FROM FARM TO FORTUNE: UNDERSTANDING THE PATH TO UPWARD MOBILITY IN RURAL AMERICA

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Abstract

Using data from the Opportunity Insights project, Stanford Education Data Archive, and U.S. Department of Agriculture, I examine the path to upward mobility in the rural United States. I aim to understand whether factors contributing to better outcomes for low-income youth differ between rural and nonrural counties, with an eye toward tangible policy solutions. Using cross-sectional analyses, I find demographic factors, including share of single mothers and social capital, play an outsized role in rural mobility. Further, while income segregation is more detrimental to mobility in nonrural counties, single motherhood and migration are more detrimental in rural. In a fixed effects model, controlling for educational opportunity, race, and socioeconomic status, I find race and socioeconomic status explain most within-county variation in mobility, though educational opportunity remains a significant predictor, and achievement scores are relatively more important within rural counties than nonrural. Finally, I conduct a novel analysis of the relationship between agricultural subsidies and rural upward mobility. After controlling for community characteristics, I find no significant correlation between farm subsidies and mobility. The only policy factor which significantly predicts rural mobility is state Earned Income Tax Credit exposure, suggesting rural policy must focus specifically on initiatives aimed at improving outcomes for low-income rural youth.

Keywords: Rural America, upward mobility, education, agricultural subsidies

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1 Introduction

Upward mobility rests at the center of American conceptions of opportunity, encompassing the notion that with hard work and dedication, individuals can build a life more prosperous than that of their parents. Recent findings from the Opportunity Insights project, led by Harvard economist Raj Chetty, have renewed interest in the concept of intergenerational mobility and revealed striking levels of geographic variation in opportunity across the United States. One of the project's more surprising revelations is that average levels of upward mobility are higher in rural areas than urban ones. In recent years, the growing threat of automation, a bitterly divisive national politics, and the continued flight of young workers to coastal metropolises have drawn attention to the challenges of growing up in rural America and bolstered the narrative that rural communities remain left behind as urban ones prosper, rendering Chetty's results somewhat counterintuitive. Despite these findings, little research has sought to understand whether the unique socioeconomic characteristics of a rural place may influence those factors often associated with opportunity. Further, there remains a dearth of policy that explicitly addresses the challenges unique to rural regions, suggesting policymakers are insufficiently aware of how geographic dynamics may influence the efficacy of attempted reforms. In this project, I will identify the factors most strongly correlated with rural upward mobility and the extent to which the effect of those factors differs across rural and nonrural space. I attend particularly to community characteristics with demonstrated relevance to shaping life outcomes, and which differ substantively between rural and nonrural regions, based on my examination of prior literature. I conclude by analyzing the role of agricultural subsidies in shaping rural mobility, with the goal of understanding how policy decisions may improve long-term outcomes in areas which lack many of the economic and cultural resources of a metropolis.

This project will be the first to use the latest editions of the Opportunity Insights and Stanford Education Data Archive (SEDA) databases to analyze upward mobility in the rural context. These data are comprehensive, covering over 85 percent of counties in the rural United States, and allowing this project to provide a more complete illustration of U.S. mobility than previous studies. Using these data, I investigate mobility differences by race/ethnicity, gender, and income subgroup, providing a novel contribution to the rural mobility literature. After describing mean mobility by rurality and subgroup, I examine the relationship between mobility and various demographic, educational, economic, and social characteristics of counties. In addition, I briefly discuss the extent to which college degree completion serves as an intermediary step to economic mobility, given historically low college completion rates among rural adults (Marré, 2017). My analyses should be understood as descriptive in nature, rather than causal.

The future of rural America remains uncertain. While it is impossible to address every factor with the potential to disrupt rural life outcomes, this research will help policymakers understand which community characteristics have historically been linked to long-term economic outcomes. This attention is needed given that rural issues have drawn considerably less academic attention than urban ones, and given that state and federal lawmakers are often unfamiliar with the unique settings of rural communities. My hope is that regardless of how the future of these regions unfolds, this research will be able to inform the development and prioritization of local and national reforms aimed at promoting equality of opportunity across the rural-urban divide.

2 Background

2.1 Understanding Upward Mobility

Upward mobility in the U.S. has received substantial scrutiny in recent literature, especially in the wake of novel findings from the Opportunity Insights project, which unearthed striking geographic disparities in economic outcomes. Upward mobility metrics generally capture the extent to which one's background affects one's life outcomes. Mobility may be differentiated into such metrics as occupational mobility, class mobility, or earnings mobility, and is computed differently across disciplines. Sociologists traditionally measure this concept in terms of occupations and movements across social classes, whereas economic definitions are usually derived from intergenerational earnings or income levels (Torche, 2013). Further, economic mobility can be studied at individual or household levels, by computing metrics based on individual earnings or by pooling between spouses. What differentiates upward mobility from other economic metrics of prosperity, such as homeownership and wealth, is the added consideration of the extent to which a person's standing has improved throughout their life.

It is necessary to emphasize that upward mobility is a specific metric of economic success, not a holistic one. This outcome intends to capture the ability of lower-income individuals to reach higher economic classes. It is not necessarily a measure of current economic prosperity, and critics have noted that mobility metrics provide little insight into current standards of living or recent economic growth (Gilbert, 2017). Some have also argued that enhancing the ease of relative upward movement within the national economic distribution necessitates downward movements from members of the upper classes; in other words, for every action, there must be an equal and opposite reaction;. I attempt to circumvent the latter criticism by analyzing absolute upward mobility, instead of relative mobility. While relative mobility measures the outcomes of children in low-income families in relation to those of children from higher-income families, absolute mobility allows one to study the only the outcomes of children at a given income level. The two are highly correlated, but not identical (Chetty, Hendren, Kline, & Saez, 2014).

Further, one may question the societal value of improving mobility rates beyond current levels. In addition to ensuring the legitimacy of the American meritocracy, improving chances of upward mobility can reduce the need for government transfer payments and indirectly promote economic growth (Chetty, Hendren, Kline, & Saez, 2014). Therefore, understanding the factors which generate better outcomes for the lower classes is paramount to designing policies aimed at promoting greater prosperity for all.

Defining upward mobility as “the degree to which a child’s social and economic opportunities depend upon [their] parents’ income or social status,” recent studies led by Chetty and colleagues have offered the first large-scale, data-driven windows into intergenerational mobility (Chetty, Hendren, Kline, & Saez, 2018). The authors find that upward mobility varies extensively by geography. While mobility is lowest across the Southern states, many high-opportunity regions are clustered in the Upper Midwest. Chetty and colleagues also note that outcomes are more highly correlated to community settings than to an individual’s own family situation; for example, even if a child lives in a two-parent family, if she resides in a neighborhood with a high number of single mothers, her mobility outcomes are likely to resemble those of her peers in one-parent households. Further, these projects have begun the important work of understanding which factors are most strongly associated with mobility. A 2014 paper identifies six: racial demographics, residential segregation, income inequality, primary schools, social capital, and family stability (Chetty, Hendren, Kline, & Saez). A 2017 update to this research, looking specifically at county-level trends, finds that areas with favorable levels of those characteristics, along with lower concentrations of poverty, lead to more favorable outcomes for poor children (Chetty & Hendren, 2017). Chetty's most recent publication, a paper entitled "The Opportunity Atlas," tracks results to the Census tract level, identifying many of the same key covariates and also highlighting the influence of mean household income on mobility outcomes (Chetty, Friedman, Hendren, Jones, & Porter, 2018). Despite this increasingly granular analysis, however, none of these projects specifically compare these factors and their effects across the rural-urban spectrum.

2.2 Understanding Rurality

The unique characteristics of rural places suggest that rurality may incur a differential effect on life outcomes. Defining those characteristics, however, is no small feat; academics have long disagreed upon which places ought to be classified as rural, and the U.S. government employs dozens of definitions for classifying a location as such. Generally, rural areas share a handful of spatial factors, including low population density, a unique economic base, and geographic isolation. As a result of these characteristics, many rural places face limited access to crucial resources, such as healthcare and broadband. However, they also boast a greater reliance upon key community institutions such as churches and schools, along with tight-knit social networks, which foster higher levels of social capital community-wide (Phillips & McLeroy, 2004; Schafft, 2016). Unfortunately, such close ties are not always positive, and may actually incur exclusionary feelings among outsiders, especially minority groups (Ring & Peredo, 2010). Elevated social pressures in rural regions have been proven to impact decision-making among impoverished individuals. Specifically, social capital can "pressure…the poor to behave in ways that are consistent with local values," instead selecting the optimal choice for advancing their economic standing (Sherman, 2006). Though close communities are often touted as a benefit of rural areas, the impact of these regions' unique characteristics is likely more mixed.

Economist Bruce Weber has been one of the first to recognize the unique potential for rural places to influence life outcomes, pioneering much of the existing literature on rural mobility. His 2017 study of mobility across metropolitan, micropolitan, and non-core (rural) counties examines the six core factors identified in Chetty's 2014 paper. He concludes that absolute upward mobility is statistically different in micropolitan areas than in non-core and metropolitan ones, and that while race and single-parent households are most strongly correlated with upward mobility across all geographies, rural mobility is more closely tied to higher rates of out-migration (Weber, Fannin, Cordes, & Johnson, 2017). In a related study, Weber and colleagues note that lower levels of inequality, higher social capital, and better job matching enhance opportunity for youth in rural areas (Li, Goetz, & Weber, 2018). I will build upon this research by examining a greater number of covariates and by analyzing policies which may specifically affect rural America, along with using the latest version of the relevant data to examine within-county variation and mobility by subgroup.

2.3 Rural-Nonrural Differences among Community Characteristics

While rural mobility literature is not itself robust, there are several factors which have permeated Chetty's mobility studies and on which some degree of literature can be found regarding their differing effects in rural areas. I highlight some of this research below.

2.3.1 Demographics

Disparities in race, age, socioeconomic status, and family structure commonly define the rural-urban divide, with rural America stereotyped as homogenously older and white. While racial diversity has generally been much lower in these regions, growing Hispanic immigrant populations have increased rural racial diversity in recent years. The nonmetro Hispanic population was historically concentrated in the southwestern U.S. but is now increasingly scattered across the nonmetro midwestern and eastern regions (Kandel & Cromartie, 2004). This growth has lowered the average age of some rural counties, while other counties have witnessed an influx of retirement-age individuals, a trend which threatens to strain the already-stressed infrastructure of many of these areas as the population continues to age (Johnson, 2006).

Nonmetro poverty rates surpass those of metro poverty in every region of the United States (Farrigan, 2020). Lichter and McLaughlin consider the sources of rural poverty and note the disproportionate rise in rural poverty rates (1995). They first observe that the effects of demographic factors on rural poverty decline from 1980 to 1990, before concluding that differential poverty rates between rural and nonrural areas are not wholly explained by industry presence, employment patterns, or demographic composition alone, implying a unique rural effect on poverty (Lichter & McLaughlin, 1995). Demographic and economic factors further interact in relation to family life. Research has shown that rural families are uniquely vulnerable to the stress of macroeconomic shifts, and that this stress is particularly acute for rural single mothers. Evidence suggests traditional anti-poverty policies are less effective at moving rural than nonrural women out of poverty, particularly because of the nature of local labor markets (Lichter & McLaughlin, 1995). While the phenomenon of single motherhood is more prevalent in urban regions, rural mothers face unique challenges finding jobs to match their skill levels (Porterfield, 2001). These trends would suggest meaningful mobility differences across rural-nonrural space, and indeed, Chetty and others have found demographic factors to be some of the strongest correlates with mobility. Whether they have a differential effect across rural-nonrural space, however, warrants further analysis.

2.3.2 Economics

Demographic factors are naturally intertwined with economic ones, so as one might predict, these factors also manifest differently across geographies. The relationship between poverty and work is especially notable. Weber has posited that labor market differences are a significant driver of poverty rate disparities across rural and nonrural space (2007). Specifically, he notes that employment itself is less effective at transitioning rural individuals out of poverty, as working poverty is more prevalent in rural than nonrural areas. While the presence of work is one labor market condition which could impact economic outcomes for local youth, other factors also merit consideration. One analysis found rural areas were slower to return to normal unemployment levels following the 2008 financial crisis, and that approximately half of this lag can be attributed to their slower population growth (Johnson, 2006). While this study examines years not included in the Chetty data, it may still hold that slower population growth drives differential economic impacts in rural areas. Further, teenage labor force participation may also prove significant, as it has been cited in Chetty's work, and one might expect higher participation in rural areas if educational attainment rates are lower.

Migration has also received special focus in much of the rural-urban mobility research, given the continued trend of young people moving out of rural America. In their 2018 study, Weber and colleagues observe that the most upwardly mobile rural areas tend to have the highest rates of out-migration, and that migration is more strongly associated with mobility outcomes for rural children than urban ones (Li, Goetz, & Weber, 2018). An earlier project by Weber and colleagues hypothesizes that rural migration, particularly by more affluent individuals, occurs because remote regions lack sufficient opportunities for higher education (2007). Given the correlation between out-migration and greater upward mobility, one might believe out-migration must be tied to economic opportunity and higher incomes. However, as Weber notes, many counties with high out-migration are relatively prosperous, with low unemployment rates and low high school dropout rates (Weber et al, 2007). This potentially debunks the hypothesis that migration itself is solely responsible for better outcomes, stressing a need for greater insight into the migration-mobility relationship.

2.3.3 Education

One of the key sociological factors which distinguishes remote communities from their metropolitan counterparts is the importance of community institutions, particularly schools. While schools play central roles in many communities, research suggests that they often operate as more prominent hubs of social, cultural, and economic activity in rural regions than urban ones. In the more intimate rural context, educators are often held more accountable for students' success; because of a more robust community buy-in, schools become catalysts for local development, providing a locus of community investment and integration (Schafft, 2016). In recent years, for example, several rural communities have sought to capitalize on the link between education and economic development through the creation of school-community partnerships and grow-your-own teacher initiatives. Given the strength of this connection between rural schools and their communities, I consider education not only as a correlate with upward mobility broadly, but as a factor potentially driving a differentiated path to upward mobility in rural regions.

