The Intergenerational Transmission of Lifetime Earnings: Evidence from Brazil

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Abstract

This paper uses unique household survey data from Brazil and recently developed econometric techniques to estimate the transmission of lifetime earnings in Brazil and to examine effects of earnings measurement on estimates of intergenerational mobility. The level of intergenerational earnings transmission in Brazil is estimated to be among the highest observed for any country. Observations of earnings across the life-cycles of fathers and sons are used to form estimates of the transmission of lifetime earnings and to study life-cycle measurement effects on earnings transmission estimates. The use of earnings of relatively young sons, common in previous studies, is found to underestimate the true level of transmission of lifetime earnings. This paper provides two methods to obtain improved measures of lifetime earnings transmission. This paper also finds that education may be the most significant pathway by which earnings are transmitted intergenerationally.

KEYWORDS: intergenerational transmission, earnings transmission, earnings mobility, intergenerational mobility, intergenerational earnings elasticity

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1. Introduction - Studies of Intergenerational Earnings Mobility

To what degree are earnings transmitted from one generation to the next? The answer to this question has significant implications for a number of important economic topics. The level of cross-sectional inequality, for instance, may be significantly influenced by the degree of intergenerational transmission of earnings. Earnings transmission shapes the progression of inequality over time and may significantly affect the impact of public policies designed to reduce cross-sectional inequality. The level of intergenerational earnings transmission, in particular the degree of poverty persistence, also has implications for poverty alleviation and economic development. Chronic poverty calls for very different policy instruments than does short-term poverty (Lipton and Ravallion, 1995). Poverty that is persistent across generations presents serious challenges to economic development.

The measurement of intergenerational earnings transmission is an important topic of economic analysis. It is only recently, however, that this question has garnered substantial attention in the economics literature. In the past fifteen years a number of studies have used new data and improved econometric techniques to accurately estimate the degree of intergenerational earnings transmission in a number of high-income countries. Far less information, however, exists on earnings transmission in the developing world. This lack of information has restricted the application of this line of research to economic development analysis and has limited our knowledge of transmission pathways.

1.1 International comparisons of intergenerational earnings mobility

The most common measure of the intergenerational earnings mobility is the intergenerational earnings elasticity of sons’ earnings with respect to the earnings of their fathers, as described in Mulligan (1997) and Solon (1999). Prior to 1992, the few existing measures of intergenerational earnings transmission were largely biased downward (towards an indication of more mobility) by unrepresentative samples of sons and noisy single-year measures of the earnings of fathers, as shown by Solon (1989, 1992) and Zimmerman (1992). While many other studies examined intergenerational relationships in education or occupation, these relationships are not necessarily indicative of those in earnings and may not provide easily comparable quantitative results. Since 1992, a number of studies using representative samples and better measures of fathers’ earnings have typically found the intergenerational earnings elasticity to be in the range of 0.3 to 1.

1 Fathers’ and sons’ earnings are most commonly used in this literature as they have traditionally made up the majority of family labor market earnings and require less severe selection concerns than do females’ earnings. Studies including the earnings of females, however, may very well prove enlightening and valuable.
0.5 in the United States. Studies of other high-income countries have found elasticities to range from under 0.2 in Sweden and Finland to near 0.5 in England. The findings of a broad cross-section of studies of intergenerational earnings mobility are described in Solon (1999, 2002) and Corak (2006).

### 1.2 Benefits of a Brazilian mobility study

While earnings mobility has been estimated in a number of countries, few developing countries have been included in this analysis. Grawe (2001), in one of the few studies that have been able to examine intergenerational earnings mobility in the developing world, explains that credit constraints or industrialization itself may lead to important differences in mobility between developed and developing countries. Studies involving developing countries may also provide unique information regarding the determinants of intergenerational mobility. As Solon (1999, p. 1787) points out, “A more thorough comparison across countries, preferably including less developed countries, may eventually prove to be a useful way of generating clues about the determinants of intergenerational transmission of earnings status.”

Data limitations have presented a significant roadblock to the estimation of intergenerational mobility in developing countries. Most studies of intergenerational mobility have been conducted using nationally-representative panel data, such as the PSID and NLS, in which fathers’ earnings are observed several decades before those of their sons. Because no large-scale panel data of sufficient length exist in the developing world, standard methods of estimation can not be applied. This paper surpasses these limitations by combining recently developed two-sample instrumental variables empirical methods and Brazilian data including unique questions on intergenerational mobility.

Papers by Ferreira and Veloso (2006) and Andrade, Ferreira, Madalozzo, and Veloso (2003) are excellent companions to this paper. These papers also apply two-sample instrumental variables empirical methods to the Brazilian data used in this paper in order to study intergenerational earning transmission in Brazil. The work of Ferreira and Veloso estimates the intergenerational transmission of wages in Brazil and examines differences in mobility across individuals by region, race, and cohort. The work of Andrade, Ferreira, Madalozzo, and Veloso extends that analysis to the consideration of evidence of borrowing constraints through the use of quantile regression analysis.²

This paper’s scope extends beyond those of Ferreira and Veloso and Andrade, Ferreira, Madalozzo, and Veloso in that it examines time trends in

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² The works of Ferreira and Veloso (2006) and Andrade, Ferreira, Madalozzo, and Veloso (2003) were performed independently from the work described in this paper. Drafts of all papers began circulating around the same time.
Brazilian mobility, utilizes those trends to separate age and cohort effects in order to form improved estimates of lifetime mobility in Brazil, and examines the underlying determinates of intergenerational earnings transmission. Additional comparisons between the methods and results of this paper and those of Ferreira and Veloso and Andrade, Ferreira, Madalozzo, and Veloso are found in Sections 3.3 and 4.2.

1.3 What this paper demonstrates

This paper first provides estimates of mobility in a developing country using methods comparable to those of previous studies. In Section 2, I describe the data used and available methods of estimation. In Section 3, I report mobility estimates using sons of age 25-34, a sample comparable to those of other studies. I estimate the intergenerational earnings elasticity in Brazil to be 0.53 using OLS methods and 0.69 using IV estimation. Both of these figures point to a level of earnings transmission among the highest currently observed in any country.

In Section 4, the impact of age of earnings observation on mobility estimates is investigated. I find that the age of observation of both fathers and sons has a significant effect on the estimated level of intergenerational transmission of earnings. I then calculate the improved estimate of 0.85 as the intergenerational elasticity of lifetime earnings observed in Brazil. This figure is 23% higher than that obtained using sons of age 25-34 and fathers of age 30-50.

In Section 5, data from three survey years are employed, allowing for control of the effects of age of earnings observation. Forming pseudo-panels of both sons and fathers based on the reported level of father’s education, I estimate the true level of lifetime earnings elasticity by birth cohort.

In Section 6, I investigate the reductions in intergenerational earnings transmission that have occurred over time in Brazil and find that Brazil may have significantly reduced its level of earnings transmission through increases in the equality of educational attainment.

2. The PNAD Data and Methods of Mobility Estimation

The principal requirement of data to be used in the analysis of intergenerational earnings mobility is the joint observation of fathers’ and sons’ earnings. Many authors have used panel data to provide this information, while others have used census data, income tax records, or other data that specifically link the earnings of fathers and sons. Large-scale data linking fathers’ and sons’ earnings is largely unavailable for the developing world, however, contributing to the current scarcity of mobility studies for these countries. In this section, I describe the unique data and econometric methods that allow this study to overcome these limitations.

