State Policies and Intergenerational Income mobility

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Abstract

Existing theoretical models suggest that the primary mechanisms driving geographic differences in income mobility are policies that are controlled at the state level in the United States. Empirical investigation further suggests that there are substantial state level differences in these policies. Thus, our study considers whether the large geographical variation in levels of intergenerational mobility in the United States can be explained primarily through state-level policy differences. Through comparisons of county differences within states versus those between states, we test for the effect of specific policy differences on mobility. We also develop an omnibus test for general state policy differences that extends these principles. We find little positive evidence that commonly hypothesized policy differences including education funding or tax rates explain observed differences in income mobility. Though such policies may have small effects they are relatively unimportant in explaining contemporary geographical differences in income mobility. This key finding suggests that policy prescriptions for improving income mobility will need to look beyond the current common state policy menus.

1. Introduction

Many Americans consider intergenerational economic mobility, the ability to change our economic fortunes from those experienced by our parents, to be an important element of the American Dream. Thus, the emergence of data showing that there are substantial differences in the degree of intergenerational income mobility across countries, with the United States experiencing lower mobility than many other developed nations, has inspired strong emotional reactions and expanded scientific curiosity about the mechanisms underlying these differences[1]. However, the paucity of comparable data make it difficult to create a convincing cross-country empirical case that separates government policy interventions from cultural or geographical elements.

The recent work of Chetty, Hendren, et al. (2014a) demonstrates that there is also a substantial geographical dimension to income mobility in the U.S. That is, there are large differences in intergenerational mobility across U.S. commuting areas. Subsequent work shows that these differences are strongly persistent across a couple of decades (Chetty, Hendren, et al. 2014c). These scholars argue that these patterns are not merely due to selection of different people into different neighborhoods, but that there are causal effects of some characteristics that vary at a local geographical level, such as the neighborhood. (Chetty & Hendren, 2015; Chetty, Hendren, et al. 2015).

In contrast with the neighborhood factors suggested by these studies, the models most often cited by empiricists to explain why there are income mobility differences across geographic regions emphasize policy choices that are most frequently made on the state level in the U.S. These include different levels of public educational investments (Solon, 2004) , differences in political structures (Ichino, Karabarbounis, et al., 2011) and differences in tax rates (Lefgren, McIntyre, et al., 2015). Because states play a large role in setting relevant economic policies, especially those concerning taxation, public welfare generosity, and public education spending, there is substantial cross-state variation in these policies.

Although these, and other, candidate mechanisms are widely believed to either promote or retard intergenerational income mobility, there is little cross-state empirical work formally testing the theoretical predictions. The few notable exceptions do not offer a clear pattern of results. The first example is the work of Mayer and Lopoo (2008), which examines the relationship between educational spending and income mobility and finds a positive effect of additional spending. However, the relationship is only statistically significant when comparing groups of the highest and lowest spending states. This idea also finds support in the work of Pekkarinen, Uusitalo, et al. (2009) which shows how comprehensive education reform in Finland led to an increase in economic mobility, though it is unclear exactly what such a policy study predicts about the existing differences between education policies of U.S. states. In contrast, the work of Grawe (2010) concludes that U.S. states with smaller class sizes actually experience less mobility.

[1]Important efforts to provide comparable data across several countries include Corak (2006), Jantii, Bratsberg, et al. (2006), and Blanden (2009).

The small number of studies testing the mechanisms of these models is likely due to the difficulty of convincingly identifying the impacts of state policies on intergenerational economic mobility. Longitudinal comparisons require variation in policies that could plausibly drive economic mobility as well as longitudinal estimates of economic mobility itself. Identification is further complicated by the fact that even a sharp change in policies will typically have only a gradual effect on mobility as the duration of treatment increases smoothly with cohort age.

In contrast, while cross-sectional estimates have the advantage of relying on stable policy differences that create variation in the duration of treatment across populations, they are always open to concerns about bias arising from the omission of relevant factors from the regressions. It seems likely that places with different policies may also have different populations. In particular, to the extent that pro-mobility policies occur in areas with a culture or population that has unobservable characteristics that promote income mobility, the observed impact of such polices will be overstated. The converse would be true if pro-mobility policies occur in areas with unobservable barriers to mobility. These problems are likely exacerbated when comparing locations that are spatially and culturally distant. Given a method to construct a plausible control group, however, the cross sectional approach would be favored due to the extreme difficulty of constructing consistent measures of state-level mobility over multiple generations.

In this paper we provide a cross sectional test of whether commonly theorized state policies are a major determinant of the substantial geographic variation in income mobility in the United States. In doing so we provide the first contemporary, causal evidence on the impact that important state policies have on intergenerational income mobility. We do this by expanding on methods previously used to detect the effects of cross-state policy variation on manufacturing viability (Holmes, 1998) and the effects of minimum wage policies on employment and earnings (Dube, Lester, et al., 2010). Underlying this approach is the idea that if state-level policies are an important source of geographic differences in intergenerational mobility, we would expect to see discontinuous differences in levels of intergenerational mobility as we cross state borders. Thus we hope to make comparisons among populations exposed to different polices that have similar cultural elements and other unobservable determinants of income mobility.

While it is still possible that the endogenous sorting of populations to states could lead to unobservable differences in adjacent counties, we can show that adjacent counties in different states are much more similar on the basis of observable characteristics than two counties taken at random. Additionally, we can characterize how observable characteristics vary as we move across state borders with different economic policies. We find that the few statistically significant differences in observable characteristics that exist between neighboring counties tend to have little predictive power for intergenerational income mobility. Further, our policy impact estimates tend to be very similar whether we control for observable characteristics or not.

We find little statistical evidence that either state public education investments, state investments in broader social welfare spending, or tax rate differences affect mobility. Even if we were to pick out the one specification in which educational resources have a statistically significant effect (and ignore the others), we find that a doubling of school resources would increase mobility by less than a standard deviation. Thus, the effects of these policies do not seem large

enough to be a primary determinant of substantial observed mobility differences. The observed confidence intervals also suggest that any effects that are too small to discern through our methodology are also too small to count as primary mobility determinants.

Because there are a host of other state level policies that might be alternative mechanisms for generating observed geographic patterns of income mobility, we develop an omnibus test for the effect of the entire observed portfolio of state policy differences on mobility. We find that the observed pattern of state-level policy differences provides a poor explanation for the geographical differences in income mobility. In particular, we find no discernable differences in income mobility from moving across state lines as opposed to county lines within a state, even when we choose the sample to focus on adjacent states with the largest average mobility differences.

The remainder of the paper proceeds as follows. Section 2 discusses the data used in the paper. Section 3 motivates and presents our baseline methodology and results. Section 4 further develops the omnibus test of state policies that may be linked to inequality while Section 5 explores possible identification concerns. Section 6 discusses the implications of the results and concludes the paper.

2. Data

This paper brings together county and state-level data from a variety of sources. As a measure of intergenerational mobility we use the county level rank-rank slope as calculated for the 1980-1982 child birth cohorts by the Equality of Opportunity Project (Chetty, Hendren, et al., 2014b). This is the estimated slope coefficient from a regression of child income percentile rank (within their county) on their parents' percentile rank. However, the results are quite similar if we instead use the expected percentile rank of children whose parents are at the 25th percentile of the national income distribution, a measure of absolute upward mobility.[2]

The Equality of Opportunity Project dataset also includes county level demographic measures, derived from census data, including the fraction of live births in the county with teenage mothers, the fraction of county families considered middle class, that is between the 25th and 75th percentile of the national income distribution, and various centile points of the county family income distribution.

In order to test specific state-level policies, we have assembled detailed data on a number of plausible candidates. Data on per-pupil educational expenditure comes from the National Center

[2] In their later paper Chetty, Hendren et al. (2015) compute quasi-experimental county level estimates that they refer to as the causal effects of being raised in that county on upward mobility. We choose not to use those estimates for our county-level mobility measure because they are produced by Bayesian shrinkage to covariate predictions. As a result, the causal estimates for counties with fewer household observations (such as our border counties) are largely reflective of exactly the covariates we will show do not change discontinuously across border counties. Thus, using such estimates would bias us toward a conclusion of no state policy effects based on variation that is explicitly not policy induced. One could use the raw measures of mobility that are not shrunken. However, these tend to be computed on extremely small sample sizes for most border counties.

of Education Statistics (NCES) Longitudinal Fiscal-Non-Fiscal data file. From this file we take the district revenue data for the 1990-1991 school year, which corresponds to when the children in the equality sample were 8-10 years old, or roughly 3rd through 5th graders. Using this data, which breaks down school district revenues by source, we have computed a per-pupil measure of state and local source funding as well as a measure of total per-pupil funding. We match this at the district level to demographic information from the NCES common core of data for the same years.

We then assign school districts to counties based on the headquarters location of the district and use data on district enrollments to produce a pupil-weighted average funding measure for each county for the 1990-1991 school year. We also obtain county level teacher and pupil counts for that same year and use them to produce a county pupil-teacher ratio. We chose the 1990-1991 school year because it was the earliest year in which the NCES fiscal data covered the universe of districts, as opposed to a sample, in all states, and because it corresponds to a time when our mobility cohort is in elementary school. However, our results are essentially the same if we average measures of spending or school resources for a district over a much longer period (the 1990-1991 to 2000-2001 school years).

We use information on state taxes for representative taxpayers provided by the TAXSIM generated tables maintained by the National Bureau of Economic Research (Feenberg and Coutts, 1993).[3] These data show marginal tax rates for households with $10,000, $50,000, and $100,000 in adjusted gross income, measured in 2005 dollars. We refer to these categories as low, medium, and high income households. The tax rates are measured in decimals so a tax rate of 0.1 represents a marginal tax rate of 10 percent. Since we are interested in the relationship among incomes across generations, both the tax rates faced by parents early in a child's life, and the tax rates faced by the child as she becomes an adult could be important income determinants. Consequently, we average the calculated rates between 1985 and 2010, which spans the lives of the children in our sample.

To obtain a measure of the relative generosity of various state social-safety nets in this time period, we use the March Current Population Survey (CPS) from the years 1988-92. These years were chosen to be in the middle of the childhood of the cohort for whom we have mobility measurements and to represent a time period in which the CPS questions on the receipt of public assistance were constant. Using this data we compute the average amount of assistance received by households in poverty with at least one child present in each state-year from a combination of heating assistance, food stamps. Unemployment Insurance, Workers Compensation benefits, Supplemental Security Income, and cash welfare programs such as AFDC, in other words programs considered in the CPS for which benefit rules can vary due to state policy.