Further, there is widespread evidence that educational attainment is lower in rural areas (Marré, 2017; Roscigno & Crowle, 2001; *Understanding Economic Challenges*, 2017). Given that college degrees are traditionally viewed as reliable levers of economic mobility, this disparity highlights a need to understand whether rural upward mobility is driven largely by those students who do succeed in completing four-year degrees, or whether rural mobility is simply less reliant upon higher education as a vehicle for economic prosperity. Examining potential drivers of lower attainment across rural areas, Roscigno and Crowle note that rural family and school factors strongly influence educational outcomes and are potential causes for deficits between rural and nonrural areas, corroborating existing literature that institutions and social factors may work together to help or hinder youth outcomes (2001).

2.3.4 Social Factors

In this vein, rural communities are stereotypically known for their small town, close-knit communities, or centers of "social capital." Social capital is broadly defined as interpersonal "connections that matter," a metric of the strength of the social networks in which an individual is imbedded (Cook, 2014, p. 207). Hofferth and Iceland outline social capital as a summation of the relationships linking individuals to their communities, granting access to resources, and crucially, providing "a safety net in time of need, and even information and employment help" (1998, p. 576). In this way, the tight-knit social networks and "norms of neighborliness, self-help, and reciprocity" which contribute to higher levels of social capital in rural communities may strongly influence life outcomes of individuals within them (Phillips & McLeroy, 2004, p. 1663). In addition to traditional measures of network connections, social capital-adjacent factors, including crime rates and religious engagement, are relevant. One study suggests interactions between the two, noting that violent crime tends to be lower in rural areas with larger numbers of churches (Lee, 2006). Religion may also impact rural life outcomes, as another author finds that during the 1980s agricultural recession, religious involvement improved health and well-being outcomes of farm families (Meyer & Lobao, 2003). This bolsters the notion that social capital is important to understand, not only for its status as a defining feature of remote areas, but because of its relevance to life outcomes.

2.3.5 Regional Dimensions

Given the myriad definitions of "rural" which are used throughout academia, it is worth considering how the rural-urban divide should be defined for a study such as this. Weber and coauthors primarily focus on the role micropolitan regions occupy along the rural-urban spectrum. In explaining their choice to analyze three geographic categories, these researchers argue that most research obfuscates key socioeconomic differences by omitting intermediate regions and focusing spatial analysis on the traditional rural-urban dichotomy (Weber, Fannin, Cordes, & Johnson, 2017). I extend this analysis by examining rurality at a more granular level, utilizing the U.S. Department of Agriculture's nine rural-urban continuum codes (RUCCs). A 2017 study from Eleanor Krause and Richard V. Reeves at the Brookings Institution also employs the RUCC classification. However, their report focuses primarily on the nation's most remote regions (RUCCs 7 through 9), which encompass only 13 million people, and does not draw other overarching rural-urban comparisons (Parker, 2019). Analyzing all RUCCs allows me to determine whether the difference between categories such as 6 and 7 (two levels of rural counties with lower-population urban counties) is relevant to mobility outcomes.

An additional factor in need of further exploration, though not previously cited in mobility literature, is regional economic dependency. The USDA has developed a series of county typology codes which identify counties that are primarily dependent on certain industries, such as agriculture or mining. Economic dependency has proven relevant to broader conversations in rural sociology; rural migration, in particular, has been shown to vary with economic dependency, as agriculture-dominated counties tend to experience greater out-migration (Johnson, Winkler, & Rogers, 2013). Previous findings also note that resource-based economies are more vulnerable to economic shifts (Tickamyer & Duncan, 1990). To enhance an understanding of the role that community economic bases play in shaping life outcomes, I will incorporate the USDA economic dependency codes into my analysis.

2.4 The State of Rural Policy

The differential nature of mobility-related factors in rural areas suggest that policies explicitly accounting for rural needs have become a necessity. To date, rural policy is ambiguously defined and somewhat elusive in policy literature, largely owing to a dearth of legislation directly aimed at rural areas. As one researcher notes, “U.S. rural policy has become a motley collection of many different policies, with no unifying mechanism, and leaning mainly on farm policy for its focus” (Drabenstott, 2005, p.1). Indeed, among what does exist, poverty and agriculture have been common subjects of focus, owing to the dominance of the farming industry in many rural places, along with entrenched cycles of rural poverty in others. These initiatives have led to varying degrees of success.

Given that rural policy has been somewhat synonymous with farm policy, much of federal rural policymaking has operated through the USDA Farm Bill. Agricultural subsidies are one of the hallmark tools, aimed at stabilizing farm incomes against the threat of commodity price swings and natural disasters. Three key programs serve this purpose, two of which will be analyzed in this paper. The first is the Direct and Countercyclical Payments (DCP) program, which compensates farmers for the difference between market prices and set target prices for each commodity. The second is the federal crop insurance program, which guards against losses in revenue in the event of a natural disaster. Ostensibly, these policies have strived to support not only farm owners and operators, but also rural communities as a whole. However, evidence of community economic effects of these programs is mixed. A common hypothesis is that direct payments have become increasingly ineffective at bolstering rural economic development as the number of farm-dependent counties has fallen from over 2,000 in 1950 to 400 in 2000, the fraction of the workforce involved in agriculture has declined over time, and farm sizes have increased, meaning that subsidy payments are increasingly concentrated among a smaller fraction of the farm population (Drabenstott, 2005; Ulrich-Schad, Grimm, & Jackson-Smith, 2013). Some researchers thus argue that while DCP may stabilize farm incomes in the short term, thereby mitigating potential shocks to local rural economies, they do not provide a sufficiently stimulating effect to be considered reliable economic development tools (Ulrich-Schad, Grimm, & Jackson-Smith, 2013). The calculus is slightly different for crop insurance programs, which inherently hold more community development value by necessitating the operation of private insurance companies; however, there has yet to be conclusive research establishing a link between these programs and positive economic outcomes in surrounding communities.

Though agriculture has remained a dominant focus in the rural policy landscape, the past 30 years have borne witness to an increase in place-based policies oriented toward a variety of other domains (Parker, Tach, & Robertson, 2020). As opposed to reforms targeted at individuals, place-based initiatives supply investment and support toward whole communities. A notable example was the Clinton Administration's Empowerment Zones and Enterprise Communities initiative, the broader goals of which were to alleviate poverty & generate economic development in 3 rural regions and 30 rural communities across the U.S. by supplying loans to fortify infrastructure and create jobs (Marshall, 2001). However, while there is evidence that place-based reforms have improved economic outcomes—specifically individual income and earnings—in metropolitan areas, there is no statistical correlation between those investments and outcomes in rural areas (Parker, Tach, & Robertson, 2020). This differential effect could be due to the presence of other expenditures, such as agricultural subsidies, or to implementation challenges inherent to rural regions. In their working paper, Parker, Tach, and Robertson also observe that the connection between place-based initiatives and other vehicles of community opportunity remains relatively unclear; in other words, there may be other factors which usually bolster success of these programs, such as population density, which limit their effectiveness in rural settings (2020). While there exists promise in place-based policies, there also clearly remains a need to examine their efficacy in the rural context and consider potential alternatives.

Along with place-based initiatives and farm subsidies, other policy tools have been touted for their applicability in the rural context. One of these is the state Earned Income Tax Credit (EITC), a refundable tax credit for low-income workers and families. The EITC is particularly suitable for rural areas given their disproportionate level of eligible beneficiaries—rural counties have lower average incomes, and many of the rural poor are working poor (Weber, 2007). Berube conducts an interesting analysis of the proportions of EITC benefits compared to farm subsidies in Montana and South Carolina, finding that that in the former, farm subsidy expenditures outpace EITC benefits by a ratio of 3:1, while in the latter, EITC claims have reached figures over six times greater than farm payments (2005). Emphasizing the diversity of rural areas in the U.S., Berube notes that EITC benefits are accessible to a wider population than farm subsidies, though he cautions it is challenging to quantify benefits beyond examining magnitude of expenditures (2005). He further adds that tax credits are better poised to provide relief in rural areas than tax deductions, given lower home values and correspondingly lower mortgage payments. I explore the possible link between EITC exposure and rural mobility later in my analysis.

3 Research Questions

The primary aim of this project is to identify factors strongly associated with upward mobility in rural counties, with an eye toward policy solutions. I conduct an initial descriptive analysis of upward mobility across rural and nonrural counties, examining differences by gender, race, and economic status, to understand whether, and for whom, rural or urban areas offer greater opportunities for mobility. I explore whether mobility varies among different types of rural counties, as defined by U.S. census divisions, rural-urban continuum codes, and economic subtypes. I then examine the correlations between mobility outcomes and demographic, educational, social, and economic community characteristics, fitting cross-sectional and fixed effects models. Finally, I consider the role of agricultural subsidies and other policy covariates in shaping rural mobility. Again, I do not attempt to draw conclusions based on causality.

4 Data

4.1 Outcome Data

The primary outcome of interest for this paper is household upward mobility. Data for this outcome are collected from the Opportunity Atlas data set, which is publicly available at the Opportunity Insights website (Opportunity Insights, 2019). This sample was constructed from 20.5 million income tax records from children born from 1978 to 1983, along with the income tax records of their parents. It includes individuals who were either born and raised in the U.S. or who immigrated at an early age, and who were claimed as dependents by at least one parent. The sample is comprehensive, including 96.2 percent of children in the 1978 through 1983 birth cohorts (Chetty, Friedman, Hendren, Jones, & Porter, 2018).

To quantify absolute upward mobility, Chetty and colleagues construct a national income ranking for every birth cohort in the sample. To do so, every person in the sample is assigned a rank according to their location in the income distribution of all individuals born in the same year, as measured in 2014. A parental income ranking is also constructed, comparing the incomes of all parents with a child in that birth cohort. To translate this ranking into a measure of mobility, Chetty then calculates the predicted percentile rank in the national income distribution among all individuals whose parents were ranked at a certain income percentile in a single county. In this analysis, "upward mobility" is based on this predicted rank from the 25th percentile, with one exception: the upward mobility metric for the non-economically disadvantaged subgroup is defined as the predicted percentile rank for individuals whose parents were ranked at the 75th income percentile. This ranking method, while perhaps less intuitive than directly comparing intergenerational income levels, helps mitigate outlier bias and increase stability, compared to income measurements using dollar amounts (Chetty, Friedman, Hendren, Jones, & Porter, 2018). Further, note that the unit of analysis for this research is the county; while Opportunity Insights also provides tract-level outcome data, I conduct my analysis at the county level to maximize covariate availability. Note that by using the data provided by Chetty and colleagues in this analysis, I necessarily limit my analysis to economic mobility. However, spatial differences in social or occupational mobility could provide an interesting avenue for future research, given that rural areas are historically entrepreneurial but also traditionally house industries dependent upon manual labor.

Chetty and colleagues further differentiate upward mobility by constructing household and individual mobility outcomes. To calculate the former, children are ranked based on their position in the household income ranking, for which their income and that of their spouse are combined, based on marital status in 2014. Individual mobility is constructed based only on the child's annual income. I use household mobility as the primary outcome in this paper, given it is less prone to annual fluctuations and generally preferred throughout Chetty's research (Chetty, Hendren, Kline, & Saez, 2014).

Outcome data are available by subgroup, including race/ethnicity and gender. I also construct economically disadvantaged and non-economically disadvantaged subgroups; the former uses the standard mobility metric for children born into households at the 25th income percentile, while the latter is constructed using the mobility outcome for children born into households at the 75th income percentile. While categorizing by subgroup is useful, there remain challenges with data availability in more remote counties, particularly by race. Table 6 in the Descriptive Statistics section highlights the number of observations available for each subgroup outcome in rural and nonrural counties, along with additional descriptive statistics.

4.2 College Completion Data

In addition to absolute mobility outcomes, Chetty and colleagues calculate the fraction of children in the sample who attain a four-year college degree. Given the disparities in educational attainment between rural and nonrural individuals, I periodically include this college completion outcome as a covariate in my analyses to discern the extent to which educational attainment serves as a mechanism for economic mobility in rural counties. However, I do not categorize four-year completion rate alongside other covariates, since it directly captures the fraction of cohort members earning four-year degrees, and therefore does not describe a broad, community-level characteristic. In this way, it is also a more accurate measure of the impact of college completion on mobility than broader, county-wide measures of educational attainment would be.

These data are also available by subgroup, enabling their inclusion in fixed effects models. Descriptive statistics are presented alongside those of other covariates in Table 7.

4.3 Covariate Data

To analyze which factors may correlate to rural upward mobility, I incorporate a series of county-level covariates with demonstrated relevance to upward mobility, or that may display meaningful differences between rural and nonrural areas. I classify these covariates into one of five categories: demographic, educational, economic, social, and policy factors. Demographic covariates include fraction above the poverty line, fraction black, fraction with single mothers, Gini coefficient for the bottom 99 percent of earners, household income per capita, and income segregation. Education covariates include growth rates and third-grade achievement, while fraction with commute time less than 15 minutes, teenage labor force participation, unemployment rate, and in- and out-migration comprise the economic covariates. For social characteristics, I include fraction religious, violent crime rate, and a social capital index created using principal components analysis on county-level voter turnout rates, Census response rates, and number of political, civic, recreational, business, and non-profit establishments per capita (Goetz & Rupasingha, 2014). The policy category includes agricultural subsidies, average state Earned Income Tax Credit (EITC) exposure from 1990 to 2001, local government expenditures per capita, local tax rate per capita, and school expenditures per pupil. While these five categories are not always mutually exclusive, this is an initial attempt at gathering a holistic view of what drives rural mobility, with an eye toward tangible policy takeaways.

All demographic, social, and economic covariates, along with state EITC exposure, local government expenditures per capita, local tax rate per capita, and school expenditures per pupil, are collected at the county level from the publicly available data set used in Chetty & Hendren

(2017; Opportunity Insights, 2018). These covariates are generally collected from the year 2000, the earliest year with reliable federal data, and a year in which the cohort members were reaching late adolescence to early adulthood, though there are some exceptions with regard to local spending and EITC exposure. These exceptions are listed in Table A1 along with data sources. I standardize each covariate to have a mean value of 0 and standard deviation of 1, to enable comparability among regression coefficients.