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2.1 The PNAD data

Estimates of intergenerational mobility in Brazil in this paper are based on data from the Pesquisa Nacional por Amostra de Domicílios (PNAD), a repeated cross-sectional household survey of approximately 400,000 individuals per year. While individuals are included in the PNAD sample with a likelihood that varies by place of residence, all analyses of this paper weight individuals according to this probability, making the sample representative of all Brazil excluding the sparsely-populated (and not sampled) rural North. The PNAD contains basic demographic and labor market data, including the education and labor market earnings of all individuals over age ten.

In this paper I employ two general methods of intergenerational mobility estimation. The 1982, 1988, and 1996 PNAD surveys asked all heads of household and their spouses to report the highest level of education completed by each of their parents. This question provides the necessary link between earnings in one generation and the next. Using two-sample instrumental variables methods (TSIV) fathers’ earnings may be imputed from the information on fathers’ levels of education, using the relationship between earnings and education established in a second sample. This procedure then provides matched estimates of sons’ earnings and fathers’ earnings. Sons’ earnings may then be regressed on predicted values of fathers’ earnings to estimate intergenerational earnings mobility. These TSIV estimates are comparable to IV estimates which use fathers’ education as instruments for fathers’ earnings in a single data set. This estimation procedure is described in detail in Section 2.3. Descriptions of the specific samples used and estimation results are presented in Sections 3.1 through 3.3.

The Brazilian PNAD data also permit the more common OLS method of mobility estimation for a smaller sample of individuals. Fathers’ and sons’ earnings are observed jointly for all father and son pairs residing in the same household. While this sample of individuals is neither large nor representative of all individuals, I contend that OLS estimates formed using this sample provide lower bounds on those that would be obtained using the larger sample. This sample is further discussed in Sections 3.1 and 3.4 and regression results are presented in Section 3.5.

2.2 Estimating mobility through OLS and IV regression

The desired parameter of estimation in studies of intergenerational earnings mobility is the intergenerational elasticity of lifetime earnings. The most ideal condition under which one could estimate this parameter is when lifetime earnings of sons and fathers are observed free from error. If this were the case, the intergenerational elasticity of lifetime earnings could be estimated consistently
through an OLS regression of sons’ log lifetime earnings on fathers’ log lifetime earnings. Instead, single measures of earnings in the past month or year are the most common observations for both fathers and sons. As Solon (1989, 1992) and Zimmerman (1992) point out, using short-run measures of fathers’ earnings (which will include both measurement error and transitory fluctuations in earnings uncorrelated with true lifetime earnings) will decrease intergenerational elasticity estimates (classical errors-in-variables).

One method used to reduce the downward-inconsistency of OLS mobility estimates, when using panel data, is to average several years of father’s earnings. As Mazumder (2001, 2005) describes, however, the presence of an autoregressive error term in single measures of fathers’ earnings would mean that short-term averages of earnings may be largely ineffective in reducing the errors-in-variables bias.

An alternative is to instrument for fathers’ lifetime earnings using fathers’ education, or a similar measure. It is likely that education is free from much of the transitory variation present in short-run earnings, therefore making education a relatively stable proxy for lifetime earnings. Instrumenting for fathers’ earnings with fathers’ education therefore eliminates the downward-inconsistency of estimates of the elasticity of lifetime earnings.

There is, however, a potential drawback of this method. Fathers’ education may be correlated with sons’ earnings even after controlling for fathers’ earnings. In other words, knowledge of a father’s education may give additional information as to the earnings of his son, even if the earnings of the father is already known. If this is the case, the IV elasticity estimate will be inconsistent, as Solon (1992) shows. If highly educated fathers (controlling for fathers’ earnings) tend to have high-earnings sons, the IV estimator will be upward-inconsistent. If, on the other hand, highly educated fathers are likely to have low-earning sons, an IV estimate will be downward-inconsistent. For further explanation of OLS and IV estimates of intergenerational mobility see Solon (1999), Naga (2001), and Corak (2006).

2.3 Estimating mobility through TSIV

Just as Solon and Zimmerman used IV estimation in a single sample, the instrumentation of fathers’ earnings by education can be performed across multiple samples. Angrist and Krueger (1992) and Arellano and Meghir (1992) each showed that, given reasonable assumptions, moments from multiple data sets may be combined for consistent IV estimation. One data set will contain the dependent variable and the instrument, while a second data set contains the instrument and the independent variable. Dearden, Machin, and Reed (1997), Björklund and Jäntti (1997), and Grawe (2001, 2004) have applied a similar
framework to intergenerational mobility estimation. They perform a two-stage least squares estimate across two independent samples.

In the first stage of this procedure, the relationship between fathers’ earnings and fathers’ education (or another instrument) is established. In the second stage, sons’ earnings are regressed on estimates of fathers’ earnings predicted by fathers’ education. The two-sample innovation is important because the sample used in the first-stage regression need not include the actual fathers of sons observed in the second-stage sample. The requirement for consistency is only that the relationship between fathers’ earnings and fathers’ education in the first-stage sample equal that same relationship for the actual fathers of the observed sons. While this requirement can not be tested, it is addressed by selecting a first-sample with observable characteristics similar to those that the true fathers of the observed sons hold.

Dearden, Machin, and Reed used fathers’ education as an instrument for fathers’ lifetime earnings with British data. Björklund and Jäntti estimated intergenerational mobility in Sweden using eight categories of fathers’ occupations, whether the fathers attained higher than compulsory education, and whether the fathers lived in Stockholm as instruments for fathers’ lifetime earnings. Björklund and Jäntti also used father’s education and occupation as instruments with PSID data and compared their results for Sweden and the U.S. Grawe (2001, 2004), using World Bank Living Standards Measurement Study data and using fathers’ education to instrument for fathers’ earnings across two samples, is able to provide estimates of the intergenerational transmission of earnings or income for Ecuador, Nepal, Pakistan, and Peru. In comparison to previous estimates of mobility in high-income countries, Grawe’s results suggest “far less mobility in the non-industrialized countries.” For the case of Ecuador, the intergenerational elasticity of earnings is found to be even greater than one.

The data on fathers’ education present in the 1982, 1988, and 1996 PNAD, along with TSIV methodology, allow this paper to overcome previous barriers limiting studies of intergenerational mobility in the developing world. In the next section, I use a sample of sons of age 25-34 to produce estimates of mobility in Brazil comparable to those of other countries. Household heads of all ages, however, report the education of their fathers. Thus, unlike previous studies, I need not limit my analysis to sons of particularly young ages. In Sections 4 and 5 I report estimates of mobility for sons from age 20 through 64, enabling a

3 An earlier study by Treiman and Hauser (1977) uses the same concept.
4 While with a single sample the instrumental variables estimator is identical to the two-stage least squares estimator, when using two samples the instrumental variables estimator used by Angrist and Krueger (1992) and Arellano and Meghir (1992) is distinct from the two-stage least squares estimator used by Björklund and Jäntti (1997), Dearden, Machin, and Reed (1997), Grawe (2001, 2004), and in this paper. For a comparison of the two-sample instrumental variables estimator and the two-sample two-stage least squares estimator see Inoue and Solon (2006).
significantly improved estimate of the intergenerational elasticity of lifetime earnings.

