Health, Race, and the Spatial Distribution of Opportunity in America

Health, Race, and the Spatial Distribution of Opportunity in America

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Abstract

What explains the spatial variation in intergenerational economic mobility across the United States? This dissertation will look to health and race to understand subnational variation in intergenerational economic mobility, and explore how public policy can increase upward mobility. I examine economic mobility not just as an individual level process but as a community level process, conditioned by both past history and current policy, that shapes individual outcomes.

Chapter 2, a co-authored version of which was published in Demography, investigates how population health in early life contributes to socioeconomic disparities in adulthood. Using Vital Statistics data, a population level dataset, and data from the Equality of Opportunity Project, we investigate the importance of birth weight for future economic outcomes. Low birthweight serves as both an indicator of parental disadvantages and a potential pathway for reproducing economic disadvantages in the next generation.

To further understand the relationship between health, race, and mobility, the next chapter investigates the impact of access to Medicaid at different ages on the test score gap between black and white children. Using test scores data from the National Assessment of Educational Progress (NAEP) and an instrumental variable approach that isolates the policy effect of changes in Medicaid eligibility, I find that among students eligible for Medicaid, the

positive effect of health insurance on test scores is statistically significant only among black students.

The final substantive chapter builds on my findings of racial differences in the impact of public policy by investigating whether economic mobility differs in majority white versus majority black counties. In this chapter, I first use both aggregate and individual data from the NLSY97 to establish that the distribution of mobility outcomes in majority black versus majority white counties is indeed quite different for individuals from apparently similar families. I then seek to explain this difference. I find that a significant part of the racial gap in mobility outcomes between majority black and majority white counties is more correlated with the weakness of local organized labor and the history of discrimination in a county, rather than more commonly cited sources of the gap, such as high levels of poverty and single parenthood. While we can isolate the correlates of economic mobility in majority white counties, it is far more difficult to identify correlates of upward mobility in majority black counties.

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Chapter 1

Introduction

The American dream is that all children who work hard should be able to succeed, regardless of their parents' situation. However, economic opportunity is not evenly distributed. Measures of economic mobility tell us well parents' rank in the income distribution predicts their children's rank, demonstrating the openness and in some ways equity of the economic stratification system.

Until recently one important gap in our understanding of mobility has been that although researchers had identified variation in mobility by race and gender, we knew almost nothing about geographic variation in mobility across the United States. Recent work had shown that differences between states and counties can be as large as the differences between the United States and other nations (Chetty et al, 2014; Chetty and Hendren, 2016). However, we have only just begun to investigate *why* children's chances of moving up or down the economic ladder are so spatially contingent. Why, in other words, do children born to parents at the bottom of the income distribution in one place have a better chance of upward mobility than children born to parents with the same income in another place?

This dissertation looks at the roles of health and race in explaining the spatial distribution of intergenerational economic mobility, focusing on the role of public policy. It moves beyond individual-level analysis towards a more contextual understanding of mobility, demonstrating that factors such as a place's racial composition, population health, and health policy have significant effects on intergenerational economic mobility.

Though a large sociological literature discusses the role of neighborhoods in determining children's economic prospects, systematic comparisons between neighborhoods have been impossible due to data limitations. Recently, however, new sources of data have allowed analysis of mobility differences among states, counties, and commuting zones in the United States, opening new avenues of research and suggesting some reevaluation of prior knowledge. If place is predictive of mobility outcomes, then the focus of prior research on the role of individual characteristics may have overemphasized the individual level and underestimated the social and contextual level, resulting in conclusions that may or may not hold once the effect of contextual factors on the individual are taken into account.

This dissertation investigates the sources of subnational variation in intergenerational economic mobility in the United States. I examine economic mobility not just as an individual level process but as a community level process conditioned by past history and by current policy that shape individual outcomes. First, I will demonstrate how health, as both a cause and consequences of an individual's place in the social world, is central to the process of economic mobility. Second, I will demonstrate how race conditions the experience of mobility and moderates the effect of policies and variables that policy makers and researchers examine as predictors of mobility. Focusing on population health, a contextual factor above the individual, and race, a characteristic that has predictive power because of its social meaning, will better allow us to understand mobility as a stratification process as opposed to an individual level process.

Intergenerational Economic Mobility

Economic mobility is an important feature of social stratification and has been the focus of a large body of sociological literature and economic research. Historically, sociologists focused on mobility between occupations across generations to better understand the impact of mobility on social classes. Conversely, economists have examined income mobility, using intergenerational income elasticities as well as rank-rank correlations between parents and children.

Research on mobility has also explored the importance of family structure (Bloome, 2014); education (Brand and Xie, 2010); gender (Beller, 2009); and economic disadvantage in early life (Wagmiller et al., 2008Ongoing research into the specific micro-level processes underlying these associations covers everything from parenting (Lareau, 2003) to school quality (Haskins et al, 2008). It continues both to reveal new mechanisms for the transmission of social position and to highlight how institutions, policies and social contexts can disrupt the persistence of economic rank from one generation to the next. Additionally, the relationship between inequality and mobility has attracted considerable attention. The "Great Gatsby" curve indicated that inequality was associated with lower mobility in international comparisons (Corak, 2013). Interestingly, longitudinal data and data at other levels of analysis did not confirm this finding, indicating that the relationship between inequality and mobility at the international level may be a proxy for other social investments and policies (Bloome, 2014; Chetty et al, 2014).

However, Chetty et al. (2014) have also demonstrated that these studies miss an important source of variation in economic mobility: geography. Chetty et al. provide the first reliable estimates of the spatial variation in income mobility across the United States. Geography can greatly alter the probability of either a poor child's upward trajectory or a rich child's downward trajectory, regardless of individual characteristics. By incorporating contextual factors, this dissertation will show how population health and race also affect the likelihood of upward economic mobility for individuals lower down in the income distribution.

Research consistently demonstrates that health status early in life—from the fetal period to infancy to early childhood—has an independent effect on later life health, educational attainment and labor market outcomes, all key determinants of intergenerational economic mobility (Haas et all 2011; Haas 2006; Smith 2009). However, measures of health and health policy have been curiously absent from recent work on economic mobility, which is surprising given the growing literature detailing how policy context shapes health disparities (e.g., Sosnaud 2017) and the central role of health as a pathway for the transmission of economic status across generations (Kane 2015; Haas, Glymour and Berkman 2011; Haas 2006). This dissertation will examine both population health and health insurance to understand their effects on mobility, as well as the mechanisms linking health to mobility.

I will also examine the importance of race in shaping the process of mobility. Race is a crucial axis of stratification in America, and understanding how the racial mix of an area can alter both the probability of mobility and the effect of interventions on mobility will provide new directions for interventions in the future. Prior research has demonstrated that African Americans experience greater downward mobility than their white counterparts, experience a lower return to education, and are more likely to experience negative outcomes from growing up in a single parent home (Mazumder, 2011; Bloome, 2014). However, this research does not explore how racial segregation has conditioned the African American experience and thus the process of mobility. This dissertation will demonstrate the effects of spatial variation on racial disadvantage in economic mobility.

Chapter 1: Infant Birthweight and Intergenerational Economic Mobility

Chapter 1, a co-authored version of which was published in Demography,[1] investigates how population health in early life contributes to socioeconomic disparities in adulthood. Using Vital Statistics data, a population level dataset, and data from the Equality of Opportunity Project (give a reference), we investigate the importance of birth weight for future economic outcomes. Low birthweight serves as both an indicator of parental disadvantages and a potential pathway for reproducing economic disadvantage in the next generation.

Using cross-sectional and fixed effects regression models, we find that children born to parents near the bottom of the income distribution experience less upward economic mobility and are more tied to their parents' economic position in counties that have unusually high proportions of low birthweight children. This finding suggests that the ecological context of health status at birth may have far-reaching consequences across the life-course. It also highlights the importance of addressing spatial variation in intergenerational economic mobility.

In order to test whether health policy interventions can impact the relationship between infant health and economic mobility, we then exploit the variation in when Medicaid became available to children born from 1980-1986 to determine the causal effect of access to Medicaid on mobility outcomes. Interestingly, access to Medicaid does not decrease the prevalence of low-weight births, but it does have an overall effect on mobility. This demonstrates that access to health insurance in childhood has a causal effect on the mobility outcomes of children in adulthood, illustrating both the importance of health interventions in the stratification process and that social policy can have a positive impact on low-income children's chances of mobility Poor population health ties children more closely to their parents economic position.

[1] Co-authored with Rourke O'Brien. I am first author. Give reference in footnote, including title of paper.

Chapter3: Medicaid and the Achievement Gap

To further understand the relationship between health, race, and mobility, the second chapter investigates the impact of access to Medicaid at different ages on the test score gap between black and white children. While previous research has shown that access to health insurance increases test scores, it has not discussed whether the benefits of insurance coverage change racial disparities in achievement. Given that poverty is experienced differently by blacks and whites, this is an important omission.

Using test scores data from the National Assessment of Educational Progress (NAEP) and an instrumental variable approach that isolates the policy effect of changes in Medicaid eligibility, I find that among students eligible for Medicaid, the positive effect of health insurance on test scores is statistically significant only among black students. This black-white difference may be traceable to the fact that health insurance has a larger impact on school attendance among blacks than whites. This paper points to the importance of looking at heterogeneous effects when studying how best to reduce inequality, because in this instance, the net effect of heterogeneous effects by race is to close the achievement gap. Future research should continue to examine how seemingly unrelated policy interventions affect racial and socioeconomic achievement gaps. Test score gaps have consequences for adult wage gaps, so shrinking test score gaps may also reduce racial and economic inequality among adults.

Chapter 4: Race, Space, and Intergenerational Economic Mobility

The third chapter builds on my findings of racial differences in the impact of public policy by investigating whether economic mobility differs in majority white versus majority black counties. Previous research has examined racial differences in the process of mobility, but no research to date has investigated spatial differences in mobility processes by race. Given the large literature demonstrating the unique historical experiences of majority black areas, and the longstanding lack of investment in majority black areas by both the private and public sectors, this is an important omission.

In this chapter, I first use both aggregate and individual data from the NLSY97 to establish that the distribution of mobility outcomes in majority black versus majority white counties is indeed quite different for individuals from apparently similar families. I then seek to explain this difference. Controlling for rates of poverty, single parenthood, and crime does not explain much of the difference, nor does expanding my analysis to include a wider array of policy interventions and local labor market conditions. I show that although the levers of mobility identified by prior research are extremely important in white counties, they are not important in black counties. The only variables that somewhat shrink the gap between white and black outcomes are union coverage and having been a slave state, indicating that the relative power of organized black versus white labor may be an important factor in economic mobility outcomes. I conclude that we need a more comprehensive understanding of how the relative power of labor and historical processes affect economic opportunity, and that race-specific understandings of mobility are essential for policy makers to intervene effectively. Taken together, these findings suggest that a significant part of the racial gap in mobility outcomes between blacks and whites counties is potentially attributable to the weakness of local organized labor and the history of discrimination, rather than the traditionally cited sources of the gap, such as high levels of poverty and single parenthood. While we can isolate the correlates of economic mobility in majority white counties, it is far more difficult to identify correlates of upward mobility in majority black counties.

Limitations

This dissertation has several limitations. The first is the unit of analysis. While I chose the county level as a meaningful geographic unit that structures the distribution of resources, it is also limiting. Counties are not entirely comparable across the country – for example, they are very large in California, and far smaller in places like Kentucky – indicating that I may not be comparing comparable units. Second, this level of aggregation makes it difficult to identify mechanisms. While I seek to rule out competing explanations, I will only be able to do so definitively with individual level data. With individual data, it would be important to understand which units of analysis are the most predictive of individual outcomes: block, tract, county, commuting zone, or state.

Furthermore, the policy impacts that I measure may not be comparable in future interventions. Because the group of people who became eligible for Medicaid in the 1990s were more vulnerable than the people who would become eligible if Medicaid were further expanded today, the impact of such a policy intervention would probably be lower.

Additionally, because of the manner in which economic mobility is calculated, it is not entirely clear whether or not the individual who experiences mobility remains in the county the mobility parameter is assigned to or if they move. Future research at the individual level can help answer this questions.

Finally, the chapter on race and mobility focuses on the mobility experienced by those in the counties that are majority African American. Though I tried to use the NLSY 97 to determine whether both blacks and whites experienced worse mobility in these counties, the NLSY did not have sufficient sample size to answer this question. Future work with individual level data will seek to answer this question.

Chapter 2

Health Endowment at Birth and Variation in Intergenerational Economic Mobility: Evidence From U.S. County Birth Cohorts[2]

[2] This work was coauthored with Rourke O'Brien. I am the primary author, and the first author of the published manuscript. Citation: *Robertson, C, and Rourke O'Brien. 2018. "Health Endowment at Birth and Variation in Intergenerational Economic Mobility: Evidence From US County Birth Cohorts." Demography. 2018 Feb;55(1):249-269*

Introduction

New estimates of intergenerational economic mobility reveal substantial variation in the spatial distribution of economic opportunity in the United States (Chetty et al. 2014**a; 2014b**). 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-minute 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; 2014b). Moving from the bottom to the top quintile was almost three times as common in Sussex as in Essex County.

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; 2014b). 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 Bennet 2000). 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; Black et al. 2007[; Case et al. 2005; Conley and Bennet 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).

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.