The educational opportunity variables used in this analysis are drawn from the Stanford Education Data Archive (SEDA, version 3.0), which provides nationally standardized student achievement and growth estimates for nearly every county, district, and school in the United States (Reardon et al, 2019). SEDA data are constructed from raw data from the U.S. Department of Education's ED*Facts* database, and from the Common Core of Data and Civil Rights Data Collection. The data include annual third through eighth-grade assessment scores in mathematics and English/Language Arts (ELA) from each state, spanning the 2008-09 through 2015-16 school years. Reardon and colleagues link these raw scores to a national scale using the National Assessment of Educational Progress, enabling comparison of achievement scores across the nation (Reardon, Kalogrides, & Ho, 2019). Per Reardon et al's interpretation, average local educational opportunity can be measured using average third grade achievement scores and average learning rates (which I refer to here as "growth rates"). The former are considered a measure of early childhood opportunities, which are closely tied to socioeconomic resources within the child's community, both in and out of school (Reardon, 2019). Growth rates are measured as the grade slope on mean achievement from grades three through eight and are intended to reflect the amount of material learned annually, which is largely a reflection of school quality. I standardize both third grade scores and growth rates to have county mean values of 0 and standard deviations of 1. Data for both covariates are available by race/ethnicity, gender, and income within counties, enabling county-level fixed effects analysis, though fewer observations are available for certain subgroups, as shown in Table A2.

In addition to achievement and growth scores, I include the SEDA county-level socioeconomic composite for the fixed effects analysis. This composite, which is available for white, black, and Hispanic subgroups in version 3.0, is constructed using estimates of median family income, the proportion of adults with a bachelor's degree or higher, proportion of unemployed adults, proportion of households receiving SNAP benefits, household poverty rates, and proportion of households with children that are headed by a single mother (Fahle et al, 2018).

One drawback with utilizing SEDA data is that the assessments in question are collected from the 2008-09 through 2015-16 school years, meaning these estimates highlight achievement for individuals from the 1995-2008 birth cohorts, unlike the 1978-1983 cohorts within the Chetty data. Fortunately, Chetty and coauthors find that the predictive power of their mobility estimates declines by just 1 percent per year within a decade of their outcome data (Chetty, Friedman, Hendren, Jones, & Porter, 2018). I conduct consistency analyses on the SEDA data, obtaining a correlation coefficient above 0.90 between the 2009 and 2016 estimates for both English Language Arts and math achievement scores, suggesting a strong association between estimates across years. Note that this analysis must be conducted separately by subject, given that a pooled achievement score is not currently available on a per-year basis. Correlation coefficient output can be found in Tables A5-A6. After calculating these estimates, I fit bivariate regression models on mobility, using 2009 SEDA estimates and 2016 estimates to highlight differences in associations over time. As shown in Tables 1 and 2, coefficients are relatively stable over this seven-year period, with eighth grade ELA coefficients declining only 3 percent over the seven-year period, while third grade coefficients both fall only 1.5 percent from 2009 to 2016. Coefficients are also consistently significant, and they remain so even with demographic, economic, and other controls (see Appendix for further consistency results).

Table 1: Bivariate Consistency Analysis, 8th Grade Achievement and Mobility

	Mobility		Mobility		Mobility		Mobility	
2009 ELA estimates	0.095	***						
	(0.004)							
2016 ELA estimates			0.092	***				
			(0.004)					
2009 math estimates					0.099	***		
					(0.003)			
2016 math estimates							0.099	***
							(0.003)	
Intercept	0.436	***	0.436	***	0.435	***	0.433	***
	(0.001)		(0.001)		(0.001)		(0.001)	
Observations	3086		3086		3084		3073	
R-squared	0.19		0.17		0.24		0.24	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses.

Table 2: Bivariate Consistency Analysis, 3rd Grade Achievement and Mobility

	Mobility		Mobility		Mobility		Mobility	
2009 ELA estimates	0.068	***						
	(0.004)							
2016 ELA estimates			0.067	***				
			(0.004)					
2009 math estimates					0.071	***		
					(0.003)			
2016 math estimates							0.070	***
							(0.003)	
Intercept	0.429	***	0.429	***	0.429	***	0.429	***
	(0.001)		(0.001)		(0.001)		(0.001)	
Observations	3081		3081		3081		3081	
R-squared	0.10		0.10		0.12		0.12	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses.

Given that both achievement and mobility estimates change at a rate of 1 percent or less each year, I accept the results of my later analysis at face value. It is theoretically possible that the change in achievement scores was stifled during this time period because of recovery from the 2008 financial crisis, or that other intervening factors would lead to inconsistencies in the 15 to 30 years between the SEDA and Opportunity Insights cohorts, generating a slightly noisier analysis. However, SEDA is now one of the most comprehensive educational data sources in the U.S., and the only one to provide data on learning and growth rates, making it an invaluable addition to any contemporary mobility research.

Data for agricultural subsidies are drawn from the U.S. Census Bureau Consolidated Federal Funds Report, publicly available on the USDA website (*Federal Funds*, 2019). These data include annual per-county spending for each Federal Department program from 2004 through 2010. I collect data for two of the most prominent farm spending programs, the Direct and Countercyclical Payments (DCP) program and crop insurance program, to create a total subsidy expenditure variable. The third prominent source of agricultural spending, Commodity Loans and Loan Deficiency Payments, is omitted from this analysis, since its funding levels are not consistent from 2004 to 2010. With the total subsidy covariate, I calculate the log of per-capita spending, then standardize to have a county mean of 0 and standard deviation of 1. I then correlate values from 2004 and 2010, to ensure funding consistency in the years available and to predict consistency prior to 2004. As shown in Tables 3 and 4, total funding for these programs are strongly correlated across this seven-year period and are correlated with upward mobility at consistent levels. Note that differences in the number of observations between years are largely due to discrepancies in funding levels within nonrural counties, which are not the primary focus of this analysis. Though data are unavailable prior to 2004, this consistency suggests 2004 data will convey the relationship between farm subsidies and upward mobility with an acceptable level of accuracy, especially given most covariate data from Opportunity Insights are dated just four years prior. Further, the USDA Economic Research Service notes these program data are accurate at the county level, unlike other program data, which may be distributed to state-level programs instead of directly to individual counties (*Federal Funds*, 2019).

Table 3: Correlation Coefficient, 2004 and 2010 Farm Subsidy Funding Levels

	Total 2004 subsidies per capita, logged	Total 2010 subsidies per capita, logged
Total 2004 subsidies per capita, logged	1.0000	
Total 2010 subsidies per capita, logged	0.9414	1.0000

Table 4: Bivariate Consistency Analysis, Farm Subsidies and Mobility

	Mobility		Mobility	
Total 2004 subsidies per capita, logged, standardized	0.024	***		
	(0.001)			
Total 2010 subsidies per capita, logged, standardized			0.027	***
			(0.001)	
Intercept	0.431	***	0.429	***
	(0.001)		(0.001)	
Observations	2966		2946	
R-squared	0.156		0.168	

* $p<0.05$, ** $p<0.01$, *** $p<0.001$. Standard errors shown in parentheses.

Finally, I incorporate three regional dimension covariates to gauge whether the type of rural county is relevant to its mobility prospects. These dimensions include U.S. Census geographic division, level of rurality, and economic subtype. Recognizing that the concept of rurality is not easily defined or measured, I ultimately utilize the U.S. Department of Agriculture's 2003 Rural-Urban Continuum Code (RUCC), which assigns each county a classification of 1 (most urban) through 9 (most rural) based on population density and adjacency to a metropolitan area (Cromartie, 2019). This classification allows one to examine variation across multiple levels of rurality, as opposed to a simple rural-nonrural binary. To divide the sample into rural and nonrural counties, however, I construct a rural indicator variable, for which counties with RUCCs 1-3 have values of 0, while RUCCs 4-9 have values of 1. To classify counties by economic subtype, I use the 2004 USDA county typology metric, which identifies counties dominated economically by industries including farming, manufacturing, mining, federal and state government, and services. ERS assigns these classifications based on proportion of labor earnings in relation to a set threshold; in other words, if a county's agricultural earnings sit above a certain proportion of total county earnings, then this county is eligible for the farming-dependent classification (Pender, 2019). The six categories are mutually exclusive, with counties classified into the category in which they are the largest degree above the set threshold. Distributions of economic dependencies by rurality are listed in Table 5 while definitions for geographic division and rural-urban continuum code are available in Tables A3 and A4.

4.4 Analytical Sample

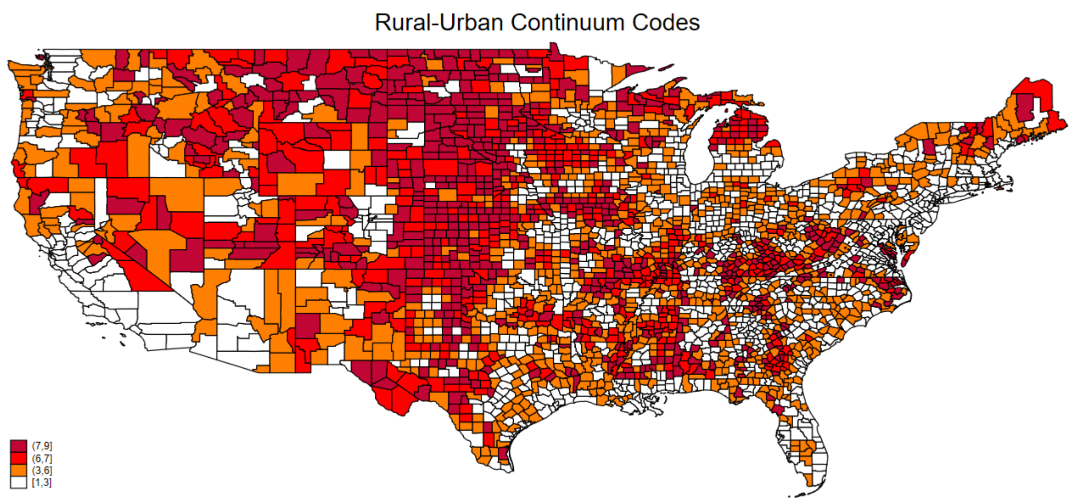
Of the 3,143 U.S. counties in 2010, this project's core sample includes 3,136, or 99.8 percent. Two-thirds (2,047) of these counties are rural. While seven counties are excluded because of missing upward mobility data, and four are excluded because of missing Chetty covariate data, the comprehensiveness of this sample is a marked improvement over previous studies of rural mobility based on the Chetty 2014 data set, which lacked outcome data for 336 rural counties (Weber, Fannin, Cordes, & Johnson, 2017).

The sample used for simple regression analysis is dependent upon availability of each covariate; Table 7 shows the number of observations and other descriptive statistics for each. Regressions on regional dimensions and covariate categories are fit on a consistent sample of 1,726 rural counties, which excludes counties with missing covariate values. This sample represents 84 percent of rural counties in the U.S. The corresponding nonrural sample includes 927 nonrural counties, or 85 percent of that group. For the fixed effects analysis, I omit observations with missing values for SEDA achievement, growth, and socioeconomic covariates.

4.5 Descriptive Statistics

Figure 1 highlights the distribution of rural and nonrural counties across the United States. As shown, the nation's most remote counties are generally located in the central U.S., Great Plains, and parts of Appalachia. Many of the Western states are nearly entirely rural, while some small states on the East Coast are completely nonrural. Table 5 describes how economic subtypes vary across the rural-urban continuum. Urban counties appear more service-dependent, and rural ones are more likely to rely on farming and mining, while manufacturing- and government-dependent counties are fairly evenly distributed by rurality.

Figure 1: U.S. Counties by Rural-Urban Continuum



Rural counties colored by rural-urban continuum code, with more remote counties in darker shades. Nonrural counties colored in white.

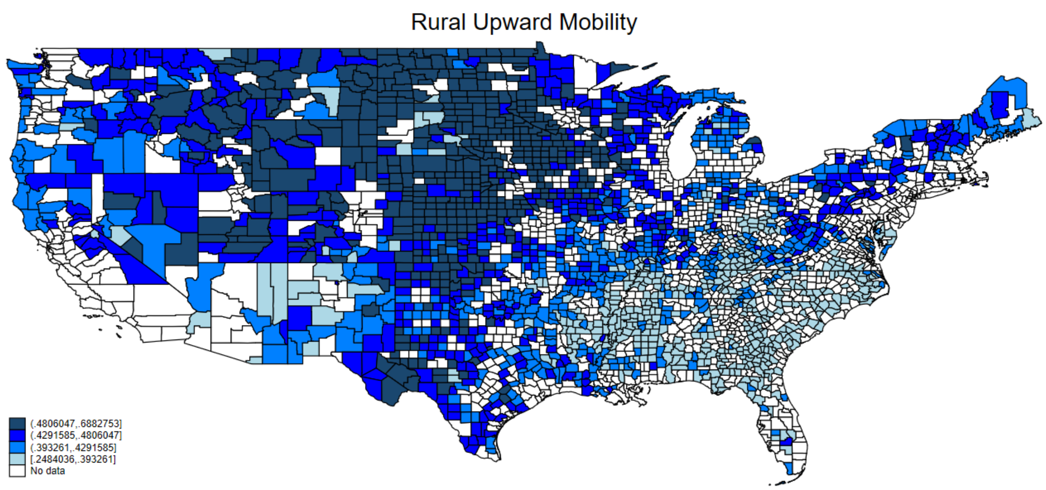
Table 5: County Distribution by Rural-Urban Continuum and Economic Dependency

RUCC	Non-specialized	Farming-dependent	Mining-dependent	Manufacturing-dependent	Government-dependent	Service-dependent	Total
1	139	1	3	98	45	128	414
2	97	12	4	110	46	56	325
3	97	24	8	111	68	42	350
4	52	4	7	99	31	25	218
5	31	1	5	21	32	15	105
6	190	46	30	260	63	19	608
7	169	55	36	110	49	32	451
8	76	63	12	49	24	11	235
9	98	231	22	45	23	11	430
Total	949	437	127	903	381	339	3,136

The geographic variation in levels of upward mobility across rural counties is depicted in Figure 2, while Table 6 displays mean values and standard deviations in rural and nonrural counties, along with the *p*-value of the difference between those means. Table 6 estimates are weighted by the number of children in each subgroup with parents below the median income percentile. Whether mobility is higher in rural or nonrural areas depends upon the subgroup examined. While rural regions report higher levels of household mobility for both income groups, this finding appears to be driven by Simpson's paradox; for every racial minority, mobility is significantly lower in rural areas or statistically equal between rural and nonrural counties. However, statistically insignificant differences between white rural and nonwhite rural mobility, and higher levels of male mobility in rural areas, result in greater overall mobility in rural areas than nonrural.