Descriptive Statistics are given in Table 1. The first column of the table treats the county as the unit of observation, while the second considers states as whole entities. For either unit, the table reveals the wide variability of state mobility levels and policies. The average county has a parent

[3] The tables can be obtained at http://users.nber.org/~taxsim/state-tax-tables/ They were accessed on 6/2/2014.

child income rank correlation of 0.331 with a standard deviation of 0.072. This high variance can also be seen in contemporary inequality measures for the parents' generation, as the standard deviation of the Gini coefficient is 0.086 across counties and 0.076 across states. By way of comparison, the standard deviation of the 2010 Gini coefficents for the 26 OECD countries that report a figure is 0.043.[4] Examining state polices shows that the standard deviation of non-federal education spending is over $1,400 per-pupil and that for the high and medium tax scenarios the standard deviation of marginal rates is more than half the mean. There is also substantial variation in the generosity of state-level transfer payments

Finally, in order to check for potentially confounding effects of migration we collected county-to-county migration data for 2004 and 2005 from the Statistics of Income (SOI) division of the Internal Revenue Service (IRS). Using records of all individual income tax forms filed each year, the SOI is able to track year-to-year individual migration in the United States in a systematic way. Since this data is obtained from tax records, they are the most reliable, comprehensive, and widely used source of migration data in the U.S. It is believed that the data captures about 95-98% of the migration of tax filers and their households in the United States (Gross, 2005).[5]

3. The impact of specific state policies on intergenerational mobility

In this section we motivate and detail our baseline empirical approach, then present its results. As previously mentioned, there are several simple, theoretical models of intergenerational income transmission that provide insights regarding how state policies could generate differences in intergenerational income mobility. Building on the work of Becker and Tomes (1979), Solon (2004) describes how progressive government investments in education can overcome credit market failures that prevent low income parents from making efficient human capital investments for their children. Similarly, other social welfare policies which increase the incomes of poor parents may also increase intergenerational mobility if such policies relax budget constraints that prevent parents from investing in their children. Furthermore, other models, such as Ichino, Karabarbounis et al. (2011) focus on differences in political institutions, which are understood to produce the variation in education policies that drives differences in economic mobility. Nor is public social spending the only potential source of relevant policy differences. Lefgren, McIntyre, et al. (2015) discuss how labor market distortions, including wage taxation, can decrease intergenerational income mobility by limiting the correlation between human capital and income.

[4] The OECD gini numbers can be found at http://stats.oecd.org/ and were accessed on June 10, 2014.

[5] While this is considered the best available migration data available, the data has some well-known limitations. For example, since the data is based on income tax returns, if a household is not required to file a tax return they will not be represented in the data. Thus the data tends to underrepresent the very poor and the elderly who may not be required to file tax returns. Also, late filers (who tend to be very wealthy) that were granted a filing extension past late September are excluded. Thus the data also tends to underrepresent the very wealthy. Finally, the publicly available data does not provide the demographics of the migrants. For additional discussion on these and other issues with the data see Gross (2005).

There is also a large amount of geographic variation in income mobility in the United States which these mechanisms might help to explain. Figure 1 provides a map depicting county level mobility rates in the United States taken from data assembled by Chetty, Hendren, et al. (2014b). State borders are indicated in bold and white areas indicate counties where there is no mobility data. The darkest shaded areas represent the quintile of counties with the least amount of upward mobility while the lightest shaded areas have the most upward mobility. For enhanced visibility, Figure 2 focuses more tightly on a central region of the United States, which was selected for its many state borders. Here we see substantial variation in mobility within a small group of states. Furthermore, a casual inspection suggests that moving from the darker to lighter areas (higher to lower mobility) seems more likely to happen within a given state than when crossing state borders. Though this informal inspection is not definitive, it does suggest possible limitations to the role that state policies might play in creating mobility differences, relative to social factors that diffuse seamlessly across state borders.

3.1 Statistical Model

To understand how we propose to analyze the mobility evidence it is helpful to consider a simple statistical model. This model may be useful for understanding how we might measure the impact of state policies on income mobility. It also clarifies the limitations of an analysis that identifies policy effects through the differences in mobility across adjacent states. Intuitively, we wish to compare mobility rates between adjacent counties across state borders. Our assumption is that such counties will be sufficiently similar that we can isolate the impact of differing state policies. Suppose that intergenerational mobility within a county is determined by the following equation:

(1) $M_{is} = X_{is}\beta + D_s + \epsilon_{is}$.

In this model, intergenerational mobility in county *i* and state *s* is indicated by M_{is}. Furthermore, mobility is a linear function of county-level observable characteristics, X_{is}, a particular, measurable policy variable, or vector of state-level policy variables D_s, and an error term, ϵ_{is}, which includes unobserved county-level factors driving mobility as well as measurement error.

In a standard cross-sectional setting, we worry that D_s may be correlated with ϵ_{is}. This would be true if culture and other economic phenomena that drove mobility were also correlated with the policies under examination. For example, ethnic homogeneity of the population may reduce social distance between the rich and poor, increasing intergenerational economic mobility, while at the same time leading voters to favor greater redistribution.

To mitigate such bias, we estimate the following equation:

(2) $M_{is} - M_{i's'} = (D_s - D_{s'})\alpha + (X_{is} - X_{i's'})\beta + \epsilon_{is} - \epsilon_{i's'}$.

Where counties *i* and *i'* are adjacent counties in states *s* and *s'* which are also adjacent. Our identifying assumption in this context is that the differences in the state policy variables across

these adjacent counties are uncorrelated with differences in unobserved county-level determinants of mobility. Given the close spatial proximity of the counties, it seems plausible that cultural factors driving mobility are likely to be very similar. However, our assumption might fail to hold if state level policy variables, such as differences in schooling expenditures, were correlated with other state differences such as the availability and effectiveness of early childhood education programs that also affected intergenerational mobility. Strong sorting across state lines on the basis of unobserved characteristics could also be problematic. We will address both of these concerns in a later section.

In all empirical specifications, we cluster correct the standard errors at the border level. In particular, we allow for arbitrary dependence among all adjacent county-pairs along the same bi-state border. For example, we allow dependence in all comparisons along the Pennsylvania-Ohio border.

3.2 Educational Investment

As previously mentioned, the primary policy variable set forth as an explanation of polity level differences in economic mobility is government investment in the human capital of children of less advantaged families. In the U.S. a primary mechanism through which the government makes such investments is the public provision of elementary and secondary education. As an empirical matter, there is a large literature and no firm consensus on the general subject of the marginal effects of school spending on contemporary outcomes.[6] However, a strong argument can be made for the existence of historic episodes in which the provision of additional school resources for disadvantaged groups have led to a reduction in contemporary skill and income gaps (Card and Krueger, 1992). While there is much less empirical work on the relationship between educational resources and intergenerational economic mobility in the U.S, it is similarly discordant. Mayer and Lopoo (2008) find the theoretically predicted relationship between education spending and mobility, while Grawe (2010), does not.

Of course, not all school funding decisions are made at a state or local level. In particular, federal funding during this period primarily reflects Title I programs that are designed to provide compensatory funding to schools with high numbers of students from high poverty backgrounds. Hence federal funding is likely endogenous to social factors that may determine intergenerational income mobility. This could be a problem for state and local funding as well. Additionally, institutional spending patterns may well reflect unobserved characteristics of a community that drive levels of economic mobility.

We address this issue in a couple of ways. First, since we are interested in policy variation at the sub-national level we eliminate federal funding dollars from our financial measure. Second, we take the average of the remaining per-pupil revenues (state and local) as well as the student teacher ratio across the entire state. The resulting average resource measures reflect the state school finance policy, independent of county or district-level characteristics. For robustness, we

[6] See, for example the analysis in Hanushek (1986) versus the rejoinder of Hedges, Laine, et al (1994).

also examine an alternative measure, county-level averages of per-pupil revenue from state and local sources as well as county-level student teacher ratios.[7] Our identifying assumption in this context is that the unobserved determinants of income mobility do not differ across adjacent counties in different states. To the extent that unobservable factors vary in a manner similar to observed characteristics, we can examine the plausibility of this assumption by examining the sensitivity of our results to the inclusion of covariates.

Figure 3 illustrates average state differences in non-federal revenues. It shows that there is substantial variation in state educational resources, which do appear to follow standard geographical patterns. States in the South have, on average, lower spending than those in the northeast, for example. However, there are some exceptions. For example, Virginia has substantially higher levels of funding than West Virginia, Kentucky, and Tennessee. Similarly, Florida and Wyoming have much higher funding levels than their neighbors.

Table 2 presents the coefficient estimates of equation (3) with the difference in per-pupil state and local revenue (in thousands of dollars) as the independent variable of interest. The standard errors are cluster-corrected to take into account any correlation across counties along a particular interstate border. The estimates in Column 1, from a model with no covariates, suggest that there is virtually no impact of per-pupil revenues on mobility rates. However, the standard errors are sufficiently large such that we cannot formally reject the possibility of moderately sized effects. For example, if the true effect of the difference in expenditures was -0.009, the lower confidence limit of our interval, a large $3,000 increase in per-pupil expenditures (about 70 percent of the average level of state and local revenue) would increase mobility by about half a standard deviation in the state level distribution of income mobility. Examining columns 2 and 3, we see that the results are similar if we weight the county pair by the average population in the two counties or include as covariates the contemporaneous cohort inequality measures for parents and children, as well as family structure.

The remainder of the table uses the county level average measure of state and local revenue. In this context we see a statistically significant effect of state and local schooling revenues on mobility if no covariates are included. The point estimate suggests that a $1,000 increase in revenues (just over 20 percent of the average) could reduce the correlation between parents' and children's' income ranks by 0.008 or about 17 percent of a standard deviation in the state-level distribution. This represents a moderately sized effect. This effect may not have this causal interpretation, however, instead reflecting that richer or more mobile counties may be able to generate higher funding levels. We note that either weighting observations by the average population in the county pair or including covariates causes the coefficient to drop substantially and become statistically insignificant. The fact that including covariates causes the results to

[7] As school districts do not necessarily stay within county borders, we assign districts to the county in which the district headquarters exists. We then construct county level averages of per-pupil revenues and the student teacher ratio, weighting each school district by its enrollment of students.

drop is consistent with the original relationship being driven largely by county-level income characteristics.

In Table 3, we use an alternate measure of state policy differences, the student teacher ratio difference across adjacent counties. Without included covariates, we find no significant impact of the student-teacher ratio on mobility rates. The same holds when we weight by the population average of the county pair. Here, the upper limit of the confidence interval could suggest moderately sized impacts of teacher resources, but the point estimate itself is of the wrong sign. Including covariates in column 3 leads to estimates that are statistically significant at the 10 percent level. The point estimate suggests that cutting the average student teacher ratio by 8 (which would roughly cut average class size in half), would reduce the correlation between parents' and children's income rank by .016, or about a third of a standard deviation in the state-level distribution. The remainder of the table shows that an examination of county-level measures of the student-teacher ratio produces no significant effects on mobility rates.