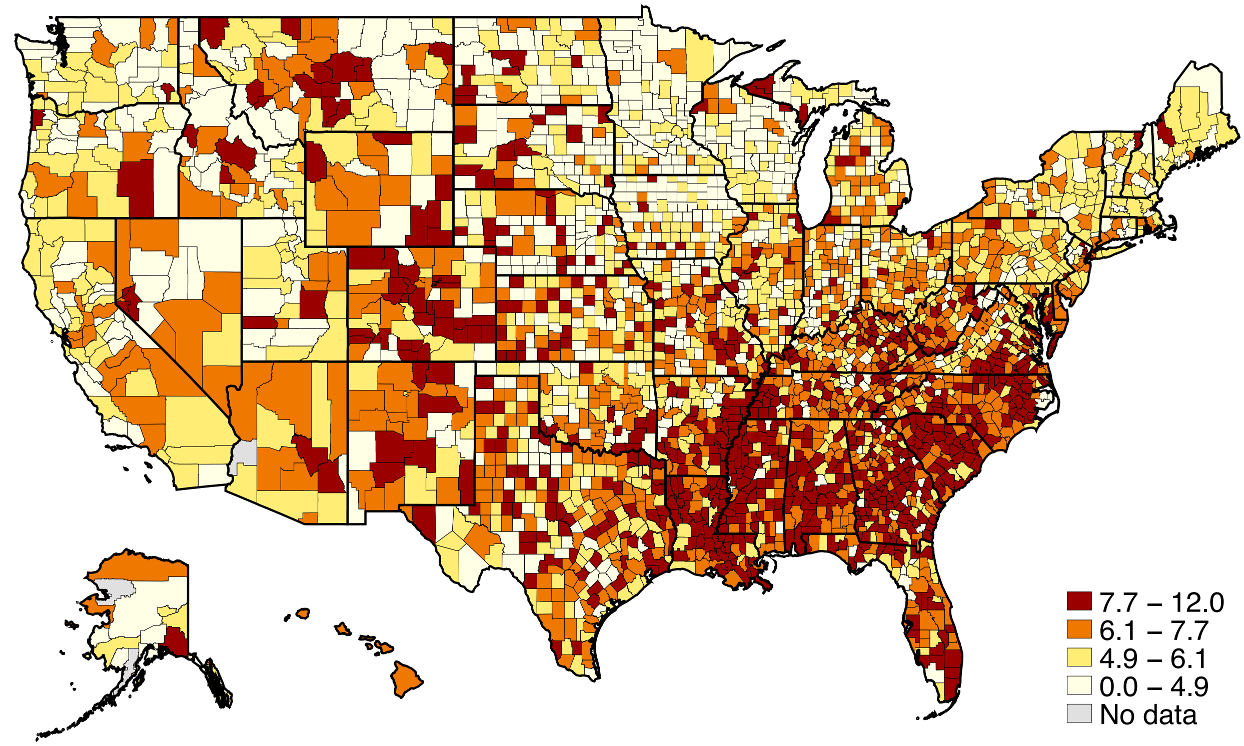

Fig. 1.1 Incidence of low-weight births, by county

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 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. We then test a possible mechanism, Medicaid eligibility, to see if early life health insurance can improve upward mobility. 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

Fundamental cause theory, first proposed by Link and Phelan (1995), argues that social factors such as socioeconomic status (SES) and social support are fundamental causes of health disparities because they affect multiple disease outcomes through multiple mechanisms. Although intervening mechanisms might be interrupted, the association between SES and disease persists. This theory argues for a greater understanding of the social patterning of disease, because health effects of inequality cannot be eliminated by addressing only those mechanisms that seem to link it to health without others coming to the fore (Link and Phelen 1995; Phelan et al. 2010). From this perspective, infant birth weight is one mechanism through which the social becomes physical, linking SES and health. Thus, birth weight both reflects existing social inequalities and reproduces them.

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. A large and growing literature spanning the social and medical sciences has demonstrated 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 postneonatal 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 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; 2014b) 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 Chetty and Hendren (2015**).** 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; 2014b) 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. Therefore, the 25th percentile and the 75th percentile that we use to calculate other points in the distribution are predicted values from a linear regression, not raw data. Our interpolation is drawn from the same equation that Chetty and Hendren used to generate the 25th and 75th percentile (2015) (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. (2014**a)** 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 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.[3]

Our analytic sample consists of all counties for which Chetty and Hendren[2015] 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.

Table 1.1 Means for key independent and dependent variables (standard deviations in parentheses)

	Mean	1 %	99 %
Proportion Low-Weight Births	.634 (.270)	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 (5.1101)	34.784	59.307
Mean Income Rank at 50th Percentile of Parental Income	52.280 (3.9856)	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 (0.0830)	0.077	0.460
County Population	188,059.6 (423,760)	24,849	1,623,018

[3] 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 (2015) 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:

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

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 $__C$and year$__T$ β_t fixed effects, as well as a vector of time-varying county-level covariates$_X_{TC}$, 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).

Table 1.2 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***	0.004***	0.001	0.001*
	(0.002)	(0.001)	(0.000)	(0.000)
Total Population (log)		0.011***		–0.039
		(0.003)		(0.045)
Population Density (log)		0.005*		0.002
		(0.002)		(0.042)
Black (%)		0.001**		–0.005***
		(0.000)		(0.001)
Latino (%)		–0.001**		–0.004*
		(0.000)		(0.002)
Single-Parent Households (%)		0.002		–0.004
		(0.002)		(0.004)
College Graduate (%)		–0.000		–0.003***
		(0.001)		(0.001)
Less Than High School (%)		0.001		–0.005***
		(0.001)		(0.001)
Some College (%)		–0.002**		–0.001
		(0.001)		(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		0.009***
		(0.001)		(0.002)
Foreign-born (%)		–0.006***		0.005**
		(0.001)		(0.002)
Median Household Income (log)		0.005		0.116**
		(0.017)		(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 and robust standard errors clustered at county level.
*$p < .05$; **$p < .01$; ***$p < .001$

Table 1.3 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

Table 1.3 (*Continued)* Ordinary least squares models of economic mobility outcomes by income percentile on incidence of low-weight births

		(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-born (%)		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
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 1.4 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*	–0.058**	–0.043*	–0.044**	–0.020	–0.021*	0.002	0.003
	(0.023)	(0.020)	(0.018)	(0.015)	(0.012)	(0.009)	(0.015)	(0.014)
Total Population (log)		–1.424		–2.014		–2.998		–3.981
		(2.219)		(1.961)		(2.019)		(2.615)
Population Density (log)		–1.652		–1.620		–1.568		–1.515
		(1.692)		(1.493)		(1.704)		(2.396)
Black (%)		0.134		0.055		–0.077		–0.210**
		(0.079)		(0.066)		(0.059)		(0.073)
Latino (%)		0.324**		0.270*		0.179		0.089

		(0.123)		(0.110)		(0.097)		(0.101)
Single-Parent Households (%)		0.428		0.361		0.250		0.138
		(0.249)		(0.215)		(0.187)		(0.210)
College Graduate (%)		0.236***		0.190***		0.114***		0.037
		(0.043)		(0.036)		(0.030)		(0.032)
Less Than High School (%)		0.174***		0.102***		–0.016		–0.135***
		(0.035)		(0.030)		(0.026)		(0.030)
Some College (%)		-0.027		–0.038		–0.057*		–0.076**
		(0.036)		(0.031)		(0.026)		(0.027)
Unemployed (%)		0.532***		0.510***		0.474***		0.437***
		(0.100)		(0.082)		(0.063)		(0.066)
Labor Force Population		0.108		0.103		0.095		0.087
		(0.087)		(0.073)		(0.066)		(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***		–0.424***		-0.201*		0.023
		(0.125)		(0.107)		(0.090)		(0.096)
Foreign-born (%)		–0.596***		–0.523***		–0.402***		–0.281**
		(0.107)		(0.095)		(0.087)		(0.096)
Median Household Income (log)		–17.730***		–15.990***		–13.091***		–10.191***
		(2.988)		(2.556)		(2.117)		(2.202)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
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.
*$p < .05$; **$p < .01$; ***$p < .001$

Table 1.4 (*Continued)* Ordinary least squares models of economic mobility outcomes by income percentile on incidence of low-weight births, fixed effects

Models 3 and 4 present results from fixed-effects models estimating the association between of 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.

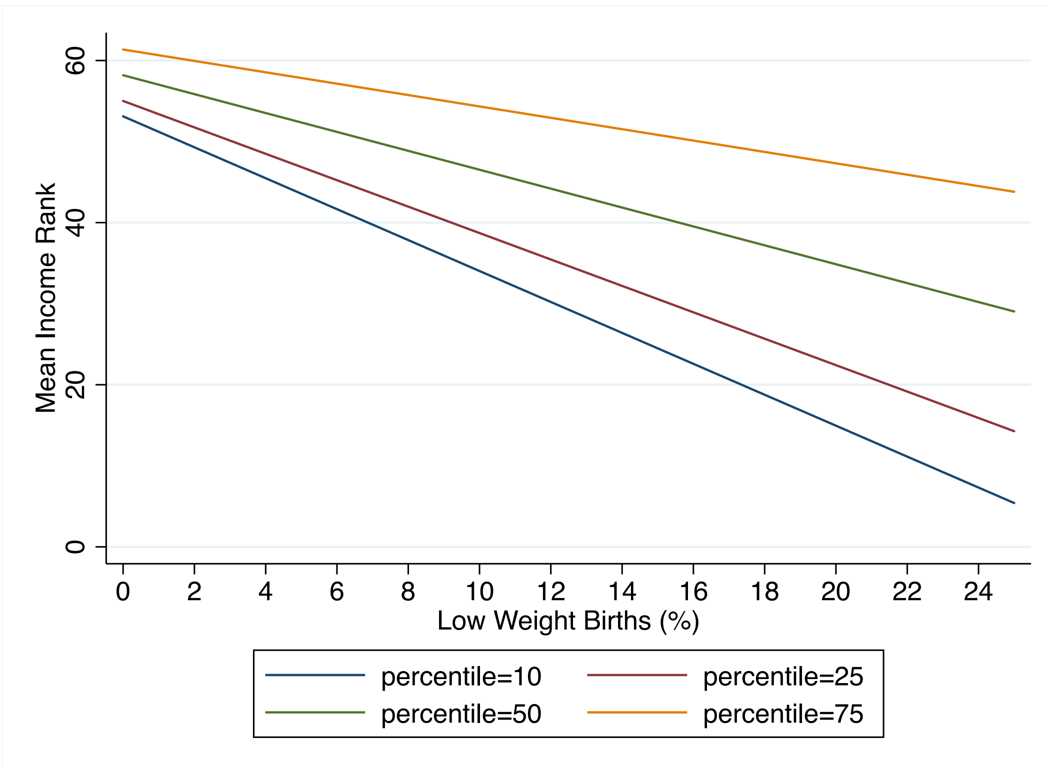

Fig. 1.2 Effect of low-weight births on estimated mean income rank for children in a given income percentile

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. (2014 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 **(2015)** 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 and mobility. At the same time, the pathway 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 (2015) 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.

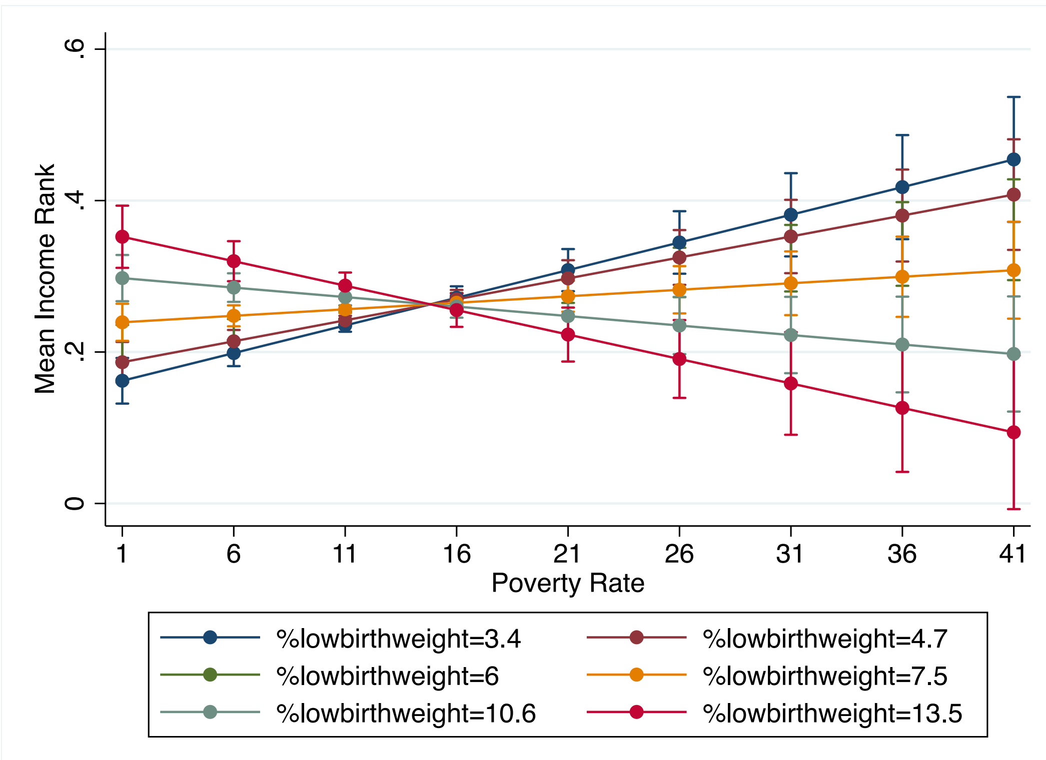

Fig. 1.3 County-level mean predicted income rank by low birth weight and poverty

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.[4]

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

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[4] 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).

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.

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.

Chapter 2

Medicaid Expansions and the Achievement Gap

Introduction

Educational outcomes in America are sharply demarcated by the "color line." African American students score from half to a full standard deviation lower than their white peers, and have a high school graduation rate almost twenty percentage points lower (CEPA, 2017). Although it shrank during the years following the civil rights movement, progress has now stalled (Rothstein, 2014).

Most policies that aim to address achievement gaps, such as No Child Left Behind and the Race to the Top, focus on what happens in school. But children's ability to succeed in school is deeply affected by the cognitive, emotional, and physical resources they bring with them to school (Duncan and Magnuson, 2005; Magnuson and Duncan, 2006; Heckman, 2006). In particular, we know that children's health and their access to health insurance affect their academic achievement (Jackson and Lee, 2015; Cohodes et al, 2016). Children who have health insurance coverage have higher test scores and graduate from high school at higher rates. Over the long run, they are also more likely to attend college and have higher incomes than children who did not have health insurance (Ross, 2014; Levine and Schanzenbach, 2009; Cohodes, 2015; Gross & Notowidigdo 2011; Brown et al, 2015). However, research on the educational effects of health insurance coverage does not discuss whether the benefits of insurance coverage vary by race or change disparities in achievement between black and white children. Indeed, the literature rarely mentions race. Given that poverty is experienced differently by blacks and whites due to both the concentration of disadvantage and racially discriminatory public policy, this is an important omission (Wilson, 1979; 1987; Massey and Denton, 1993).

The concentration of poverty in neighborhoods where many black children grow up means that African American children usually grow up in quite different social contexts from their poor white peers (Sharkey, 2013; Sampson, 2008; Wilson, 1987). Poor black children are exposed to worse housing, more violence, more stress, more environmental toxins, worse funded schools, and poverty more amplified by more discrimination than their white peers. Because black children's poverty is exacerbated in these ways, we might expect welfare state interventions to have a greater impact. Specifically, poor African American children might gain more from access to professional health care than poor white children, because they are starting from further behind.

Until 1980, prenatal Medicaid eligibility was tied to AFDC eligibility, which was set by individual states. This system led to significant state-to-state variation in eligibility for Medicaid. In an effort to reduce infant mortality, Congress began expanding coverage for low-income pregnant women who were not in the welfare system in the early 1980s by requiring states to cover all pregnant women meeting the financial hardship requirement for AFDC regardless of whether they received AFDC benefits. This requirement was followed by a series of reforms that increased poor children's access to Medicaid.

If African Americans had less access to health care than whites, and if health care had greater average benefits for blacks than whites, the expansion of Medicaid in the 1980s and 1990s should have helped shrink achievement gaps. However, past research has not considered whether Medicaid expansion affected racial disparities in school achievement.