Distinctions between rural and nonrural mobility are further evident depending on the economic type and Census division in question. Rural mobility is higher in the Midwest, West South Central, and Mountain regions, but lower across the South. Rural counties with significant employment in state and local government report higher levels of mobility than nonrural ones, while rural farm-dependent counties appear more upwardly mobile than the few nonrural counties with large fractions of agricultural employment. On average, mobility appears greatest in the most remote counties, RUCCs 7 through 9, and lowest in all three metropolitan categories. However, like Krause and Reeves, I observe greater extremes in rural areas, as the maximum and minimum for nearly all subgroups and regions are recorded in rural counties (2017).

Figure 2: Upward Mobility in the Rural United States



Darker shades indicate higher mean upward mobility. Nonrural counties colored in white.

Table 6: Outcome Descriptive Statistics

	Nonrural					Rural					
	Mean	Max	Min	Std Dev	N	Mean	Max	Min	Std Dev	N	*p*-value
Male	0.390	0.664	0.277	0.040	1089	0.406	0.678	0.219	0.054	2036	0.00
Female	0.422	0.617	0.310	0.039	1089	0.422	0.748	0.243	0.052	2034	0.81
Asian	0.567	0.789	0.234	0.041	782	0.515	0.813	0.240	0.065	469	0.00
Black	0.326	0.636	0.204	0.025	959	0.318	0.548	0.185	0.022	956	0.00
Hispanic	0.430	0.582	0.223	0.026	1009	0.429	0.677	0.211	0.043	1327	0.60
Native American	0.337	0.585	0.150	0.051	637	0.318	0.748	0.149	0.057	444	0.00
White	0.450	0.596	0.358	0.038	1089	0.448	0.696	0.314	0.048	2038	0.17
Economically disadvantaged	0.406	0.608	0.293	0.038	1089	0.414	0.688	0.237	0.052	2044	0.00
Non-economically disadvantaged	0.576	0.698	0.447	0.029	1089	0.590	0.895	0.355	0.040	2044	0.00
New England	0.435	0.504	0.397	0.025	34	0.426	0.507	0.384	0.018	33	0.27
Middle Atlantic	0.429	0.520	0.366	0.035	89	0.439	0.530	0.408	0.019	61	0.30
East North Central	0.388	0.532	0.344	0.032	173	0.424	0.550	0.274	0.036	264	0.00
West North Central	0.422	0.583	0.327	0.048	112	0.474	0.688	0.293	0.062	504	0.00
South Atlantic	0.379	0.512	0.307	0.035	289	0.368	0.475	0.311	0.029	299	0.00
East South Central	0.362	0.473	0.293	0.027	118	0.375	0.473	0.315	0.026	246	0.00
West South Central	0.406	0.608	0.331	0.027	143	0.419	0.600	0.322	0.037	325	0.00
Mountain	0.412	0.561	0.367	0.031	62	0.438	0.648	0.294	0.052	218	0.00
Pacific	0.430	0.504	0.366	0.021	69	0.417	0.525	0.237	0.040	93	0.09
Nonspecialized	0.411	0.548	0.312	0.030	333	0.419	0.614	0.245	0.051	614	0.01
Farming-dependent	0.403	0.583	0.328	0.043	37	0.455	0.688	0.316	0.078	400	0.00
Mining-dependent	0.429	0.608	0.345	0.036	15	0.436	0.590	0.242	0.051	112	0.43
Manufacturing-dependent	0.398	0.537	0.316	0.040	319	0.400	0.585	0.308	0.045	583	0.51
Government-dependent	0.390	0.528	0.307	0.035	159	0.405	0.582	0.237	0.044	221	0.00
Services-dependent	0.410	0.561	0.293	0.041	226	0.419	0.601	0.294	0.036	113	0.45
RUCC 1	0.406	0.608	0.293	0.038	414						
RUCC 2	0.409	0.532	0.293	0.039	325						
RUCC 3	0.399	0.561	0.307	0.034	350						
RUCC 4						0.401	0.510	0.314	0.038	218	
RUCC 5						0.413	0.528	0.319	0.044	105	
RUCC 6						0.409	0.590	0.311	0.048	608	
RUCC 7						0.424	0.614	0.242	0.057	448	
RUCC 8						0.429	0.667	0.274	0.063	235	
RUCC 9						0.451	0.688	0.294	0.075	427	

Means are weighted by number of children below 50th percentile in each subgroup. *p*-value reported for t-test of differences between rural and nonrural means.

The mean values, standard deviations, and number of observations for each covariate are highlighted in Table 7. There are significant differences in rural and nonrural means for nearly all covariates. Rural areas are less racially diverse, but are less segregated racially and by income. With higher unemployment and poverty rates, rural counties perform worse economically. However, they have greater levels of social capital and religious participation, along with lower crime rates and lower fractions of single-mother households. Both per-capita and per-pupil expenditures are higher in rural areas, though there is no significant difference in growth rates between rural and nonrural counties, and rural counties report lower average test scores despite higher per-pupil spending. Finally, there is no statistical difference in college degree completion in this sample, despite widespread literature highlighting lower educational attainment in rural areas. This could be attributed to differences between the Chetty sample and the broader U.S. population, or this could be evidence that the odds of earning a college degree are equal across geographies after controlling for income.

Table 7: Covariate Descriptive Statistics

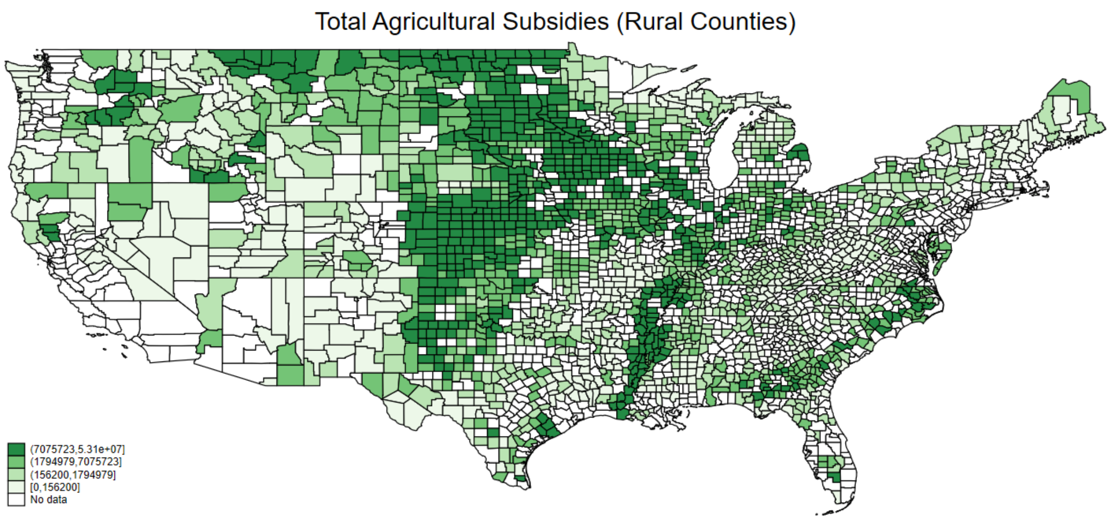
	Nonrural			Rural			
	Mean	Std Dev	N	Mean	Std dev	N	*p*-value
Demographics							
Fraction above poverty line	0.40	0.81	1088	-0.21	1.03	2044	0.00
Fraction black	0.12	0.94	1088	-0.07	1.02	2044	0.00
Fraction with single mothers	0.09	0.97	1088	-0.05	1.01	2044	0.00
Gini coefficient, bottom 99%	0.19	1.08	1083	-0.11	0.94	1951	0.00
Household income per capita	0.53	1.15	1088	-0.28	0.77	2044	0.00
Income segregation	0.68	1.09	1088	-0.36	0.73	2044	0.00
Education							
Growth rates	0.01	0.91	1086	-0.01	1.05	2043	0.57
Grade 3 achievement	0.20	0.94	1086	-0.11	1.02	2043	0.00
Economy							
Fraction with commute < 15 mins	-0.71	0.65	1088	0.38	0.95	2044	0.00
In-migration	0.73	1.10	1088	-0.40	0.66	1957	0.00
Out-migration	0.71	1.11	1088	-0.40	0.66	1957	0.00
Teenage labor force participation	-0.16	0.77	1088	0.08	1.09	2044	0.00
Unemployment rate	-0.26	0.77	1088	0.14	1.08	2041	0.00
Social							
Fraction religious	-0.25	0.82	1088	0.13	1.06	2043	0.00
Social capital index	-0.27	0.82	1084	0.15	1.05	2019	0.00
Violent crime rate	0.14	0.94	1018	-0.08	1.02	1937	0.00
Policy							
Agricultural subsidies	-0.43	0.89	1017	0.22	0.98	1949	0.00
Local gov't expenditures per capita	-0.04	0.59	1088	0.02	1.16	2043	0.00
Local tax rate per capita	0.02	0.46	1088	-0.01	1.19	2043	0.52
School expenditures per pupil	-0.07	0.61	1065	0.04	1.15	2041	0.00
State EITC exposure	0.00	0.98	1088	0.00	1.01	2043	0.00
Intermediate factor							
Four-year college completion rate	-0.02	0.87	1088	0.01	1.06	1966	0.41

p-value reported for t-test of differences between rural and nonrural means. Note that covariates are standardized to have a mean value of 0 and standard deviation of 1.

Figure 3 provides a more detailed overview of farm subsidy distribution across the United States (note that this highlights total subsidy expenditures, not per-capita funding). Counties in the Corn Belt, along with parts of Texas, the Mississippi Delta, and the Southeast receive the greatest levels of subsidy funding. Comparing Figures 2 and 3, many counties receiving large levels of farm subsidies are also those with the highest levels of upward mobility.

Notable exceptions to this trend are counties in the South, suggesting that subsidies alone are not drivers of upward mobility.

Figure 3: Distribution of Agricultural Subsidies across Rural Counties



Darker shades indicate greater levels of farm subsidies. Nonrural counties colored in white.

Table 8 details the intensity of subsidy expenditures in rural and nonrural counties. Note that subsidies are paid directly to individuals, not to the county as a whole; these data indicate the total level of subsidies among all recipients in each county. The magnitude of these programs is worthy of note; despite claims that subsidies have become relevant to a declining fraction of the population, 95 percent of U.S. counties receive funding from agricultural subsidies, with the average county collecting over $4 million annually. Even in nonrural areas, subsidy levels average $75 per capita. I find also that household income is slightly higher in farm-dependent rural counties than other rural counties, and that farm-dependent counties do receive more subsidies. Even in rural agricultural counties, however, average household income is over $5,600 lower than in the average nonrural county.

Table 8: Agricultural Subsidy Descriptive Statistics

Per-county subsidies, 2004	Overall	Rural		Nonrural
		Farm-dependent	Non-farm-dependent	
Total expenditures	$4,086,983	$8,477,216	$3,621,841	$3,171,348
Per-capita expenditures	$368	$1,794	$213	$75
Fraction receiving subsidies	95%	94%	94%	92%
Household income	$32,872	$30,941	$30,883	$36,587

The data show there are meaningful differences in mobility across a variety of places and subgroups. The next step is to discern is why these disparities manifest. Though the data currently available are a limiting factor in establishing causality in this analysis, understanding even the correlations between upward mobility and community characteristics across these spaces will help guide future policymaking.

5 Methodology

To develop a rudimentary understanding of the factors most strongly correlated with upward mobility, along with the extent to which these factors differ in effect between rural and nonrural areas, I fit the simple regression model outlined in Equation 1 for each continuous covariate, using all counties in the sample. This model will indicate the strength of the association between the covariate and mobility in rural counties (β_1) along with the difference in this association between rural and nonrural counties (β_3). The model takes the form

$$\hat{Y}_i = \beta_0 + \beta_1 X_i + \beta_2 N_i + \beta_3 X_i N_i + \epsilon_i, \tag{1}$$

where $\hat{Y}_i$ is the estimated average household upward mobility in county i, X_i is a standardized county covariate, and N_i is a binary variable indicating whether the county is rural ($N = 0$) or nonrural ($N = 1$).

Recognizing the potential for endogeneity among these covariates, I next fit a series of multivariate cross-sectional regressions using only rural counties. This model is outlined below:

(2) $$\hat{Y}_i = \beta_0 + \mathbf{X}_i\mathbf{B} + \epsilon_i,$$

where $\mathbf{X}_i$ is a vector of covariates in rural county i. For any models involving categorical covariates, such as economic subtype, $\mathbf{X}_i$ will include dummy variables for all but one category of the variable in question.

After a broad analysis of factors associated with rural mobility, I fit a series of within-county fixed effects models, using race-, income-, and gender-specific outcomes and education covariates for each county to further evaluate the relationship between educational opportunity and upward mobility. These models take the form

(3) $$\hat{Y}_{si} = \beta_0 + \beta_1 Achievement_{si} + \beta_2 Growth_{si} + \mathbf{X}_{si}\mathbf{B} + \Lambda_s + \Gamma_i + \epsilon_{si},$$

where $\hat{Y}_{si}$ is the estimated average for the outcome in question for subgroup s in county i, *Achievement* and *Growth* are subgroup-specific values of the educational opportunity covariates, $\mathbf{X}_{si}$ is a vector of covariates, including the socioeconomic composite and four-year college completion rate, and Λ_s and Γ_i are subgroup and county fixed effects. By controlling for variation across counties, the fixed effects analysis provides a more powerful indication of which characteristics determine the likelihood of upward mobility within a given place.

The foremost limitation of this methodology is that the estimates from these models cannot be interpreted causally. Further, while county-level analysis is useful for identifying trends across communities, it insufficiently granular to illuminate resource trends at the neighborhood or individual level. However, this methodology enables descriptive insight into factors which could be central to the success of children in rural communities, thereby serving as a guide for future policymaking and causal research.

6 Results

Table 9 reports coefficients from simple bivariate regressions on household mobility outcomes for each of the continuous covariates. These regressions examine the significance of each factor in rural areas (β_1), along with their additional significance in nonrural areas (β_3). I find statistically significant differences in rural and nonrural effects for nearly all covariates. Notably, the single mother and social capital covariates are the strongest predictors of rural mobility but are less strongly predictive in nonrural areas. Agricultural subsidies show a weaker correlation with nonrural outcomes than rural, and the magnitude of this correlation is stronger than that of other policies with rural mobility. Unexpectedly, the correlation between college completion rates and mobility is lower in nonrural counties, and further, growth rates are more strongly associated with nonrural mobility, while achievement scores appear to matter more for rural outcomes. While these results inform preliminary conclusions about which factors are most important for long-term outcomes of rural youth, the significance of these factors will be explored in more depth using multivariate regressions.