3. Comparable Estimates of Intergenerational Earnings Mobility in Brazil

In this section, I report estimates of intergenerational mobility in Brazil using sons of age 25-34 in 1996. I use this age of sons because it is most comparable to previous studies of mobility in other countries. I first describe the two samples of sons used in the analysis of this paper – that used for TSIV estimation and that used for single-sample IV and OLS estimation. In Section 3.2, I describe the sample of fathers used in the first stage of the TSIV procedure. In Section 3.3, I report the TSIV elasticity estimates. I then turn to the sample of individuals living with their fathers, discussing selectivity concerns in Section 3.4 and reporting single-sample IV and OLS elasticities in Section 3.5.

3.1 Two samples of sons age 25-34

The sample of sons used in the TSIV estimates of this paper consists of males with positive earnings and a report of their father’s education. In Sections 3 and 4 of this paper I use ten categories of fathers’ education as instruments for fathers’ lifetime earnings. I term this sample of individuals the Full Sample. Table 1 outlines the selection of observations into the Full Sample.

5 Father’s level of education is observed in one of two ways in the 1996 PNAD, depending on the residential status of the son. If the son is identified as a child of the head of the household, then the education of the father is directly observed when a male head or spouse is present (this male head or spouse is defined as the father). In less than 0.5% of the cases in which the father is present is his education missing. If the son is a head of household or spouse of a head, his father’s education is observed through the additional question in the 1996 PNAD survey asking him to report the highest completed level of education of his father, in these ten categories: zero years of completed education, 1-3 years (incomplete lower primary), 4 years (complete lower primary), 5-7 years (incomplete upper primary), 8 years (complete upper primary), 9-10 years (incomplete secondary), 11 years (complete secondary), 12-14 years (incomplete university – includes complete two-year degree), 15 years (complete university), or 16-18 years (at least some postgraduate education). While this question was posed to all heads of household and spouses, not all individuals were able to answer it. Father’s education was not reported for 21.6% of male heads of age 25-34. Sample selection issues that may arise from these missing reports are discussed in Section 3.1. Throughout Sections 3 and 4 of this paper, the education of both fathers and sons will be placed into these ten categories, using the median number of years of education completed to represent each category.
The 1996 PNAD is estimated to have included approximately one in every 500 residents of Brazil, a sampling proportion that largely holds true for males age 25 to 34 as well. The ‘Weighted %’ row in Table 1 indicates the fraction of all Brazilian males age 25 to 34 that each column is estimated to represent. The majority of males of age 25-34 in 1996 fall into the category of head of household or spouse. In 97.4% of the cases these individuals are the head, and as such I will refer to both head and spouse as the head. Of these individuals, who are placed in columns (i) through (vi), those in column (ii) are included in the Full Sample. Sons identified as children of the head of household are reported in column (v) or (vi) if their father is also present in the household. Those individuals of column (vi) (those with positive earnings) are included in both the Full Sample and the OLS Sample, which is described in more detail in Section 3.4. Other individuals are neither the head of a household nor a child of the head of a household in which a male is present as head or spouse. These individuals are shown in columns (vii) and (viii) and, as father’s education is not available, they are not included in this analysis.

There are essentially three dimensions by which the Full Sample is selected. First, individuals must fall into the categories of either “Household Head” or “Living with Father” (columns (i) through (vi)). 17% of individuals do not meet this requirement. While these individuals have mean education of 6.67

Notes: This table includes all males age 25-34 in the 1996 PNAD. “Household Head” includes male spouses of head. Individuals with missing earnings (N=399) are coded as having zero earnings.
years (nearly identical to that of all individuals, which is 6.64), the mean reported log earnings\textsuperscript{6} of 5.68 for those individuals of this group with positive earnings is substantially below (though not statistically different from) the mean earnings of all individuals reporting positive earnings, which is 5.87. This means that selection on this dimension keeps an unrepresentatively high-earning group of sons. While this fact could suggest that the relationship between these sons’ earnings and those of their fathers is also unrepresentative, this need not be the case. As father’s education is missing for the excluded group, the data can not provide an indication as to whether this is the case.

The second dimension on which the Full Sample of sons are selected is the voluntary reporting (or knowledge) of father’s education for household heads. The sons excluded from the sample by this requirement (13\% of all individuals) report relatively low levels of earnings. The elimination of this group of sons again keeps an unrepresentatively high-earnings group of individuals. As father’s education (and thus any measure of earnings) is unavailable for the dropped sons, we unfortunately can not tell whether the individuals dropped from the sample by the first and second selection criteria are unrepresentative of the population in terms of the similarity between sons’ and fathers’ earnings.

The third dimension on which sons are selected into the Full Sample is the reporting of positive earnings. An additional 9\% of all individuals are dropped from the sample as a result of this requirement. This standard of selection (and magnitude of selection) is consistent most other studies of intergenerational earnings mobility. The requirement of positive earnings for inclusion in the sample is justified by more than necessity for the use of standard estimation methods. Reports of zero earnings for Brazilian males are frequently a result of temporary unemployment. While these unemployment spells will certainly have an effect on lifetime earnings, they are not an indicator that the lifetime earnings of these individuals will be near zero. Assigning unrepresentatively low values of earnings to the temporarily unemployed (when using these earnings as approximations of lifetime earnings), could inappropriately designate these individuals as having among the lowest lifetime earnings. This inappropriate designation could significantly bias estimates of the intergenerational elasticity of earnings. The alternative that I choose to follow is to drop individuals with no reported earnings from the sample.

3.2 The first-stage sample of fathers

The sample of individuals used in the first-stage of the TSIV intergenerational mobility estimation will establish the relationship between fathers’ education and fathers’ earnings. The objective in selection of this sample of “representative-fathers” is for the observed relationship between education and earnings to most accurately reflect the relationship between the education and lifetime earnings of the true fathers of sons in the Full Sample. As I do not observe the latter relationship, this objective cannot be tested. As such, I select the first-stage sample to best match the true fathers along the observable characteristics of birth cohort and education. I then select a period to observe the representative-fathers when their earnings are most likely to accurately represent lifetime earnings, ages 30-50.

The sons of the Full Sample were born between 1962 and 1971, with a mean birth year of 1966. Using data from the 1981 PNAD (the earliest available with appropriate information), I find the median age of fathers of newborns to be 31. This single statistic suggests that the median year of birth of the fathers of sons of the Full Sample is approximately 1935. This would make these fathers 41 years old in 1976 (the first year of PNAD available). Earnings around this age, in what is generally considered the ‘prime earnings years’, are likely to comparatively accurately reflect permanent earnings. In order to maintain a relatively large sample, I expand the age of individuals to include in the sample of representative-fathers to 30 through 50. My resulting sample of first-stage representative-fathers consists of males of age 30-50 with positive earnings\(^7\) in the 1976 PNAD. Supporting this choice of representative-fathers, I find that sons’ reports of their father’s education nearly perfectly match (in terms of mean and standard deviation) the self-reported education of the representative-fathers when weighting by number of children born to each father (on average by level of education)\(^8\). This result provides support for the conclusion that the sample of males 30-50 in 1976 (the first-stage sample) are representative of the true fathers of 25-34 year-old sons in 1996.

The summary statistics on age, education, and earnings of the sons and fathers used in the TSIV estimates are reported in Table 2. Sons show mean levels of education of 7.0 years and mean earnings of 614 Reais per month. Using the prevailing exchange rate near 1 US$ to 1 Real in 1996, this level of earnings equals approximately $7,400 per year. Fathers’ earnings (also expressed in 1996 Reais per month) average just under $8,000 per year.

