (0.000)		0.000* (0.000)
Poverty Rate		−0.558*** (0.125)		−0.424*** (0.107)		−0.201* (0.090)		0.023 (0.096)
Foreign-bom (%)		−0.596*** (0.107)		−0.523*** (0.095)		−0.402*** (0.087)		−0.281** (0.096)
Median Household Income (log)		−17.730*** (2.988)		−15.990*** (2.556)		−13.091*** (2.117)		−10.191*** (2.202)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	10th Percentile (1)	10th +Controls (2)	25th Percentile (3)	25th +Controls (4)	50th Percentile (5)	50th + Controls (6)	75th Percentile (7)	75th + Controls (8)
Number of Observations	9,409	9,409	9,409	9,409	9,409	9,409	9,409	9,409
R^2	.020	.121	.015	.156	.004	.215	.005	.164

Note: Robust standard errors are shown in parentheses.

* $p < .05$;

** $p < .01$;

*** $p < .001$