Abstract

Intergenerational mobility is central to the conception of America as a land of opportunity: the common belief is that anyone who works hard should have the opportunity to improve their family’s social standing generation-over-generation. There is a large and growing literature on positive income persistence that explores many of the covariates associated with mobility. However, there is relatively little literature that discusses the role of government spending and welfare programs in intergenerational mobility. This paper seeks to first consider the related literature and then lay the groundwork for future work discussing the impact of government programs on the persistence of income across generation.

Keywords: intergenerational mobility, government spending, welfare programs, poverty, inequality

1 Introduction

A high degree of intergenerational mobility has long been associated with an equal society, one in which a family’s financial status does not completely determine the financial success of their children. The value placed on this ideal stems from the belief that outcomes should
be the product of effort (and to some degree, ability): if an individual works hard, he or she should have the opportunity to attain a higher level of social and financial status. A great deal of research has been done attempting to quantify the exact degree of intergenerational mobility in the United States. They have found that despite these beliefs about mobility, the United States lags far behind many other well-established countries in providing equality of opportunity to future generations. A number of papers have found that the elasticity of incomes across generations (a common measure of intergenerational mobility) to be roughly twice what is found in European countries, indicating less intergenerational mobility.

Relatively few papers have discussed the role of education in the transmission of earnings across generations, and even fewer discuss the broader role that government programs might play in increasing mobility.\(^1\) While education is a key transmission mechanism and potential source for government to increase mobility, there are a number of other programs whose effects are unclear: government spending has been analyzed in aggregate (Mayer and Lopoo, 2008), but little is known about the effects of these individual programs.

There have been a number of papers that attempt to provide a theoretical background for the transmission of inequality over generations; most have focused on human capital acquisition decisions as the basis for bimodal income distributions. Papers have shown that in the presence of large fixed costs of education, there may be a group of families who attain low levels of education (Galor and Zeira, 1993). Further papers have explored the effects of clusters of high and low-education populations as well as a school-quality effect in a theoretical framework. There has, however, been a large divide between these theoretical models and the empirical literature.

Section 2 reviews a theoretical model of income transmission. Subsequently, I will consider the empirical frameworks commonly employed in the literature in section 3, before discussing some of the results and where they may fit in considering the role of government spending in section 4. Finally, section 5 will contain concluding remarks and suggestions for expanding the current literature.

\(^1\)See Chusseau and Hellier (2012) for an overview.
2 Theoretical Models

Income persistence within an economy has been modeled in a number of ways. Here, I will focus on the transmission of human capital over generations. As is shown in the later empirical sections, education is an important determinant of income. Furthermore, households have direct control over their acquisition of human capital, unlike some of the less-accessible determinants of income. Additionally, there is an important role for government in providing quality education to all of its citizens, making the analysis of human capital transmission my goal with this paper. Using a theoretical framework, I might be able to determine optimal government programs that could aid in the acquisition of human capital and increase intergenerational mobility, should that be deemed the objective. Because I will be focusing on the transmission of human capital through education across generations, each of these theoretical frameworks will be based upon an overlapping generations model (OG).\textsuperscript{2}

2.1 Fixed-Cost of Education - Galor and Zeira (1993)

Galor and Zeira (1993) use the basic OG framework with a bequest motive over generations. That is, parents have utility over the happiness of their children and therefore leave some fraction of their savings to them. These children then optimally choose to become educated or to save this money and start working. Each agent lives for three periods: in the first, they choose to work or increase their human capital; in the second, they work at a wage given by their human capital; in the third, they retire, exit the model and leave a bequest for their children. Their utilities in the last period of life are given in the following way:

\[ u = \alpha \ln(c) + (1 - \alpha) \ln(b) \]

They analyze such an economy in a partial equilibrium framework by setting the world rate of interest to \( r \) in each period. In addition to this, individuals can evade repaying their debt: for this reason, borrowers are assessed a risk-premium in order to insure banks

\textsuperscript{2}See Romer (2006) for more extensive a summary of the basic model.
against default. The result is credit market imperfections that cause the rate at which one can borrow to exceed this world interest rate. This by itself would not produce human capital divergence; fixed-costs, or indivisibility of human capital in order to be paid according to the high-productivity wage are also required. Including an incentive compatibility constraint yields the following market interest rate:

\[ i_d = \frac{1 + \delta r}{\delta - 1} > r \]  