\(^7\) The positive earnings requirement for fathers also matches those of most other mobility studies.

\(^8\) The discrepancies between fathers’ own reports of their education and sons’ reports of their fathers’ education follow an interesting pattern. Sons’ reports match those of fathers with the exception that sons tend to neglect the partial completion of levels of education by their fathers.
Table 2: Characteristics of the Full Sample
Sons: males 25-34 with positive earnings and non-missing father’s education in 1996
Fathers: males age 30-50 with positive earnings in 1976

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std.Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Son’s report (1996)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Son's age</td>
<td>14,872</td>
<td>29.6</td>
<td>2.9</td>
<td>25</td>
<td>34</td>
</tr>
<tr>
<td>Son's education</td>
<td>14,817</td>
<td>6.97</td>
<td>4.41</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>Son's earnings</td>
<td>14,872</td>
<td>614</td>
<td>901</td>
<td>10</td>
<td>50,000</td>
</tr>
<tr>
<td>Son's log earnings</td>
<td>14,872</td>
<td>5.93</td>
<td>0.95</td>
<td>2.30</td>
<td>10.82</td>
</tr>
<tr>
<td>Father’s education</td>
<td>14,872</td>
<td>3.11</td>
<td>3.67</td>
<td>0</td>
<td>17</td>
</tr>
</tbody>
</table>

| **Father’s report (1976)**|      |       |          |      |      |
| Father’s age              | 37,396 | 39.0  | 6.0      | 30   | 50   |
| Father’s education        | 37,396 | 3.81  | 4.03     | 0    | 17   |
| Father’s earnings         | 37,396 | 657   | 1680     | 0.2  | 129,447|
| Father’s log earnings     | 37,396 | 5.87  | 1.00     | -1.60| 11.77|

3.3 TSIV estimated elasticity

To apply the TSIV framework to the PNAD data, I first obtain the relationship between fathers’ earnings and fathers’ education through a standard education-earnings regression on the representative-fathers (30-50 year-old males with positive earnings in 1976):

\[
y_0 = \alpha_0 + \sum_{j=1}^{10} \chi_{1j} E_{0ji} + \chi_{2} ag_{bi} + \chi_{3} age_{bi}^2 + \epsilon_{0i}.
\]

In this equation, \( y_0 \) represents the natural log of fathers’ earnings and \( E_{0} \) represents the vector of ten dummy variables for the levels of education. \( Age \) and \( age^2 \) control for the age of fathers.

The results of this regression clearly indicate the strong dependence of earnings on education in Brazil. The earnings of males with 16 or more years of education (college is completed at grade 15) are 2.9 log points higher (or 18 times greater) than males with no schooling. Substituting a linear education term for the categorical values results in a coefficient estimate of 0.165, a value that is extremely high by international standards (Psacharopoulos, 1994; Card, 1999). As will be explored in detail in Section 6, this high rate of return to education may be a primary factor contributing to Brazil’s high rate of intergenerational earnings elasticity.

The second stage of the TSIV process uses the estimated \( \hat{\chi}_1 \) vector from Equation 1, along with sons’ reports of their fathers’ education, to predict fathers’
log earnings, \( y_o \). The second-stage procedure then entails an OLS regression of
sons’ log earnings on fathers’ predicted log earnings and controls for sons’ ages:

\[
y_{yi} = \alpha + \beta_1 y_o + \beta_2 \text{age}_{yi} + \beta_3 \text{age}_{y1}^2 + \epsilon_{yi}.
\]

The estimated \( \hat{\beta}_1 \) from Equation 2 is the TSIV estimate of
intergenerational earnings elasticity. The results of this regression are presented
in Table 3. Because predicted values of fathers’ earnings are used in this
regression, the computer-reported standard error of \( \hat{\beta}_1 \) (which is 0.011) will be
inconsistent, as Pagan (1984) describes. I therefore report the bootstrap standard
error estimate of 0.014. Other standard errors are heteroskedasticity robust, as
are those presented throughout Sections 3 and 4. The TSIV estimated
intergenerational earnings elasticity reported in Table 3 is 0.688. This estimate of
intergenerational earnings elasticity is among the highest observed for any
country previously studied.

### Table 3: Intergenerational Earnings Elasticity

**Regression Results**

Sons: males 25-34 in the Full Sample, 1996

Fathers: males 30-50 in the Full Sample, 1976

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coef.</th>
<th>Std.Err.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fathers’ predicted log earnings</td>
<td><strong>0.688</strong></td>
<td><strong>0.014</strong></td>
</tr>
<tr>
<td>Sons’ age</td>
<td>0.227</td>
<td>0.061</td>
</tr>
<tr>
<td>Sons’ age(^2)</td>
<td>-0.003</td>
<td>0.001</td>
</tr>
<tr>
<td>Constant</td>
<td>1.546</td>
<td>0.897</td>
</tr>
</tbody>
</table>

Note: The standard error reported for fathers’ predicted log earnings
coefficient is the bootstrap estimate.

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\(^9\) The bootstrap standard error was calculated as follows: First, a random sample of fathers was
drawn (with replacement) from the sample of representative fathers equal in number to the sample
size (N=37,396). The relationship between fathers’ earnings and education was estimated using
this sample. Then, a random sample of sons of the Full Sample was drawn (with replacement)
equal in number to the sample size of sons of the Full Sample (N=14,872). Fathers’ earnings were
imputed using the relationship between fathers’ earnings and education established by the first
sample. A single point estimate of the intergenerational elasticity of earnings was then calculated.
This process was repeated K=1,000 times and the sample standard deviation was used as the
bootstrap standard error.
The use of males 30-50 in 1976 to characterize the relationship between education and lifetime earnings of fathers assumes that this relationship is relatively stable over one’s life. In Section 4, I investigate the effect of observing fathers at ages other than the 30-50 range. As a simple check of the effect of variation in this relationship across time, however, I now substitute males of age 30-50 in years other than 1976 for the representative-fathers used in the first stage of the TSIV procedure. I leave the age (25-34) and year of observation (1996) of sons unchanged. The following elasticity estimates are obtained observing fathers’ earnings in the indicated year: 1976 = 0.688, 1977 = 0.696, 1978 = 0.696, 1979 = 0.700, 1981 = 0.723, 1985 = 0.724, 1990 = 0.731, 1996 = 0.767. These statistics indicate that the elasticity results are quite robust to changes in the year of observation of fathers. Even observing fathers a full twenty years later, in 1996, results in an elasticity estimate of 0.78, just 13% higher than that using fathers’ earnings observed in 1976.

Ferreira and Veloso (2006) also provides an estimate of wage mobility in Brazil that may be compared to those of other countries and examines differences in mobility across individuals by region, race, and cohort. Though on the whole similar, the methods of estimation and samples of fathers and sons used by Ferreira and Veloso differ slightly from those of this paper. \(^{10}\) A comparable estimate to the 0.69 intergenerational earnings elasticity estimate reported in Table 3 for sons of age 25-34 in 1996 is comparable to Ferreira and Veloso’s 0.68 intergenerational wage elasticity estimate for sons 25-65 in 1996, controlling only for age in the second-stage regression. While the subsequent analysis of elasticity changes over the life-cycle will show substantially different estimates of intergenerational mobility across sons’ ages, the work of Ferreira and Veloso confirms the finding of this paper that the level of intergenerational mobility is extremely low in Brazil by international standards.