Following a large body of prior research on Medicaid, I use an instrumental variable approach to isolate the policy impact of expanded access to Medicaid. This approach allows me to exclude the effects of other stable characteristics of state populations' that might have changed children's academic skills. While other studies have used this instrumental variable approach to look at academic achievement, they have not applied it to the achievement gap (see Cohodes et al, 2015). I model the effect of increased access to Medicaid on eight different demographic groups (whites, blacks, those eligible or ineligible for free or reduced priced lunch, and eligibility for free and reduced price lunch by race), as well as the achievement gap itself. I use four years of state-level NAEP data and instrument for Medicaid eligibility to identify the effect of the policy change.

I address three questions. First, did Medicaid expansions improve the achievement of poor African American children more than the achievement of poor white children? Second, how much did racial gaps in achievement change as a result of the Medicaid expansion? Third, what mechanisms might plausibly link Medicaid expansion to improved school performance?

I find that the Medicaid expansion increased the test scores of poor African American children more than it increased the test scores of poor white children, narrowing the racial achievement gap. I also present evidence that that increased school attendance by African American students may have been one mechanism by which increased access to health care improved their test scores relative to whites.

These findings have obvious policy implications. Test score gaps have proven hard to alter with school-based programs. If access to health care improves low-income black children's test scores, improving access may have far-reaching implications not only for their health, but also for their other life outcomes. Test score gaps have consequences for adult wage gaps, so shrinking school achievement gaps by improving the performance of disadvantaged children may also reduce racial and economic inequality among adults. Finally, more educated parents tend to have more educated children. If access to health insurance narrows racial disparities in not only in test scores but children's educational attainment, access to health insurance may also reduce the intergenerational transmission of racial disadvantages.

In Section 2, I provide background on the racial achievement gaps in the U.S. In Section 3, I discuss the intersection between race and poverty in order to explain why we might expect improved access to health care to have particular benefits for black children from low-income families. In Section 4, I review recent research on the links between children's health, access to health care, and school performance. Section 5 explains my data and methods and Section 6 describes the results. Section 7 concludes with a discussion of limitations, policy implications, and directions for future research.

The Achievement Gap

Despite a sustained effort to reduce racial disparities in educational achievement, the racial test-score gap remains wide (Reardon et al, 2017). In 1965, when the Coleman Report was released, the difference in black-white test scores was 1.1 standard deviations. Fifty years later it was 0.9 standard deviations (Hanushek, 2016). Though the Civil Rights movement and *Brown v. Board of Education* were supposed to usher in a new era of equity, the demise of Jim Crow did not have the equalizing effect that was hoped for.

The sources of the gap lie both inside and outside schools. Within school factors that contribute to the achievement gap include low expectations of students, lack of rigor in the curriculum, the tracking of students, and low levels of safety, the concentration of poverty, parental incarceration, parent work schedules, and exposure to neighborhood violence (Morsy & Rothstein 2015, 2016, and Sharkey & Sampson, 2010).

Many of the factors that have been proposed as sources of the black-white achievement gap are, in fact, based on economic disadvantage as well as racial disadvantages, as poor children also do worse in school (Guo and Harris, 2000). The sources of the achievement gap discussed above tend to be race-blind, in that they have a negative impact on students regardless of race, but because black children are more likely to be poor than white children, economic disadvantages affect black children more often than white children. But as I discuss below, the concentration of disadvantage and overlapping socioeconomic and racial disadvantage also render black poverty deeper than white poverty.

Researchers have long acknowledged that inequalities outside of the school, in families and in neighborhoods, contribute to the achievement gap (Coleman, 1966). A relatively small number of high-profile interventions, such as Moving to Opportunity (Chetty et al, 2016), have tried to change children's neighborhoods as a route to improving school performance, among other outcomes. However, there has not yet been research on the effect of health care on the achievement gap.

Inequality by Race

Poor African American children grow up in environments of deeper poverty than their white counterparts, in which discrimination, social isolation, and the concentration of poverty, joblessness, and single parenthood compound to render these children "truly disadvantaged" (Wilson, 1987). There are no white neighborhoods comparable to those in which most poor African American children live if one takes crime, segregation, income, and other measures into account (Sharkey, 2013). Although half of all black families have lived in the poorest American neighborhoods for the last two generations, only 7 percent of white families have lived in poor white neighborhoods for the past two generations. Furthermore, even if their parents have comparable incomes, poor black children live in worse neighborhoods than their poor white counterparts. This concentration of disadvantage means that children in poor black neighborhoods are more exposed to extreme poverty, single parenthood, crime, joblessness, poor housing stock, and environmental dangers than poor white children (Wilson, 1987; Sampson, 2008) Disadvantage and its associated conditions, particularly the concentration of other students who are also disadvantaged, reduces student achievement (Brooks-Gunn and Duncan, 1997) Rothstein, 2014). Indeed, by some measures, segregation in American schools has not improved since the late 1960s. While half of poor white students attend high poverty schools, 80% of poor black students attend high poverty schools (Orfield 2006; Carnoy & Garcia, 2017). This demonstrates that poor African Americans experience a deeper poverty than that of whites, and that the effect of access to health insurance might therefore be larger.

This paper suggest that the Medicaid expansions did not contribute the same gains to all groups. Instead, the gain was proportional to students' initial disadvantages. Prior research demonstrates that this pattern is not unusual. For example, the fluoridation of drinking water had a differential impact across gender and social status, with the largest effect occurring among the poorest women (Glied and Niedel, 2010). Similarly, Bhatt and Sague (2015) find that increasing Medicaid eligibility decreased infant mortality the most among African American children, who had the highest baseline infant mortality rate. Finally, Cohodes et al (2015) found that the increase in high school completion due to increased access to Medicaid was confined to African American children. This paper will use an identification strategy similar to Cohodes et al, but it will look at a longer timeframe and model the racial gap explicitly.

Health and Race

Socioeconomic status and health are intimately related, and because African Americans are more likely to be poor, health and mortality compound the differential experiences between poor blacks and whites in America (Geronimous, 1996; Adler et al, 1994; Sharkey, 2011). Although the early twentieth century saw large absolute decreases in the racial infant mortality gap, there has been little improvement in relative gaps ensuing decades (Troesken, 2004). African American babies are also more likely to be born at a low birth weight or preterm (Aber et al, 1997). Given the problems a low birth weight child will often face, higher rates of low weight births among African American children are cause for concern. This pattern persists regardless of socioeconomic status among African Americans (Kreiger et al 2008; Luke and Brown, 2006; Paneth, 1995). In utero stress, which is one cause of low infant birth weight, is more common among minority women, who are more exposed to domestic violence and stress, both of which negatively impact children in utero (Paneth, 1995; Aizer, 2011; Geronimous, 1996). This indicates that health interventions may be particularly powerful at early stages and for racial minorities if low weight infants benefit more from immediate care (Aizer, 2011; Geronimous, 2006). This study will both test the impact of earlier interventions and will also examine whether or not later interventions ameliorate prior harm.

The impact of societal institutions that, without necessarily intending to discriminate, nonetheless limit opportunities more for blacks than whites can also have serious health impacts for minorities (Aber, 1997). Racial residential segregation, a result of redlining, restrictive covenants, and other discriminatory practices, pushed minorities into less desirable areas, exposing individuals to greater environmental dangers, such as poor quality water, air pollution, exposure to lead paint, mold, dust and vermin, less access to nutritious food, and fewer community resources (Liu and Lewis, 2014). Children are particularly vulnerable to these disadvantages. Ignoring the racial disparities in disadvantages obscures the possibility that health interventions such as Medicaid will have more impact on the most disadvantaged racial groups.

Many of the factors identified above, such as infant birthweight, student health at home, and access to health services are impacted by access to Medicaid (Bhatt and Sague, 2015; Miller and Wherry, 2017). If access to Medicaid varies by race or has different effects by race, making it available to low-income families should have consequences for the racial achievement gap.

Medicaid, Health and Child Outcomes

A fairly large literature in economics has examined the impact of Medicaid on academic achievement. This literature finds that increased access to health insurance raised test scores, increased the probability of high school graduation and college attendance, and raised income (Ickovics et al, 2014; Levine and Schanzenbach, 2009; Cohodes et al, 2015; Gross & Notowidigdo 2011; Brown et al, 2015). However, as I have already noted, this literature does not discuss whether these benefits of insurance coverage varied by race or narrowed racial disparities in achievement.

Medicaid Expansions: 1980s and 1990s

In the early 1980s and 1990s, Medicaid eligibility for low–income pregnant women and children expanded dramatically at the federal level (for overviews see Miller and Wherry 2017; Currie & Gruber 1996). Before this expansion, Medicaid had been tied to state set eligibility thresholds for AFDC, which resulted in significant cross-state variation in who qualified for Medicaid. AFDC eligibility was usually restricted to those far below the poverty line, so those who qualified for Medicaid had extremely low incomes. In the 1980s Congress began to expand Medicaid coverage for low-income pregnant women and their infants, mandating that, regardless of whether a woman participated in AFDC, any eligible woman would be covered. Later federal expansions ensured that women in households with income up to 133% of the federal poverty line were covered, allowed states to expand coverage up to 185% of the poverty line. This resulted in a substantial increase in Medicaid eligibility for pregnant women, with significant variation across states and over time.

The combination of changes imposed by Congress and changes in each state's rules led to great variation in the evolution of Medicaid policies, both between states and over time. States with lower income cutoffs for AFDC —and thereby Medicaid coverage—before the expansions saw larger increases in the percentage of women eligible for Medicaid than states that covered a greater percentage of women from the start. Changes in the demographics of each state were another source of variation. For example, if a state's poverty rate rose, the proportion of pregnant women eligible for Medicaid would increase because more women would fall below the new threshold for eligibility , even if the generosity of the state's AFDC regime did not change.

Data

Medicaid Eligibility

My analyses will use an instrumental variable approach to isolate the unique effect of Medicaid policy shifts on eligibility, net of shifts in states' economic and demographic characteristics. I instrument for Medicaid generosity using simulated Medicaid generosity, a measure first used by Currie and Gruber (1996) and Cutler and Gruber (1996), and reconstructed by Miller and Wherry (2017).

This measure is generated by applying state–year specific Medicaid eligibility rules to a nationally representative sample of women aged 15–44 drawn from the Current Population Survey. This generates a state–year specific estimate of the fraction of women who would be eligible for coverage if they became pregnant that is unaffected by any changes in state demographic or economic characteristics. This is a simulated measure of Medicaid generosity that only varies with policy changes, netting out any other factors that could lead to eligibility changes.

Tables A1 and A2 in the appendix display the real and simulated percentages of women aged 15–44 who would be eligible for Medicaid coverage if they became pregnant by state for selected years as well as the percent change over this time period. Simulated eligibility is higher than real eligibility in states with relatively low poverty rates (eg. Massachusetts), and it is lower than real eligibility in states with relatively high poverty rates during the relevant time period (e.g. Texas), demonstrating that the simulated measure is capturing only variation in eligibility.

I use a similar measure to examine the effect of increased Medicaid coverage across childhood. This measure is generated by calculating the fraction of children eligible for Medicaid coverage at each age, given a specific birth year and state. The fraction of children eligible is then summed at each age across state and birth cohort, which yields a measure representing the cumulative average for all years of public eligibility during childhood (all children are measured throughout childhood to age 18). Because this measure is subject to the same issues of prenatal eligibility, the simulated measure of childhood Medicaid eligibility is also used. This measure is constructed by creating a nationally representative draw of 1,000 children of a specific age from the ACS, and then applying the state–year specific eligibility criteria for this simulated cohort. Then the fraction of children eligible at each year is averaged to generate a simulated average of cumulative eligibility across childhood.

Dependent Variable

I use state scores on the National Assessment of Educational Progress (NAEP) tests of 8th graders' math skills, which are publicly available from the National Center for Education Statistics. These data cover representative samples for all states in selected years, scored on a 500-point scale. Between 1990 and 2013 the average score in my sample increased by 22 points, from 263 to 285 points. The state-level standard errors range from 0.4 to 2.1. I use the data from the 1982, 1984, 1988, and 1992 birth cohorts, which cover the years with the largest changes in Medicaid policy. I then model changes in both the test score gap and each racial group's scores.

Table 2.1. Average Math Score by Race and Reduced Priced Lunch Eligibility, 1996 and 2009

	1996	SD	2009	SD
Black Average Score	243.26	7.01	260.49	6.72
White Average Score	278.45	6.34	290.91	6.62
Reduced Priced Lunch Eligible Average Score	254.02	8.54	267.71	6.53
Reduced Priced Lunch Not Eligible Average Score	277.95	8.54	292.32	6.72
Black Average Score, Reduced Priced Lunch Eligible	237.33	6.39	255.30	6.40
Black Average Score, Reduced Priced Lunch Not Eligible	251.60	7.56	270.24	7.32
White Average Score, Reduced Priced Lunch Eligible	265.38	6.61	276.90	5.47
White Average Score, Reduced Priced Lunch Not Eligible	281.79	5.73	295.78	5.71

Analytic Strategy

To estimate the effect of Medicaid coverage on the achievement gap, I match birth–cohort specific NAEP scores to the state level estimates of Medicaid coverage (both real and simulated) in the same year. For children born later in the calendar year, this measure captured the entire prenatal period, whereas for children born earlier in the calendar year this measure captured coverage levels for more of the first year of life (given a 40 week gestation). However, in utero coverage and coverage in infancy are highly correlated because Medicaid coverage was typically extended simultaneously to pregnant women and their infant children under age one.

To analyze the effect of Medicaid coverage on test scores, I estimate:

$$\boldsymbol{Y_{st} = \beta(MedElig_{st}) + \beta X_{st} + \gamma_t + \alpha_s + \varepsilon_{st}}$$

where Y_{st} is the mean state level NAEP score of children born in year *t* and state *s*. X_{st} is a vector of time–varying state–level covariates, namely the percentage of the population with at least a high school degree, percent black, the percent Hispanic, the percent single parent households, the percent below the poverty line, the percent unemployed; and the log of mean household income in the state. These covariates were taken from the Current Population Survey (IPUMS). I also included a measure of mean per capita state and local non–health spending to net out potential confounding due to simultaneous policy shifts at the state or local levels. All models include state fixed effects ($\boldsymbol{\alpha_s}$) to net out time–invariant characteristics of the state as well as year fixed effects ($\boldsymbol{\gamma_t}$) to net out trends that affect all states equally. The first stage of the 2SLS model specification takes the form:

$$\boldsymbol{MedEligReal_{st} = \beta(MedEligSimulated_{st}) + \beta X_{st} + \gamma_t + \alpha_s + \varepsilon_{st}}$$

where the simulated eligibility coverage at the state level predicts variations in eligibility due to generosity rather than population size or other population characteristics.