Table 9: Bivariate Regressions

	β_1		β_3	
Demographics				
Fraction above poverty line	0.0275	***	-0.0010	
Fraction black	-0.0352	***	0.0057	**
Fraction with single mothers	-0.0479	***	0.0177	***
Gini coefficient, bottom 99%	-0.0347	***	0.0157	***
Household income per capita	0.0300	***	-0.0169	***
Income segregation	-0.0176	***	0.0107	***
Education				
Growth rates	0.0077	***	0.0058	*
Grade 3 achievement	0.0307	***	-0.0089	***
Economy				
Fraction with commute < 15 mins	0.0342	***	-0.0234	***
In-migration	-0.0233	***	0.0246	***
Out-migration	-0.0206	***	0.0207	***
Teenage labor force participation	0.0398	***	-0.0082	***
Unemployment rate	-0.0335	***	0.0172	***
Social				
Fraction religious	0.0287	***	-0.0107	***
Social capital index	0.0410	***	-0.0166	***
Violent crime rate	-0.0277	***	0.0106	***
Policy				
Agricultural subsidies	0.0285	***	-0.0203	***
Local gov't expenditures per capita	0.0056	***	-0.0033	
Local tax rate per capita	0.0077	***	0.0158	***
School expenditures per pupil	0.0091	***	0.0079	*
State EITC exposure	0.0152	***	-0.0005	
Intermediate factor				
Four-year college completion rate	.03570	***	-.01219	***

* p<0.05, ** p<0.01, ***p<0.001

I next limit my sample only to rural counties, to examine the correlations among demographic, economic, educational, and social factors, along with regional dimensions and college completion rates. As shown in Table 10, regional dimensions, including rural-urban continuum codes, economic dependencies, and Census division, account for a striking 60 percent of all variation in rural mobility. The magnitude of these coefficients declines as other covariates are added, suggesting that regional dimensions are partially correlated with demographics, economics, and other local factors. Even after controlling for other dimensions, however, I find that less remote counties, manufacturing-dependent counties, and Southern counties remain negatively associated with mobility, while mining-dependent counties retain their positive association.

These models reveal several surprising findings. First, out-migration is consistently insignificant, while in-migration has a negative correlation with mobility. At first glance, this is noteworthy given that much of the literature associates rural out-migration with worsening economic outcomes. However, upon further analysis, I find that when included separately, out-migration and in-migration are both negatively associated with mobility to a significant degree, suggesting the negative out-migration becomes insignificant only after accounting for in-migration. It is worth investigating the nature of the negative correlation of in-migration, given one might expect population growth to boost a community's economy. One possible explanation is that rural infrastructure is insufficiently equipped to welcome population influxes, particularly if those influxes are largely comprised of older population in need of greater medical care.

Among continuous covariates, college degree completion displays the largest positive coefficient, suggesting educational attainment, even in rural areas, is a positive driver of mobility. Further, county-level income and unemployment are no longer significant once college completion is added, suggesting an individual's decision to attend university may counteract the effects of negative economic conditions in their home community. However, share of single mothers is still the most significant factor, and is negative, with a coefficient nearly three times larger than the next in magnitude. Fraction black also remains a significant predictor after controlling for other characteristics, showing that county demographic characteristics are still the most likely predictors of life outcomes. In sum, I explain 84 percent of variation in rural household mobility simply by describing community characteristics. This finding is both disheartening and promising, in that one's life outcomes can largely be predicted based on the community characteristics in one's childhood county, but also in that many of the most significant factors are identifiable, meaning policymakers can work toward crafting tangible solutions.

The next set of analyses aims to understand whether existing policies may have significantly improved life outcomes for low-income youth. These findings are outlined in Table 11. By itself, and after accounting for regional variation, the agricultural subsidy covariate does positively predict rural mobility. However, it becomes insignificant once controlling for economic factors, suggesting that at the community level, farm subsidies are less impactful than reigning economic trends. Note that the effects of all policy factors, not just subsidies, are lessened once one accounts for teenage labor force participation, unemployment rates, and migration trends. This confirms suggestions in the literature that farm subsidies are insufficient for shaping rural economic prosperity. It appears other policies, such as state EITC, impact rural areas more, despite the fact that farm policy has generally been considered the primary vehicle for rural policy. One possible explanation is that as agriculture's share of the national workforce has fallen, the number of subsidy recipients have fallen, and that even in farm-dependent communities, the number of primary farm operators is so small that subsidies are too concentrated to generate broader community benefits.

Table 10: Multivariate Regression Results, Covariate Effects on Rural Mobility

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
RUCC 4	-0.032	***	-0.016	***	-0.033	***	-0.025	***	-0.023	***	-0.009	**	-0.010	**
	(0.004)		(0.004)		(0.004)		(0.004)		(0.004)		(0.003)		(0.003)	
RUCC 5	-0.038	***	-0.012	**	-0.035	***	-0.035	***	-0.029	***	-0.011	**	-0.012	**
	(0.005)		(0.004)		(0.005)		(0.005)		(0.004)		(0.004)		(0.004)	
RUCC 6	-0.022	***	-0.010	***	-0.019	***	-0.018	***	-0.015	***	-0.005	*	-0.004	
	(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.002)		(0.002)	
RUCC 7	-0.019	***	-0.004		-0.017	***	-0.022	***	-0.017	***	-0.009	***	-0.008	***
	(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.002)		(0.002)	
RUCC 8	-0.003		-0.002		-0.001		0.004		0.001		0.005	*	0.005	
	(0.004)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)	
Middle Atlantic	0.022	*	0.012		0.032	***	0.047	***	0.022	**	0.017	**	0.018	**
	(0.009)		(0.007)		(0.008)		(0.008)		(0.008)		(0.006)		(0.006)	
East North Central	0.002		-0.011		0.008		0.017	*	-0.005		-0.010		-0.003	
	(0.008)		(0.006)		(0.007)		(0.007)		(0.007)		(0.006)		(0.005)	
West North Central	0.056	***	0.034	***	0.060	***	0.047	***	0.030	***	0.015	**	0.018	***
	(0.008)		(0.006)		(0.007)		(0.007)		(0.007)		(0.006)		(0.005)	
South Atlantic	-0.057	***	-0.042	***	-0.031	***	-0.013		-0.028	***	-0.024	***	-0.020	***
	(0.008)		*0.006*		(0.007)		(0.007)		(0.007)		(0.006)		(0.006)	
East South Central	-0.049	***	-0.033	***	-0.021	**	0.006		-0.034	***	-0.019	**	-0.016	**
	(0.008)		(0.006)		(0.007)		(0.007)		(0.007)		(0.006)		(0.006)	
West South Central	-0.006		-0.004		0.019	**	0.029	***	0.000		0.000		0.004	
	(0.008)		(0.006)		(0.007)		(0.007)		(0.007)		(0.006)		(0.006)	
Mountain	0.031	***	0.017	**	0.039	***	0.038	***	0.036	***	0.014	*	0.015	**
	(0.008)		(0.006)		(0.007)		(0.007)		(0.007)		(0.006)		(0.006)	
Pacific	0.007		0.006		0.030	***	0.047	***	0.031	***	0.022	**	0.024	***
	(0.009)		(0.007)		(0.008)		(0.009)		(0.008)		(0.007)		(0.007)	
Farming	0.030	***	0.018	***	0.029	***	0.015	***	0.017	***	0.005	*	0.003	
	(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.002)		(0.002)	
Mining	0.024	***	0.015	***	0.027	***	0.028	***	0.027	***	0.018	***	0.021	***
	(0.005)		(0.004)		(0.004)		(0.004)		(0.004)		(0.003)		(0.003)	
Manufacturing	-0.006	*	-0.012	***	-0.008	***	-0.005	*	-0.006	*	-0.010	***	-0.008	***
	(0.003)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)	
Government	-0.003		0.003		-0.001		-0.002		0.003		0.001		-0.001	
	(0.004)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)	
Services	0.010	*	-0.002		-0.003		-0.007		0.008		0.000		0.000	
	(0.005)		(0.004)		(0.004)		(0.004)		(0.004)		(0.003)		(0.003)	
Income segregation			0.001								0.001		0.002	
			(0.002)								(0.002)		(0.002)	
Fraction above poverty line			-0.005	**							-0.007	***	-0.004	*
			(0.002)								(0.002)		(0.002)	
Fraction black			0.013	***							0.015	***	0.013	***
			(0.002)								(0.001)		(0.001)	

Household income per capita		0.013 ***				0.004 *	0.002
		(0.002)				(0.002)	(0.002)
Gini coefficient, bottom 99%		-0.005 ***				-0.004 ***	-0.003 ***
		(0.001)				(0.001)	(0.001)
Fraction with single mothers		-0.039 ***				-0.036 ***	-0.034 ***
		(0.002)				(0.002)	(0.002)
Growth rates			0.013 ***			0.003 **	0.002 *
			(0.001)			(0.001)	(0.001)
Grade 3 achievement			0.023 ***			0.002	0.000
			(0.001)			(0.001)	(0.001)
Fraction with commute < 15 mins				0.003 *		0.006 ***	0.005 ***
				(0.002)		(0.001)	(0.001)
Teenage labor force participation				0.021 ***		0.009 ***	0.008 ***
				(0.002)		(0.001)	(0.001)
In-migration				-0.006 **		-0.007 ***	-0.005 **
				(0.002)		(0.002)	(0.002)
Out-migration				-0.004		-0.001	-0.001
				(0.002)		(0.002)	(0.002)
Unemployment rate				-0.010 ***		-0.002 *	-0.001
				(0.001)		(0.001)	(0.001)
Social capital index					0.018 ***	0.009 ***	0.006 ***
					(0.001)	(0.001)	(0.001)
Fraction religious					0.012 ***	0.005 ***	0.005 ***
					(0.001)	(0.001)	(0.001)
Violent crime rate					-0.012 ***	-0.003 **	-0.003 **
					(0.001)	(0.001)	(0.001)
College completion rate							0.010 ***
							(0.001)
Intercept	0.447 ***	0.448 ***	0.434 ***	0.422 ***	0.438 ***	0.437 ***	0.435 ***
	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Observations	1726	1726	1726	1726	1726	1726	1726
R-squared	0.60	0.76	0.69	0.71	0.71	0.82	0.84

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in italics. RUCC 9, New England division, and nonspecialized economic dependency serve as reference categories.

As mentioned, state EITC positively predicts mobility, though including neither this policy nor other policy factors reduces the coefficient of demographic factors, including share of single mothers (compare to model 7 in Table 10). Further, once all controls are included, this is the only policy factor which appears significant. Therefore, it appears existing policies are no more useful in explaining economic outcomes for low-income youth than demographic and economic characteristics are, prompting a need for more effective policy interventions. The insignificance of government expenditures per capita as a covariate suggests that blanket government spending is not the solution; policies ought to be more direct and strategic in their approach.

Though the explicit goal of this paper is to understand the path to rural upward mobility, it is useful to understand the extent to which that path differs spatially. With this in mind, I explore whether these factors are more instrumental in rural mobility, nonrural, or neither, using nonrural interaction terms while controlling for all covariates. Table 12 highlights these findings, with model 1 including only the interactions with significant differences. Fraction black and income segregation are more detrimental for mobility outcomes in nonrural counties, while single motherhood and migration, in both directions, are more detrimental in rural. The migration finding is especially notable given its insignificance in the rural-only model.

Table 11: Multivariate Regression Results, Policy Effects on Rural Mobility

	(1)		(2)		(3)		(4)		(5)	
RUCC 4	-0.032	***	-0.032	***	-0.026	***	-0.009	**	-0.010	**
	(0.004)		(0.004)		(0.004)		(0.003)		(0.003)	
RUCC 5	-0.037	***	-0.038	***	-0.035	***	-0.011	**	-0.012	**
	(0.005)		(0.005)		(0.005)		(0.004)		(0.004)	
RUCC 6	-0.023	***	-0.023	***	-0.018	***	-0.005	*	-0.005	*
	(0.003)		(0.003)		(0.003)		(0.002)		(0.002)	
RUCC 7	-0.020	***	-0.020	***	-0.022	***	-0.009	***	-0.008	***
	(0.003)		(0.003)		(0.003)		(0.002)		(0.002)	
RUCC 8	-0.003		-0.004		0.002		0.004		0.004	
	(0.004)		(0.004)		(0.003)		(0.003)		(0.003)	
Middle Atlantic	0.020	*	0.033	***	0.050	***	0.019	**	0.020	***
	(0.009)		(0.009)		(0.008)		(0.006)		(0.006)	
East North Central	-0.002		0.016	*	0.025	***	-0.004		0.003	
	(0.008)		(0.008)		(0.007)		(0.006)		(0.005)	
West North Central	0.047	***	0.066	***	0.056	***	0.022	***	0.025	***
	(0.008)		(0.008)		(0.007)		(0.006)		(0.006)	
South Atlantic	-0.060	***	-0.031	***	-0.005		-0.018	**	-0.015	*
	(0.008)		(0.008)		(0.007)		(0.006)		(0.006)	
East South Central	-0.052	***	-0.019	*	0.014		-0.013	*	-0.010	
	(0.008)		(0.008)		(0.008)		(0.006)		(0.006)	
West South Central	-0.010		0.015		0.037	***	0.007		0.010	
	(0.008)		(0.008)		(0.007)		(0.006)		(0.006)	
Mountain	0.027	***	0.049	***	0.050	***	0.022	***	0.022	***
	(0.008)		(0.008)		(0.008)		(0.006)		(0.006)	
Pacific	0.005		0.029	**	0.057	***	0.029	***	0.030	***
	(0.009)		(0.010)		(0.009)		(0.007)		(0.007)	
Farming	0.025	***	0.025	***	0.016	***	0.006	*	0.005	*
	(0.003)		(0.003)		(0.003)		(0.002)		(0.002)	
Mining	0.027	***	0.021	***	0.026	***	0.016	***	0.019	***
	(0.005)		(0.005)		(0.004)		(0.003)		(0.003)	
Manufacturing	-0.006	*	-0.004		-0.004		-0.009	***	-0.007	***
	(0.003)		(0.003)		(0.002)		(0.002)		(0.002)	
Government	-0.002		0.001		-0.001		0.001		0.000	
	(0.004)		(0.004)		(0.003)		(0.003)		(0.002)	
Services	0.015	**	0.008		-0.006		0.002		0.002	
	(0.005)		(0.005)		(0.004)		(0.004)		(0.003)	
Agricultural subsidies per capita, logged	0.006	***	0.005	***	0.000		0.000		0.000	
	(0.001)		(0.001)		(0.001)		(0.001)		(0.001)	
School expenditures per pupil			0.002		0.002		0.002	*	0.002	
			(0.001)		(0.001)		(0.001)		(0.001)	
State EITC exposure			0.007	***	0.004	***	0.003	***	0.003	***
			(0.001)		(0.001)		(0.001)		(0.001)	
Local tax rate per capita			0.020	***	0.006	*	0.003		0.002	