### 3.4 Direct mobility estimates using the OLS Sample

The majority of papers on intergenerational mobility have used OLS estimation with direct observation of both sons’ and fathers’ earnings. Corresponding OLS estimates for Brazil would enhance international comparisons. Moreover, OLS estimates could provide a lower bound for true earnings elasticity.

\(^{10}\) Ferreira and Veloso use information on both father’s education and father’s occupation (at the time the son was 15) for TSIV analysis, categorizing occupations into six categories according to occupational prestige. The sample of first-stage fathers consists of males 25-65 working 40 or more hours per week in all jobs and living in urban areas, combining individuals present in the 1976, 1981, 1986, and 1990 PNAD surveys that fit these criteria. Ferreira and Veloso’s second-stage sample of sons consists of males in the 1996 PNAD survey reporting their father’s education and occupation, working 40 or more hours per week in all jobs, and living in urban areas.
OLS estimates for Brazil are not straightforward, as father’s earnings are directly observed only for sons residing in the same households as their fathers. Additionally, because the data are not panel, sons’ and fathers’ earnings must be observed at a single point in time, requiring significant age disparity. Column (vi) of Table 1 included those sons of age 25-34 with positive earnings who were living with their fathers in 1996. Of these 2,885 individuals, 1,649 individuals have fathers who also report positive earnings. For these 1,649 individuals, direct OLS estimation of intergenerational earnings mobility may be carried out. I term these individuals the “OLS Sample” and report their summary statistics in Table 4. The use of sons residing in the same households as their fathers for intergenerational mobility estimation is not without precedent. Hertz (2001) estimated intergenerational earnings mobility in South Africa using co-residing sons and fathers observed in the 1993 Project for Statistics on Living Standards and Development household survey. Although sample sizes were small and the data necessitated methods different from other studies, Hertz concluded that “intergenerational correlations in log monthly earnings among employed parent-child pairs are extremely high in South Africa.” Additionally, Sánchez Hugalde (2004) quantifies Spain’s intergenerational income mobility and intergenerational education mobility using similar techniques.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std.Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Son’s report (1996)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Son’s age</td>
<td>1,649</td>
<td>27.9</td>
<td>2.7</td>
<td>25</td>
<td>34</td>
</tr>
<tr>
<td>Son’s education</td>
<td>1,645</td>
<td>7.62</td>
<td>4.57</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>Son’s earnings</td>
<td>1,649</td>
<td>483</td>
<td>626</td>
<td>13</td>
<td>6,000</td>
</tr>
<tr>
<td>Son’s log earnings</td>
<td>1,649</td>
<td>5.71</td>
<td>0.93</td>
<td>2.56</td>
<td>8.70</td>
</tr>
<tr>
<td>Father’s report (1996)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Father’s age</td>
<td>1,649</td>
<td>57.6</td>
<td>6.8</td>
<td>40</td>
<td>89</td>
</tr>
<tr>
<td>Father’s education</td>
<td>1,649</td>
<td>3.91</td>
<td>4.26</td>
<td>0</td>
<td>17</td>
</tr>
<tr>
<td>Father’s earnings</td>
<td>1,649</td>
<td>709</td>
<td>1592</td>
<td>10</td>
<td>40,000</td>
</tr>
<tr>
<td>Father’s log earnings</td>
<td>1,649</td>
<td>5.86</td>
<td>1.07</td>
<td>2.30</td>
<td>10.60</td>
</tr>
</tbody>
</table>

A particular advantage of the Brazilian data is that the sample of co-residing sons can be compared to the larger Full Sample to examine sample selectivity. Before reporting the estimates of mobility for the OLS Sample, I examine the representativeness of this sample and implications for mobility estimation through a comparison of the OLS Sample to the individuals who are
included in the Full Sample but not the OLS Sample. The predominant concern is that the individuals who reside with their fathers may differ in intergenerational earnings mobility from the individuals of the same age not living with their fathers (see Solon (1992)), thus making mobility estimates formed using the OLS Sample unrepresentative of the population as a whole.

Estimates of the intergenerational correlations of education and TSIV earnings elasticity estimates suggest that the samples do not differ in terms of the intergenerational association in education and sons’ earnings and fathers’ levels of education appear, in fact, to be less similar in the OLS Sample that in the TSIV sample. Estimates of intergenerational mobility based on the OLS Sample are, therefore, unlikely to overestimate the true intergenerational elasticity for the population as a whole.

3.5 OLS and single-sample IV estimated elasticity

The standard OLS estimation procedure of intergenerational earnings mobility is the regression of the natural log of sons’ earnings on the natural log of fathers’ earnings and controls for the ages of both fathers and sons:

$$y_{ii} = \alpha + \beta_1 y_{0i} + \beta_2 \text{age}_{0i} + \beta_3 \text{age}_{0i}^2 + \beta_4 \text{age}_{0i}^3 + \beta_5 \text{age}_{0i}^4 + \text{age}_{ii}.$$

I perform this estimation on the OLS Sample. I also perform single-sample IV estimation, which follows similar form but uses ten categories of fathers’ education to instrument for fathers’ earnings.

The results of the OLS and IV estimation of mobility for the OLS Sample are shown in Table 5. The previously reported TSIV estimates for the Full Sample and OLS Sample are also reported for reference. The IV estimate of intergenerational mobility, 0.69, equals the TSIV estimate for the Full Sample and is 0.03 units higher than the TSIV estimate for the OLS Sample. This result suggests that the relationship between fathers’ earnings and education is quite similar between the representative-fathers of the Full Sample (30-50 year-olds in 1976) and the true fathers of the OLS Sample (fathers of 25-34 year-olds in 1996), as I do find to be the case. The OLS-estimated elasticity for the OLS Sample is 0.53. This estimate suggests, as did the TSIV estimate, that the intergenerational transmission of earnings in Brazil is among the highest currently observed for any country.
4. Life-Cycle Bias and the Age at Observation

Intergenerational mobility calculations ideally estimate the elasticity of sons’ lifetime earnings with respect to the lifetime earnings of fathers. Rarely, however, are the lifetime earnings of either son or father observed. Instead, earnings are observed over a short time span and assumed to approximate earnings over the entire lifecycle. As this section shows, this assumption is far from innocuous. Significant life-cycle patterns are shown to exist in relative earnings, and these patterns are found to substantially influence intergenerational elasticity estimates. The ages at which earnings of both sons and fathers are observed appreciably shape the estimated elasticity. The use of relatively young sons, which is pervasive throughout the intergenerational mobility literature, is shown to produce significantly lower elasticity estimates than would the use of lifetime earnings.

4.1 Theory of life-cycle effects on mobility estimates

Empirical observation shows that measured relative earnings are highly dependent on the age at which they are observed. The gap in earnings between two individuals, measured in percentage terms, is shown to grow throughout much of the life-cycle. This is explained by Lillard’s (1977, page 45) observation that “earnings rise over the lifetime and rise more rapidly for the more educated”. This result holds true for earnings growth in Brazil. Figure 1 plots the log

Table 5: Summary of Intergenerational Earnings Elasticity Regression Results
Sons 25-34 in 1996

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>OLS Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>14,872</td>
<td>1,649</td>
</tr>
<tr>
<td>TSIV</td>
<td>0.69</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Direct IV</td>
<td>-</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.03)</td>
</tr>
<tr>
<td>OLS</td>
<td>-</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.02)</td>
</tr>
</tbody>
</table>

(Huber-White corrected standard errors in parentheses.)
earnings of males with positive earnings by their level of education, across ages 20 through 64 in 1996. A similar pattern exists for males in 1976. These results indicate that the gap in relative log earnings by education grows through at least age 50. Figure 1 shows that the gap in earnings between males with 8-10 years of schooling and those with no schooling grows from just over one log point at age 30 to 1.5 log points at age 50.