Results

Table 2 presents results. Model 1 estimates the effect of prenatal Medicaid eligibility on the math scores of black students, while Model 2 estimates the effect on white students. Increasing prenatal Medicaid eligibility has a positive and statistically significant effect on the test scores of black students, and an insignificant effect on the math scores of white students. Table 2 suggests that a 20-percentage point increase in prenatal Medicaid eligibility (slightly less than the mean change in eligibility between 1996 and 2009) would result in a 2.94-point increase in black students' mean math score, compared to a 0.539 point increase in white students' mean score. The estimate for whites is not significantly different from zero.

Model 3 estimates the effect of prenatal Medicaid eligibility on the math scores of all students eligible for a reduced priced lunch, while Model 4 estimates the effect of prenatal Medicaid eligibility on the math scores of all students not eligible for a reduced price lunch. Prenatal Medicaid eligibility has a positive but weakly significant effect on the test scores of all students receiving free or reduced priced lunch, as we would expect given that this estimate is for students who became newly eligible for Medicaid. Unsurprisingly, the test score differences for those not on reduced priced lunch are very small and not significantly different from zero.

To place the coefficient in context, these results indicate that increasing the proportion of students eligible for Medicaid by 0.20 (20 percentage points) would yield a 1.606-point increase in the mean score of all students receiving free or reduced priced lunches.

Models 5 through 8 estimate the effect of increases in prenatal Medicaid eligibility by both race and reduced price lunch eligibility. Medicaid has no statistically significant effect on the mean math scores of white children, regardless of eligibility. However, there is a stronger, significant effect on the scores of black children who receive reduced priced lunches, and an even larger (though still insignificant) effect on the test scores of black children who do not receive free or reduced-priced lunches. An 0.20 increase in the proportion of students eligible for Medicaid results in a 3.9-point increase in mean math scores among black students eligible for a subsidized lunch (about half a standard deviation). This suggests that the racial achievement gap is in part attributable to inadequate healthcare. However, while white children who receive free and reduced-priced lunches score approximately 16 points lower than white children who are not eligible (see Table 1), the small coefficient and lack of significance indicate that access to health care may not contribute to this gap, suggesting that the challenges facing black and white children may be quite different.

Furthermore, there is suggestive evidence that expanding eligibility may affect not only black students who are Medicaid-eligible, but also those who may not be eligible, as demonstrated by the large but imprecisely estimated positive coefficient in Model 6. Although the populations that receive Medicaid and free or reduced price lunch do not match perfectly, they should be fairly similar (given the time lag, it is impossible to match the two populations perfectly, but imperfect matching should bias the estimates downward by including children who did not qualify for Medicaid). The large coefficient of eligibility among ostensibly ineligible black students is therefore surprising, even though it could arise by chance. This finding will be discussed in a subsequent section. One explanation for this finding could, however, be that, according to the National Center for Education Statistics, about three quarters of African American children attend schools where most of their classmates are low income. Conversely, only one third of white students attend schools where the most students are low income (National Center for Education Statistics, 2016). This could indicate that because African American students who are not eligible for free and reduced priced lunch are more often surrounded by children who are eligible, they benefit from the improved achievement and behavior of those who are eligible.

Table 2.2. Effect of Prenatal Eligibility on All Samples (IV regressions)

	Model 1: Black Average Score	Model 2: White Average Score	Model 3: Reduced Lunch Eligible	Model 4: Reduced Lunch Not Eligible	Model 5: Black Reduced Lunch Eligible	Model 6: Black Reduced Lunch Not Eligible	Model 7: White Reduced Lunch Eligible	Model 8: White Reduced Lunch Not Eligible
Prenatal Medicaid eligibility	0.147*	0.027	0.080	0.050	0.195**	0.121	0.018	0.0353
	(0.067)	(0.032)	(0.043)	(0.032)	(0.072)	(0.086)	(0.040)	(0.031)
State Non-Health Spending	14.844**	10.209**	13.260**	10.192**	13.166*	8.141	14.814**	12.389**
	(5.229)	(3.112)	(3.784)	(2.845)	(5.814)	(7.385)	(4.094)	(3.240)
Unemployment Rate	-1.686**	0.023	-0.613	0.094	-2.068**	-0.338	-0.074	0.123
	(0.536)	(0.275)	(0.363)	(0.273)	(0.630)	(0.812)	(0.346)	(0.274)
Percent Less than HS	0.014	-0.147	-0.492**	-0.169	0.144	-0.574	-0.506**	-0.171
	(0.272)	(0.141)	(0.190)	(0.143)	(0.313)	(0.414)	(0.178)	(0.141)
Percent Some College	-0.104	-0.249	-0.492**	-0.195	0.118	-0.064	-0.342	-0.160
	(0.270)	(0.139)	(0.187)	(0.141)	(0.302)	(0.412)	(0.177)	(0.140)
Percent College Grad	0.116	-0.013	-0.132	-0.080	0.102	-0.344	-0.192	-0.570
	(0.260)	(0.129)	(0.171)	(0.129)	(0.289)	(0.355)	(0.163)	(0.129)
Percent Black	-0.317	-0.124	-0.500*	-0.284	-0.183	-0.470	0.043	-0.005
	(0.283)	(0.178)	(0.214)	(0.161)	(0.306)	(0.372)	(0.239)	(0.002)
Percent in Poverty	0.016	0.219	0.145	0.036	-0.141	0.051	0.181	0.014
	(0.284)	(0.153)	(0.199)	(0.150)	(0.308)	(0.388)	(0.192)	(0.152)
Percent Single Parents	-0.138	-0.181*	-0.216*	-0.146	-0.211	-0.012	-0.295**	-0.137
	(0.156)	(0.082)	(0.109)	(0.082)	(0.176)	(0.235)	(0.104)	(0.082)
Log Family Income	0.147*	0.027	0.080	0.050	0.195**	0.121	0.018	0.048
	(0.067)	(0.032)	(0.043)	(0.032)	(0.072)	(0.086)	(0.040)	(0.054)
R2	0.68	0.76	0.70	0.78	0.71	0.61	0.68	0.80
N	183	231	234	234	165	136	229	229

- p<0.05; ** p<0.01, t p<0.1

Tab

Table 2.3. Effect of Prenatal Eligibility on Test Score Gap

	Model 1: Black White Gap, Reduced Priced Lunch Eligible	Model 2: Overall Black White Gap
Prenatal Medicaid eligibility	-0.168*	-0.105
	(0.071)	(0.063)
Unemployment Rate	7.712	-3.969
	(7.140)	(5.557)
Non-Health Spending (Log)	1.792**	1.208*
	(0.662)	(0.520)
Proportion Less than HS	-0.500	-0.127
	(0.314)	(0.255)
Proportion Some College	-0.447	-0.007
	(0.304)	(0.254)
Proportion College Grad	-0.291	0.090
	(0.297)	(0.248)
Proportion Black	0.123	0.246
	(0.351)	(0.292)
Fraction in Poverty Rate	0.395	0.147
	(0.320)	(0.277)
Proportion Single Parents	-0.011	0.016
	(0.182)	(0.149)
Log Family Income	6.000	5.257
	(10.646)	(9.377)
N	161	180
R2	0.21	0.16

* $p<0.05$; ** $p<0.01$

Table 1.33 demonstrates the change in the overall gap between the different categories of students associated with prenatal Medicaid expansion. Model 1 demonstrates the change in the test score gap between eligible black and eligible white children, showing a significant and large reduction in the black-white gap for such children. Model 2 shows the gap between black and white students overall, showing a smaller and statistically insignificant effect. These models reveal that access to Medicaid has a clear effect on the achievement gap between black and white students who are eligible for free or reduced price lunch. The size of the coefficient is very similar to that of the increase in test scores of African American students eligible for free and reduced priced lunch.

Possible Mechanisms

One mechanism through which better health could improve test scores is increased school attendance, since health problems are an important cause of absenteeism (Diette et al, 2000). I If children with asthma (which is more common in minority populations) get treatment, they may miss fewer days of class. As Table 4 demonstrates, there is suggestive evidence that this is indeed the case. Prenatal Medicaid eligibility has no statistically significant effect on the attendance of white students. For African American students, there is no statistically significant effect on the number of students who miss 1 to 4 days of class, but there is a statistically significant negative effect on the number missing 5 to 10 days (the data is provided in ranges, so I have kept to the original data structure). This indicates that access to health insurance may decrease chronic absenteeism. As the sample size is small, I cannot generate reliable estimates with a full set of covariates, but these models do instrument for prenatal Medicaid eligibility using simulated eligibility, and they include year and state fixed effects. Although the evidence is only suggestive, it does provide some support for a mechanism through which increased access to health insurance could decrease the black-white test gap.

Table 2.4. Effect of Prenatal Eligibility on Attendance

	Black Eligible			White Eligible		
	1 to 2 Absences	3 to 4 Absences	5 to 10 Absences	1 to 2 Absences	3 to 4 Absences	5 to 10 Absences
Prenatal Eligibility	-18.304	-23.425	-45.507*	1.835	7.213	-11.02
	(12.275)	(18.976)	(17.864)	(4.477)	(6.089)	(7.982)
R^2	0.34	0.34	0.88	0.48	0.43	0.54
N	99	71	17	171	169	142

* $p<0.05$; ** $p<0.01$, includes state and year fixed effects

Evidence Across Childhood

Despite clear evidence in the literature that infant health is important for future development, access to health insurance throughout childhood could have an even more beneficial impact on test scores, even if the effect of health insurance were mostly prenatal. As demonstrated in Appendix tables 5 through 12, when predicting test scores using an instrument for prenatal Medicaid eligibility and then eligibility at ages 1-4, 5-10, and finally 11-14, only prenatal eligibility has a significant effect. Given how the legislation was enacted, there is significant collinearity among these measures, particularly up to age 4. Nevertheless, I am not able to show that increased eligibility at later ages improves outcomes.

Heterogeneous Treatment Effects

Heterogeneous treatment effects have long been of interest to social scientists (Bjorklund and Moffitt, 1987; Brand and Xie, 2010; Brand, 2010). Two important sources of heterogeneous effects are pre-treatment heterogeneity and treatment effect heterogeneity (Morgan and Winship, 2007). Pre-treatment heterogeneity would, in this case, stem from differences in pre-existing characteristics correlated with access to health insurance and education, such as poverty or race. Variation in the effect of access to health insurance on education would then be deemed treatment effect heterogeneity. Heterogeneity in treatment is important for policy making, as policy makers usually have to allocate scarce resources, making efficient targeting important (Manski, 2007; Xie and Brand, 2012). It is also important if we are interested in reducing inequality between groups. This study adds to this literature and points to the importance of understanding heterogeneous effects when studying how best to reduce inequality. The net effect of heterogeneous effects by race in this case is to change the achievement gap.

Conclusion

This paper has demonstrated that access to health insurance has a significant effect on the racial but not the socioeconomic achievement gap. On the basis of other evidence suggesting that poor blacks and poor whites experience somewhat different types of disadvantage, I have argued that anti-poverty policies such as Medicaid are likely to have different effects on different ethnic groups. The expansion of prenatal Medicaid appears to be such a case, with quite different effects on the eligible black and white populations. I also suggest that a possible mechanism through which access to health insurance increases school attendance is by decreasing absenteeism, but more research is required to determine whether this effect is real. .

The negative consequences of a black-white test score gap are substantial. As Jencks and

Phillips (1998) argue, closing the black-white test score gap would advance racial equality more than any other type of intervention because of its many downstream consequences. It would reduce the racial gap in college graduation rates, and reduce wage disparities, while impacting health and fertility choices (Altonji and Doraszelski, 2005; Wolfe and Haveman). More than half of the racial wage gap disappears when we compare black and white workers with similar test scores, suggesting that closing the gap could help alleviate wage disparities (Neal and Johnson, 1996).

This paper diverges from the economics literature by taking racial gaps as an outcome that deserves analysis. Education is a key pathway through which economic mobility is achieved. The racial gap in achievement is a major obstacle to reducing racial disparities in earnings, and it is probably also a significant source of other racial disparities among adults. Medicaid makes a significant dent in the black-white achievement gap and is thus a leveling mechanism, not just a way to ensure the poor do not fall further behind.

Future research should continue to investigate how seemingly unrelated policy interventions affect racial and socioeconomic achievement gaps. Scholars should examine these policies through the lens of heterogeneous effects. This paper demonstrates such effects and contributes to that growing literature. As others have noted, this is particularly important in times of budget constraints (Brand, 2010). It is especially vital given that policy interventions may only be successful for the most vulnerable groups but not for the population as a whole.

Chapter 4

Race, Place, and Intergenerational Economic Mobility

Introduction

The essence of the "American Dream" is that regardless of where a child comes from, he or she should be able to achieve economic success. However, research has shown that this is often not the case (Chetty et al, 2017). Understanding what helps low-income children escape from poverty is thus of great concern to both scholars and policy-makers. There is great variation in mobility rates both across time (Chetty et al, 2017) and, perhaps even more importantly, across places (Chetty et al, 2014). Although researchers have compared individual mobility rates of blacks and whites (Bloome, 2014; Mazumder, 2011; Western, 2002), no research to date has investigated whether minority counties differ from white counties in this respect.

Given that research has shown that geographic variation within the United States is larger than variation between the United States and other developed nations, understating these geographpic differnces within the United Sates is potentially valuable to understanding racial disparities in mobility. African American counties have long been recognized as uniquely disadvantaged by the concentration of poverty and a historical legacy of discriminatory policy (Sampson, 2012; Massey and Denton, 1993). If mobility studies do not take into account these place-based differences in the experiences of blacks and whites, we lose sight of an important dimension of varying mobility processes.

There is a large, rich literature pointing to the ways in which the concentration of poverty is a legacy of discriminatory policy and racism that continues to this day. Sociological research focused on the concentration of poverty and disadvantage in minority counties has argued that the experience of this deeper historical disadvantage is unique and reduces upward mobility (Wilson, 1989; Sharkey and Elwert, 2011). However, this insight has been sparingly applied to studies of intergenerational economic mobility (with the exception of Sharkey and Graham, 2014, and Sharkey, 2013). The present paper is motivated by the finding that more than 70% of African American children who grow up in the poorest quarter of American neighborhoods remain in poor neighborhoods as adults (Sharkey 2008). However, it remains unclear how this maps on to larger economic mobility trends, or whether this finding obscures broader variation in race and space.

This paper will bring together the finding that African American counties are uniquely disadvantaged, that their disadvantages are extraordinarily durable, and that economic mobility varies greatly by geography. Taken together, these findings provide the basis for the central claim of this study: a significant part of the racial gap in mobility outcomes between blacks and whites is potentially attributable to the weakness of local organized labor and the history of discrimination, rather than the conventionally cited sources of the gap, such as higher levels of poverty and single parenthood.

since the 1970's, attempts to improve economic mobility in low mobility areas have focused mainly on helping people move out of distressed counties or improving children's tests scores, in the hope that these changes would make more black children upwardly mobility. Studies such as *Gautreaux* (which came out of a consent decree) and Moving to Opportunity provide insight into the potential importance of neighborhoods for an individual's prospects, but moving everyone out of distressed neighborhoods is neither feasible nor necessarily desirable (Briggs, 1997; Keels, 2005; DeLuca and Dayton, 2009; Mendenhall et al, 2009). This study will therefore ty to identify institutions and policies within distressed neighborhoods that help produce above-average results, by examining the dynamics at work in majority black neighborhoods, rather than extrapolating from research that looks at nationally representative samples.