However, the previous literature, most notably Solon (2004), explicitly suggests that it may not be the level of human capital expenditures that matters for mobility, but rather the progressivity of these expenditures. To investigate this we sort counties by the number of free lunch eligible students into quintiles within each state, and produce an average state and local revenues measure for counties in the top and bottom quintile of each state. A state's progressivity measure is then derived by dividing the revenue of the highest free-lunch quintile by the revenue of the lowest free-lunch quintile. Note that a higher value of this measure proxies a funding system that provided relatively more resources to counties with a higher proportion of poor children.

Figure 4 shows how this progressivity measure varies across states. Note that progressivity is not highly correlated with the level of funding. Utah has low funding levels but is highly progressive while Wyoming has both high funding levels and is also quite progressive. On the flip side, New York and Tennessee are examples of states with high and low funding levels, respectively, that both have relatively low levels of progressivity.

In Table 4 we follow the regression specifications from columns 1-3 of Table 2. Now, however, the difference in our progressivity measure becomes the main explanatory variable of interest. In column 1, when no covariates or weights are present, it appears that more progressive states actually have less mobility. Of course, the obvious hypothesis that both the greater progressivity and lesser mobility can be explained by other factors is confirmed by the other two columns of the table. In the end there is no evidence that progressivity has large impact on mobility. Of course, this is only one possible measure of progressivity, out of many we could construct. However, if progressive education spending were truly the primary driving force behind large geographical differences in mobility we might expect to pick up some indication through this proxy.

Collectively, there is little evidence to suggest that educational spending at the state and local level is a major factor in the currently observed geography of mobility. However, because adjacent states tend to have similar levels of spending, this reduces the amount of variation we

have at our disposal to estimate the impact of funding. Consequently, we lack the precision to rule out the possibility that large spending changes could have moderate effects on income mobility.

3.3 Tax Rates

Lefgren, McIntyre, et al. (2015), along with Holter (2015) provide models where marginal income tax rates may have a causal effect on intergenerational mobility. This is due to the potential impact of income tax rates on both human capital investments and occupational choice. Additionally, high tax rates may generate revenue to engage in compensatory educational investments or provide other public services with similar aims.

Both these studies also contain empirical results that suggest these tax effects may be more important to explaining national differences in mobility in developed countries than differences in educational expenditures. However, the vast differences in cultural, institutional and geographical factors between nations such as Sweden and the United States make such results highly speculative. In examining mobility differences at a finer geographical level, we may be able to more convincingly investigate this proposed mechanism of mobility differences.

Figure 5 shows that there are indeed wide differences in state level income tax rates, even between adjacent states. This is true with New York and New Jersey, Texas and Oklahoma, and Washington and Oregon. All have large differences in marginal tax rates for middle income families. The differences are similar if we examine high income families.

Table 5 shows the results of estimating equation (3) using the differences in TAXSIM generated marginal tax rates between adjacent states as the primary independent variable of interest. As in our prior analysis, we cluster correct the standard errors to take into account potential non-independence between pairs of counties along the same interstate border. In columns 1 to 3 we present the estimates from bivariate regressions of the difference in mobility rates on the difference in marginal tax rates for each of low, medium, and high income households. The coefficients are all statistically insignificant. The magnitudes are also small. Raising the marginal tax rate by .03 (three percentage points), which is more than a standard deviation in the distribution of tax rates, would reduce the correlation between parents' and children's income rank by less than one tenth of a standard deviation regardless of which tax measure we use. Even looking at the limits of the confidence intervals doesn't suggest a large role for state income taxes in determining income mobility.

In column (4), we include all three tax rates and find that the coefficients are even less precisely estimated. This is due to the fact that the marginal tax rates are highly correlated for medium and high income households (the correlation exceeds 0.9). In column (5), we weight county pairs by the average number of children in each county pair while in column (6) we include covariates. Once again, while our results do not rule out some role for tax rates, they provide no positive evidence for such a relationship and rule out the kind of effects that we would label state-level income tax rate differences as a major determinant of geographical differences in U.S.

mobility. In other unreported results, we find similar estimates using average tax measures in place of marginal ones.

3.4 Social Welfare Expenditures

Proponents of economic models suggesting a large role for policy programs in determining economic mobility, such as the previously considered model by Solon (2004), might argue that the use of educational expenditures is a convenient shorthand for a much more comprehensive commitment to provide a safety net to the families of poor children. To the extent that this is not highly correlated with direct education funding, our results above might not capture the actual essence of such policy differences.

Thus, we have used the March Current Population Survey (CPS) from 1988-1992 to create a state level index measure of aid received by the families of poor children as described in our data section. Figure 8 shows these differences graphically. As with educational expenditures we find a wide variation in the generosity of social welfare programs from state to state.

Using these indices as the primary policy variable in equation (3) we find some evidence of a correlation between benefit generosity and intergenerational mobility. However, these coefficients have the wrong sign to support the hypothesis that more social spending leads to less intergenerational correlation in incomes. Furthermore, the significance of this relationship is not robust to population weighting and is relatively small in magnitude, with a doubling of real per-capital assistance required to change mobility by one-third of a standard deviation

Thus, to this point we find little positive evidence for the primacy of the most commonly suggested state-level policy mechanisms in explaining observed differences in income mobility. There may be some concern that these results are attenuated due to omission of relevant state level factors. We will address this possibility in the next section.

4. *An Omnibus test of the importance of state policies*

While the policy tests of section 3 possess the advantage of narrowly targeting specific policies that we have theoretical reasons to believe should matter a lot for mobility, there is some concern that they may fail to capture important policy differences that affect mobility and may thus present a biased picture of policy affects. In response we use the county level differences in mobility, together with the conceptual framework sometimes imprecisely referred to as a geographical discontinuity framework to develop an omnibus test for the income mobility effects of state-level policy differences in their totality. This will formalize the visual intuition provided by figures (1) and (2) about the relationship between state boundaries and mobility changes.

4.1 Model

We begin by specifying a statistical model of mobility, similar to equation (1).

(3) $M_{is} = X_{is}\beta + \theta_s + \epsilon_{is}$.

As before, mobility in a particular state-county-observation depends on county specific demographic factors and state-specific characteristics. Now, however, these state characteristics include all relevant policy distinctions.

First, consider the difference in mobility between adjacent counties in adjacent states, which is given by:

(4) $M_{is} - M_{i's} = (X_{is} - X_{i's})\beta + \epsilon_{is} - \epsilon_{i's}$.

Now, however, we focus on the variance of the unobserved component of this difference:

(5) $var(\epsilon_{is} - \epsilon_{i's}) = 2\sigma_\epsilon^2 - 2cov(\epsilon_{is}, \epsilon_{i's})$.

Equation (5) suggests an important statistical detail, namely if the unobserved determinants of mobility between adjacent counties within the same state are highly correlated, the variance of this unobserved difference may be quite small.

Now consider the difference in mobility between adjacent counties in adjacent states, which is given by:

(6) $M_{is} - M_{i's'} = (X_{is} - X_{i's'})\beta + \theta_s - \theta_{s'} + \epsilon_{is} - \epsilon_{i's'}$

The variance in the difference of unobserved determinants of mobility in this context is given by:

(7) $var(\theta_s - \theta_{s'} + \epsilon_{is} - \epsilon_{i's'}) = 2\sigma_\epsilon^2 - 2cov(\epsilon_{is}, \epsilon_{i's}) + 2\sigma_\theta^2 - 2cov(\theta_s, \theta_{s'})$

This statistical model suggests a general identification strategy for examining the variance in state-level determinants of intergenerational mobility. In particular, we regress the between county difference in intergenerational mobility on the corresponding differences in covariates as in equations (4) and (6). We then calculate the residual for each pair-wise difference between counties i and i', which we designate $\hat{e}_{ii'}$. We then square this residual and perform the following second stage regression:

(8) $\hat{e}_{ii'}^2 = \gamma_0 + \gamma_1 different\ state_{ii'} + \eta_{ii'}$.

In this model, the estimate of γ_0 converges to the variance of the differences between unobserved determinants of mobility across adjacent counties within the same state, $2\sigma_\epsilon^2 - 2cov(\epsilon_{is}, \epsilon_{i's})$. Similarly, the estimate of γ_1 converges to the variance of the differences between unobserved determinants of mobility across adjacent states, $2\sigma_\theta^2 - 2cov(\theta_s, \theta_{s'})$. A failure to reject the null hypothesis that $\gamma_1 = 0$ suggests that the unobserved determinants of mobility are no different across county lines that cross state borders than across county lines within a state. This could be because σ_θ^2 is small, meaning there is little variation generally across state policies that would translate into differences in intergenerational mobility. Alternatively, $cov(\theta_s, \theta_{s'})$ could be positive and large if adjacent states tended to have more policy similarities than all states as a group. On the other hand, if we reject the null hypothesis to find that $\gamma_1 > 0$, we can conclude

that mobility varies more across state lines than county lines within a state. As long as adjacent states were more similar than states in general, this procedure would provide a lower bound for the importance of state policies in determining intergenerational mobility.

4.2 Omnibus Tests in the Entire Sample

Table 7 reports the results of this exercise. Column (1) contains results from a model with no covariates. The constant can be interpreted as an estimate of the variance in the difference in mobility rates across adjacent counties within the same state. Taking the square root of this coefficient estimate (0.00479), produces an implied standard deviation of the difference in mobility rates across adjacent counties within the same state of 0.069. In this same regression, the coefficient on the different state dummy variable can be interpreted as an estimate of how much greater the variance in mobility rates is when considering adjacent counties in different states. If state policies were primarily responsible for the county-level differences in mobility, we might expect this term to be large and positive, indicating there is more variation in mobility outcomes when we cross a state border than an intra-state county border. However, the estimated coefficient is 0.0002 and is statistically insignificant from zero. Even taking the coefficient estimate as the truth would mean that the standard deviation of the difference in mobility rates across adjacent counties that also cross state lines is 0.071, which is almost the same as for intra-state borders. Even accepting the largest value in the 95 percent confidence interval would translate to a standard deviation of the difference in mobility rates across states no larger than 0.076, again quite close to the difference in mobility rates across counties within a state. Weighting the regression by the average number of children in a county pair, shown in column 2, makes little difference.

While there is little evidence that observable characteristics differ more across state borders than county borders, it may nevertheless be useful to examine how our primary results differ when we control for observable characteristics. To do so we first estimate equation (6) in which we regress the difference in mobility rates across adjacent counties on a vector of differences in observed characteristics.