Note that the authors assume two wages in this economy: a high wage that is obtained by those with high levels of human capital and a low wage by those with little or no human capital. Then, there is some level of human capital, \( h \), necessary for earning the high wage in the economy. Letting \( x_t \) denote the bequests left for the following generation in period \( t \), it turns out that the bequests evolve within a family in the following way:

\[
x_{t+1} = \begin{cases} 
    b_n(x_t) = (1 - a)[(x + w_n)(1 + r) + w_n] & \text{if } x_t < f \\
    b_s(x_t) = (1 - a)[w_s + (x_t - h)(1 + i)]Q & \text{if } f \leq x_t < h \\
    b_s(x_t) = (1 - a)[w_s + (x_t - h)(1 + r)] & \text{if } h \leq x_t
\end{cases}
\]

For some levels of bequests, families choose no education and achieve a low-skill level. In some intermediate range, they are forced to borrow, but they still achieve a high skill level wage. At the top of the income bracket, they do not need to borrow and earn interest on savings not invested in education. It turns out that such an economy will generate dynamics that can be represented graphically:

The key for analyzing dynamics in this framework is identifying convergence: for families starting with bequests between points \( g \) and \( h \), they will have to borrow but converge upwards to point \( \bar{x}_s \). For families between points \( g \) and \( f \), they will borrow to finance their own education, but be forced to leave less as a bequest to their children than they received;

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3 The presence of only credit market imperfections extends convergence time, but does not cause the divergence that will show up here. See Chusseau and Hellier (2012) for more details.

4 In practice, these are equivalent: one must pay to achieve some level of human capital before they see any benefit.
these families will converge to the lower level of human capital $\bar{x}_n$. In the long-run, a group of families converge to each of the different steady-states, given by $\bar{x}_s$ and $\bar{x}_n$. Galor and Zeira are further able to use this framework to show that there are associated welfare costs with a high degree of inequality. The most important takeaway, however, is that a simple fixed-cost and borrowing constraint is able to generate a very simple form of the inequality across human capital that is observed empirically.

3 Empirical Framework

For many years, economists have attempted to estimate intergenerational mobility by relating the log of father’s lifetime income to the log of his son’s lifetime income. Using this approach yields an estimate of the elasticity of son’s income with respect to his father’s income; more mobile societies are likely to have lower coefficients of intergenerational elasticity (IGE), as family income would explain less of the transmission across generations of income. This approach has been widely used in a number of papers, starting with the United States and expanding to other countries, including those of Europe (Bjorklund and Jantti, 1997) and Asia. Recently, some of the flaws in this estimation technique have been exposed by
researchers (Dahl and DeLeire, 2008). Instead, a number have proposed using a linear regression of child’s percentile ranks within the income distribution upon their parents’ rank in the income distribution. As in the IGE specification, the intergenerational rank association (IRA) specification will indicate higher degrees of mobility in areas in which the coefficient is smaller. As noted, there has been a large divide between theoretical and empirical models that attempt to describe intergenerational mobility.

3.1 Intergenerational Elasticity - Solon (1992)

Perhaps the seminal empirical paper on analyzing intergenerational mobility was Solon (1992). A number of researchers had already suggested using a log-log specification in order to obtain estimates of intergenerational mobility. They were estimating equations given in the following way:

\[
\ln(y_{it}) = \beta_0 + \beta_1 \ln(x_{it}) + \epsilon_{it}
\]  

(3.1)

where \(y_{it}\) was son’s income in year \(t\), and \(x_{it}\) a fixed number of years earlier. These researchers had found estimates of intergenerational elasticity within the United States that suggested a very high degree of mobility.\(^5\) However, these papers were attempting to proxy lifetime earnings with repeated single-year measures of father’s income. As Solon noted, these results could suffer from a serious degree of attenuation bias. He further noted that the equation in question was really given by:

\[
\ln(y_i) = \beta_0 + \beta_1 \ln(x_i) + \epsilon_i
\]  