I examine predictors of economic mobility drawn from three literatures: the neighborhood disadvantage literature, the policy intervention literature, and the literature on historical disadvantage experienced by black counties. Using new data from the Equality of Opportunity Project, which estimated mobility in every county in America, I compare upward mobility and the reproduction of poverty in white versus black counties. I confirm my findings using individual level data from the NLSY97, matching individuals to their counties. These two rich data sets measure overlapping cohorts. The Equality of Opportunity data includes all children born between 1980 and 1986, while the the NLSY97 sample includes respondents born between in the United States between 1980 and 1984.

The paper proceeds as follows. First, I discuss the importance of geography in conditioning mobility outcomes, followed by a discussion of race specific mobility processes and the relationship between racial disadvantage and space. I then overview the data and methods. Finally, I present results and discuss their implications.

Predictors of Mobility

Economic mobility is an important feature of social stratification and has been the focus of a large body of sociological literature. Research on mobility has explored the importance of family structure (e.g., Bloome, 2014); education (e.g., Brand and Xie, 2010); gender (e.g., Beller, 2009); and economic disadvantage in early life (e.g., Wagmiller et al., 2008). Low mobility is a measure of the degree to which economic and social inequality persist within families, from one generation to the next. Ongoing research into the specific micro-level processes underlying these associations covers everything from parenting practices (e.g., Lareau, 2003) to school quality (Haskins et al, 2008), and it continues both to reveal new mechanisms for the transmission of social and economic position across generations and to highlight how institutions, policies and social contexts can disrupt the persistence of economic rank from one generation to the next.

Receet research by Chetty et al. (2014) demonstrates that these studies have missed one important source of variation in economic mobility, namely geography. These studies cannot speak to the question of whether the actual processes of mobility differ across race and place, because they focus on individual-level mobility using intergenerational panels. Longitudinal studies, such as NLSY or PSID, have too few respondents to generate reliable local mobility rates. While they can explore the effect of neighborhood characteristics such as the poverty rate on an individual's chances of mobility, they cannot generate reliable measures of average mobility for each geographic area. Chetty et al. (2014) provide the first reliable estimates of spatial variation in income mobility across the United States at the county level. Counties appear to have a direct causal effect on children's mobility prospects, and the effect increases the more years a child lives in a county. Geography can greatly alter the probability of a child's upward trajectory, regardless of individual characteristics (with a range of over 10 percentage points).

Chetty et al.'s estimates of intergenerational economic mobility circumvent the problem of small sample size by using data from federal tax records, which provide a picture of almost the entire population. However, they do not provide information on taxpayers' race, and these authors do not focus on differences in counties' racial composition. I will use Census data to identify majority black and majority white counties, and operationalize these data in a new way by looking at just majority black areas.

Economic Mobility, Race, and Place

Race and space serve as means of socially organizing economic inequality. Given that both race and geography matter for intergenerational economic mobility, the question remains: How does the interaction of race and place influence mobility? African Americans generally experience higher rates of downward mobility than whites (Corcoran and Adams, 1997; Mazumder, 2011). Rising income inequality is also associated with racial segregation and isolation of minorities (Watson, 2009). These facts imply that the transmission of disadvantage cannot be fully understood without taking neighborhoods and the persistence of neighborhood inequality into account. Growing up in neighborhoods of concentrated disadvantage, that are both racially segregated and have high poverty rates, predicts below-average educational and economic outcomes, increased welfare receipt, reduced test scores, and lower rates of high school graduation (Harding, 2003; Leventhal and Brooks-Gunn, 2000; Vartanian and Buck, 2005; Sampson, Sharkey and Raudenbush, 2008). Policy often attempts to intervene in order to increase mobility and improve the adult outcomes for children growing up in these areas. However, no research has yet investigated how mobility processes actually function in these areas, or whether it is different from mobility processes in white counties. This paper tries to do that.

Variation across places signals that differences in social structures, institutions, local industries and public policies affect mobility at the subnational level (Mayer & Lopoo 2008). Systems of stratification are organized and endure along spatial lines, whether through geographically concentrated disadvantage, racial segregation, public investment, or all three (Sampson, 2012; Sharkey, 2013; Sharkey and Faber, 2014). Sharkey argues that "the spatial clustering of resources, institutions, and social phenomena means that the life chances of individuals are directly linked to their location in residential space," and African Americans are more likely than whites to spend multiple generations in poor, under resourced neighborhoods than whites (2008). If the neighborhood is an independent dimension of stratification, any analyses of intergenerational economic mobility that ignore geography lack an important component.

African American counties are disadvantaged in different ways than white counties (Wilson, 1980; 1989; Massey and Denton, 1993). However, this finding has yet to be incorporated into studies of intergenerational economic mobility, which assume that the same covariates have the same effect in black and white counties. Discrimination and oppression in African American counties have interacted with technological and economic changes to permanently marginalize these counties (Wilson, 1980). Individual disadvantages can be compounded in counties of concentrated disadvantage, isolating community members and inhibiting their upward mobility. While this has led to the systematic disadvantage of black counties, it has also advantaged white workers, implying a potential impact on mobility rates for the two groups.

Majority African-American counties experience have higher levels of crime, poverty, and female headed households than white counties, the result structural constraints and cultural responses to these constraints (Wilson, 1987). With decreasing numbers of young African American in labor market, single parenthood increased, accelerating the concentration of disadvantage in these areas. This concentration is the crucial difference between black and white poverty: poor blacks are isolated and concentrated in poor urban neighborhoods, while poor whites are more spread out in white neighborhoods. This has an impact on crime, mortality, test scores, and housing options (Card and Rothstein, 2007; Collins and Williams, 1999; Cutler and Glaeser, 1997; Krivo et al, 2009; Massey et al, 1987; Sampson et al, 1997). The social isolation of these counties, removed from jobs and powerful individuals and institutions, makes upward mobility more difficult. It also suggests that children will more often inherit their parents' disadvantage.

Segregation conditions the experience of disadvantage. By not taking this into account when studying mobility, we lose an important theoretical explanation of varying mobility processes. From this literature, one would expect that single parenthood, poverty and crime, three metrics on which black counties look especially disadvantaged, may be responsible for the gap in mobility between blacks and whites. However, given the different historical experiences and legacy of disadvantage in these areas, that need not be the case.

Origins of Segregation and Racial Space

Historically, African American counties have experienced unique policy regimes which continue to have far reaching consequences (Massey and Denton, 1993; Wilson, 1987). White Americans, at the individual, institutional, and policy level produced and reinforced spatial segregation. Violence against blacks in white areas, racial covenants, blockbusting, redlining, Jim Crow, and rapid deindustrialization accelerated and institutionalized racial segregation. By isolating African American counties, economic and social problems were concentrated and magnified, and a feedback loop in which segregated areas were more vulnerable, particularly to the effects of deindustrialization (Massey and Fischer, 2000; Massey et al, 1991). Thus while attributes such as poverty and single parenthood are more prevalent in these counties, their concentration was magnified by historical processes, demonstrating that the past is still a powerful predictor of disadvantage today (Bayer et al, 2004; Bifulco and Ladd, 2007).

The political dynamics of racially diverse areas may also contribute to the perpetuation of inequality. The more diverse a community, the greater the reluctance to invest in public goods

(Alesina et al. 1999). Racial distinctions were built into the foundation of the welfare state by reflecting and reproducing racial divisions, thus perpetuating inequality (Lieberman, 2001; Katznelson, 2005) This could have far reaching consequences with regard to mobility processes in segregated black counties, as previous research demonstrates the importance of funding welfare state activities, such as education and health.

Inequality and racialized poverty in diverse areas can be understood as a result of a combination of both exploitation and competition. Low economic mobility might also be explained by the marginalization of organized labor labor (Tomasky-Devey & Roscignio, 1996). As Wilson (1987) explained, "class has become more important than race in determining black access to privilege," indicating that understanding the labor context in which individuals are trying to move up the ladder may be key to understanding their success or failure.

Finally, political attitudes may be indicative of unobserved discrimination, and in the southern United States, preferences such as modern voting patterns can be traced back to slavery and an area's dependence on slave labor (Acharya et al., 2017). These mechanisms might also have an effect on economic mobility outcomes through the policy preferences of elected officials. Key (1949) argued that whites in former slave states had the greatest investment in perpetuating white supremacy, and this required lower economic mobility among blacks. This paper will also bring in larger contextual factors with an emphasis on understanding the distribution of economic and political power.

Mobility Regimes of Racially Segregated Counties

The unique historical experience of segregated African American counties could indicate that the process of mobility out of poverty might differ significantly in these counties from most majority white counties. The probability of upward mobility should be lower in majority black counties, while the probability of intergenerational poverty should be higher. Furthermore, the variables that are often suggested as levers or barriers to mobility might function differently in such segregated counties. For example, single parenthood, poverty, school funding, and access to supplemental income might have different impacts in these counties, given the different historical experiences and the varying levels of these covariates. Finally, county-wide sources of historical disadvantage, such as the power of organized labor, the historical legacy of slavery, and political attitudes, may explain rates of mobility out of poverty in low income black counties better than individual attributes, as this deficits are experienced at the community level above the individual.

This suggests three hypotheses:

1. The distribution of mobility outcomes will vary between black and white counties.
2. The predictors of mobility in white counties will differ in black and white counties.
3. Historical disadvantage is a source of lower mobility in black counties.

Data and Analytic Strategy

My dependent variable is a measure of economic mobility generated by Chetty et al (2014). They created estimates of intergenerational economic mobility using federal tax records for nearly all of the 40 million children born between 1980 and 1993 and their parents (though the transition matrices use only 1980-1982). They ranked children within each birth-year cohort based on their family income when they were in their late twenties. Then they ranked the parents of these children relative to each other based on the parents' income when the child was 16.

Chetty et al. were able to generate mobility estimates for children in approximately 3000 counties in the United States. This paper will use their quintile transition matrices as the source of various outcomes. These transition matrices show the proportion of the children from each of the five quintiles of parental income when the children were 16 in each of five income categories of their own cohort in adulthood.

To make sure that I am correctly assigning mobility outcomes to the right county, I use a sample of "stayers" that includes only the parents and children who remained in the same county until the child was at least 18 years old. I use the transition matrices to create two categories of mobility: upward mobility in a county (the proportion of individuals born to parents in the bottom quintile who move to one of the top three quintiles of their cohort in adulthood) and the reproduction of poverty (the proportion of individuals who were born to parents in the bottom quintile and remain there in the bottom quintile).

I then use three sets of independent variables drawn from the literature above to predict who falls into each of these two groups. The first analysis looks at on three variables derived from the literature on neighborhood disadvantage, poverty, crime and single motherhood. Single motherhood and poverty were two of the most important correlates of mobility in the analyses by Chetty et al., so we would expect them to be powerful predictors of mobility in black counties. These variables are the same used by Chetty et al in his analysis in order to be able to directly compare results, and they are drawn from the census.

The second set of independent variables draws on the policy tools used to combat low economic mobility: access to the EITC, median rents (to understand the importance of affordable housing), school dropout rates, school spending, the county's Gini coefficient, a social capital index, and median household income. These variables are drawn from Chetty et al., in order to make direct comparisons possible.

The final set of variables is drawn from the literature on these counties' historical marginalization. I measure union membership (as a fraction of employment) in 2010, voting Republican in 2000, support for affirmative action in 2000, and the slave population as a percent of the total population in 1860 as a measure of historical legacy. I also include proxy measures for the economic dynamism of the county, including migration inflows, unemployment, and the average employee wage. The union data is drawn from Hirsch and Macpherson's 2010 CPS estimates, and the measures of economic dynamism are from Chetty et al (2014) with the exception of average employee wage, which is from the 2010 BLS estimates of county business patterns data. The rest of the variables are from Acharya et al. (2017).

I divide the sample into two parts: counties that are more than 50% African American and counties that are not when measured in 1980 (results are substantively similar using a cut off of 40%). This yields 78 majority black counties (out of 3,142 counties). I then run separate analyses on each sample, looking at the relative importance of each coefficient in the majority white sample and the majority black sample. These are essentially fully interacted models, which are both easier to interpret and more substantively relevant to my research question than models with only one or two interaction terms. The results of fully interacted models also yeild a better test of whether the interaction effects are significant (though I also run a single regression with an interaction term on each coefficient to compare results). This analysis will demonstrate the relative importance of each covariate for mobility outcomes in segregated black counties.

Finally, I use individual level data from the geocoded NLSY97. These individuals were born at the same time, but the longitudinal, individual level data allows me to test covariates on individual outcomes. I match both parents' income and children's income to the quintiles identified by Chetty et al. in the national tax data, and then use this result to determine whether these children remained in the bottom quintile or rose to the third, fourth or fifth quintile.

I also decompose my results to better understand which covariates are contributing to inequality in mobility outcomes. This will demonstrate whether the disparities in mobility between predominantly black and predominantly white counties were driven by differences between counties in the means of individual characteristics, differences in the predictive power of those characteristics, or differences in the interaction between the two. While this method is usually used to better understand wage discrimination, it can be usefully applied to this context as well.

Tables 1 and 2 provide descriptive statistics on the white and black samples. To take one example, the mean poverty rate in white counties is lower than in majority black counties, but the maximum poverty rate is higher in white counties, indicating that the distributions of the covariates are overlapping.

Table 3.1. Descriptive Statistics of Selected Covariates in White Counties

Covariate	Mean	Std. Dev.	Min	Max
Poor Share	0.14	0.06	0.02	0.52
Household Income	33182.9	7013.9	13646.95	77942.65
GINI	0.38	0.08	0.16	1.10
EITC	1.49	4.04	0.00	21.33
Expenditure per Student	5.99	1.74	3.03	53.26
Dropout Rate	0.00	0.02	0.04	0.24
Social Capital Index	-0.05	1.28	-4.26	7.31
Fraction of Single Parent Families	0.19	0.06	0.06	0.50
Median Rent	479.94	169.87	143.96	1484.96
Affordability for Low Income Households Index	135.62	16.93	107.27	235.25

Table 3.2. Descriptive Statistics of Selected Covariates in Black Counties

Covariate	Mean	Std. Dev.	Min	Max
Poor Share	0.27	0.08	0.08	0.41
Household Income	25986.2	5415.7	17196.85	48273.49
GINI	0.48	0.10	0.33	0.80
EITC	0.31	1.80	0.00	11.43
Expenditure per Student	5.45	1.02	3.60	8.98
Dropout Rate	0.02	0.03	0.05	0.10
Social Capital Index	-1.03	0.91	-3.10	1.56
Fraction of Single Parent Families	0.40	0.07	0.21	0.54
Median Rent	338.71	148.90	166.63	927.77
Affordability for Low Income Households Index	124.69	11.18	107.15	186.64

Results

Figures 1 and 2 provide the empirical foundation for the following analysis. Figure 1 simply shows the distribution of upward mobility in majority black and majority white counties, while Figure 2 shows the concentration of disadvantage. Each observation denotes the percentage of individuals in a community who were both born to parents in the bottom income quintile and remain in the bottom income quintile in adulthood (Figure 2), and the percentage of individuals who start in the first quintile and reach the third, fourth or fifth income quintile in adulthood. In both cases, the means are significantly different ($p<0.01$), indicating that the distributions of opportunity and disadvantage are markedly different in majority black and majority white counties.