Table 8 presents the estimates from this preliminary regression. It shows that teen birth rates have a large impact on income mobility. In particular, a ten percentage point increase in the fraction of children born to teen mothers increases the rank-rank slope between parents' and children's incomes by .04, which represents more than half a standard deviation in the distribution of mobility rates across counties. This suggests that in counties with high levels of teen pregnancy, mobility rates are much lower than in counties with few teen births. Further investigation of the table shows that mobility rates are significantly higher (the intergenerational correlation in income lower) in counties with more middle class families and in counties with more egalitarian incomes for the child's cohort (increases in the bottom end of the income distribution and reductions in the upper end).

We then take the residuals from this regression, square them, and then use them as the dependent variable when we estimate equation (8). This provides us with the estimates found in column 3

of Table 7. Recalling that the estimate of the constant term measures the variance in the unobserved determinants of mobility across adjacent counties, we see that the addition of covariates has the expected effect of reducing the variance due to unobserved factors to 0.0035, implying a standard deviation 0.059. However, the coefficient on different state remains small and statistically insignificant. Taken at face value it denotes an increase in variance associated with moving across state lines only .0003 greater than across county lines (implying a standard deviation of the difference in mobility rates of adjacent counties in different states of 0.062).

4.3 *Looking Where the Differences Are Greatest*

The initial evidence suggests that differences in state policy menus have, on average, little impact on income mobility differences of adjacent states. However, this may be because most adjacent states have similar policy bundles. This could lead to a situation in which average differences in mobility across state lines appear small, but some relevant areas exist in which the differences are actually large. To examine this possibility, we restrict our sample to pairs of neighboring states that have the starkest differences in intergenerational mobility levels.

To illustrate this process, consider an example involving the adjacent states of Texas and Louisiana, which have a large difference in average income mobility. In Texas the rank order correlation between parents and children's income is 0.319, in Louisiana it is 0.394. Some of this difference may be due to state policies in Texas that increase economic opportunity relative to Louisiana. It is also possible, however, that the differences are not driven by state policies but merely correspond to differences in culture, geography or economic conditions that change smoothly within and across states.

Figure 7 shows a county map of the Texas-Louisiana border region. It shows that Panola County, Texas and DeSoto Parish, Louisiana share a common border. On the other hand, Rusk County, Texas is adjacent to Panola County but does not border Louisiana. Similarly, Red River Parish, Louisiana is adjacent to DeSoto Parish but not to Texas. Our methodology suggests that if the differences in mobility between states are not attributable to state policies, the differences in mobility across the state border should be similar to the differences across the adjacent counties within both Texas and Louisiana. If, on the other hand, the differences are caused by state policies, we should expect a larger difference in mobility between Panola County and DeSoto Parish than between either the Panola - Rusk or DeSoto - Red River pairs.

In this example the mobility differences are 0.023 for Panola – Rusk and 0.120 for DeSoto - Red River but only 0.019 for the DeSoto – Panola difference. Since the difference across the state border is less than the difference from moving across county borders within either state, this example would provide no evidence that policy differences between Texas and Louisiana are important determinants of income mobility differences.

Generalizing from this example, we focus our analysis on comparisons between all adjacent states that have differences in the mobility rate that exceed one standard deviation in the overall distribution of state mobility rates. We exclude the District of Columbia and Delaware from this

analysis since they have no non-border counties. Our analysis includes 12 comparisons between states with very different mobility rates.[8] Figure 8 illustrates the relevant states and borders as well as the counties included in the analysis sample. Within this sample, the average rank-order correlation between parents' and children's income is 0.30 in the more mobile states and 0.36 in the less mobile states.

Because this approach focuses on comparisons between states with different levels of mobility, mobility measures will tend to increase as we move away from the center of the less mobile state towards the center of the more mobile state, regardless of whether state polices have any impact or not. To address this concern, we implement a strategy inspired by the regression discontinuity design (RD) commonly used in empirical microeconomic research. In this analysis, our unit of observation is the county. We limit our sample to those counties on the border between the two states under examination as well as the counties that lie adjacent to the border counties but that aren't on the border themselves, which we call second-tier counties. We define the treatment as being in the higher mobility state and allow the degree of mobility to vary linearly across counties near the state line. This means we assign an index variable that takes on a value of 0 for border counties in the high mobility state while second-tier counties in that state are assigned an index value of 1. Border counties in the low mobility state receive an index value of -1 while second-tier counties in that same state are assigned an index value of -2. More formally, our specification is:

$$(9) \quad M_{is} = \beta_0 + \beta_1 treament_s + \beta_2 index_{is} + \beta_3 X_{is} + \epsilon_{is}$$

If the differences in mobility between these states is driven by differences in polices, we expect β_1 to be positive and statistically significant. However, if the differences in mobility are driven by spatially correlated cultural or demographic factors, we would expect β_2 to be statistically significant but β_1 to be statistically insignificant.

We report the results of this analysis in Table 9. All standard errors are cluster-corrected at the state level.[9] All specifications include fixed effects for each pair of states under consideration (for example a single fixed effect for all counties in Texas and Louisiana). For column 1, we modify equation (9), by omitting both the index variable and all state level covariates other than the comparison fixed effects. By construction, the treatment or mobile state indicator in this context measures the average difference in mobility between the border and second tier counties associated with being in the more mobile state of each selected pairing, which in this case is -.015. Column 4 alters the regression by weighting using the number of children used to compute the mobility measure in each county. The coefficient rises in absolute value to -.039. It is notable, however, that both of these estimates are smaller than the average difference in

[8] The twelve comparisons include Arkansas and Mississippi, Florida and Alabama, Iowa and Illinois, Michigan and Ohio, Texas and Louisiana, California and Arizona, Colorado and Kansas, Colorado and Oklahoma, Colorado and Nebraska, Texas and Arkansas, Virginia and North Carolina, and Wyoming and Nebraska.

[9] We only leverage information from 19 separate states, which may be small relative to what is preferred when using cluster-corrected standard errors. However, in this case our inference is similar to what we find using White standard errors that only correct for potential heteroskedasticity.

mobility between the mobile and immobile states, suggesting that counties along the borders are more similar than their states as a whole.

With this as a baseline we next implement our RD inspired approach by inserting the geographical index variable. In columns 2 and 5, we present the results for the unweighted and weighted cases, respectively. In both cases the addition of the index variable sees the state indicator coefficient attenuate in magnitude by roughly two-thirds. Additionally, in this setting we are unable to reject the null hypothesis that there are, in fact, no mobility differences due to crossing a state boundary. This pattern of results is consistent with a hypothesis that the differences in state average mobility rates are driven by spatially correlated factors that are unrelated to state policies. The addition of the measures of family structure and income previously used as covariates (see Table 8) in columns 3 and 6 only strengthens this conclusion, as the high mobility coefficient further attenuates. Or put more simply, even the states which have the largest average differences in mobility appear to differ in characteristics that change smoothly across state borders. Taking the coefficients of columns 3 and 6 as given would suggest that only a small portion of average mobility differences, at most 2.5%-11.5%, could be explained by state-level policy differences, even when looking in the starkest state contrasts.

5. Threats to Identification

5.1 Non-random sorting across state borders

All of the analyses we have performed to this point implicitly assume that there is no sorting across state lines on the basis of unobservable characteristics in a manner that would mask the effects of state policies. This is not as tenuous an assumption as it might seem at first glance. To overturn our results, sorting would require less income mobile families to disproportionately locate in states with mobility enhancing policies in a sort of perverse matching. Also, the fact that our results tend to be quite robust to the inclusion of observable characteristics makes this possibility seem even less likely. Nevertheless, the issue of sorting in border counties is still worth empirical examination.

In our examination of the potential mobility effects of specific policies in Section 3, we assumed that any differences in unobservable population characteristics across state borders are uncorrelated to differences in policy measures. To assess the plausibility of this assumption, we examine whether differences in policy measures correlate with differences in observable characteristics.[10] To aggregate our covariates into a single index of mobility, we regress county-level income mobility rates on these sixteen observable characteristics. The predicted mobility rate becomes a summary measure of all covariates.

For Table 10, we re-estimate equation (2) but instead of focusing on differences in mobility as the dependent variable, our dependent variable becomes an observable characteristic or our index of observable characteristics. These estimates are unweighted and include no covariates on the

[10] These covariates include the fraction of children born to teen parents, fraction of middle class families, as well as income statistics for families in both the parents and children's cohorts.

right hand side. We report p-values for tests in which the null hypothesis is that differences in state policies are unrelated to differences in the specified observable characteristic.

Focusing first on the index of mobility that combines all observable population characteristics, we find that differences in per-pupil funding, marginal tax rates, and social welfare expenditures are all uncorrelated with this index. However, areas with larger student-teacher ratios have characteristics predicting slightly higher levels of mobility, though this is significant at only the 10 percent level. If unobservable characteristics have the same relationship with this policy as observable factors, the impact of student-teacher ratio on intergenerational mobility is likely to be somewhat understated. We see evidence of the magnitude of this impact when observables are included in Table 3**.** However, we also find that the results are insensitive to the use of covariates once we weight counties by population.

On the other hand, border counties in states with more progressive educational funding structures have observables that predict more income mobility. This would suggest that any observed impact of progressivity might be overstated. Table 4 shows that controlling for observables does eliminate the observed impact of progressivity. Once again, weighting the results by population reduces the sensitivity of the estimates to the inclusion of covariates. Marginal tax rates are not correlated with the index of mobility.

If we look in more detail to see what type of sorting occurs on the basis of observable characteristics, we notice that states that spend more on education have higher income households on average. However, this does little to explain mobility rates. Student teacher ratio has little relationship with any single covariate, despite its marginally significant relationship with the index itself. Progressivity of education funding is associated with improvements in the bottom part of the income distribution of the child's generation. Households with higher incomes sort to states with lower marginal tax rates, though this does little to predict income mobility rates.

Collectively, though sorting does occur on the basis of policy variables, it does not appear that such sorting, at least on the basis of observable characteristics, is a plausible reason that we find little impact of state policies on mobility.

Moving on to our first omnibus test of the impact of state policies, we assume that the unobservable characteristics vary no more across state lines than they do across county lines. While this is not empirically testable, we can test whether observable county characteristics differ more between adjacent counties in different states than between other adjacent counties. We do so in a manner analogous to our analyses from Section 4. We compute the difference in the observable county characteristics shown in Table 1 across adjacent counties and square it. We then regress this squared difference on a constant and a dummy variable indicating whether the adjacent county is in a different state.

Table 11, Column 1 provides p-values for the standard hypothesis test on each of those factors. We find that of sixteen different observable characteristics, only one, the income share of the top 1%, varies more significantly across state borders than across county borders. This is significant at only the 10 percent level. Our index of observable characteristics does appear to vary slightly

more across state lines than county lines. This is significant at only the 10 percent level. Combining these results with the fact that the Table 2 estimates are similar with and without covariates suggests that those Table 2 findings are unlikely to be meaningfully influenced by the non-random sorting of households across state borders.