Figure 1: The Relationship between Earnings and Education across Age in 1996

The above empirical findings suggest that single measures of log earnings be modeled with age-varying multipliers on lifetime earnings:

(4) \[ y'_{it} = \lambda^f y^L_{it} + v'_{it} \] and

(5) \[ y^s_{ot} = \lambda^s y^L_{ot} + v^s_{ot} \]

The age-varying multipliers \( \lambda^f \) and \( \lambda^s \) of these equations capture the possibility of steeper growth for higher paid individuals, for both sons and fathers, respectively. These multipliers will exceed one at ages where the variation in transitory earnings (excluding measurement error) is greater than the variation in lifetime earnings, and will be less than one at ages where the variation in transitory earnings is less than that of lifetime earnings. The lambda multipliers may therefore be expected to be lowest (and less than one) at very young ages and highest (and greater than one) at older ages just before retirement (peaking between age 45 and 60). Of course, measurement error will also affect earnings.
observations. If the variance of measurement error is greater at some ages than
others, observations of the lambda multipliers may be artificially inflated or
deflated. I make the assumption throughout this paper that the variances of
transitory errors in earnings are stable across ages and across time.

Haider and Solon (2006) describe the implication of these life-cycle
earnings patterns for intergenerational mobility estimation. In particular, they
show that OLS estimates of the intergenerational earnings elasticity will equal the
true lifetime elasticity multiplied by an adjustment for attenuation bias and life-
cycle effects. The measured intergenerational elasticity will therefore be lower
than would be estimated using lifetime earnings if life-cycle effects accentuate the
attenuation bias, which is likely to be the case when sons are observed earlier in
life than are fathers.

A similar result applies to estimates of mobility formed using IV methods.
If we assume that a father’s education, controlling for his earnings, does not affect
his son’s earnings (the potential cause of an upward bias on IV estimates), then
life-cycle earnings patterns result in IV estimates of elasticity as follows:

\[ \lim_{t \to \infty} \beta_{st}^{IV} = \beta \left[ \lambda' / \lambda \right]. \]

The implications of this result for mobility estimates in Brazil are examined in
Sections 4.2 and 4.3.

4.2 Observed life-cycle effects on mobility estimates

In addition to Haider and Solon, several other researchers have examined the
theoretical possibilities or empirical realities of life-cycle biases in estimates of
intergenerational mobility, including Jenkins (1987), Reville (1995), Mazumder
(2001, 2005), Chadwick and Solon (2002), Böhlmark and Lindquist (2006), and
ages of sons. Each study finds that elasticity estimates increase as the ages of
sons increases. Because these studies rely on panel data, however, they are
restricted to the examination of sons under age 40. Grawe also estimates mobility
across ages of fathers, finding mixed results.

Ferreira and Veloso (2006) examine differences in the intergenerational
wage elasticity across Brazilian cohorts between the ages of 25 and 64 in 1996.
The sample of fathers (age 25-65) is held constant in their analysis. They find
significantly lower wage elasticity estimates for younger sons / sons born later
(0.48 for 25-29 year-olds) than for older sons / sons born earlier (0.67 for 60-64
year-olds) but stress the “impossibility of identifying cohort and age effects form
a cross-section of just one year.” The analysis shown in Section 5 of this paper
overcomes this difficulty by examining sons in 1982, 1988, and 1996, while the
analysis in this section addresses (but does eliminate) the issue by examining variation across both son’s and father’s ages.

The data and analytical methods used in this paper are able to address the issue of life-cycle biases in ways not possible with many other datasets. Father’s education is available for most heads of household and for all individuals living in the same household as their father, together including individuals of almost every age. Because labor market earnings are also available for all individuals age ten and over, TSIV intergenerational mobility estimates can be made varying both the ages of sons and fathers over very wide ranges. In the analysis that follows in this section, I estimate intergenerational mobility by TSIV, first by varying the age of son while holding age of father constant, then by varying the age of father while holding age of son constant, and finally varying both sons’ and fathers’ ages from 20 through 64. In Section 4.3, I form estimates of the transmission of lifetime earnings.

I first vary the ages of sons from 20 through 64 (in 1996) for TSIV estimates of intergenerational earnings elasticity. I perform 45 regressions (one for each age of sons), using in each all sons with positive earnings, non-missing reports of father’s education, and age within two years of the age of interest. The sample of sons used in the regression reported for sons of age 21, for example, includes all sons between 19 and 23. Sample sizes at each age are at least 1,300 sons and generally over 4,000. I hold the age and year of observation of the first-stage sample of fathers constant, at 30-50 year-olds in 1976, assuming cohort effects to be minimal. Holding the year of observation of sons constant at 1996 means that both age and cohort effects will be captured by variation across age. In Section 5, I compare the magnitude of each of these effects in great detail.

Figure 2 plots the TSIV estimates and 95% confidence intervals of intergenerational earnings elasticity for sons of age 20 through 64. Extensive variation in estimated elasticity across ages of sons is evident. Sons of age 20 show an intergenerational elasticity of 0.42, and this figure grows tremendously with age, reaching a maximum of 1.02 for sons of age 49, before falling slightly as sons age further. The maximum elasticity estimate of 1.02 implies that the difference in earnings between fathers at age 30-50 is expected to equal the gap in their sons’ earnings at age 49. An examination of the relationship between sons’ log earnings in 1996 and their fathers’ levels of education shows this to be true.
The second examination of the impact of age of observation involves the variation of fathers’ ages while holding sons’ ages constant. This procedure parallels the previous one. I hold the sample of sons constant, including all sons in 1996 with positive earnings, non-missing fathers’ education, and ages from 30 through 50. I vary fathers’ ages from 20 through 64, again using five-year centered samples. Sample sizes are at least 2,300 fathers. Variation across fathers’ ages in 1976 will again capture both age and cohort effects. Figure 3 plots the regression results. The elasticity estimate of 0.86, seen for fathers of age 40 (with sons of age 30-50), matches the 0.86 elasticity estimate seen in Figure 2 for sons of age 40 (with fathers age 30-50). Figure 3 shows that the use of fathers younger than 40 increases the elasticity estimate, with the estimate increasing precipitously if fathers under age 30 are used. The use of fathers over age 40 produces remarkably stable elasticity estimates. In fact, the use of fathers of any age between 30 and 64 produces an estimated intergenerational earnings elasticity between 0.78 and 0.88. Therefore, as long as fathers of at least age 30 are used in 1976, the age at which fathers’ earnings are observed in the PNAD appears to have much less effect on mobility estimates than does the age at which sons’ earnings are observed.
As a natural extension of the two previous inquiries, I now vary the ages of both sons and fathers between ages 20 and 64 simultaneously, holding constant the year in which sons (1996) and fathers (1976) are observed. For this analysis, I group sons and fathers each into five-year age groups, creating a nine-by-nine matrix of elasticity estimates, as shown in Table 6. Standard errors for each observation range from 0.01 to 0.07, according to sample size, and average less than 0.03. The results are consistent with linear combinations of the previous analyses.