(3.2)

where \(y_i\) and \(x_i\) were the permanent components of father’s and son’s income, respectively. By using single-year measures of father’s income in order to proxy lifetime, or permanent components of father’s earnings, authors risked seriously overstating the degree of mobility present in the United States. Suppose (3.2) is estimated but our variables are subject to

\(^5\)Behrman and Taubman (n.d.), for example, find a coefficient of 0.07.
'classical' measurement error:

\[ x_{it} = x_i + \eta_{it}, \quad \eta_{it} \sim N(0, \sigma^2_\eta) \]

\[ y_{it} = y_i + \nu_{it}, \quad \nu_{it} \sim N(0, \sigma^2_\nu) \]

If the errors are assumed to be uncorrelated with each other, and that the ‘true’ values of lifetime earnings are also uncorrelated with the measurement errors, the standard OLS estimator of \( \beta_1 \) (dropping the constant, for convenience) will result in:

\[
\text{plim}(\hat{\beta}_1) = \text{plim}\left[ \frac{\sum_{i=1}^{n} \ln(y_{it})\ln(x_{it})}{\sum_{i=1}^{n} \ln(x_{it})^2} \right] \\
= \text{plim}\left[ \frac{\sum_{i=1}^{n} \beta_1 \ln(x_i)^2}{\sum_{i=1}^{n} \ln(x_{it})^2} \right] \\
= \beta_1 \frac{\text{Var}(x_i)}{\text{Var}(x_i) + \text{Var}(\eta_i)} < \beta_1
\]

In this case, bias must be accounted for by using either averages of father’s income or an instrument variable.\(^6\) Solon finds that rather than a coefficient around 0.1, the United States has an IGE coefficient of 0.413 using a five-year average of father’s earnings from the Panel Study of Income Dynamics (PSID), which was the limitation imposed by his data. Turning to an instrument variable approach to solving this problem, he uses education to instrument for father’s lifetime wages, \( x_i \). Under this IV specification, he finds the IGE to be 0.526, again much higher than previously believed. He notes that because son’s earnings to be correlated to father’s education even outside of its influence through his father’s income that the coefficient is likely biased upwards. Taken together, he suggests these two alternatives provide an upper and lower bound on the ‘true’ value of intergenerational mobility in the United States.

A number of authors have pointed other pitfalls of this method in addition to attenuation bias. Researchers have been inconsistent in dealing with fathers and sons who report or have

\(^6\)See Appendix Figure 6.1 for degree of bias shown by Solon.
zero income during some years; those who do include years of zero income in averaging report lower elasticity coefficients. More importantly, these and other estimation methods are highly sensitive to "life-cycle bias." This occurs when the data for child’s income is taken before their earnings stabilize: if income measures are used from ages prior to 32, the IGE estimate will be biased downward (Haider and Solon, 2006).

3.2 Intergenerational Rank Association - Dahl and DeLeire (2008)

Because there are a number of sources of bias in using the IGE specification, researchers in this area have sought a more robust method to estimate measures of intergenerational mobility. Beginning with Dahl and DeLeire (2008), authors have used an Intergenerational Rank Association (IRA) approach. In order to do this, fathers and sons are ranked according to their income or average income in the national income distribution for the years in which they are measured. Then they are assigned a percentile rank within this distribution and the relationship is estimated. The equation of interest is given by:

\[ p^y_i = \alpha + \beta_1 p^x_i + \epsilon_i \quad (3.3) \]

Like the IGE estimation, a high \( \beta_1 \) will correspond with more persistence of income rank across generations and thus less intergenerational mobility. Additionally, if \( \beta_1 \) is multiplied by 100, which is equivalent to the difference in expected percentiles between the lowest and highest income percentiles, which gives a tangible measure of inequality. Using Social Security Administration data on earnings, Dahl and DeLeire compare IGE and IRA estimates in order to assess the robustness of both specifications. Because these are SSA datasets rather than PSID surveys, there will be efficiency gains due to a decrease in measurement error.