In the second column of Table 11, we estimate equation (9), replacing the mobility rate with the covariate in question. We test to see if there exist discrete changes in observable characteristics between adjacent states for which mobility differences are the greatest. The table reports the p-values testing the null that the specific observable characteristic does not significantly change at the border between the mobile and less mobile state. We find that none of the observable characteristics are significantly different as one moves from the less mobile to the more mobile state. Furthermore, the index of mobility does not change significantly as one crosses from an immobile to a mobile state.

5.2 Migration

Migration also has the potential to obscure real policy impacts across state borders. There are two potential problems associated with migration in our scenario. First, non-random migration may lead to observable and unobservable differences across state borders with the consequences discussed in the previous section. Second, even random migration will lead to an attenuation of observed policy effects since a person born in a particular state is not exposed to that state's policies for their entire life. Instead, they are exposed to that state's policies until they move, at which point they are exposed to a different policy menu.

To obtain a rough approximation of how much migration might matter for attenuation through reduced policy exposure, we examine the distribution of birth-state residence for individuals in the 2000 Census Public Use Microsamples (Ruggles, Alexander, et al. 2010). In Figure 9, we examine the fraction of individuals at each age that currently live in the state in which they were born. This allows us to approximate the extent to which the analysis cohort was exposed to the policies of their birth state in childhood. We see that at age 17, eighty percent of youth are still living in the state in which they were born. This suggests that our strategy is likely to be effective at identifying the impacts of state policies that affect primarily young people, such as those regarding school and taxation of parents' incomes. However, the figure also suggests that the effectiveness of this identification strategy is clearly decreasing in the age at which the policy is expected to impact the cohort, so that, for example, estimates for labor market policies that increase mobility by improving the outcomes of adults in their thirties are likely to be more attenuated.

It is also helpful to examine directly the extent to which individuals in border counties migrate to other states and whether this migration appears non-random. To do so we collected IRS SOI migration data for 2004-2005, as described in our data section. Using this migration data, we calculate the total migrant inflows and outflows for each of the 125 counties in our border-

county analysis sample.[11] These inflows of migrants could have originated from anywhere in the U.S. or even from other countries, whereas the outflows, by definition, must have come from that particular county. We then calculate the total inflow of migrants for each county that originated in one of our defined "border counties" in the *same* state. Next we calculate the total migrant inflows into each county from one of the "border counties" in the *adjacent* state. If these migrant inflows are large, we would be particularly concerned that there was systematic migration across borders, potentially as a result of policies or characteristics which influence income mobility. We transform each of our total migrant inflow and outflow variables into percentages of the non-migrant taxpayer population of any given county by dividing the inflows or outflows of tax exemptions by the total tax exemptions in a county.

Table 12 provides summary statistics for these inflow and outflow variables in level and percentage terms. These measurements show that the average county in our analysis sample had between 4 and 5 thousand total migrants (coming and leaving) between 2004 and 2005. Considering inflows, on average about 705 migrants came from border counties in the same state whereas only about 170 came from border counties in the adjacent state. In percentage terms, roughly 6.7 percent of the population in the average county appears to have moved in or out, but less than 1 percent came from border counties in the same state and less than 0.4 percent come from the border counties in the adjacent state. While a fair percentage of households migrate into and out of a county each year, most migration is not occurring between adjacent counties. Even less is occurring between adjacent counties in different states, which would be the case if households were making small moves on the basis of state-level policies driving income mobility.

We further separate the border counties into those from low- versus high-mobility states and examine whether there were differences in migration rates between the two groups. These results can be seen in the final two rows of Table 12. The data suggests that the 56 counties in high income-mobility states have about 0.25 percent of their population coming from the border counties of adjacent states compared to 0.46 percent for the counties in low income-mobility states. These differences are neither quantitatively nor statistically significant (their 95% confidence intervals overlap in the Table). Hence we conclude that migration differences are unlikely to markedly influence the results in our analysis through differential sorting.

6. Conclusion

There is substantial geographic variation in the intergenerational income mobility rates found in the United States. Indeed, Chetty, Hendren, et al. (2014a) note that some counties in the U.S. have mobility rates comparable to the most mobile societies in Scandinavia, while children born in different regions face mobility prospects lower than any recorded in a developed nation. Understanding why these geographical differences occur is an important element in both an academic exploration of intergenerational income correlation and any policy discussion of

[11] This uses the number of "exemptions" on filed returns that changed addresses during the 2004-2005 years. These numbers are more likely to capture numbers of people that move rather than simply household numbers.

responses to economic inequality. Furthermore, examining geographical variation within a single country complements existing cross-country research on the causes of inequality.

In this paper we investigate how much of this geographic variation can be attributed to differences in state-level policy choices, primarily over taxation and spending that have been proposed by the prior literature. The United States seems like an ideal place to do this as its federal system creates a large amount of variation in social and economic policies that are commonly believed to affect economic mobility.

We draw inspiration from common empirical microeconomic methods of identification to design a series of tests based on differences between county borders within, versus across states. Our approach to the problem first looks for statistical evidence from a few specific policy choices that economic theory suggests should be closely related to mobility. Next, we focus on identifying whether the variation in mobility rates at state borders is systematically different than the cross-county variation within states. Finally, we repeat the exercise with a focus on specific borders between states with high average income mobility differences.

Despite theoretical models suggesting a primary role for state-level policies in explaining these differences, in both omnibus tests and tests of specific policies we fail to find much evidence of a systematic relationship between state borders and changes in income mobility. While we cannot rule out small effects of specific state-level policies on mobility, our results suggest that current differences in major fiscal state policies are not the primary reason for geographic differences in income mobility across recent generations. This also suggests that low-mobility states are unlikely to acquire the higher mobility rates of other states simply by copying a higher mobility state's current tax or spending choices. This evidence is consistent with the recent work of Chetty and Hendren (2015) which implies that the primary factors leading to mobility variation occur on a much smaller geographical level, such as neighborhood sorting.

One of the primary threats to identification in our preceding analysis is the endogenous location decision. We present evidence that households with certain demographic patterns predicting income mobility do not change discontinuously at state borders. We also show that sorting and migration patterns are unlikely to account for our failure to find large policy effects for policies targeted at childhood. These findings lend support to the general invariance of most of our results to the inclusion of covariates.

However, as with all identification strategies, our analysis comes with unavoidable limitations. First, it cannot account for the effects of state policies that produce geographic spillovers, i.e. have effects beyond their own borders. Nonetheless, it seems that policies most commonly thought to drive intergenerational income mobility including taxation and education spending would not have large spillover components. These policies also seem unlikely to be the primary reasons for variation in intergenerational income mobility across states. This study is also limited to policies that vary across states, and can only comment on policies at other geographical levels to the degree that they work through similar mechanisms as those that vary across states. Similarly, we cannot rule out the existence of interactive effects of multiple policies that work in non-linear ways that our omnibus test may miss. Finally, it cannot rule out the possibility that

some common policies for which specific data is not available may have offsetting effects on mobility, leading to an overall estimate of zero effect in our omnibus tests.

Despite these limitations, this paper still provides the first causal evidence that state policies within the U.S. appear to have, at best, small effects on intergenerational income mobility. Thus, we suggest that a search for policy prescriptions to address the geographical variation in economic mobility will need to look beyond the common menus of state policies. It may be the case that policies determined on a sub-state level, such as housing regulations may exert a stronger effect, or the primary influence may be the decisions of non-governmental actors and institutions. This may be a fruitful area for further research. These results should also encourage additional work to explore alternative theoretical channels that might explain the observed differences in economic mobility across regions of the United States.

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Figure 1: County-Level Mobility Rates in the United States