### Table 6: TSIV Estimates of the Intergenerational Earnings Elasticity across Fathers’ and Sons’ Age

<table>
<thead>
<tr>
<th>Father’s Age</th>
<th>Son’s Age</th>
<th>20-24</th>
<th>25-29</th>
<th>30-34</th>
<th>35-39</th>
<th>40-44</th>
<th>45-49</th>
<th>50-54</th>
<th>55-59</th>
<th>60-64</th>
</tr>
</thead>
<tbody>
<tr>
<td>20-24</td>
<td></td>
<td>0.69</td>
<td>0.89</td>
<td>1.10</td>
<td>1.18</td>
<td>1.32</td>
<td>1.47</td>
<td>1.40</td>
<td>1.41</td>
<td>1.33</td>
</tr>
<tr>
<td>25-29</td>
<td></td>
<td>0.54</td>
<td>0.70</td>
<td>0.86</td>
<td>0.93</td>
<td>1.04</td>
<td>1.17</td>
<td>1.11</td>
<td>1.11</td>
<td>1.06</td>
</tr>
<tr>
<td>30-34</td>
<td></td>
<td>0.49</td>
<td>0.63</td>
<td>0.77</td>
<td>0.82</td>
<td>0.91</td>
<td>1.02</td>
<td>0.97</td>
<td>0.97</td>
<td>0.92</td>
</tr>
<tr>
<td>35-39</td>
<td></td>
<td>0.48</td>
<td>0.62</td>
<td>0.76</td>
<td>0.82</td>
<td>0.91</td>
<td>1.01</td>
<td>0.97</td>
<td>0.97</td>
<td>0.91</td>
</tr>
<tr>
<td>40-44</td>
<td></td>
<td>0.48</td>
<td>0.61</td>
<td>0.75</td>
<td>0.80</td>
<td>0.89</td>
<td>1.00</td>
<td>0.95</td>
<td>0.95</td>
<td>0.90</td>
</tr>
<tr>
<td>45-49</td>
<td></td>
<td>0.47</td>
<td>0.60</td>
<td>0.74</td>
<td>0.79</td>
<td>0.88</td>
<td>0.98</td>
<td>0.94</td>
<td>0.94</td>
<td>0.89</td>
</tr>
<tr>
<td>50-54</td>
<td></td>
<td>0.46</td>
<td>0.59</td>
<td>0.72</td>
<td>0.77</td>
<td>0.86</td>
<td>0.96</td>
<td>0.92</td>
<td>0.92</td>
<td>0.87</td>
</tr>
<tr>
<td>55-59</td>
<td></td>
<td>0.45</td>
<td>0.59</td>
<td>0.72</td>
<td>0.77</td>
<td>0.86</td>
<td>0.96</td>
<td>0.92</td>
<td>0.92</td>
<td>0.87</td>
</tr>
<tr>
<td>60-64</td>
<td></td>
<td>0.45</td>
<td>0.58</td>
<td>0.72</td>
<td>0.77</td>
<td>0.86</td>
<td>0.96</td>
<td>0.93</td>
<td>0.93</td>
<td>0.88</td>
</tr>
</tbody>
</table>
4.3 The intergenerational elasticity of lifetime earnings

The results of Section 4.2 indicate that the age at which earnings of both sons and fathers are observed can significantly impact the estimated intergenerational elasticity. The question now exists, which of these estimates best approximates the true elasticity of lifetime earnings? In this section I provide two approaches to estimating this lifetime earnings elasticity. The estimation procedures employed in this section require either the assumption that cohort effects are minimal or the acknowledgement that this level of transmission represents a blended average of the true levels across cohorts, a point addressed in Section 5.

The first procedure I employ to estimate the intergenerational elasticity of lifetime earnings is to construct pseudo-panels of both sons and fathers based on the reported level of father’s education. For fathers, I assume that the earnings education profile across ages (that was shown in Figure 1) represents that of individuals across the course of their lives. While this procedure relies on the assumption that cohort effects on the education/earnings profile are minimal, the general stability of this relationship across time supports this assumption. I sum earnings across the life-cycle (according to the reported level of education) and take the log of the resulting level of lifetime earnings. I do the same for sons by the reported education of their fathers. This procedure results in one report of fathers’ log lifetime earnings and one report of sons’ log lifetime earnings for each of the ten levels of fathers’ education. The desired elasticity estimate is then obtained through the regression of the estimated values of sons’ log earnings on fathers’ log earnings, weighted by the fraction of the population of sons at each level of father’s education (I choose sons of age 30-50 in 1996 for the weighting). This procedure yields an estimated intergenerational elasticity in lifetime earnings of 0.85 for Brazil.

A second method of obtaining the true lifetime elasticity is to combine the results presented in Table 6 with the theory presented in Section 4.1. Equation 6 showed that elasticity estimates using sons of age \( t \) and fathers of age \( s \) are expected to equal the true lifetime elasticity multiplied by the ratio \( (\lambda_t/\lambda_s) \), where \( \lambda_t \) and \( \lambda_s \) are the lifetime earnings multipliers shown in Equations 4 and 5. Treating each cell of Table 6 as an independent equation, the system of 81 equations has just 19 unknowns: 9 values of \( \lambda_t \), 9 values of \( \lambda_s \), and the true lifetime earnings elasticity. Two additional equations normalize the average value of lambda (the ratio of the variation in transitory earnings, excluding measurement error, over the

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11 Specifically, I regress earnings (not log earnings) on age and age-squared individually for each level of education. I then evaluate the integral of each earnings function (to sum earnings) between ages 20 and 64, and take the log of the total.
variation in lifetime earnings) in each generation to one.\textsuperscript{12} The 19 unknowns of this overidentified model can then be estimated by minimum distance estimation.\textsuperscript{13} Performing this calculation results in an estimated lifetime earnings elasticity of 0.86, nearly identical to that obtained by the first method. If I add the restriction that $\lambda^t$ equal $\lambda^s$ when age $t$ equals age $s$ (assuming the same multiplier in the fathers’ and sons’ generations and reducing the number of unknowns in the system to ten), I obtain an estimated lifetime earnings elasticity of 0.84.

It appears that the true intergenerational elasticity of lifetime earnings is on the order of 0.85 in Brazil. This figure is 23\% higher than that obtained using sons of age 25-34 and fathers of age 30-50. Estimates of mobility using sons of relatively young ages may clearly underestimate the true level of earnings transmission. The majority of previous studies of mobility have used sons with mean ages from 25 to 35. This means that estimates of earnings transmission in these studies may be significantly lower than those that would have been obtained were observations of lifetime earnings used instead.

5. Isolating Cohort Effects on Transmission of Lifetime Earnings

The estimate presented in the previous section of the intergenerational elasticity of lifetime earnings in Brazil of 0.85 was based on observations of sons earnings reported in a single year of survey data (1996). This data usage requires either the assumption that cohort effects are minimal or the acknowledgement that this level of transmission represents a blended average of the true levels across cohorts. Fortunately, three years (1982, 1988, and 1996) of PNAD surveys asked all heads of household and their spouses to report the highest level of education completed by each of their parents. Together these three years of survey data allow the separation of age effects and cohort effects on measurement of lifetime intergenerational earnings transmission. This separation allows for both clean estimates of the level of lifetime intergenerational earnings transmission for individual cohorts in Brazil and the independent identification of the effect of age of earnings observation on estimated earnings elasticity.