The IRA estimates turn out to be remarkably robust to sample definitions, while the IGE estimates vary wildly. In particular, IGE and IRA estimates are both similar for the full dataset, yielding 0.299 and 0.292, respectively; however, IGE estimates vary to as large as

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7See Dahl and DeLeire (2008) for a description.
8See Appendix Figure 6.2 for complete results.
0.632 under another common subsample, while the IRA estimates only increases to 0.395 under the same subsample. For daughters, they document similar levels of variability under IGE, finding estimates range from 0 to 0.27, while those found under IRA center around 0.1 with little variability.

Their study finds other attractive results: while IGE estimates are very sensitive to the period of life used when estimating fathers’ lifetime earnings, IRA estimates do not suffer from the same degree of life-cycle bias in the covariates. Using 16-year averages of fathers’ income measured every five years starting at age 25 results in a range of IRA estimates from 0.240 (age 25 to 40) to 0.289 (age 35 to 50). Using the same 16-year averages, the IGE coefficient ranges from 0.117 (ages 25-40) to 0.272 (ages 40-55), a much wider range. In addition, the study indicates that the IRA specification is relatively robust to attenuation bias: using a 36-year average of fathers’ lifetime earnings results in an IRA coefficient of 0.292; decreasing this number of years to 3 results in a coefficient of 0.291, with very little variability in the coefficient for intermediate numbers of years. The IGE estimate decreases from 0.299 to 0.197 by changing the number of years over which fathers’ income is averaged, indicating a lower degree of robustness.

Taken as a whole, their study strongly suggests that the IRA specification may be superior to the IGE specification. While they both appear to produce similar results under ideal conditions, the IRA specification is more robust to both life-cycle biases and attenuation biases than the IGE specification, as well as selection of different samples. Namely, IGE can vary from as small as 0.259 to as large as 0.632 under common sample restrictions. In any case, a study of intergenerational mobility should at least consider the IRA specification in addition to the more common IGE specification.

3.3 Nonparametric Estimation - Dahl and DeLeire

While the data fits a linear relationship quite well, Dahl and DeLeire note that below the 10th percentile and above the 80th percentile, families exhibit much less mobility. Because of the nonlinearities in income percentiles, Dahl and DeLeire consider two nonparametric
estimators for intergenerational mobility. First, they describe a commonly used nonparametric estimation technique called transition matrices\(^9\). As might seem clear from the name, they describe the transition probabilities of a family in each quintile of the national income distribution having a son whose earnings place him in each of the possible income quintiles. If a society were completely mobile, each of the entries in the transition matrix would be 20 percent; they find that in the United States the entries along the diagonal, those corresponding to remaining within the same quintile, are much higher than 20 percent.

Another nonparametric approach that they examine is nonlinear estimation of the IRA. As in the IRA specification, they will categorize fathers and sons by the percentile ranks within the national income distribution, and then attempt to describe average mobility. In this case, however, they will construct 96 “blocks” in which they will estimate the outcomes of the median son, the 20th percentile son and the 80th percentile son. Each block will include 5 percentile ranks, starting at those from 1 to 5 and ending with those from 96 to 100. For sons, they find that mobility again decreases at the tail probabilities of the income distribution.\(^{10}\) Interestingly, for daughters they find that having a father with an income above the 90th percentile actually decreases the median income of their daughters. They attribute this to the increased likelihood of finding a husband who makes a great deal of money (assortative mating).\(^{11}\)

4 Selected Results

There is a very large literature on the transmission of income status across generations. Most of these papers employ the methods by Solon, accounting for attenuation life-cycle biases as well as they can. Authors have studied the intergenerational mobility in different countries, generally finding that those with larger welfare states enjoy higher degrees of mobility. They have also studied the mobility among different groups of individuals, chiefly the mobility of daughters instead of sons. A number of papers have also explored other transmission

\(^9\)See Appendix Figure 6.3 for the transition matrices estimated by Dahl and DeLeire.

\(^{10}\)See Appendix Figure 6.4 for the plot of these estimates.

\(^{11}\)See Chadwick and Solon (2002) for more details on assortative mating.
mechanisms for income mobility, most commonly education. In addition, government spending often varies with income, often making it difficult to determine the individual effects of parents’ income and government spending.

Unfortunately, the literature to this point has had little to say on the impact of government on intergenerational mobility. This has been largely due to data limitations: studies like Solon and Dahl and DeLeire require good cross-sectional data over a period of 30 to 40 years. While there are some datasets that have individual characteristics over such a period, the authors that have explored the impact of government spending on mobility have noted that the data is often presented at a disaggregated level, making it hard to tease out the individual effects of particular programs.