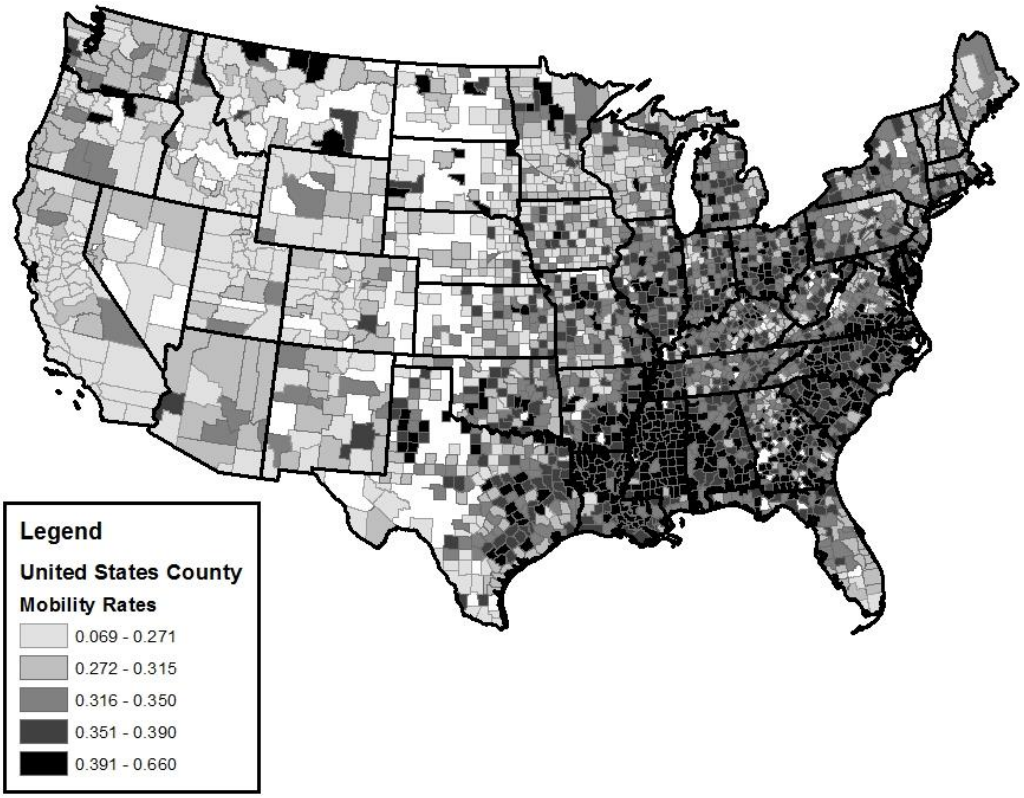

Figure 2: County-Level Mobility Rates Zoomed-In on Kentucky

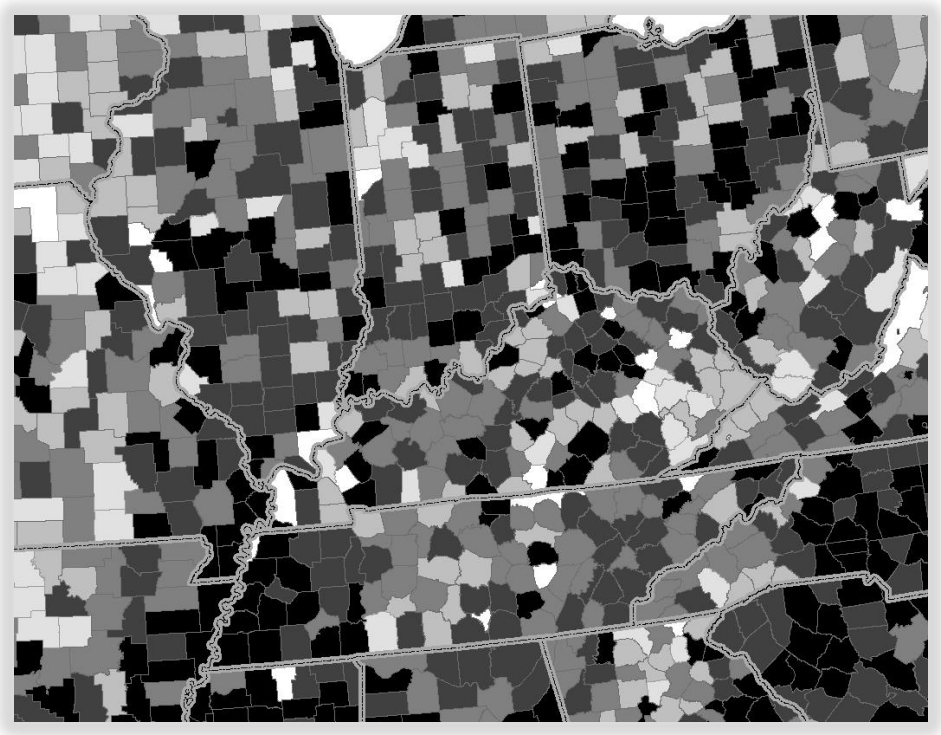

Figure 3: State Differences in the Levels of Non-Federal Education Spending

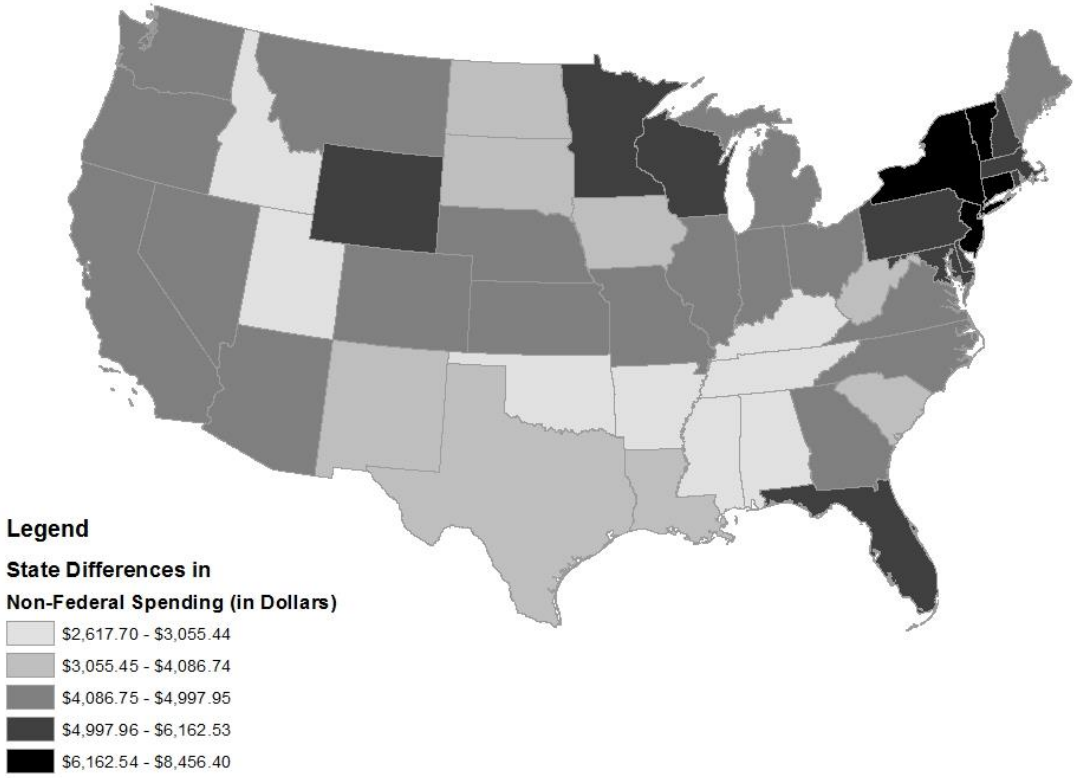

Figure 4: State Differences in Spending Progressivity Based on Free Lunch Quintiles

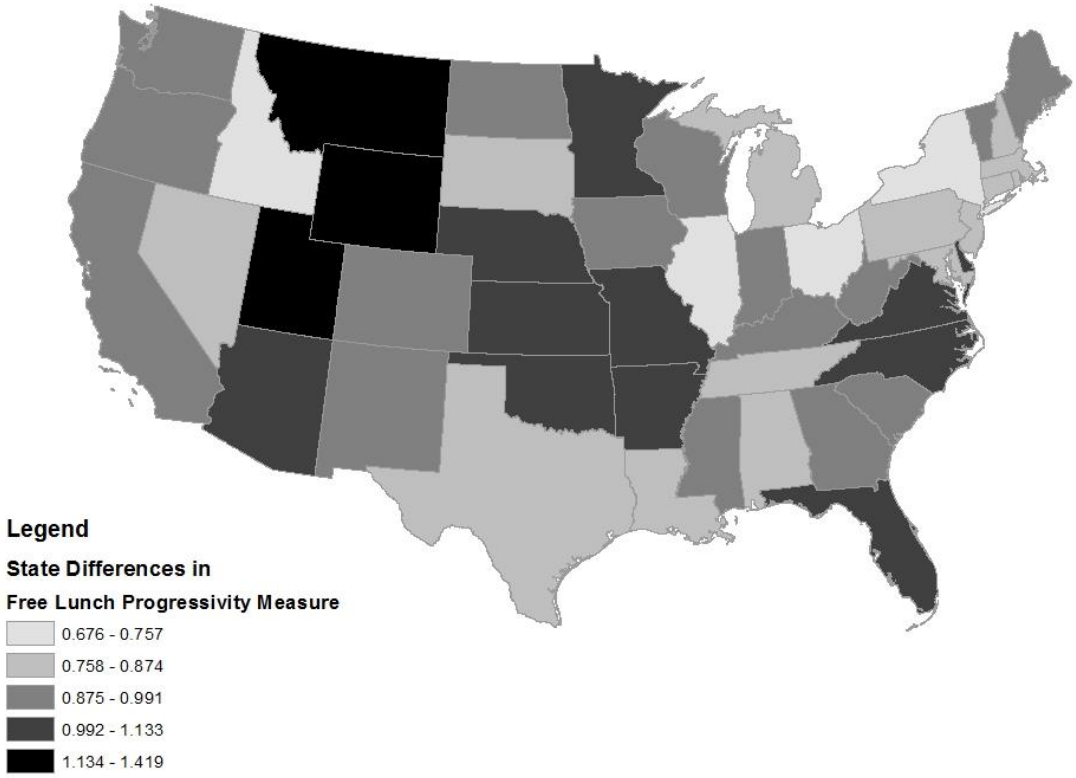

Figure 5: State Differences in Marginal Tax Rate for Middle Income Families

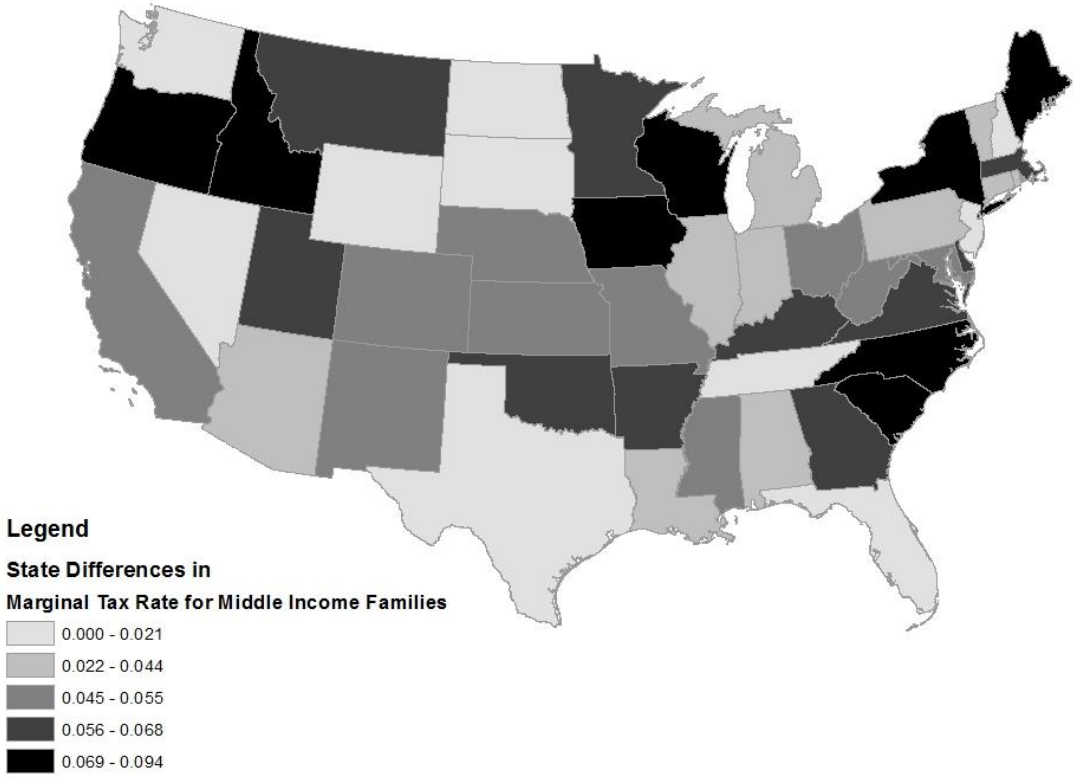

Figure 6: State Differences in Aid Available to the Families of Poor Children (CPS Data)