			(0.003)		(0.003)		(0.002)		(0.002)	
Local gov't expenditures per capita			-0.001		-0.001		0.001		0.002	
			(0.002)		(0.002)		(0.001)		(0.001)	
Fraction with commute < 15 mins					0.003		0.006	***	0.005	***
					(0.002)		(0.001)		(0.001)	
Teenage labor force participation					0.018	***	0.007	***	0.005	***
					(0.002)		(0.001)		(0.001)	
In-migration					-0.006	**	-0.006	***	-0.005	**
					(0.002)		(0.002)		(0.002)	
Out-migration					-0.004	*	-0.002		-0.002	
					(0.002)		(0.002)		(0.002)	
Unemployment rate					-0.011	***	-0.003	**	-0.002	*
					(0.001)		(0.001)		(0.001)	
Income segregation							0.001		0.002	
							(0.002)		(0.002)	
Fraction above poverty line							-0.007	***	-0.004	*
							(0.002)		(0.002)	
Fraction black							0.015	***	0.013	***
							(0.001)		(0.001)	
Household income per capita							0.003		0.001	
							(0.002)		(0.002)	
Gini coefficient, bottom 99%							-0.004	***	-0.004	***
							(0.001)		(0.001)	
Fraction with single mothers							-0.037	***	-0.034	***
							(0.002)		(0.002)	
Growth rates							0.003	***	0.002	**
							(0.001)		(0.001)	
Grade 3 achievement							0.002		0.000	
							(0.001)		(0.001)	
Social capital index							0.008	***	0.006	***
							(0.001)		(0.001)	
Fraction religious							0.005	***	0.005	***
							(0.001)		(0.001)	
Violent crime rate							-0.003	**	-0.003	**
							(0.001)		(0.001)	
College completion rate									0.010	***
									(0.001)	
Intercept	0.452	***	0.430	***	0.413	***	0.431	***	0.428	***
	(0.008)		(0.008)		(0.007)		(0.006)		(0.006)	
Observations	1726		1726		1726		1726		1726	
R-squared	0.61		0.63		0.71		0.82		0.84	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in italics. RUCC 9, New England division, and nonspecialized economic dependency serve as reference categories

Table 12 confirms that even when controlling for migration levels, movement out of communities is more harmful for the mobility outcomes of rural counties, supporting the theory that rural counties have been losing their high-potential young people in recent decades. Note this does not suggest that out-migration is detrimental to individual mobility outcomes—the opposite may actually be true—but that out-migration in a county simply correlates to lower mobility chances in that county. However, to reconcile with previous findings, it is possible that while migration is comparably more important for rural outcomes, within the context of only those counties, migration is either captured by or rendered less important than other covariates. Surprisingly, there is no significant difference among educational covariates, though I examine this more closely with fixed effects analysis. The full results of the interaction analysis, including coefficients for all control variables, is available in Table A11.

Table 12: Differential Rural vs. Nonrural Covariate Effects on Mobility

	(1)		(2)	
Ag subsidy × nonrural			0.001	
			(0.001)	
Income segregation × nonrural	-0.006	***	-0.006	**
	(0.002)		(0.002)	
Fraction poverty × nonrural			-0.003	
			(0.003)	
Fraction black × nonrural	-0.008	***	-0.011	***
	(0.002)		(0.002)	
Household income × nonrural			0.000	
			(0.002)	
Gini coefficient × nonrural			-0.003	*
			(0.002)	
Single mother × nonrural	0.009	***	0.013	***
	(0.002)		(0.003)	
Growth rate × nonrural			0.000	
			(0.001)	
Grade 3 achievement × nonrural			0.003	
			(0.002)	
Commute time × nonrural			-0.001	
			(0.002)	
Teen labor participation × nonrural			-0.003	
			(0.002)	
Migration inflow × nonrural	0.006	***	0.006	*
	(0.001)		(0.002)	
Migration outflow × nonrural			0.001	
			(0.002)	
Unemployment × nonrural			-0.002	
			(0.002)	
Social capital × nonrural			-0.003	
			(0.002)	
Fraction religious × nonrural			0.002	
			(0.001)	
Violent crime × nonrural			0.003	*
			(0.001)	
School expenditures × nonrural			-0.003	
			(0.002)	
State EITC × nonrural			0.001	
			(0.001)	
Local tax rate × nonrural			0.006	
			(0.004)	
Gov’t expenditures × nonrural			-0.001	
			(0.002)	

College completion × nonrural			0.002	
			(0.002)	
Nonrural indicator	✓		✓	
All covariates	✓		✓	
Intercept	0.429	***	0.427	***
	0.004		0.004	
Observations	2653		2653	
R-squared	0.84		0.84	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses.

Tables 13 and 14 highlight findings from the fixed effects models. In Table 13, I find that race explains a majority of the variation in mobility within both rural and nonrural counties, and that race, socioeconomic status, and education together account for 90 percent of variation. When including eighth grade achievement, the predictive power of growth rates becomes insignificant across both geographies, suggesting that in-school learning is predictive of mobility because of its ability to land students in a more favorable position by the time they reach grade 8. With this, I also note that the predictive power of eighth grade achievement does not diminish when considering college completion. In other words, test scores likely matter more for mobility than just for sending students to college. This result could be a side effect of the binary college completion variable; perhaps eighth grade achievement is more predictive of the quality of college one attends, which could also affect the extent of mobility. Further, coefficient sizes suggest that college completion is of slightly greater importance for nonrural areas, while both third and eighth grade achievement are more predictive for rural. These two trends appear to hold when differentiating by economic group, as in Table 14. In this model, achievement scores boast more predictive power than growth rates, even when accounting for college completion. Strikingly, economic status explains nearly all variation in mobility within rural counties, and even more within nonrural.

Table 13: Fixed Effects Analysis by Race and Socioeconomic Status

	Rural					Nonrural				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Black	-0.109 ***	-0.063 ***	-0.054 ***	-0.049 ***	-0.049 ***	-0.103 ***	-0.068 ***	-0.062 ***	-0.074 ***	-0.074 ***
	(0.002)	(0.005)	(0.005)	(0.006)	(0.006)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
Hispanic	-0.043 ***	-0.021 ***	-0.011 ***	0.002	0.002	-0.036 ***	-0.016 ***	-0.011 ***	-0.010 ***	-0.010 ***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
SES		0.013 ***	0.010 ***	0.012 ***	0.012 ***		0.011 ***	0.008 ***	0.006 ***	0.006 ***
		(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Grade 3 achievement			0.011 ***	0.008 ***				0.007 ***	0.005 **	
			(0.002)	(0.002)				(0.002)	(0.001)	
Growth			0.002	0.006 ***	0.000			0.003 *	0.004 **	0.001
			(0.002)	(0.002)	(0.002)			(0.002)	(0.001)	(0.001)
College completion				0.005 ***	0.005 ***				0.006 ***	0.006 ***
				(0.001)	(0.001)				(0.001)	(0.001)
Grade 8 achievement					0.009 ***					0.005 **
					(0.002)					(0.001)
Intercept	0.459 ***	0.454 ***	0.452 ***	0.453 ***	0.453 ***	0.445 ***	0.434 ***	0.432 ***	0.434 ***	0.434 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Observations	3689	3678	3678	2376	2376	2578	2576	2576	2004	2004
Adj. R-squared	0.62	0.64	0.65	0.89	0.89	0.72	0.74	0.74	0.90	0.90

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses. White subgroup serves as reference category.

Table 14: Fixed Effects Analysis by Income

	Rural								Nonrural							
	(1)		(2)		(3)		(4)		(1)		(2)		(3)		(4)	
Economically disadvantaged	-0.167	***	-0.126	***	-0.104	***	-0.104	***	-0.168	***	-0.150	***	-0.104	***	-0.104	***
	(0.001)		(0.004)		(0.004)		(0.004)		(0.001)		(0.003)		(0.004)		(0.004)	
Grade 3 achievement			0.022	***	0.019	***					0.008	***	0.008	***		
			(0.002)		(0.002)						(0.001)		(0.001)			
Growth			0.001		0.001		-0.011	***			0.002		0.001		-0.004	**
			(0.001)		(0.001)		(0.001)				(0.001)		(0.001)		(0.001)	
College completion					0.007	***	0.007	***					0.013	***	0.013	***
					(0.001)		(0.001)						(0.001)		(0.001)	
Grade 8 achievement							0.020	***							0.008	***
							(0.002)								(0.001)	
Intercept	0.605	***	0.583	***	0.558	***	0.558	***	0.581	***	0.571	***	0.525	***	0.525	***
	(0.001)		(0.002)		(0.003)		(0.003)		(0.001)		(0.002)		(0.003)		(0.003)	
Observations	3426		3426		3426		3426		1850		1850		1850		1850	
Adj. R-squared	0.95		0.95		0.96		0.96		0.98		0.98		0.98		0.98	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses. Non-economically disadvantaged subgroup serves as reference category.

To gauge the amount of within-county variation captured in fixed effects, I fit a final cross-sectional model mirroring the fixed effects regressions. As shown in Table 15, analyzing within-county variation with fixed effects explains 8 to 15 percent more variation in rural counties, and 19 to 27 percent more in nonrural counties, than simple cross-sectional models. The discrepancy here is intuitive; one would expect nonrural counties to be more diffuse and therefore home to more within-county variation. Finally, though not a primary element of my analysis, I include tables in the appendix to highlight the predictive power of race, socioeconomic status, and education on college outcomes.

Table 15: Cross-Sectional Regression with Fixed Effects Controls

	Rural		Nonrural	
RUCC 2			0.003	
			(0.002)	
RUCC 3			0.015	***
			(0.002)	
RUCC 4	-0.03	***		
	(0.003)			
RUCC 5	-0.033	***		
	(0.004)			
RUCC 6	-0.016	***		
	(0.002)			
RUCC 7	-0.014	***		
	(0.002)			
RUCC 8	-0.003			
	(0.003)			
Farming	0.029	***	0.014	**
	(0.006)		(0.005)	
Mining	0.020	***	-0.005	
	(0.006)		(0.005)	
Manufacturing	0.049	***	0.027	***
	(0.006)		(0.005)	
Government	-0.013	*	-0.026	***
	(0.006)		(0.005)	
Services	0.007		-0.017	**
	(0.006)		(0.005)	
Middle Atlantic	0.024	***	0.007	
	(0.006)		(0.005)	
East North Central	0.031	***	0.021	***
	(0.006)		(0.006)	
West North Central	0.029	***	0.014	*
	(0.007)		(0.006)	
South Atlantic	0.015	***	0.019	***
	(0.002)		(0.004)	
East South Central	0.021	***	0.019	**
	(0.003)		(0.007)	
West South Central	-0.008	***	-0.003	
	(0.002)		(0.002)	
Mountain	-0.003		-0.013	***
	(0.003)		(0.003)	
Pacific	-0.014	***	-0.015	***
	(0.003)		(0.002)	
SES	0.032	***	0.024	***
	(0.001)		(0.002)	
Grade 3 achievement	0.001		0.005	***
	(0.001)		(0.002)	
Growth rate	0.002	*	0.003	**
	(0.001)		(0.001)	
Fraction children with four-year degree	0.012	***	0.008	***
	(0.001)		(0.001)	
Intercept	0.434	***	0.406	***
	(0.006)		(0.005)	
Observations	1726		927	
R-squared	0.80		0.71	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses.

7 Discussion

With this paper, I attempt to understand the factors most strongly correlated to rural upward mobility, to help guide future policymaking. Five primary conclusions can be drawn from this analysis.

First, consistent with previous literature, mobility varies by geography, though we now know it varies also by subgroup and rurality, across different regions of the country and by different economic types. While average upward mobility is higher in rural areas, mobility is higher in nonrural counties for black, Asian, and Native American subgroups. This suggests that the factors driving higher mobility outcomes in rural regions may not be accessible to all, a finding which merits additional research.

Observable community characteristics explain an extraordinary 84 percent of variation in nonrural areas and 82 percent in nonrural ones. Though it is potentially disheartening that one's life outcomes can be predicted based on the characteristics of one's childhood county, knowing which factors are most important to shaping upward mobility is useful for developing viable policy solutions.

The path to upward mobility is differentiated across the rural-urban divide; certain factors matter more in rural than nonrural areas, and vice versa. Mobility is higher in rural and nonrural areas with greater social capital and fewer single mothers. Upon comparing covariate interactions, I find that in nonrural counties, a higher fraction black population and greater income segregation are more detrimental for mobility outcomes, while a greater number of single mothers and higher levels of migration are more detrimental in rural. In terms of policy, one might consider whether rural migration is driven by lack of social cohesion, and whether efforts to encourage social interactions could remedy these effects.

Fixed effects analysis reveals that when considering within-county effects, college attainment is slightly more predictive of mobility outcomes within nonrural counties than rural. This suggests it is less detrimental to upward mobility to forgo a four-year degree when one grows up in a rural area than when one is from an urban area. However, this does not mean education is insignificant in rural counties; in fact, it is just as critical to ensure high-quality education in these areas, since areas with higher grade 3 and grade 8 achievement scores have relatively higher mobility, among rural counties. Note that this finding does not hold in the cross-sectional models, suggesting that the power of these disparities is limited to within-county effects.