4.1 Selected Intergenerational Mobility Results

Solon (1992) started a cascade of papers exploring the intergenerational mobility within different countries, while correcting for as much attenuation bias as the data would allow. Bjorklund and Jantti (1997) estimated the intergenerational elasticity of income using a number of comparable datasets across countries. They find substantially more mobility among the Scandinavian countries than they did in the United States and the United Kingdom, but it should be noted that they average over fewer years in the Scandinavian country and their results appear to potentially be subject to a lot of attenuation bias: They suggest that the causes for this might be government intervention in social outcomes, but they do not explore this possibility extensively.

A number of authors consider the impact of education on intergenerational mobility. Building upon Bjorklund and Jantti, Blanden et al. (2005) explore the portion of intergenerational elasticity that can be explained by education. In particular, they explore how the impact of education has evolved by comparing the 1958 cohort and the 1970 birth cohorts. They estimate persistence through education as:

\[
\rho_e = \phi_j \psi_j
\]
where \( \phi \) is the return to education and \( \psi \) is the relationship between parental income and education. They find that persistence caused by education was 0.077 in 1958 (out of an elasticity of 0.205), while this number had increased to 0.101 in 1970 (out of a total elasticity of 0.291). Ueda (2013) adopts a similar approach, estimating the transmission of income elasticity through education in Japan and South Korea. Instead of estimating a single return to education, he estimates returns to different levels of education, writing the model in the following way:

\[
\ln(Y_{it}) = \gamma_0 + a_1 A_{it} + a_2 A_{it}^2 + \{\gamma_1 g_{1i} + ... + \gamma_K g_{Ki}\} + \epsilon_{it}
\]  

(4.2)

He lets \( \gamma_i \) correspond to the \( i \)-th level of educational attainment. He then estimates intergenerational elasticity due to education in the following way:

\[
\rho_S = \sum_{k=1}^{K} \gamma_k \left( \frac{\partial g_{ki}}{\partial x_i} \right)
\]  

(4.3)
He estimates the change in the propensity to attain a level of education for a change in parents income \( \left( \frac{\partial g_{ki}}{\partial x_i} \right) \) by using a logit specification. He also estimates the intergenerational elasticity using the framework put forth in Solon. He finds that 43.8\% of intergenerational transmission is the result of differences in education caused by income in Japan, and an even higher 46.5\% in Korea. Of note is the particular venue through which transmission occurs: increasing parental income increases the probability that one ends with a university education by 47.3\% percent.

A number of authors also consider the intergenerational mobility of different subgroups. While most studies deal exclusively with the persistence transmitted from a father to their son, Chadwick and Solon (2002) consider the impact of income on outcomes for daughters.\(^{12}\) They discuss the possibility of "assortative mating": that daughters from wealthier families may marry men with higher incomes. In particular, they estimate the elasticity of son’s income with respect to his wife’s parents’ income. They find that the elasticity to be 0.360, indicating that there is likely a degree of assortative matching that increases persistence in income.\(^{13}\)


Very few papers in the literature consider the function of government in intergenerational mobility. The first that does is Mayer and Lopoo (2008), which uses the log-log framework to describe how government spending might impact intergenerational mobility. They write an econometric model in the following way:

\[
\ln(Y_{st}) = \beta_0 + \beta_1 \ln(X_{st}) + \beta_2 \ln(G_{st}) + \beta_3 (\ln(X_{st}) \ast \ln(G_{st})) + \epsilon_{st} \tag{4.4}
\]

Government spending is defined to be the local expenditures that occur while a son is

\(^{12}\)Many papers include estimates of intergenerational elasticity for daughters with respect to their parent’s income. Dahl and DeLeire, for example find an IGE estimate of 0.177 and IRA estimate of 0.120.