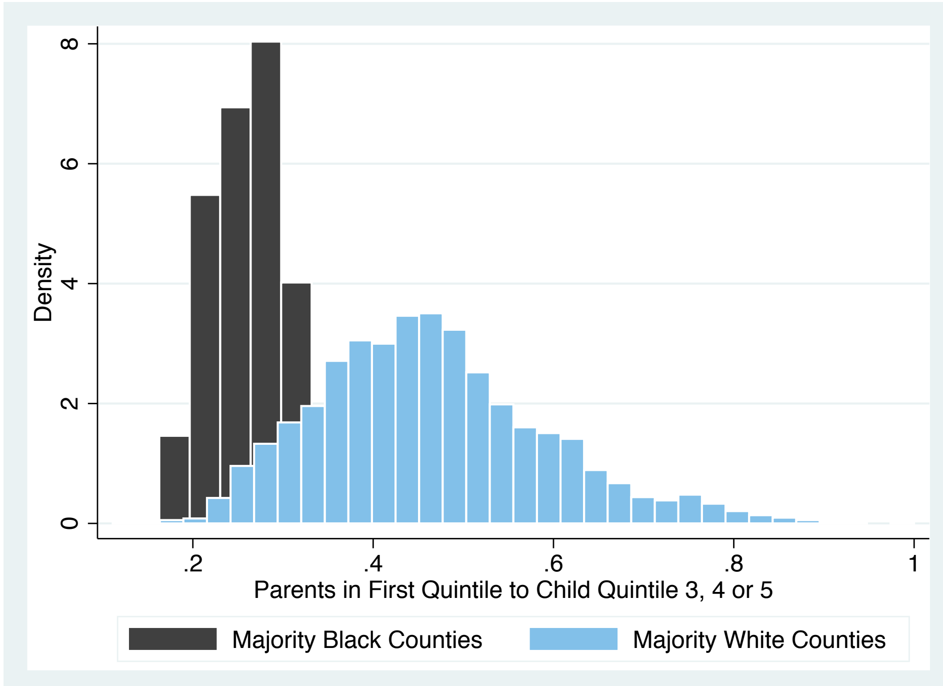

Figure 3.1. Upward Mobility in Majority Black and Majority White Counties

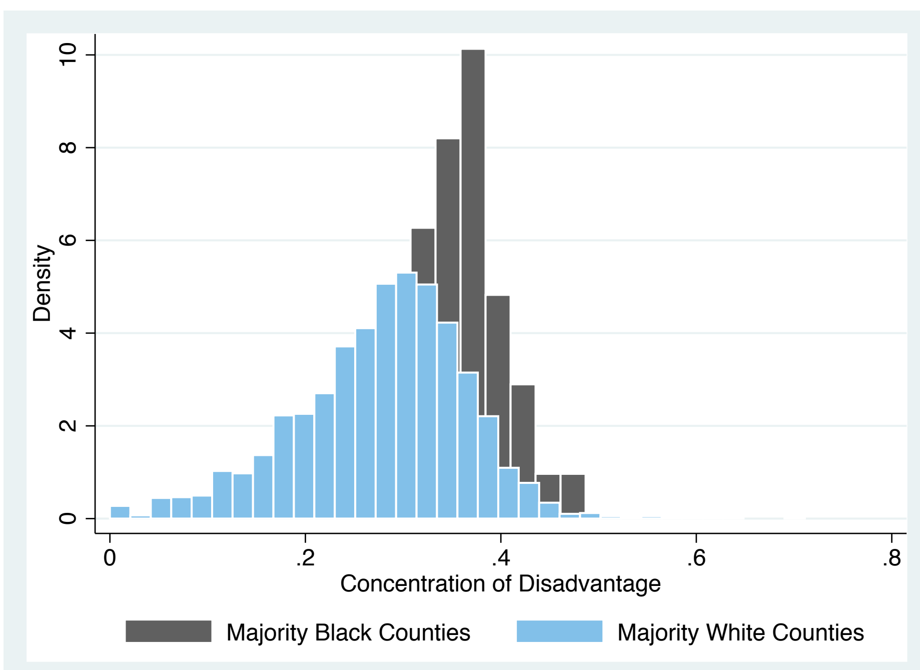

Figure 3.2. Reproduction of Disadvantage Among Majority Black and Majority White Counties

Analyses Motivated by Neighborhood Literature

Figures 3, 4, and 6 demonstrate the relationship between economic mobility and crime, poverty, and single parenthood, the three variables identified in the literature as being crucial sources of inequality between white and black counties. Quantile regression lines denote the 25th and 75th percentiles, and the solid black line denoting the 50th percentile. The more sparsely populated scatterplot shows majority black counties; the more populated plot shows majority white counties. Figure 3 demonstrates that although we see a very strong positive relationship between crime and the reproduction of poverty in white counties, increasing crime has little impact on rates of upward mobility in black counties. We also see that at higher levels of crime there is less variation of mobility in the white plot, while the 25th and 75th percentile lines do not converge on the black plot. The relationship between crime and upward mobility is stronger in majority white counties than majority black counties.

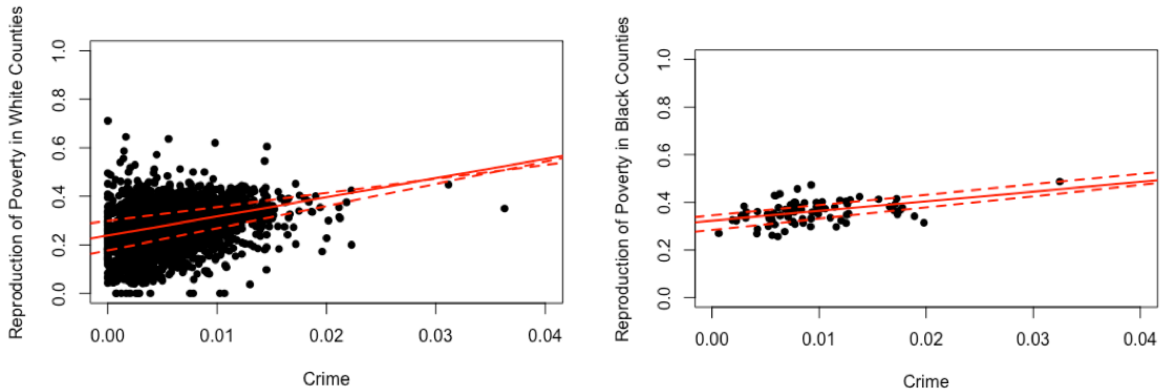

Figure 3.3. Scatterplot of Crime on Reproduction of Poverty in White and Black Majority Counties

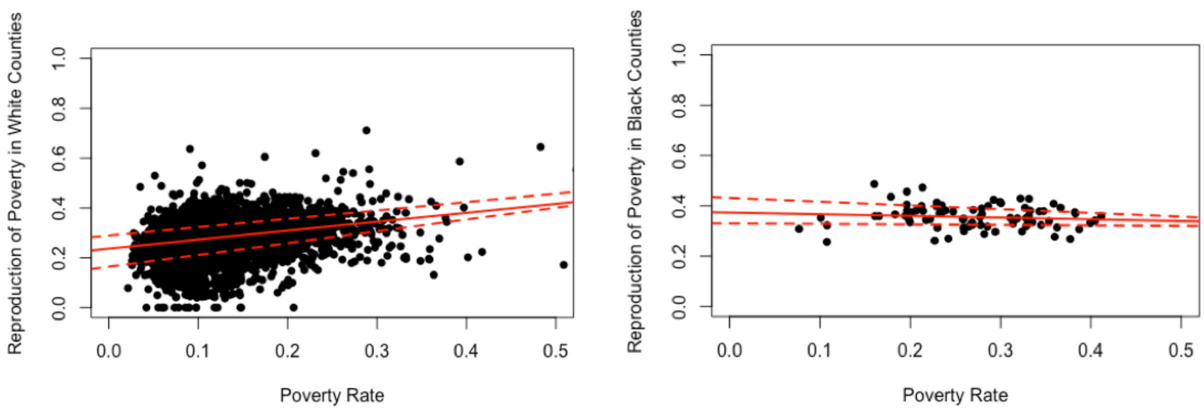

Figure 3.4. Scatterplot of Poverty Rate on Reproduction of Poverty in White and Black Majority Counties

Figure 4 reproduces the same chart for the poverty rate, and we see a similar relationship: a strong positive correlation between the poverty rate and the intergenerational reproduction of poverty in white counties, and a weaker relationship in black counties. Figure 5 shows the marginal effects from the full sample, with a continuous interaction term for percent black. The left four panels show the relationship between poverty and upward mobility by percent black, while the four panels on the right show the reproduction of poverty. Here we see that when the county is majority white, poverty has the predicted effects, but the slope changes direction in majority black counties, and the interaction term is significant.

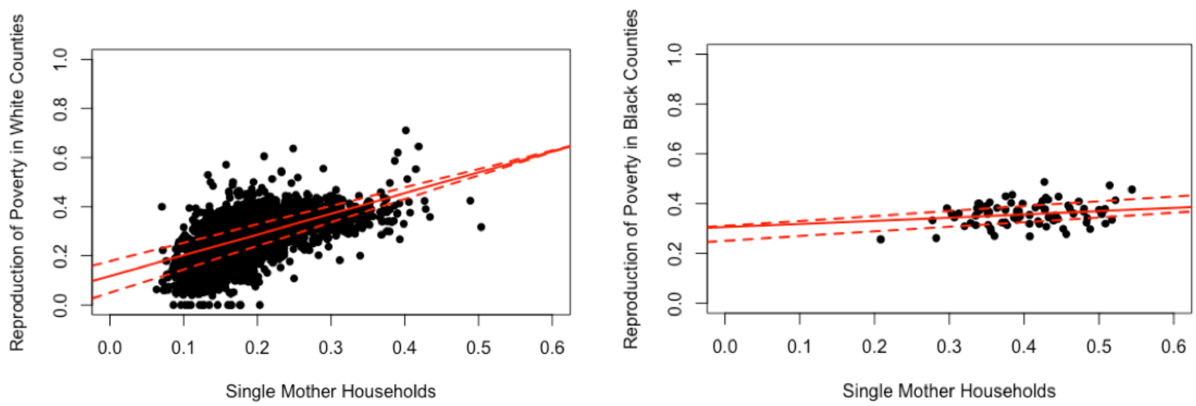

Figure 3.5. Scatterplot of Female Headed Households on Reproduction of Poverty in White and Black Majority Counties

Perhaps the most surprising visuals, Figure 5, shows that the relationship between single parenthood and the concentration of disadvantage is strong in white counties, which is the same as the finding of Chetty et al., and very weak in black counties. Looking at only the higher part of the distribution for white counties does not eliminate this relationship, which is surprising given the large literature on single parenthood and racial disadvantage. Thus, the relationship between single mother households and the reproduction of poverty is stronger in majority white counties than majority black counties. Figure 6 shows the marginal effects from the full sample, with a continuous interaction term for percent black. The four panels on the left show the relationship between single parenthood and upward mobility by percent black, while the four panels on the right show the reproduction of poverty. Here we see that when the county is majority white, single parenthood has the predicted effects, but that the slope changes direction in majority black counties. The interaction term is significant.

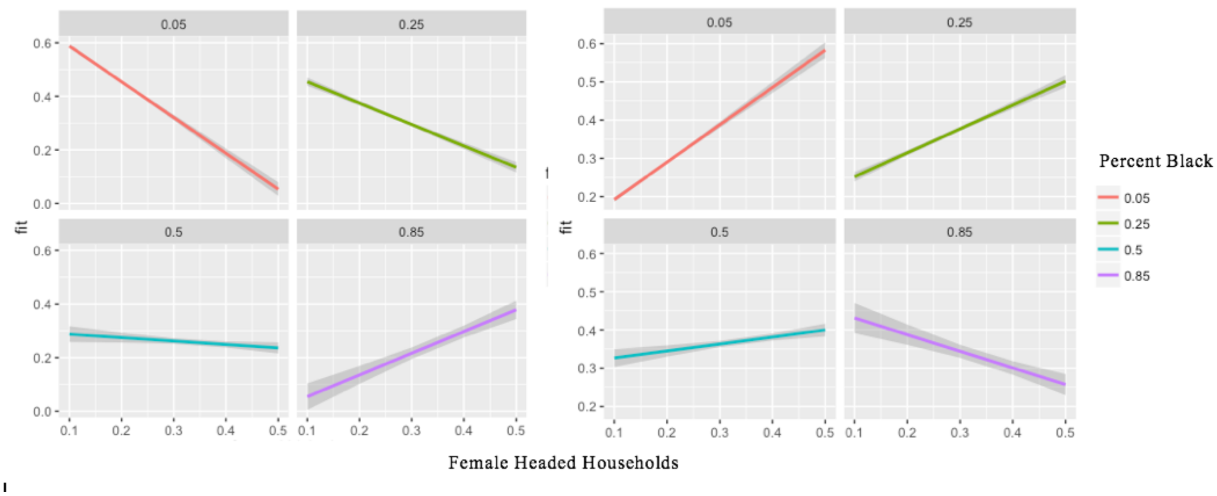

Figure 3.6. Marginal Effects of Poverty Rate on Upward Mobility and Reproduction of Poverty by Female Headed Households

Table 3.3. OLS Regressions of Poverty, Single Parenthood and Crime on Reproduction of Poverty and Upward Mobility in White and Black Majority Counties

	Dependent variable:			
	Reproduction of Poverty		Upward Mobility	
	(White)	(Black)	(White)	(Black)
Poor Share	0.050*	0.196**	−0.021	−0.255***
	(0.028)	(0.076)	(0.036)	(0.085)
Proportion Single Mothers	0.872***	0.281***	−1.466***	−0.259**
	(0.033)	(0.089)	(0.043)	(0.099)
Total Crime	1.078**	2.985***	−1.637***	−0.814
	(0.427)	(0.951)	(0.556)	(1.059)
Constant	0.111***	0.271***	0.761***	0.450***
	(0.005)	(0.029)	(0.007)	(0.032)
Observations	2,628	79	2,628	79
R^2	0.324	0.262	0.460	0.344
Adjusted R^2	0.323	0.232	0.459	0.317

Note: *p<0.1; **p<0.05; ***p<0.01

Turning to Table 3, which includes the three variables of interest in a simple OLS regressions by race, we see that although crime and upward mobility both have a strong, significant negative effect on upward mobility in white counties, the effect is far smaller, and not significantly different from zero, in black counties. Looking at single parenthood and the reproduction of poverty in particular, we see that single parenthood has a much larger association with economic mobility in white counties than in black counties.