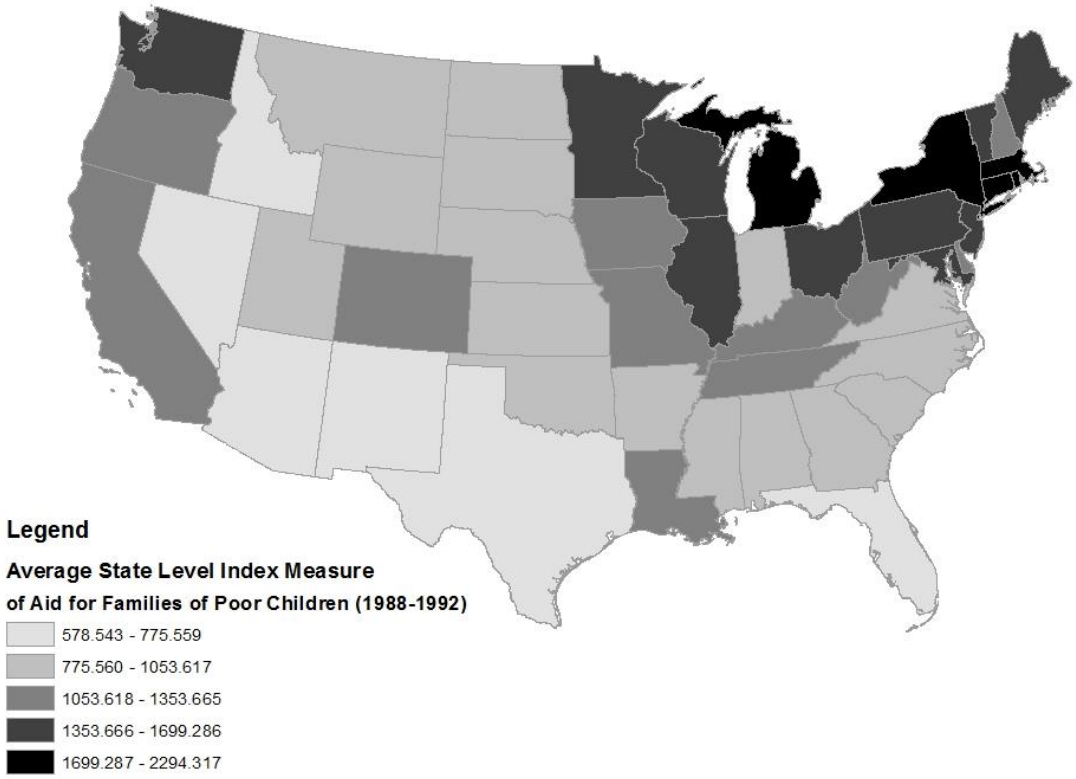

Figure 7: Border County Identification Strategy—Texas, Louisiana Close-Up

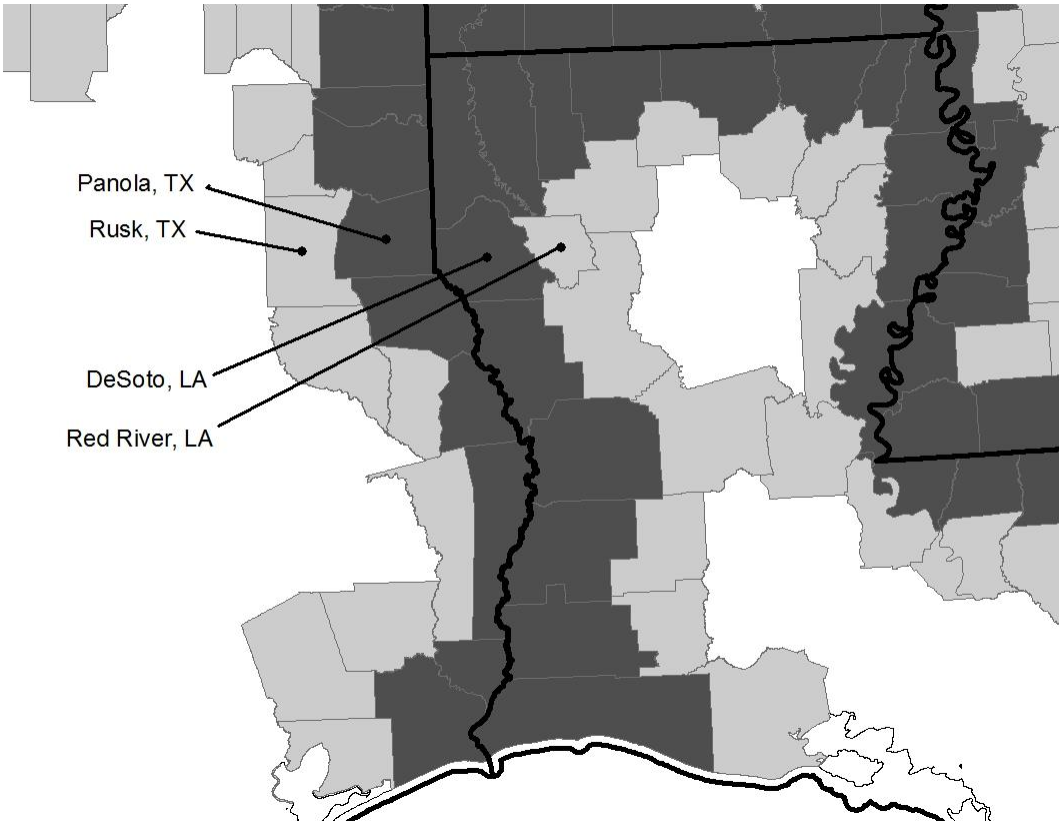

Figure 8: Analysis Sample

Figure 9: Fraction Residing in Birth State by Age

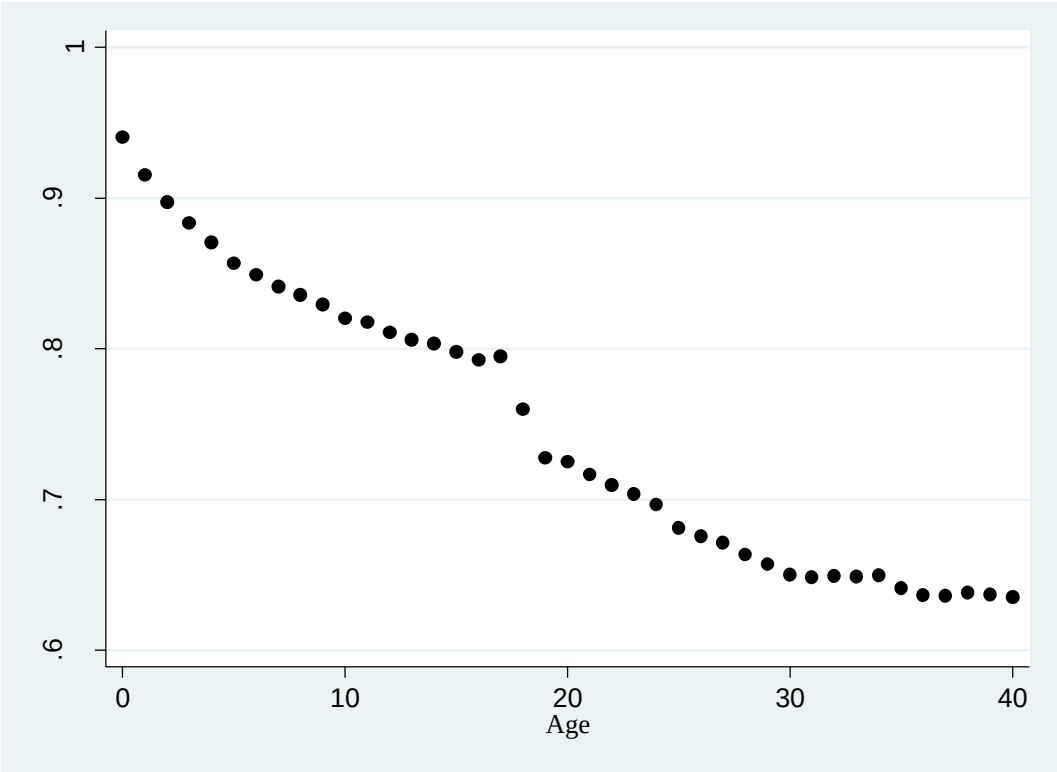

Table 1: Summary Statistics

Variable	County-Level Summary Statistics	State-Level Summary Statistics
Rank Correlation	0.331 (0.072)	0.323 (0.048)
Fraction Teen Mothers	0.165 (0.058)	0.144 (0.040)
Fraction Middle Class	0.550 (0.090)	0.520 (0.052)
Parents' Income		
Gini Coefficient	0.384 (0.086)	0.425 (0.076)
Income Share of Top 1 Percent	0.096 (0.050)	0.126 (0.032)
Mean	$67,346 (24,421)	$85,284 (15,648)
25th Percentile	$30,397 (10,453)	$35,070 (7,925)
50th Percentile	$52,974 (15,805)	$62,245 (11,571)
75th Percentile	$81,610 (20,510)	$96,513 (14,338)
90th Percentile	$115,807 (33,866)	$143,025 (23,406)
99th Percentile	$322,165 (208,310)	$490,903 (148,516)
Children's Income		
Mean	$45,803 (8,777)	$48,184 (6,437)
25th Percentile	$16,435 (5,509)	$16,486 (3,967)
50th Percentile	$35,654 (8,748)	$36,435 (6,358)
75th Percentile	$63,791 (11,674)	$66,186 (8,745)
90th Percentile	$94,776 (13,399)	$99,904 (10,637)
99th Percentile	$190,236 (39,269)	$210,134 (26,412)
School Finance 1990		
Per-Pupil Revenue (No Federal)	$4,238 (1,403)	$4,956 (1,338)
Pupil-Teacher Ratio	16.145 (2.752)	17.369 (2.072)
Progressivity of Funding	0.939 (0.134)	0.936 (0.148)

Marginal Tax Rate (1985-2010)		
Income = $10,000	-0.002 (0.019)	-0.005 (0.022)
Income = $50,000	0.043 (0.025)	0.045 (0.026)
Income = $100,000	0.047 (0.027)	0.050 (0.029)
Real Per-Capita State Assistance to Households with Children	$1,114 (337)	$1,208 (409)

Standard deviations are given in parentheses below means.

Table 2: Examining Impact of Differences in State and Local Educational Per-Pupil Revenue on Differences in County Mobility Rates of Adjacent Counties in Different States

	Specification					
Coefficient	(1)	(2)	(3)	(4)	(5)	(6)
Difference in 1990 State and Local Revenue—State Average	-0.001 (0.004)	-0.002 (0.004)	-0.001 (0.003)	--	--	--
Difference in 1990 State and Local Revenue—County Average	--	--	--	-0.008** (0.003)	-0.005 (0.003)	-0.004 (0.003)
Weight by Average Number of Children in County Pair	No	Yes	No	No	Yes	No
Covariates	No	No	Yes	No	No	Yes
R-Squared	0.001	0.001	0.244	0.016	0.009	0.249
Observations	1,938	1,938	1,938	1,922	1,922	1,922

Notes: The standard errors are cluster corrected at the state-border level. * indicates statistical significance at the 10 percent and ** indicates significance at the 5 percent level.