\(^{13}\)They do, however show that the transmission is still much larger for sons, indicating that outcomes are less determined by income for daughters.
between 15 and 17 per child. They note that this framework can allow elasticity of son’s income with respect to father’s income to be written as:

\[
\frac{\partial \ln(Y_{st})}{\partial \ln(X_{st})} = \beta_1 + \beta_3 \ln(G_{st})
\]  

(4.5)

Under this specification, if \( \beta_3 < 0 \), then government spending decreases intergenerational transmission of income. That is, government spending will make the outcomes of children less dependent upon their parents’ incomes. The authors have neither a direct measure of parental investment in children, nor a measure of government investment; for this reason, they use aggregate government spending per child. They estimate three separate models: a baseline model, a model with state fixed effects, and a model controlling for individual characteristics as well as fixed effects.

They find the sign of \( \beta_3 \) to be consistent under the hypothesis that government spending decreases intergenerational elasticity. However, the coefficient is insignificant under any specification.\(^{14}\) Using an F-Test, they do find that government spending plays a significant role in explaining mobility. They interpret to mean that government spending is strongly correlated with income so that the individual effect is difficult to determine, but should still be considered when constructing a model, as it has a statistically significant effect jointly.

They reconsider the question by dividing the sample into three categories of state spending. They find that low-spending states have a much higher intergenerational elasticity:

The differences between low and high-spending states turns out to be positive and significant. These results are not ideal when interpreting the relationship between government spending and mobility, as they only indicate that lower spending states have lower mobility. Given that some papers have noted nonlinearities in intergenerational persistence, there would be differences simply because of the correlation between income and government spending.

This specification that includes government spending has only been sparsely used in the literature. One such example is Liu et al. (n.d.), that considers the impact of govern-

\(^{14}\)See Appendix Figure 6.5 for results.
Estimates of the elasticity of children’s income with respect to parents’ income for children in states with low, medium and high total state expenditures

<table>
<thead>
<tr>
<th>State spending level</th>
<th>Difference in elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Medium</td>
</tr>
<tr>
<td>Model 1: Baseline</td>
<td></td>
</tr>
<tr>
<td>0.302***</td>
<td>0.407***</td>
</tr>
<tr>
<td>(0.042)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>Model 2: State FE</td>
<td></td>
</tr>
<tr>
<td>0.493***</td>
<td>0.567***</td>
</tr>
<tr>
<td>(0.044)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>Model 3: Add race/ethnicity, parental education, and year indicators</td>
<td></td>
</tr>
<tr>
<td>0.246***</td>
<td>0.254***</td>
</tr>
<tr>
<td>(0.043)</td>
<td>(0.054)</td>
</tr>
</tbody>
</table>

Figure 4.2: Reconsidering intergenerational mobility with government spending. Source: Mayer and Lopoo (2008)

ment spending in China on intergenerational mobility. They find a much higher degree of intergenerational persistence in income ($\beta_1 = 0.830$), and again are unable to say that $\beta_3$ is significantly negative. They attribute much of the persistence to differences in spending on education at the university level, for which there is very little governmental funding.

4.3 Local Mobility using Tax Records - Chetty et al. (WP)

Chetty et al. (2014a) gain access to more than 40 million tax records of parent-child pairs and use the intergenerational rank association specification of Dahl and DeLeire. They analyze mobility across regions within the United States to explore whether different areas of the United States experience different degrees of mobility. They define the areas of study to be "commuting zones": areas that are similar to metro areas, but designed to include rural communities as well. These commuting zones can generally be thought of as about the size of four counties. They find a great deal of differences in outcomes across these commuting zones: with regions accounting for as much as a 10 percent difference in expected outcomes within the national income distribution among children.

As in Dahl and DeLeire, Chetty et al. sort parents by their income into percentile ranks and do the same for their sons. They first estimate mobility nationally by using both the rank-rank and the log-log approaches. They find a coefficient of around 0.34 under both specification; however, including fathers with years of zero income (while averaging) under the log-log specification radically alters the estimates, while the rank-based approach is
shown to be relatively robust to different samples. At the national level, they also find that moving from the lowest to highest income percentiles is associated with a 67.5% increase in the likelihood of college attendance.

They estimate model given in equation (3.3) for each of the 709 commuting zones in the United States. In order to assess mobility within a region, they consider two measures of mobility:

- **Relative mobility**: a comparison of how unequal outcomes will be across generations within the region. They measure this by using $\beta$ from equation (3.3), which describes how much better off (in percentile ranks) a wealthy individual’s child can expect to be than a poor individual’s.