To the matter of policy, I find that agricultural subsidies are not significant predictors of rural mobility, though state Earned Income Tax Credit exposure is. This finding is consistent with much of the literature. Instead of using farm policy as the linchpin for rural mobility policy, I suggest considering an expansion of state EITC benefits in states with large rural populations. Future research could also examine other Farm Bill programs; Ulrich-Schad, Grimm, & Jackson-Smith, have argued the "most important farm bill programs for the wellbeing of most U.S. rural communities are the rural development and nutrition programs," not farm subsidies, due to their broad reach (2013, p. 24). Regardless of what precise steps are taken, however, policy must be developed thoughtfully and must attend to unique rural characteristics.

The nature of rurality in America is extraordinarily diverse, and as a result, the rural-urban distinction is sometimes perceived as less valuable than an examination of specific locations. However, by noting substantive differences in mobility outcomes and in factors predictive of mobility across rural and nonrural areas, this paper lends credence to value of the rural-nonrural distinction in policymaking and research. Though rural areas have their strengths in community and social networks, their geographic isolation often limits access to the economic and cultural resources found in a metropolis. This proves especially detrimental for rural single mothers—and their children—attempting to move out of poverty. One policy option for rural areas to consider is to leverage community resources and close social ties to support single mothers in the community. Further, though historically less critical in rural areas, the value of obtaining a college education is still an unmatched step toward greater upward mobility. In recent years, several Promise programs have been implemented in states with prominent rural populations. Future research can analyze the success of these programs in encouraging rural educational attainment and bolstering upward mobility.

However, the challenges lie not simply in which policies are apt to pursue, but also in the success with which they can be implemented. Weber cites several reasons why traditional poverty policy is less effective in rural areas; one such example is that the lack of matched job opportunities and limited service availabilities in rural areas exacerbate the challenges of escaping poverty for single mothers (2007). Further, Meckstroth et al find that when implementing rural policy, special care must be taken to recruit and retain qualified, well-trained staff, as many rural communities lack the project development and management expertise to drive needed developments (2006). These researchers also find evidence of greater social shame in receiving assistance in smaller environments. Thus, rural areas require strengthened public institutions and a sort of accountability mechanism for unbiased policy implementation. As such, the challenge is not only discerning what sort of agenda one would craft to encourage rural mobility, but considering the extent to which those reforms could be made feasible. With a more explicit, unifying mandate, policymakers can more effectively address unique challenges of rural areas.

This research faces several limitations. First, data on many of the covariates were drawn from the year 2000 or later, when individuals in the Chetty birth cohorts were approaching early adulthood. If the values of these covariates vary substantially over time, these estimates could misrepresent the true effect that each covariate had during the childhood of these individuals. This is a particular concern for the SEDA data, which are gathered when individuals in the Chetty data were nearing age 30, though the consistency analysis I conduct serves partially to assuage these concerns. Further, this project's primary limitation in methodology is its inability to comment on causality between these covariates and the outcomes in question. It is also unable to gauge the effects of growing up in a rural area in the wake of events such as the 2008 economic crisis, from which rural areas were slower to recover than nonrural ones. Finally, by analyzing mean values across counties, I am unable to examine individual-level mobility, thereby obfuscating edge cases which may provide useful insight into the experience of overcoming hardship in rural America.

Rural policymakers must carefully consider the context of their own regions when selecting reforms to promote local economic prosperity, along with the steps needed to ensure effective implementation. While rural America often falls to the periphery of academic research, my hope is that this project has not only highlighted the benefits and challenges of a rural upbringing, but will also draw attention to the need to develop a more concerted effort toward ensuring equality of opportunity across the rural-urban divide.

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Appendix

Table A1: Continuous Covariate Data Sources

Demographics	
Fraction above poverty line	Opportunity Atlas – 2000 Census SF3 Sample Data Table P087
Fraction black	Opportunity Atlas – 2000 Census SF1 100% Data Table P008
Fraction with single mothers	Opportunity Atlas – 2000 Census SF3 Sample Data Table P015
Gini coefficient, bottom 99%	Opportunity Atlas – Tax Records, Core Sample of Chetty et al. (2014)
Household income per capita	Opportunity Atlas – 2000 Census SF3 Sample Data Table P054
Income segregation	Opportunity Atlas – 2000 Census SF3 Sample Data Table P052
Education	
Growth rates	SEDA v3.0
Grade 3 achievement	SEDA v3.0
Economy	
Fraction with commute < 15 mins	Opportunity Atlas – 2000 Census SF3 Sample Data Table P031
In-migration	Opportunity Atlas – IRS Statistics of Income 2004-2005
Out-migration	Opportunity Atlas – IRS Statistics of Income 2004-2005
Teenage labor force participation	Opportunity Atlas – Tax Records, Extended Sample
Unemployment rate	Opportunity Atlas – Local Area Unemployment Statistics
Social	
Fraction religious	Opportunity Atlas – Association of Religion Data Archives
Social capital index	Opportunity Atlas – Rupasingha and Goetz (2008)
Violent crime rate	Opportunity Atlas – Uniform Crime Reports
Policy	
Agricultural subsidies	U.S. Census Bureau Consolidated Federal Funds Report
Local gov't expenditures per capita	Opportunity Atlas – 1992 Census of Government county-level summaries
Local tax rate per capita	Opportunity Atlas – 1992 Census of Government county-level summaries
School expenditures per pupil	Opportunity Atlas – NCES CCD 1996-1997 Financial Survey
State EITC exposure	Opportunity Atlas – Hotz and Scholz (2003)
Intermediate factor	
Four-year college completion rate	Opportunity Atlas – Tax Records, Extended Sample

Source: Chetty & Hendren, 2017

Table A2: Availability of Educational Opportunity Covariates by Subgroup

	Nonrural Observations	Rural Observations
Growth rate		
All	1086	2043
Asian	833	649
Black	987	1147
Hispanic	1049	1597
Native American	673	583
White	1084	2023
Female	1086	2040
Male	1086	2043
Economically disadvantaged	1086	2039
Non-economically disadvantaged	1082	2008
Grade 3 achievement		
All	1086	2043
Asian	833	649
Black	987	1147
Hispanic	1049	1597
Native American	673	583
White	1084	2023
Female	1086	2040
Male	1086	2043
Economically disadvantaged	1086	2039
Non-economically disadvantaged	1082	2008

Table A3: Definitions and Distribution of U.S. Census Divisions

Region	Division	States	Nonrural	Rural	Total
Northeast	New England	CT, ME, MA, NH, RI, VT	34	33	67
	Middle Atlantic	NJ, NY, PA	89	61	150
Midwest	East North Central	IL, IN, MI, OH, WI	173	264	437
	West North Central	IA, KS, MN, MO, NE, ND, SD	112	505	617
South	South Atlantic	DE, DC, FL, GA, MD, NC, SC, VA, WV	289	299	588
	East South Central	AL, KY, MS, TN	118	246	364
	West South Central	AR, LA, OK, TX	143	325	468
West	Mountain	AZ, CO, ID, MT, NV, NM, UT, WY	62	218	280
	Pacific	AK, CA, HI, OR, WA	69	96	165
		Total	1,089	2,047	3,136

Table A4: Definitions and Distribution of Rural-Urban Continuum Codes

RUCC	Description
1	County in metro area with 1 million population or more
2	County in metro area of 250,000 to 1 million population
3	County in metro area of fewer than 250,000 population
4	Nonmetro county with urban population of 20,000 or more, adjacent to a metro area
5	Nonmetro county with urban population of 20,000 or more, not adjacent to a metro area
6	Nonmetro county with urban population of 2,500-19,999, adjacent to a metro area
7	Nonmetro county with urban population of 2,500-19,999, not adjacent to a metro area
8	Nonmetro county completely rural or less than 2,500 urban population, adjacent to a metro area
9	Nonmetro county completely rural or less than 2,500 urban population, not adjacent to a metro area
	Total

Table A5: Correlation Coefficients, 2009 and 2016 8th Grade Achievement Estimates

	ELA			Math	
	2009 estimates	2016 estimates		2009 estimates	2016 estimates
2009 estimates	1.0000		2009 estimates	1.0000	
2016 estimates	0.9385	1.0000	2016 estimates	0.9164	1.0000

Table A6: Correlation Coefficients, 2009 and 2016 3rd Grade Achievement Estimates

	ELA			Math	
	2009 estimates	2016 estimates		2009 estimates	2016 estimates
2009 estimates	1.0000		2009 estimates	1.0000	
2016 estimates	0.9349	1.0000	2016 estimates	0.9362	1.0000

Table A7: Multivariate Consistency Analysis, 8th Grade Achievement and Mobility

	Mobility		Mobility		Mobility		Mobility	
2009 ELA estimates	0.008	**						
	(0.003)							
2016 ELA estimates			0.006	*				
			(0.003)					
2009 math estimates					0.007	**		
					(0.002)			
2016 math estimates							0.009	***
							(0.002)	
All covariates	✓		✓		✓		✓	
Intercept	0.438	***	0.438	***	0.438	***	0.438	***
	(0.004)		(0.004)		(0.004)		(0.004)	
Observations	2665		2665		2665		2656	
R-squared	0.82		0.82		0.82		0.82	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses.

Table A8: Multivariate Consistency Analysis, 3rd Grade Achievement and Mobility

	Mobility		Mobility		Mobility		Mobility	
2009 ELA estimates	0.007	**						
	(0.003)							
2016 ELA estimates			0.007	**				
			(0.003)					
2009 math estimates					0.008	***		
					(0.002)			
2016 math estimates							0.010	***
							(0.002)	
All covariates	✓		✓		✓		✓	
Intercept	0.438	***	0.438	***	0.438	***	0.437	***
	(0.004)		(0.004)		(0.004)		(0.004)	
Observations	2664		2664		2664		2664	
R-squared	0.82		0.82		0.82		0.82	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses.

Table A9: Consistency Analysis, 8th Grade Achievement and College Outcome

	College		College		College		College		College		College		College		College	
2009 ELA estimates	0.071	***							0.033	***						
	(0.005)								(0.006)							
2016 ELA estimates			0.071	***							0.037	***				
			(0.005)								(0.006)					
2009 math estimates					0.067	***							0.021	***		
					(0.005)								(0.005)			
2016 math estimates							0.062	***							0.018	***
							(0.004)								(0.005)	
All covariates									✓		✓		✓		✓	
Intercept	0.179	***	0.178	***	0.179	***	0.179	***	0.223	***	0.223	***	0.223	***	0.223	***
	(0.001)		(0.001)		(0.001)		(0.001)		(0.009)		(0.009)		(0.009)		(0.009)	
Observations	3035		3035		3035		3035		2665		2665		2665		2656	
R-squared	0.07		0.07		0.07		0.06		0.41		0.41		0.41		0.41	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses.

Table A10: Consistency Analysis, 3rd Grade Achievement and College Outcome

	College	College	College	College	College	College	College	College
2009 ELA estimates	0.088 ***				0.026 ***			
	(0.005)				(0.005)			
2016 ELA estimates		0.088 ***				0.031 ***		
		(0.005)				(0.005)		
2009 math estimates			0.083 ***				0.026 ***	
			(0.004)				(0.005)	
2016 math estimates				0.079 ***				0.021 ***
				(0.004)				(0.005)
All covariates					✓	✓	✓	✓
Intercept	0.185 ***	0.186 ***	0.184 ***	0.182 ***	0.221 ***	0.220 ***	0.222 ***	0.222 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)	(0.009)	(0.009)	(0.009)
Observations	3037	3037	3037	3026	2664	2664	2664	2664
R-squared	0.10	0.10	0.11	0.10	0.41	0.41	0.41	0.41

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses.

Table A11: Differential Rural vs. Nonrural Covariate Effects on Mobility, Full Results

	(1)		(2)	
Nonrural indicator	-0.007		-0.008	**
	(0.005)		(0.003)	
RUCC 2	0.000		-0.001	
	(0.002)		(0.002)	
RUCC 3	0.004		0.003	
	(0.003)		(0.002)	
RUCC 4	-0.01	***	-0.01	***
	(0.003)		(0.003)	
RUCC 5	-0.012	***	-0.012	***
	(0.003)		(0.003)	
RUCC 6	-0.005	*	-0.006	**
	(0.002)		(0.002)	
RUCC 7	-0.008	***	-0.008	***
	(0.002)		(0.002)	
RUCC 8	0.003		0.003	
	(0.002)		(0.002)	
Middle Atlantic	0.015	***	0.013	***
	(0.004)		(0.004)	
East North Central	0.000		-0.002	
	(0.004)		(0.004)	
West North Central	0.022	***	0.021	***
	(0.004)		(0.004)	
South Atlantic	-0.015	***	-0.016	***
	(0.004)		(0.004)	
East South Central	-0.011	**	-0.012	**
	(0.004)		(0.004)	
West South Central	0.011	**	0.011	**
	(0.004)		(0.004)	
Mountain	0.021	***	0.02	***
	(0.004)		(0.004)	
Pacific	0.030	***	0.027	***
	(0.005)		(0.005)	
Farming	0.004		0.004	
	(0.002)		(0.002)	
Mining	0.019	***	0.018	***
	(0.003)		(0.003)	
Manufacturing	-0.006	***	-0.006	***
	(0.001)		(0.001)	
Government	0.000		0.000	
	(0.002)		(0.002)	
Services	0.000		-0.001	
	(0.002)		(0.002)	
Agricultural subsidies per capita, logged	0.000		0.000	
	(0.001)		(0.001)	

School expenditures per pupil	0.002	*	0.001	
	(0.001)		(0.001)	
State EITC exposure	0.003	***	0.004	***
	(0.001)		(0.001)	
Local tax rate per capita	0.003		0.004	*
	(0.002)		(0.002)	
Local gov’t expenditures per capita	0.001		0.001	
	(0.001)		(0.001)	
Fraction with commute < 15 mins	0.004	***	0.004	***
	(0.001)		(0.001)	
Teenage labor force participation	0.006	***	0.005	***
	(0.001)		(0.001)	
In-migration	-0.005	**	-0.002	
	(0.002)		(0.001)	
Out-migration	-0.002		-0.004	**
	(0.002)		(0.001)	
Unemployment rate	-0.002	*	-0.002	**
	(0.001)		(0.001)	
Income segregation	0.002		0.001	
	(0.002)		(0.002)	
Fraction above poverty line	-0.004	**	-0.004	***
	(0.001)		(0.001)	
Fraction black	0.013	***	0.012	***
	(0.001)		(0.001)	
Household income per capita	0.001		0.001	
	(0.002)		(0.001)	
Gini coefficient, bottom 99%	-0.004	***	-0.005	***
	(0.001)		(0.001)	
Fraction with single mothers	-0.034	***	-0.033	***
	(0.002)		(0.001)	
Growth rates	0.002	**	0.002	***
	(0.001)		(0.001)	
Grade 3 achievement	0.000		0.001	
	(0.001)		(0.001)	
Social capital index	0.006	***	0.005	***
	(0.001)		(0.001)	
Fraction religious	0.005	***	0.005	***
	(0.001)		(0.001)	
Violent crime rate	-0.003	***	-0.002	***
	(0.001)		(0.001)	
College completion rate	0.010	***	0.011	***
	(0.001)		(0.001)	
Ag subsidy × nonrural	0.001			
	(0.001)			
Income segregation × nonrural	-0.006	**	-0.006	***
	(0.002)		(0.002)	
Fraction poverty × nonrural	-0.003			