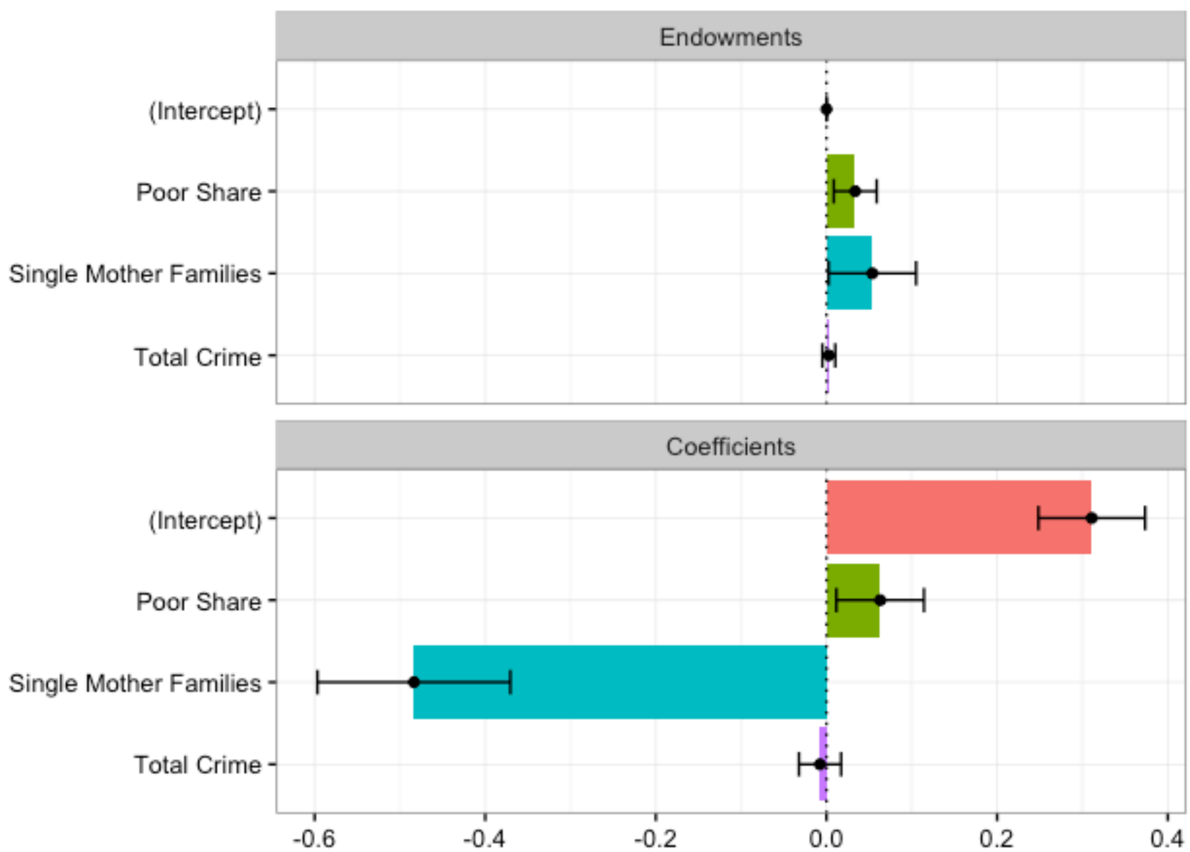

Figure 3.8. Upward Mobility Decomposition

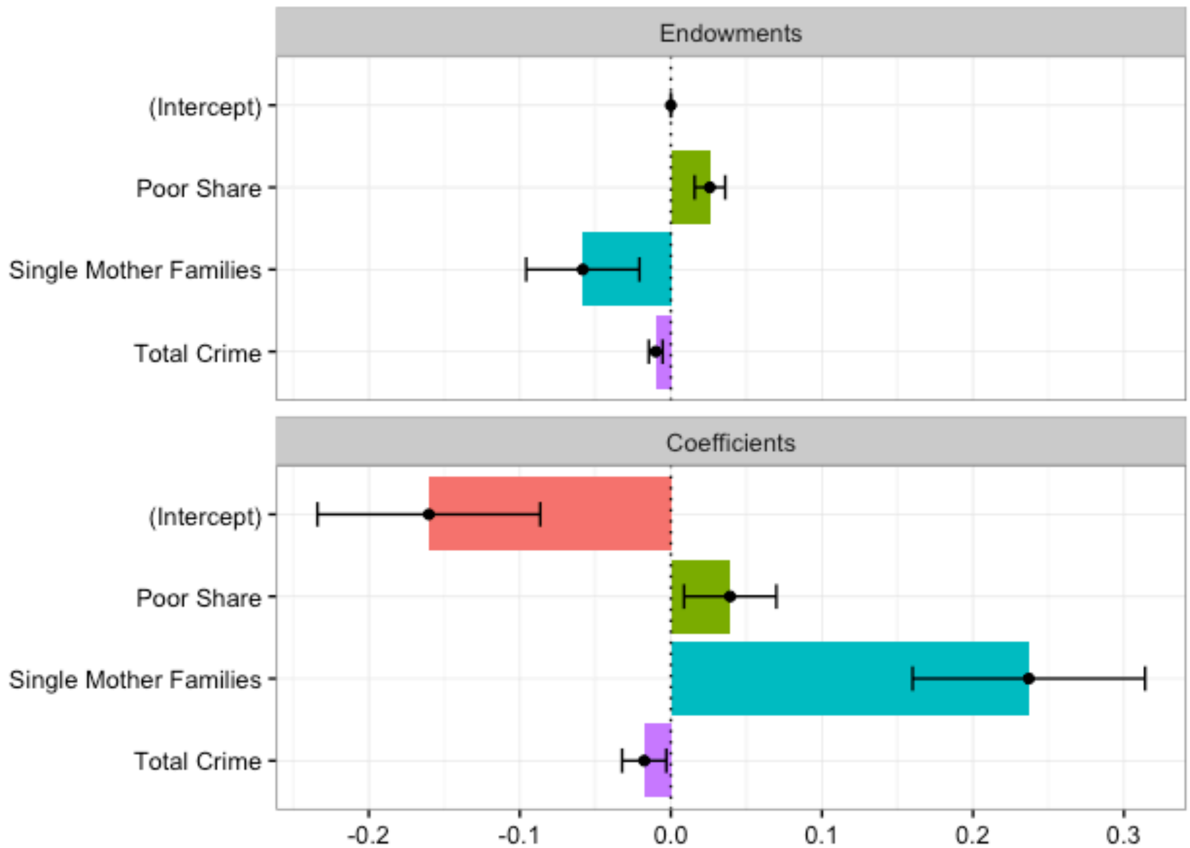

Figure 3.9. Concentration of Disadvantage Decomposition

An Oaxaca decomposition indicates that there is a 20 percentage point gap in upward mobility between black and white counties. Because both gaps are constructed the same way, the reproduction of the poverty gap is negative, as it is higher in black counties. Interestingly, the gap is larger in terms of upward mobility, and not symmetrical. Figure 8 shows how much of the gap is accounted for by each of the covariates. We see that differences in endowments may contribute to the gap, but that they do not achieve significance. The vast majority of the gap is due to the intercept, which represents the omitted variables, and in fact the gap in outcomes would be larger were it not for the different, lower effect of single parent families in black counties. This type of decomposition is usually used to understand wage disparities. In those analyses the intercept can be interpreted as omitted variables. In Figure 9, we see again that the vast majority of the gap is again due to the intercept while a small amount is due to differences in endowments of single parent children However, the different effect of single parenthood in black counties on mobility has a negative effect on the gap.

Policy Levers

The next analysis focuses on the levers that policy makers use to increase economic mobility. The only predictors that have significant coefficients when predicting the reproduction of poverty in this small sample of majority black counties are the share of individuals living in poverty and the county's affordability for low income families (Table 5). Across other predictors, almost nothing is statistically significant. While statistical significance is likely to be low in the small sample of majority black counties, the coefficients are also far smaller, suggesting that the relationship in the data is different. The correlation of single parent families with the reproduction of poverty is not only insignificant in the majority-black counties, it is only one fifth of the size of the correlation in the majority-white counties. This demonstrates that the correlates of the reproduction of poverty in majority black areas are not the same as in white counties. To understand mobility trends in these counties we need to look at other factors.

Table 3.5. OLS Regressions of Policy Covariates on Reproduction of Poverty and Upward Mobility in White and Black Majority Counties

	Dependent variable			
	Reproduction of Poverty		Upward Mobility	
	(White)	(Black)	(White)	(Black)
Poor Share	0.051	0.270*	0.194***	0.046
	(0.039)	(0.147)	(0.048)	(0.144)
Gini	0.045*	−0.095	−0.182***	−0.031
	(0.024)	(0.065)	(0.029)	(0.064)
Expenditures Per Student	−0.001	−0.005	0.002*	0.005
	(0.001)	(0.007)	(0.001)	(0.007)
Student Teacher Ratio	0.0001	−0.003	−0.003**	−0.002
	(0.001)	(0.003)	(0.001)	(0.003)
Dropout Rate	0.388***	−0.046	−0.449***	−0.230
	(0.068)	(0.164)	(0.084)	(0.160)
Social Capital Index	−0.014***	0.009	0.029***	0.004
	(0.001)	(0.008)	(0.002)	(0.007)
Single Parent Families	0.702***	0.132	−1.241***	−0.237*
	(0.038)	(0.128)	(0.046)	(0.126)
EITC Exposure	−0.001***	0.004	0.001***	0.007**
	(0.0004)	(0.004)	(0.0005)	(0.003)
Median Rent	0.0001***	0.0001	0.00000	−0.00004
	(0.00002)	(0.0001)	(0.00002)	(0.0001)
Low Income Affordability	−0.0002	−0.003***	−0.0001	0.002**
	(0.0002)	(0.001)	(0.0002)	(0.001)
Constant	0.127***	0.831***	0.795***	0.133
	(0.029)	(0.156)	(0.035)	(0.153)
Observations	1,992	68	1,992	68
R^2	0.449	0.254	0.640	0.523
Adjusted R^2	0.447	0.123	0.638	0.440
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3.6. Predicted Gap in Outcomes Between Majority White and Majority Black Counties with Selected Covariates

	Predicted Outcome in Majority White Counties	*Predicted Outcome in Majority Black Counties*	*Gap between Majority White and Majority Black Counties*
Upward Mobility from Q1 to Q345	.468	.264	.204
Concentrated Disadvantage from Q1 to Q1	.272	.353	-.082
Upward Mobility from Q1 to Q345 including slave population	.446	.263	.182
Concentrated Disadvantage from Q1 to Q1 including slave population	.284	.355	-.072
Upward Mobility from Q1 to Q345 including slave population and unions	.429	.295	.134
Concentrated Disadvantage from Q1 to Q1 including slave population and unions	.298	.362	-.064

Turning to upward mobility, we see that EITC exposure has a larger effect in majority black counties. While single parenthood still has a negative effect, similar to that in the white sample the magnitude is far smaller, a fifth of the size. Low income affordability is also significant.

To better understand the mobility processes of majority-black counties, I again decompose the results. Table 6 summarizes the difference in predicted mean outcomes. The decomposition indicates a substantial gap in outcomes. When examining the gap between majority black and majority white counties with the same concentration of disadvantage, we observe a mobility gap of 8 percentage points (35 vs. 27 percent), indicating that the reproduction of poverty in majority black counties is substantially greater. When examining endowments, or the mean differences in the variables, the only variable with a statistically significant difference in county-wide means is in the affordability index for low income individuals. No other variables, such as the poverty rate or proportion of single parents, shows a statistically significant difference in means that was driving the effect, despite the attention to these variables in the literature. Conversely, turning to the coefficients, the effect of the Gini, the dropout rate, the social capital index, the proportion of single parents with children under eighteen, and the affordability for low income households all differ somewhat between majority white and majority black counties, but only the difference in single parenthood is statistically significant, suggesting that generalizing from white to black populations may yield unreliable results.

Interestingly, the gap between black and white counties is even larger when examining upward mobility (indicating that meaningful upward mobility is more likely in white counties, as the gap is due to a combined higher level of disadvantage reproduction and movement to the second quintile). The gap here is twenty percentage points, indicating that residents of majority white counties are far more likely to experience upward mobility. Again, the difference in endowments is minimal; only the affordability for low income households is statistically significant. However, the coefficients again tell a different story; social capital, proportion of single mother families, and the affordability for low income households all have a significantly different effect in majority black counties. Similarly, when examining upward mobility, there is a large gap in the constant.

Historical Legacy of African American Counties

Finally, I turn to the results for measures of economic dynamism (unemployment, migration inflows, and the median wage), political history (share voting Republican voters in 2000, percent enslaved in 1860) and union membership in 2000. While none of the differences are significant in the majority black counties, the decomposition changes sharply when controlling for the percentage of slaves and union membership, decreasing the gap in upward mobility between black and white counties by two percentage points with the inclusion of slave population and five additional percentage points with the inclusion of union membership. This provides suggestive evidence that these places are disadvantaged partly because of the historical legacy of white supremacy which still holds down both black and white workers' wages today, which make intergenerational economic mobility less likely in these majority black counties.

Robustness Checks

Table 8 shows the results of individual level regression in majority black counties. These regressions confirm that in these counties, the variables that predict mobility in white counties do not predict mobility in majority black counties. This provides evidence at at different unit of analysis to confirm the prior findings. They show that single parenthood and living beneath the poverty line are not significant predictors of upward mobility. The sample for reproduction of poverty in these counties is extremely small, so none of these estimates can be viewed with much certainty, but crime appears to be a significant predictor. This demonstrates that even at the individual level, the relationships in white counties do not hold in black counties.

Table 3.8. Individual Level Regression of Predictors of Interest, Limited to Those in Majority Black Counties

	Dependent variable:	
	Reproduction of Poverty	Upward Mobility
	(1)	(2)
Single Parent	0.238	−0.034
	(0.142)	(0.048)
Below Poverty Line	−0.031	−0.013
	(0.137)	(0.052)
Total Crime	−32.718**	4.616
	(15.282)	(5.372)
Constant	0.294	0.105
	(0.197)	(0.066)
Observations	23	222
R^2	0.261	0.007
Adjusted R^2	0.145	−0.007
Residual Std. Error	0.266 (df = 19)	0.339 (df = 218)
F Statistic	2.241 (df = 3; 19)	0.506 (df = 3; 218)
Note:		*p<0.1; **p<0.05; ***p<0.01

A nearest neighborhood matching check was performed to understand whether non-linearites across coefficients existed in both samples. This means that I matched each majority black county to a majority white county based on the value of the covariates, and then examined the effect of those covariates in each group. This did not change my results, nor did it change the results of the decomposition, indicating that the regressions are accurately capturing the effect of the coefficients and that the effect of simply living in a majority black community has a unique impact, apart from the covariates social scientists have emphasized. This demonstrates that mean differences in residents' "standard" endowments are not the explanation for different outcomes in majority black and majority white counties. Instead, it is the effect of those endowments that differs.