Table 3: Examining Impact of Differences in Student Teacher Ratios on Differences in County Mobility Rates of Adjacent Counties in Different States

	Specification					
Coefficient	(1)	(2)	(3)	(4)	(5)	(6)
Difference in 1990 Student Teacher Ratio—State Average	0.001 (0.001)	-0.001 (0.003)	0.002* (0.001)	--	--	--
Difference in 1990 Student Teacher Ratio—County Average	--	--	--	0.000 (0.001)	-0.002 (0.003)	0.001 (0.001)
Weight by Average Number of Children in County Pair	No	Yes	No	No	Yes	No
Covariates	No	No	Yes	No	No	Yes
R-Squared	0.001	0.001	0.258	0.000	0.005	0.253
Observations	1,938	1,938	1,938	1,922	1,922	1,922

Notes: The standard errors are cluster corrected at the state-border level. * indicates statistical significance at the 10 percent and ** indicates significance at the 5 percent level.

Table 4: Examining Impact of Differences in Progressivity of School Funding on Differences in County Mobility Rates of Adjacent Counties in Different States

	Specification		
Coefficient	(1)	(2)	(3)
Difference in 1990 Progressivity of School Funding	-0.032** (0.015)	-0.006 (0.026)	-0.010 (0.017)
Weight by Average Number of Children in County Pair	No	Yes	No
Covariates	No	No	Yes
R-Squared	0.007	0.000	0.250
Observations	1,932	1,932	1,932

Notes: The standard errors are cluster corrected at the state-border level. * indicates statistical significance at the 10 percent and ** indicates significance at the 5 percent level.

Table 5: Examining Impact of Differences in Marginal Tax Rates on Differences in County Mobility Rates of Adjacent Counties in Different States

	Specification					
Coefficient	(1)	(2)	(3)	(4)	(5)	(6)
Difference in Marginal Tax Rates—$10,000 (2005 Dollars) Adjusted Gross Income	-0.171 (0.162)	--	--	-0.229 (0.167)	-0.123 (0.161)	-0.182 (0.139)
Difference in Marginal Tax Rates—$50,000 (2005 Dollars) Adjusted Gross Income	--	-0.063 (0.112)	--	0.230 (0.263)	0.550 (0.457)	0.259 (0.224)
Difference in Marginal Tax Rates—$100,000 (2005 Dollars) Adjusted Gross Income	--	--	-0.078 (0.100)	-0.315 (0.234)	-0.461 (0.435)	-0.339 (0.194)
Weight by Average Number of Children in County Pair	No	No	No	No	Yes	No
Covariates	No	No	No	No	No	Yes
R-Squared	0.000	0.001	0.002	0.009	0.019	0.217
Observations	1,944	1,944	1,944	1,944	1,944	1,944

Notes: The standard errors are cluster corrected at the state-border level. * indicates statistical significance at the 10 percent and ** indicates significance at the 5 percent level.

Table 6: Examining the Impact of Differences in Average Real Per-Capita Public Assistance for Households with Children on Differences in County Mobility Rates of Adjacent Counties in Different States

	Specification		
Coefficient	(1)	(2)	(3)
Difference in Real Per-Capita Public Assistance ($1000s)	0.022** (0.011)	0.016 (0.016)	0.022** (0.010)
Weight by Average Number of Children in County Pair	No	Yes	No
Covariates	No	No	Yes
R-Squared	0.021	0.001	0.219
Observations	1,944	1,944	1,944

Notes: The standard errors are cluster corrected at the state-border level. * indicates statistical significance at the 10 percent and ** indicates significance at the 5 percent level.

Table 7: Examining the Impact of Being in a Different State on the Variance in the Difference of Intergenerational Mobility between Adjacent Counties

	Specification		
	(1)	(2)	(3)
Constant	0.0048**	0.0036**	0.0035**
	(0.0003)	(0.0005)	(0.0002)
Different State	0.0002	0.0003	0.0003
	(0.0004)	(0.0004)	(0.0004)
Weight by Average Number of Children in County Pair	No	Yes	No
Covariates in First Stage	No	No	Yes
R-Squared	0.00	0.00	0.00
Observations	14,252	14,252	14,252

Notes: The standard errors are cluster corrected at the state-border level. * indicates statistical significance at the 10 percent and ** indicates significance at the 5 percent level.

Table 8: Regression of Difference in County Mobility Rates on Differences in Observed Characteristics

Variable (in Differences)	Coefficient
Fraction Births to Teens	0.438**
	(0.046)
Fraction of Families in Middle Class	-0.081**
	(0.027)
County Family Income Statistics of Parent Cohort ($10,000)	
Gini Coefficient	0.103**
	(0.040)
Income Share of Top 1 Percent	-0.089**
	(0.053)
Mean	0.001
	(0.002)
25th Percentile	0.004
	(0.005)
50th Percentile	0.001
	(0.006)
75th Percentile	-0.003
	(0.004)
90th Percentile	-0.003**
	(0.002)
99th Percentile	0.000
	(0.000)
County Family Income Statistics of Child Cohort ($10,000)	
Mean	-0.001
	(0.005)
25th Percentile	-0.062**
	(0.011)
50th Percentile	-0.024**
	(0.011)
75th Percentile	0.017**
	(0.004)
90th Percentile	0.024**
	(0.004)
99th Percentile	0.001**
	(0.000)
R-Squared	0.27
Observations	14,252

Notes: The standard errors are cluster corrected at the state-border level. * indicates statistical significance at the 10 percent and ** indicates significance at the 5 percent level.

Table 9: Examining Differences in Mobility of Adjacent Counties in States with Large Average Mobility Differences

	Specification					
Coefficient	(1)	(2)	(3)	(4)	(5)	(6)
Mobile State	-0.015**	-0.005	-0.004	-0.039**	-0.013	-0.007
	(0.006)	(0.012)	(0.013)	(0.009)	(0.012)	(0.016)
Index	--	-0.004	-0.004	--	-0.011*	-0.009
		(0.005)	(0.005)		(0.006)	(0.007)
State-Pair Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Covariates	No	No	Yes	No	No	Yes
Weight by Number of Children	No	No	No	Yes	Yes	Yes
R-Squared	0.537	0.538	0.718	0.834	0.839	0.919
Observations	264	264	264	264	264	264

Notes: The standard errors are cluster corrected at the state-border level. * indicates statistical significance at the 10 percent and ** indicates significance at the 5 percent level.

Table 10: Examining Relationship of Differences in State and Local Policy with Differences in Observable Characteristics of Adjacent Counties in Different States

Variable	Per-Pupil Revenues	Student Teacher Ratio	Education Funding Progressivity	Marginal Tax Rates	Social Safety Net
	(1)	(2)	(3)	(4)	(5)
Mobility Index	0.206	0.075	0.009	0.640	0.492
Fraction Births to Teens	0.160	0.321	0.286	0.799	0.012
Fraction of Families in Middle Class	0.961	0.217	0.988	0.939	0.519
County Family Income Statistics of Parent Cohort					
Gini Coefficient	0.898	0.733	0.984	0.807	0.770
Income Share of Top 1 Percent	0.244	0.461	0.266	0.171	0.345
County Mean	0.133	0.310	0.228	0.057	0.774
25th Percentile	0.012	0.176	0.053	0.000	0.037
50th Percentile	0.018	0.536	0.242	0.002	0.120
75th Percentile	0.123	0.583	0.223	0.005	0.358
90th Percentile	0.305	0.624	0.424	0.010	0.855
99th Percentile	0.428	0.409	0.331	0.023	0.695
County Family Income Statistics of Child Cohort					
County Mean	0.015	0.864	0.086	0.197	0.342
25th Percentile	0.048	0.623	0.063	0.777	0.754
50th Percentile	0.024	0.747	0.029	0.546	0.609
75th Percentile	0.047	0.754	0.131	0.194	0.228
90th Percentile	0.054	0.154	0.166	0.109	0.070
99th Percentile	0.132	0.441	0.609	0.428	0.306

Notes: The table reports p-values on the coefficient of the difference in the given state policy measure in an unweighted regression of the observed covariate on the difference in state policy. The standard errors are cluster corrected at the state border level.

Table 11: Testing Whether Observable County Characteristics Differ More across State Borders than County Borders

Variable	All states	High Contrast States
	(1)	(2)
Mobility Index	0.085	0.212
Fraction Births to Teens	0.781	0.336
Fraction of Families in Middle Class	0.983	0.435
County Family Income Statistics of Parent Cohort		
Gini Coefficient	0.317	0.857
Income Share of Top 1 Percent	0.094	0.884
County Mean	0.586	0.724
25th Percentile	0.678	0.417
50th Percentile	0.546	0.578
75th Percentile	0.727	0.600
90th Percentile	0.604	0.768
99th Percentile	0.603	0.984
County Family Income Statistics of Child Cohort		
County Mean	0.219	0.283
25th Percentile	0.123	0.252
50th Percentile	0.154	0.254
75th Percentile	0.258	0.305
90th Percentile	0.163	0.475
99th Percentile	0.990	0.441

Notes: Column (1) of the table reports p-values on the coefficient of a different state dummy variable in an unweighted regression of squared differences of observable characteristics on a constant and a different state dummy variable. Column (2) relies on only the states which are part of a pair across which the mobility contrast is greatest, as shown in Figure 4. The p-values correspond to the effect of being in the more mobile state as discussed in equation (9). The standard errors are cluster corrected at the state-border level.

Table 12: Summary Statistics of IRS County-to-County Migration Data for Analysis Sample

Variable	Obs	Mean	Std. Dev.	Min	Max	Lower C.I. bound (95%)	Upper C.I. bound (95%)
A. All border counties							
Total Migrant Inflows	125	4769	15055	29	122955		
Total Migrant Outflows	125	4116	11353	51	89353		
Total Migrant, Same State, Border County Inflows	125	705	2522	0	21192		
Total Migrant, Adjacent State Border, County Inflows	125	170	344	0	2006		
Percent Migrant Inflows	125	0.0672	0.0292	0.0349	0.2202		
Percent Migrant Outflows	125	0.0667	0.0250	0.0359	0.2545		
Percent Migrant, Same State, Border County Inflows	125	0.0096	0.0103	0.0000	0.0499		
Percent Migrant, Adjacent State, Border County Inflows	125	0.0037	0.0069	0.0000	0.0473		
B. Counties by state mobility level							
Percent Migrant, Adjacent State, Border County Inflows (Low Mobility)	69	0.0046	0.0088			0.0025	0.0068
Percent Migrant, Adjacent State, Border County Inflows (High Mobility)	56	0.0025	0.0029			0.0017	0.0033

Notes: This table provides the summary statistics of total and percentage of migration for the 125 counties in our analysis sample. Data on county-to-county migration from the IRS, 2004-2005. http://www.irs.gov/uac/SOI-Tax-Stats-County-to-County-Migration-Data-Files