	(0.003)			
Fraction black × nonrural	-0.011	***	-0.008	***
	(0.002)		(0.002)	
Household income × nonrural	0.000			
	(0.002)			
Gini coefficient × nonrural	-0.003	*		
	(0.002)			
Single mother × nonrural	0.013	***	0.009	***
	(0.003)		(0.002)	
Growth rate × nonrural	0.000			
	(0.001)			
Grade 3 achievement × nonrural	0.003			
	(0.002)			
Commute time × nonrural	-0.001			
	(0.002)			
Teen labor participation × nonrural	-0.003			
	(0.002)			
Migration inflow × nonrural	0.006	*		
	(0.002)			
Migration outflow × nonrural	0.001		0.006	***
	(0.002)		(0.001)	
Unemployment × nonrural	-0.002			
	(0.002)			
Social capital × nonrural	-0.003			
	(0.002)			
Fraction religious × nonrural	0.002			
	(0.001)			
Violent crime × nonrural	0.003	*		
	(0.001)			
School expenditures × nonrural	-0.003			
	(0.002)			
State EITC × nonrural	0.001			
	(0.001)			
Local tax rate × nonrural	0.006			
	(0.004)			
Gov’t expenditures × nonrural	-0.001			
	(0.002)			
College completion × nonrural	0.002			
	(0.002)			
Intercept	0.427	***	0.429	***
	(0.004)		(0.004)	
Observations	2653		2653	
R-squared	0.84		0.84	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses.

Table A12: Multivariate Regression Results, All Covariate Effects on Nonrural Mobility

	(1)		(2)		(3)		(4)	
RUCC 2	-0.012	***	-0.001		0.000		0.000	
	(0.002)		(0.002)		(0.002)		(0.002)	
RUCC 3	-0.001		0.004		0.005	*	0.004	
	(0.003)		(0.002)		(0.002)		(0.002)	
Middle Atlantic	0.003		0.010	*	0.008		0.008	
	(0.007)		(0.005)		(0.005)		(0.004)	
East North Central	-0.022	***	-0.016	***	-0.012	*	-0.003	
	(0.007)		(0.004)		(0.005)		(0.004)	
West North Central	0.024	***	0.010	*	0.015	**	0.019	***
	(0.007)		(0.005)		(0.005)		(0.004)	
South Atlantic	-0.054	***	-0.024	***	-0.021	***	-0.014	**
	(0.006)		(0.005)		(0.005)		(0.004)	
East South Central	-0.056	***	-0.025	***	-0.018	***	-0.010	*
	(0.007)		(0.005)		(0.005)		(0.005)	
West South Central	-0.022	**	0.005		0.009		0.016	***
	(0.007)		(0.005)		(0.005)		(0.005)	
Mountain	0.007		0.009		0.016	**	0.023	***
	(0.008)		(0.005)		(0.005)		(0.005)	
Pacific	-0.012		0.023	***	0.029	***	0.032	***
	(0.007)		(0.006)		(0.006)		(0.006)	
Farming	0.013	*	-0.003		-0.001		-0.001	
	(0.006)		(0.004)		(0.004)		(0.004)	
Mining	0.006		0.013	*	0.014	*	0.018	**
	(0.010)		(0.006)		(0.006)		(0.006)	
Manufacturing	-0.007	*	-0.006	***	-0.006	**	-0.004	*
	(0.003)		(0.002)		(0.002)		(0.002)	
Government	-0.011	**	0.000		0.001		0.000	
	(0.004)		(0.002)		(0.002)		(0.002)	
Services	-0.005		0.000		0.000		-0.001	
	(0.003)		(0.002)		(0.002)		(0.002)	
Income segregation			-0.003	**	-0.004	***	-0.004	***
			(0.001)		(0.001)		(0.001)	
Fraction above poverty line			-0.013	***	-0.011	***	-0.006	***
			(0.002)		(0.002)		(0.002)	
Fraction black			0.006	***	0.005	***	0.002	
			(0.001)		(0.002)		(0.001)	
Household income per capita			0.007	***	0.004	**	0.000	
			(0.001)		(0.001)		(0.001)	
Gini coefficient, bottom 99%			-0.008	***	-0.008	***	-0.007	***
			(0.001)		(0.001)		(0.001)	
Fraction with single mothers			-0.025	***	-0.025	***	-0.021	***
			(0.002)		(0.002)		(0.002)	

Growth rates			0.003	**	0.002	*	0.002	
			(0.001)		(0.001)		(0.001)	
Grade 3 achievement			0.006	***	0.006	***	0.003	**
			(0.001)		(0.001)		(0.001)	
Fraction with commute < 15 mins			0.004	*	0.004	*	0.002	
			(0.002)		(0.002)		(0.002)	
Teenage labor force participation			0.009	***	0.005	**	0.004	*
			(0.002)		(0.002)		(0.002)	
In-migration			-0.002		-0.001		0.000	
			(0.001)		(0.001)		(0.001)	
Out-migration			0.001		0.000		-0.001	
			(0.001)		(0.001)		(0.001)	
Unemployment rate			-0.004	**	-0.005	***	-0.004	***
			(0.001)		(0.001)		(0.001)	
Social capital index			0.005	**	0.005	**	0.004	**
			(0.002)		(0.001)		(0.001)	
Fraction religious			0.008	***	0.007	***	0.007	***
			(0.001)		(0.001)		(0.001)	
Violent crime rate			-0.001		0.000		-0.001	
			(0.001)		(0.001)		(0.001)	
Agricultural subsidies per capita, logged					0.000		0.001	
					(0.001)		(0.001)	
School expenditures per pupil					0.001		0.001	
					(0.002)		(0.002)	
State EITC exposure					0.004	***	0.004	***
					(0.001)		(0.001)	
Local tax rate per capita					0.011	***	0.008	**
					(0.003)		(0.003)	
Local gov’t expenditures per capita					0.000		0.001	
					(0.002)		(0.002)	
College completion rate							0.013	***
							(0.001)	
Intercept	0.444	***	0.431	***	0.426	***	0.421	***
	(0.006)		(0.005)		(0.005)		(0.005)	
Observations	927		927		927		927	
R-squared	0.42		0.79		0.8		0.82	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in italics. RUCC 1, New England division, and nonspecialized economic dependency serve as reference categories.

Table A13: Fixed Effects Analysis by Gender on Mobility

	Rural								Nonrural							
	(1)		(2)		(3)		(4)		(1)		(2)		(3)		(4)	
Female	0.016	***	0.015	***	0.013	***	0.013	***	0.021	***	0.026	***	0.023	***	0.023	***
	(0.001)		(0.002)		(0.002)		(0.002)		(0.001)		(0.002)		(0.002)		(0.002)	
Grade 3 achievement			-0.001		-0.001						-0.003		-0.003			
			(0.002)		(0.002)						(0.003)		(0.003)			
Growth			0.001		0.002		0.002				-0.006	**	-0.006	**	-0.003	
			(0.002)		(0.002)		(0.002)				(0.002)		(0.002)		(0.002)	
College completion					0.002	***	0.002	***					0.003	***	0.003	***
					(0.000)		(0.000)						(0.001)		(0.001)	
Grade 8 achievement							-0.001								-0.003	
							(0.002)								(0.003)	
Intercept	0.430	***	0.430	***	0.430	***	0.430	***	0.402	***	0.401	***	0.403	***	0.403	***
	(0.000)		(0.001)		(0.001)		(0.001)		(0.000)		(0.001)		(0.001)		(0.001)	
Observations	3452		3452		3347		3347		1854		1854		1844		1844	
Adj. R-squared	0.25		0.25		0.29		0.29		0.54		0.55		0.61		0.61	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses. Male subgroup serves as reference category.

Table A14: Multivariate Regression Results, All Covariate Effects on College Outcomes

RUCC 4	-0.004	
	(0.005)	
RUCC 5	-0.001	
	(0.006)	
RUCC 6	-0.008	*
	(0.003)	
RUCC 7	-0.006	
	(0.004)	
RUCC 8	0.007	
	(0.005)	
Middle Atlantic	-0.006	
	(0.009)	
East North Central	-0.063	***
	(0.008)	
West North Central	-0.033	***
	(0.008)	
South Atlantic	-0.040	***
	(0.008)	
East South Central	-0.045	***
	(0.009)	
West South Central	-0.045	***
	(0.009)	
Mountain	-0.023	**
	(0.009)	
Pacific	-0.024	*
	(0.010)	
Farming	0.011	*
	(0.004)	
Mining	-0.023	***
	(0.006)	
Manufacturing	-0.011	***
	(0.003)	
Government	0.010	*
	(0.004)	
Services	0.009	*
	(0.004)	
Income segregation	0.005	**
	(0.002)	
Fraction above poverty line	-0.030	***
	(0.003)	
Fraction black	0.017	***
	(0.002)	
Household income per capita	0.024	***

	(0.002)	
Gini coefficient, bottom 99%	-0.002	
	(0.002)	
Fraction with single mothers	-0.022	***
	(0.003)	
Growth rates	0.005	***
	(0.001)	
Grade 3 achievement	0.013	***
	(0.002)	
Fraction with commute < 15 mins	0.009	***
	(0.002)	
Teenage labor force participation	0.007	**
	(0.002)	
In-migration	-0.010	***
	(0.003)	
Out-migration	0.004	
	(0.003)	
Unemployment rate	-0.006	***
	(0.002)	
Social capital index	0.013	***
	(0.002)	
Fraction religious	0.000	
	(0.002)	
Violent crime rate	0.000	
	(0.002)	
Intercept	0.220	***
	(0.008)	
Observations	2653	
R-squared	0.41	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses.

Table A15: Fixed Effects Analysis by Race and Socioeconomic Status on College Outcomes

	Rural								Nonrural							
	(1)		(2)		(3)		(4)		(1)		(2)		(3)		(4)	
Black	-0.021	***	0.029		0.072	***	0.072	***	-0.038	***	0.036	***	0.083	***	0.083	***
	(0.005)		(0.018)		(0.020)		(0.020)		(0.004)		(0.011)		(0.012)		(0.012)	
Hispanic	-0.087	***	-0.061	***	-0.026		-0.026		-0.054	***	-0.009		0.035	***	0.035	***
	(0.006)		(0.011)		(0.014)		(0.014)		(0.004)		(0.007)		(0.009)		(0.009)	
SES			0.013	**	0.007		0.007				0.022	***	0.002		0.002	
			(0.005)		(0.005)		(0.005)				(0.003)		(0.004)		(0.004)	
Grade 3 achievement					0.031	***							0.044	***		
					(0.007)								(0.005)			
Growth					0.021	***	0.001						0.023	***	-0.006	
					(0.006)		(0.006)						(0.005)		(0.005)	
Grade 8 achievement							0.032	***							0.045	***
							(0.007)								(0.005)	
Intercept	0.187	***	0.181	***	0.174	***	0.174	***	0.189	***	0.167	***	0.146	***	0.146	***
	(0.002)		(0.003)		(0.003)		(0.003)		(0.003)		(0.004)		(0.004)		(0.004)	
N	2377		2376		2376		2376		2004		2004		2004		2004	
Adj. R-squared	0.25		0.26		0.29		0.29		0.14		0.18		0.25		0.25	

* p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors shown in parentheses.

Table A16: Fixed Effects Analysis by Income on College Outcomes

	Rural						Nonrural					
	(1)		(2)		(3)		(1)		(2)		(3)	
Economically disadvantaged	-0.275	***	-0.229	***	-0.229	***	-0.256	***	-0.253	***	-0.253	***
	(0.003)		(0.011)		(0.011)		(0.002)		(0.008)		(0.008)	
Grade 3 achievement			0.025	***					0.001			
			(0.006)						(0.003)			
Growth			0.000		-0.017	***			0.002		0.001	
			(0.004)		(0.004)				(0.003)		(0.004)	
Grade 8 achievement					0.026	***					0.001	
					(0.006)						(0.003)	
Intercept	0.454	***	0.429	***	0.429	***	0.429	***	0.427	***	0.427	***
	(0.002)		(0.006)		(0.006)		(0.001)		(0.005)		(0.005)	
N	3426		3426		3426		1850		1850		1850	
Adj. R-squared	0.85		0.86		0.86		0.94		0.94		0.94	

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses. Male subgroup serves as reference category.

Table A17: Fixed Effects Analysis by Gender on College Outcomes

	Rural				Nonrural			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Female	0.082 ***	0.095 ***	0.095 ***	0.073 ***	0.089 ***	0.089 ***	0.082 ***	0.095 ***
	(0.002)	(0.006)	(0.006)	(0.002)	(0.007)	(0.007)	(0.002)	(0.006)
Grade 3 achievement		-0.018 *			-0.022 *			-0.018 *
		(0.009)			(0.011)			(0.009)
Growth		-0.010	0.002		-0.015 *	0.000		-0.010
		(0.006)	(0.006)		(0.007)	(0.008)		(0.006)
Grade 8 achievement			-0.019 *			-0.023 *		
			(0.009)			(0.011)		
Intercept	0.135 ***	0.127 ***	0.127 ***	0.136 ***	0.133 ***	0.133 ***	0.135 ***	0.127 ***
	(0.002)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Observations	3347	3347	3347	1844	1844	1844	3347	3347
Adj. R-squared	0.41	0.41	0.41	0.54	0.54	0.54	0.41	0.41

* p<0.05, ** p<0.01, ***p<0.001. Standard errors shown in parentheses. Male subgroup serves as reference category.