Limitations

A major limitation of this paper is that, despite including an individual level analysis from the NLSY, I cannot make claims about individuals. The sample size from the NLSY is very small, so I cannot test whether black and white individuals in majority black counties have similar experiences. However, that fact that variables with the largest impact on outcomes are place based is suggestive evidence that racially segregated, black counties are unique in their mobility processes compared to majority white counties.

Furthermore, though I replicated Chetty et al's analysis for ease of interpretation and comparison, it is not clear that the years in which Chetty et al measured their covariates are the most relevant. Perhaps the ecological characteristics of a county are more important when children are extremely young, or in their teens. Finally, this analysis cannot speak to temporal variation in geographic mobility, as the economic mobility data looks at a child's income as an adult and assigns that mobility estimate to the county of origin, not the county where the income was earned. It is possible that variation in geographic mobility could be an important predictor of economic mobility that varies by race. Future research will examine this question.

Discussion and Conclusion

This article asks whether the process of mobility out of segregated African American counties is different than the process of mobility in white counties. The gap in mobility outcomes between black and white counties is large. However, this is not due to differences in the county characteristics usually identified as contributing to economic mobility. Rather, the evidence suggests that the lower levels of upward mobility outcomes in majority black counties are due to structural, historical factors not captured in previous analyses. Low rates of mobility are a property of these counties not because of individual characteristics but because they are less unionized and because of as yet unidentified legacies of slavery. This suggests that in order to improve mobility outcomes, the programs most likely to be successful will not be those that promote marriage or spend more on schools, but will instead focus on addressing longstanding structural power imbalances, and shoring up support for labor unions.

The importance of increased union coverage and the historical legacy of slavery demonstrate that power imbalances are key to understanding differential mobility rates – these counties suffer from longstanding and ongoing marginalization that can be addressed by interventions that improve worker bargaining power and reduce discrimination. This perspective on economic mobility opens up important questions for future research on how the historical legacy of places impacts the lives of individuals today, and the mechanisms by which isolation and powerlessness are transmitted.

To further contextualize these findings, future research should seek to understand variation in economic mobility as not only a result of the underlying characteristics of the individuals but also the institutions and systems that perpetuate stratification. Bringing in the importance of the carceral state, examining the relative importance of voting power, the responsiveness of democratic institutions and the local tax regimes would all provide insights into how power and privilege intersect with segregation and economic mobility.

Chapter 5

Conclusion

This dissertation moves from an individual level analysis of economic mobility towards a contextual, policy contingent perspective. By demonstrating that early life health and economic performance are tied together, that access to health insurance can reduce the intergenerational reproduction of inequality and help close the achievement gap, and that the determinants of mobility can differ by race, it shows that mobility can be improved by a variety of policy mechanisms beyond workforce development. Intergenerational economic mobility is not uniformly accessible but instead contingent upon factors over which the individual has little control. This fact should broaden the policy debate concerning mobility to consider not only individual failings t but also contextual conditions that reduce wellbeing and increase the reproduction of disadvantage.

Several unanswered questions also point to directions for new research. First, although taking account of the importance of place in analyses of economic mobility is an important first step, future work should explore the relationship between economic mobility and geographic mobility, and see how this relationship has changed over time, by gender, and by race. Geographic mobility has long been considered part of the process of economic mobility, yet it has declined in recent decades. Understanding how this change might reduce economic mobility of future generations could lead to important policy interventions.

Additionally, although health in early life is clearly an important predictor of mobility, disability, or poor health later in life, is also likely to disrupt the process of upward mobility in adulthood, and potentially for the next generation. Examining how the family can promote or hinder mobility, for example, how the health of relatives conditions future outcomes, and the importance of care labor, still has not been sufficiently clarified. Though it is evident that health endowment at birth, which is a marker of the ability of parents to pass down access to health insurance, is one mechanism through which social status is reproduced, many other mechanisms have yet to be teased out.

Though this dissertation has included some measures of the labor market, a broader understanding of how local labor market structure inhibits or promotes economic mobility should provide a clearer picture of the labor market interventions that could improve mobility for low income families. The hollowing of the labor market and the decline of labor unions have been well documented, but the effect on mobility is not well understood.

More broadly, the study of economic mobility should be expanded to focus more on institutions, discrimination, health, and how changes across the life course can impact mobility. Economic mobility is not solely an individual level process but a process that reproduces inequality. My focusing more on mobility as another facet of inequality, we will be better able to understand and generate policy to improve mobility.

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Appendix

Table A.1. Math Scores of Black Students and the Impact of Medicaid Exposure at Various Ages

	Black Average Score	Black Average Score	Black Average Score	Black Average Score
Prenatal Eligibility	0.147*	0.135	0.142*	0.141*
	(0.067)	(0.069)	(0.070)	(0.070)
Eligibility 1-4		0.039	0.038	0.037
		(0.037)	(0.037)	(0.037)
Eligibility 5-10			-0.005	-0.005
			(0.013)	(0.013)
Eligibility 11-14				-0.003
				(0.020)
R^2	0.68	0.67	0.68	0.68
N	183	183	183	183

* $p<0.05$; ** $p<0.01$

*** includes year and state fixed effects, and controls for the log of non health spending, unemployment rate, proportion less than high school, proportion some college, proportion college grad, proportion black, poverty rate, proportion of single parents, and log of family income

Table A.2. Math Scores of White Students and the Impact of Medicaid Exposure at Various Ages

	White Average Score	White Average Score	White Average Score	White Average Score
Prenatal Eligibility	0.027	0.025	0.026	0.025
	(0.032)	(0.035)	(0.035)	(0.036)
Eligibility 1-4		0.002	0.001	0.006
		(0.014)	(0.014)	(0.015)
Eligibility 5-10			-0.002	-0.002
			(0.006)	(0.006)
Eligibility 11-14				0.011
				(0.009)
R^2	0.79	0.79	0.78	0.78
N	281	281	281	281

* $p<0.05$; ** $p<0.01$

*** includes year and state fixed effects, and controls for the log of non health spending, unemployment rate, proportion less than high school, proportion some college, proportion college grad, proportion black, poverty rate, proportion of single parents, and log of family income

Table A.3. Math Scores of Students Not Eligible for Reduced Price Lunch and the Impact of Medicaid Exposure at Various Ages

	Not Eligible Average Score	Not Eligible Average Score	Not Eligible Average Score	Not Eligible Average Score
Prenatal Eligibility	0.050	0.027	0.027	0.027
	(0.032)	(0.036)	(0.037)	(0.037)
Eligibility 1-4		0.019	0.019	0.018
		(0.014)	(0.015)	(0.015)
Eligibility 5-10			0.000	0.000
			(0.006)	(0.006)
Eligibility 11-14				-0.001
				(0.009)
R^2	0.78	0.76	0.76	0.76
N	234	234	234	234

* p<0.05; ** p<0.01

*** includes year and state fixed effects, and controls for the log of non health spending, unemployment rate, proportion less than high school, proportion some college, proportion college grad, proportion black, poverty rate, proportion of single parents, and log of family income

Table A.4. Math Scores of Students Eligible for Reduced Price Lunch and the Impact of Medicaid Exposure at Various Ages

	Eligible Average Score	Eligible Average Score	Eligible Average Score	Eligible Average Score
Prenatal Eligibility	0.080	0.080	0.077	0.075
	(0.043)	(0.047)	(0.048)	(0.047)
Eligibility 1-4		0.000	0.003	0.012
		(0.018)	(0.019)	(0.019)
Eligibility 5-10			0.009	0.009
			(0.008)	(0.008)
Eligibility 11-14				0.019
				(0.012)
R^2	0.70	0.70	0.69	0.70
N	234	234	234	234

* p<0.05; ** p<0.01

*** includes year and state fixed effects, and controls for the log of non health spending, unemployment rate, proportion less than high school, proportion some college, proportion college grad, proportion black, poverty rate, proportion of single parents, and log of family income

Table A.5. Math Scores of White Students Not Eligible for Reduced Price Lunch and the Impact of Medicaid Exposure at Various Ages

	White Eligible Average Score	White Eligible Average Score	White Eligible Average Score	White Eligible Average Score
Prenatal Eligibility	0.035	0.028	0.027	0.027
	(0.031)	(0.035)	(0.036)	(0.036)
Eligibility 1-4		0.006	0.007	0.009
		(0.013)	(0.014)	(0.014)
Eligibility 5-10			0.004	0.005
			(0.006)	(0.006)
Eligibility 11-14				0.006
				(0.009)
R^2	0.80	0.80	0.79	0.79
N	229	229	229	229

* $p<0.05$; ** $p<0.01$

*** includes year and state fixed effects, and controls for the log of non health spending, unemployment rate, proportion less than high school, proportion some college, proportion college grad, proportion black, poverty rate, proportion of single parents, and log of family income

Table A.6. Math Scores of White Students Eligible for Reduced Price Lunch and the Impact of Medicaid Exposure at Various Ages

	White Eligible Average Score	White Eligible Average Score	White Eligible Average Score	White Eligible Average Score
Prenatal Eligibility	0.018	0.004	0.004	0.004
	(0.040)	(0.044)	(0.045)	(0.044)
Eligibility 1-4		0.012	0.012	0.016
		(0.017)	(0.017)	(0.017)
Eligibility 5-10			-0.001	-0.001
			(0.008)	(0.007)
Eligibility 11-14				0.012
				(0.012)
R^2	0.68	0.68	0.68	0.68
N	229	229	229	229

* $p<0.05$; ** $p<0.01$

*** includes year and state fixed effects, and controls for the log of non health spending, unemployment rate, proportion less than high school, proportion some college, proportion college grad, proportion black, poverty rate, proportion of single parents, and log of family income

Table A.7. Math Scores of African American Students Not Eligible for Reduced Price Lunch and the Impact of Medicaid Exposure at Various Ages

	Black Not Eligible Average Score	Black Not Eligible Average Score	Black Not Eligible Average Score	Black Not Eligible Average Score
Prenatal Eligibility	0.121	0.114	0.140	0.172
	(0.086)	(0.094)	(0.095)	(0.109)
Eligibility 1-4		0.089	0.084	0.099
		(0.063)	(0.060)	(0.070)
Eligibility 5-10			-0.024	-0.039
			(0.024)	(0.028)
Eligibility 11-14				-0.076
				(0.045)
R^2	0.61	0.54	0.55	0.45
N	136	136	136	136

* p<0.05; ** p<0.01

*** includes year and state fixed effects, and controls for the log of non health spending, unemployment rate, proportion less than high school, proportion some college, proportion college grad, proportion black, poverty rate, proportion of single parents, and log of family income

Table A.8. Math Scores of African American Students Eligible for Reduced Price Lunch and the Impact of Medicaid Exposure at Various Ages

	Black Eligible Average Score	Black Eligible Average Score	Black Eligible Average Score	Black Eligible Average Score
Prenatal Eligibility	0.195**	0.182*	0.213**	0.224**
	(0.072)	(0.075)	(0.075)	(0.075)
Eligibility 1-4		0.055	0.041	0.037
		(0.041)	(0.038)	(0.037)
Eligibility 5-10			-0.024	-0.027
			(0.016)	(0.016)
Eligibility 11-14				-0.039
				(0.028)
R^2	0.71	0.69	0.70	0.70
N	165	165	165	165

* p<0.05; ** p<0.01

*** includes year and state fixed effects, and controls for the log of non health spending, unemployment rate, proportion less than high school, proportion some college, proportion college grad, proportion black, poverty rate, proportion of single parents, and log of family income

Table 9. Effect of Prenatal Eligibility on All Samples (OLS fixed effects regressions)

	Model 1: Black Average Score	Model 2: White Average Score	Model 3: Reduced Lunch Eligible	Model 4: Reduced Lunch Not Eligible	Model 5: Black Reduced Lunch Eligible	Model 6: Black Reduced Lunch Not Eligible	Model 7: White Reduced Lunch Eligible	Model 8: White Reduced Lunch Not Eligible
Prenatal Medicaid eligibility	0.125*	0.029	0.075	0.027	0.162*	0.070	0.018	0.033
	(0.061)	(0.029)	(0.039)	(0.030)	(0.067)	(0.082)	(0.037)	(0.029)
Non-Health Spending (Log)	15.148**	10.185**	13.310**	10.397**	13.630*	8.543	14.824**	12.412**
	(5.483)	(3.237)	(3.933)	(2.952)	(6.135)	(7.921)	(4.258)	(3.369)
Unemployment Rate	-1.693**	0.024	-0.615	0.086	-2.070**	-0.296	-0.074	0.123
	(0.564)	(0.287)	(0.377)	(0.283)	(0.667)	(0.871)	(0.360)	(0.285)
Proportion Less than HS	0.012	-0.146	-0.492*	-0.171	0.131	-0.588	-0.506**	-0.171
	(0.286)	(0.147)	(0.197)	(0.148)	(0.331)	(0.444)	(0.185)	(0.147)
Proportion Some College	-0.105	-0.249	-0.492*	-0.192	0.108	-0.075	-0.342	-0.159
	(0.284)	(0.145)	(0.195)	(0.146)	(0.319)	(0.443)	(0.185)	(0.146)
Proportion College Grad	0.135	-0.015	-0.128	-0.063	0.123	-0.325	-0.191	-0.056
	(0.272)	(0.134)	(0.178)	(0.133)	(0.305)	(0.380)	(0.169)	(0.134)
Proportion Black	-0.322	-0.124	-0.501*	-0.284	-0.194	-0.485	0.043	-0.004
	(0.298)	(0.186)	(0.223)	(0.167)	(0.324)	(0.399)	(0.248)	(0.197)
Poverty Rate	0.009	0.221	0.140	0.018	-0.147	0.051	0.181	0.137
	(0.299)	(0.159)	(0.207)	(0.155)	(0.326)	(0.417)	(0.199)	(0.158)
Proportion Single Parents	-0.132	-0.182*	-0.216	-0.145	-0.205	-0.009	-0.295**	-0.137
	(0.164)	(0.086)	(0.114)	(0.085)	(0.187)	(0.252)	(0.108)	(0.085)
Log Family Income	-4.895	5.506	-5.314	3.256	-6.815	0.676	-2.844	4.803
	(10.443)	(5.622)	(7.485)	(5.617)	(11.247)	(15.522)	(7.077)	(5.600)
R2	0.68	0.76	0.70	0.78	0.71	0.61	0.68	0.80
N	183	231	234	234	166	137	229	229

- $p<0.05$; ** $p<0.01$