- **Absolute mobility**: a measure of the expected outcomes for children born to a family in the 25th percentile of the national income distribution within a region. This is given by $\alpha + 25\beta$, and measures where in the national income distribution a child can expect to end up having been born to a family in the 25th income percentile within a region.

A region could have low relative mobility, but high absolute mobility if everyone within a region improves over a generation, given by $\alpha$. Using these measures of local mobility, the authors find a very large difference across commuting zones: a family at the 25th percentile living in Charlotte, North Carolina, (the least absolutely mobile location in the sample) can expect their children to end up 10 percentile ranks lower than an equally wealthy family living in Salt Lake City, Utah (the most mobile location in the sample). Differences are found in relative mobility as well: a family from the 100th percentile in Cincinnati, Ohio, have expected outcomes 42.4% higher than a family from the lowest percentile. Conversely, the wealthiest families in San Jose can only expect 23.5% better outcomes than the least wealthy in the same commuting zone.

They further explore the causes of local variation in mobility. They take each of the 709 absolute mobility values and regress plausible causes of different mobility against them. For example, consider the case of segregation as a cause for differences in mobility:
$(\alpha + 25\beta_{CZ}) = \delta_0 + \delta_1 \text{Segregation}_{CZ} + \epsilon_{CZ}$ (4.6)

Using this structure, they explore the impact of the following upon intergenerational mobility: racial makeup of the CZ, the level of segregation within a CZ, the degree of income inequality, public good provision and tax policies, school quality, access to higher education, labor market structure, migration rates, social capital, and family structure. Of these potential correlates, this survey is most interested in public good provision, school quality and access to higher education, as these are the areas most likely to be affected by government expenditure. The results of their survey are displayed in figure 4.3.

They find three measures of government involvement to be significant: the local tax rate, government expenditures per capita and the level of earned-income tax credit provision. They find each measure of K-12 education to be significant in explaining differences in intergenerational mobility, with the rate of high school dropouts being the most strongly linked to intergenerational mobility. Of all the categories, they find the following to play the largest role in explaining differences in mobility:

They find that racial segregation, income inequality, high school dropout rates, and the fraction of single mothers within a CZ to have a large effect in decreasing mobility, while they find that the level of social capital plays a large role in increasing mobility within an area. This paper does a remarkable job analyzing potential causes of the variation in mobility within the United States. This may be a marginal increase over the results of this paper, but it
may be necessary to find instruments that capture many of the same effects while varying exogenously from other variables included in the model. Such a detailed dataset along with a good instrument might provide strong and conclusive results on the effectiveness of government spending in changing mobility.

5 Concluding Remarks and Extensions

Intergenerational mobility is a very important subject upon which research should continue. Recent papers have begun to incorporate the effect of government spending on intergenerational mobility, but there is a great deal of work still to be done. The dataset employed in Chetty et al. offers an opportunity to explore government programs at a local level with very high precision. In particular, it may be possible to discern how government may change mobility by measuring local spending on education, welfare programs, etc. and estimating the change in rank association.

With this consideration comes some problems, however. Much of the local variation in government spending is cyclical and likely to be highly correlated with local measures of parents’ income. Like Mayer and Lopoo, it seems likely that it will be hard to determine the relative effect of local government spending if it is relatively collinear with family income.
within the area. For this reason, it would be very beneficial to find an exogenously varying instrument that captures the effect of government spending or the quality of government programs. Future research must explore covariates that do not vary with cyclical elements of the economy, but are correlated with government spending.

Alternatively, I might want to capture some of this exogenous variation by not controlling for state fixed effects. Presumably, different states vary their spending in somewhat exogenous ways, though intra-state funding might be highly responsive to the business cycle. By using alternate controls for state fixed effects, I might be able to tease out some of the effect of varying government spending in a way that is less strongly correlated with income. A measure of state composition, like racial or income compositions might be able to capture some of these state-level effects while still allowing differences in the way states spend on education and other governmental services.

On the theory side, there is much work to be done exploring a specification that can explain empirical observations using microfoundations. Such a model might predict both the impact of a government program and the decisions made by households in response to such a policy. In the framework of Galor and Zeira, a policy need only get the "S-Curve" to shift upwards far enough that all families converge to the higher level of human capital. However, such a policy would be costly, and potentially have general equilibrium effects. There is a lot of "misallocation" literature that may be used to create similar dynamics and explain the divergence of incomes across generations.

Following up on any of these courses may be difficult, but worthwhile. It is important for such studies to take place to determine which programs might do a better job of making outcomes dependent upon work effort and ability rather than family wealth. The recent availability of detailed tax records has made studies of government spending and intergenerational mobility possible with much higher degrees of precision than in the past. Finding a source of exogenous variation along with these tax records might make it possible to determine the effect of government spending separately from income, in contrast to studies like Mayer and Lopoo. Further, bridging the gap between theory and empirics could do a great
deal explaining some of the other transmission mechanisms for income over generations, in addition to discussing welfare outcomes within a consistent framework. These should all be considerations for future research building upon the body of literature discussed here.

References


Liu, L, ZD Li, and MJ Wang, “Intergenerational Income Mobility and Public Education Spending: Evidence From China.”


6 Appendix
Figure 6.1: Solon’s estimates get larger for each additional year included in the average. Source Solon (1992).

<table>
<thead>
<tr>
<th>Year of father's log earnings</th>
<th>Measure of father's log earnings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Single-year measure</td>
</tr>
<tr>
<td>------------------------------</td>
<td>---------------------</td>
</tr>
<tr>
<td>1967</td>
<td>0.386</td>
</tr>
<tr>
<td></td>
<td>(0.079)</td>
</tr>
<tr>
<td>1968</td>
<td>0.271</td>
</tr>
<tr>
<td></td>
<td>(0.074)</td>
</tr>
<tr>
<td>1969</td>
<td>0.326</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
</tr>
<tr>
<td>1970</td>
<td>0.285</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
</tr>
<tr>
<td>1971</td>
<td>0.247</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
</tr>
</tbody>
</table>

Figure 6.2: These results show that IRA estimates are more robust to subsampling. Source Dahl and DeLeire (2008).
Figure 6.3: Transition matrices for the United States. Source Dahl and DeLeire (2008)

Figure 6.4: Non parametric estimation of the rank-rank specification. Source Dahl and DeLeire (2008)
Estimates of the elasticity of children's income with respect to parents' income

<table>
<thead>
<tr>
<th>Model 1: Baseline</th>
<th>Specification A</th>
<th>Specification B</th>
<th>Specification C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parental income (ln)</td>
<td>0.408** (0.031)</td>
<td>0.396** (0.029)</td>
<td>1.845 (1.326)*</td>
</tr>
<tr>
<td>Log government expenditures</td>
<td>--</td>
<td>--</td>
<td>1.874 (1.222)</td>
</tr>
<tr>
<td>Log parental income * log government expenditures</td>
<td>--</td>
<td>--</td>
<td>-0.153 (0.143)*</td>
</tr>
</tbody>
</table>

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<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>Log parental income</td>
<td>0.372** (0.032)</td>
<td>0.373** (0.032)</td>
<td>1.581 (1.433)*</td>
</tr>
<tr>
<td>Log government expenditures</td>
<td>--</td>
<td>--</td>
<td>1.581 (1.460)</td>
</tr>
<tr>
<td>Log parental income * log government expenditures</td>
<td>--</td>
<td>--</td>
<td>-0.123 (0.113)*</td>
</tr>
</tbody>
</table>

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</thead>
<tbody>
<tr>
<td>Log parental income</td>
<td>0.205** (0.026)</td>
<td>0.205** (0.026)</td>
<td>0.549 (1.061)*</td>
</tr>
<tr>
<td>Log government expenditures</td>
<td>--</td>
<td>-0.414 (0.364)</td>
<td>-0.026 (1.340)</td>
</tr>
<tr>
<td>Log parental income * log government expenditures</td>
<td>--</td>
<td>--</td>
<td>-0.034 (0.114)*</td>
</tr>
</tbody>
</table>

Figure 6.5: Results of the log-log estimation including government spending. Source Mayer and Lopoo (2008)