5.1 Father and son samples

The sample of individuals used in the first-stage estimation in this section of the paper will again establish the relationship between fathers’ education and fathers’

\textsuperscript{12} This normalization is an approximation of the precise (and not easily estimated) normalization desired. As long as the lambdas of each generation are normalized symmetrically, however, changes in the normalization procedure will have only minor effect on the estimated lifetime earnings elasticity.

\textsuperscript{13} I thank Atsushi Inoue for suggesting this procedure.
earnings. As was done in Sections 3 and 4, an estimate of the relationship between fathers’ education and fathers’ earnings is formed using males between the ages of 30 and 50 observed in 1976. In Sections 5 and 6 of this paper, six categories of fathers’ education instrument for fathers’ lifetime earnings: 0 years of completed education, 1-3 years (incomplete lower primary), 4 years (complete lower primary), 5-8 years (at least some upper primary), 9-11 years (at least some secondary), and 12 or more years (at least some post-secondary education).14

The sample of sons used in the second stage of the TSIV regression in Sections 5 and 6 of this paper includes individuals from age 20 through 64 in 1982, 1988, and 1996. Examining sons from this large age range in three survey years allows for the separation of age effects from cohort effects and the identification of the intergenerational transmission of lifetime earnings.

5.2 Sample selection

The sample of sons used in Sections 5 and 6 consists of males between the ages of 20 and 64 in 1982, 1988, and 1996 with positive earnings and a report of their father’s education. The selection of observations into this sample was performed similarly to that of the 1996 sample of 25-34 year-old sons, as described in Section 3.1.

There are essentially three dimensions by which this sample of sons is selected. Using the case of the 1996 data, I examine the effects of each selection dimension. First, individuals must be the head of a household. 25% of all individuals do not meet this requirement. The summary statistics indicate that this dropped group is relatively young and is disproportionately not working. The second dimension on which the sample is selected is the voluntary reporting (or knowledge) of father’s education for household heads. The individuals excluded from the sample by this requirement (19% of all individuals) report relatively low levels of earnings. The third dimension on which sons are selected into the sample is the reporting of positive earnings, a necessary selection requirement if log earnings are used in the analysis. An additional 8% of all individuals are dropped from the sample as a result of this requirement. Potential biases caused by these three dimensions of selection would be similar to those for the 1996 sample of 25-34 year-old sons, as described in Section 3.1.

14 These six categories of education were used in the 1982 and 1988 PNAD surveys. While ten categories were reported in the 1996 survey (splitting some of the six categories reported above), throughout Sections 5 and 6 I collapse these ten categories into the same six reported in the 1982 and 1988 surveys of this paper for consistency across survey years.
5.3 Changes in lifetime earnings elasticity across cohorts

In the PNAD surveys of 1982, 1988, and 1996, all heads of household are asked to report their parents’ levels of education. TSIV estimates of mobility can therefore be estimated in each of these years. Figure 4 plots these elasticities, estimated by the pseudo-panel method outlined in Section 4.3. The sample of fathers consisted of males age 30 through 50 with positive earnings observed in 1976 in the regressions of each of the three years. Holding the sample of fathers used in the first-stage regression constant maintains the same relationship between fathers’ earnings and fathers’ education, an assumption largely supported by empirical observation. The variation in elasticity estimates observed over time is therefore a result of changes in the relationship between fathers’ education and sons’ earnings.

Figure 4: Intergenerational Earnings Elasticity across Age by Year

The elasticity age profile is fairly similar in each of the three years. Although the peak of the elasticity estimates is much earlier in 1982 (at age 38) than it is in 1988 (age 47) or 1996 (age 51), a concave profile of estimated elasticity is present in each year between the ages of 20 and 55. Elasticity estimates formed using sons of 40 to 50 are roughly 60% greater than those using sons of age 20. The increases in elasticity observed after age 55 in all three years is due to significant increases in the variance of log earnings, in part a result of the reduction in work hours by some individuals. At almost any age between 20 and 45, the elasticity estimated for 1982 is significantly greater than that estimated for 1988, which is in turn greater than that estimated for 1996. At age 35, where
these differences are quite large, elasticity was estimated to be 0.96 in 1982, 0.88 in 1988, and 0.82 in 1996.

Modifying Equation 6, which described changes in elasticity estimates across age, the following equation models earnings elasticity for a particular birth cohort, c, at a particular age, a, as a function of the elasticity of lifetime earnings for this cohort and a return to education age-specific lambda coefficient:

\[
\beta_{a}^{c} = \lambda_{c}^{a} \beta_{a}^{a}.
\]

Using this equation in log form, I estimate the separate effects of age and cohort on the elasticity estimates shown in Figure 4. I regress the 135 log elasticity estimates at single ages from 20 through 64 in 1982, 1988, and 1996 on linear and squared terms for the log of age at which individuals are observed and the log of the birth cohort to which individuals belong. The results of this regression are displayed in Figures 5 and 6.

I do make the assumption that the variances of transitory errors in earnings are stable across ages and across time. If this is not the case, any of the 135 individual elasticity estimates may be biased and the observed differences in earning elasticity across age or time may in fact be due to differences in measurement error.

**Figure 5** plots the estimated partial effect of age of earnings observation on elasticity, holding the cohort constant at the 1948 birth cohort. The results indicate that elasticity estimated for any cohort of individuals across their lifecycle is expected to peak near age 45. Estimates using earnings observed at age 20 will be just 75% of those seen at age 45, while those using earnings at age 30 are expected to be just over 90% of those at age 45.

**Figure 6** plots changes in elasticity estimated across birth cohorts when age of earnings observation is held constant at 40. As Figure 6 shows, individuals born in 1935 are estimated to have experienced a 38% higher level of earnings elasticity than individuals born in 1975. In other words, elasticity is shown to have fallen by nearly 30% across a 40-year span of individuals. Section 6 will examine the possibility that changes in the intergenerational transmission of education are responsible for this decrease in intergenerational earnings transmission across cohorts.
**Figure 5: Intergenerational Earnings Elasticity across Age, Holding Cohort at 1948**

Sons: household heads with positive earn. reporting father's educ.
Fathers: males age 30-50 with positive earnings in 1976

**Figure 6: Intergenerational Earnings Elasticity across Cohort, Holding Age at 40**

Sons: household heads with positive earn. reporting father's educ.
Fathers: males age 30-50 with positive earnings in 1976
6. Educational Mobility as a Determinant of Earnings Mobility

There are a number of potential pathways the intergenerational transmission of earnings can, and likely does, take. There are genetic factors, such as ability and physical attractiveness, passed from parents to child. There are experiences, traits, and knowledge children gain through growing up with their parents. And there are experiences that parents provide children indirectly. Included in this last category is the most significant experience of most children’s lives - education. In Brazil, education is an experience that both results in significant return in the labor market and is provided severely disproportionately according to the income of one’s parents. Education may therefore be the most significant pathway by which earnings are transmitted across generations. Furthermore, it is the mechanism by which Brazil may have achieved the 30% reduction in the intergenerational transmission of lifetime earnings across forty years observed in the previous section.

This section analyzes this reduction in the intergenerational transmission of earnings that has occurred in Brazil. I present the view that the reductions in the transmission of earnings over time in Brazil were due almost entirely to reductions in the transmission of education. That is, as educational outcomes became less dependent on birth status across cohorts, equality in earnings opportunity soon followed. Lam (1999, p.2) discusses this hypothesis, stating that “unequal distribution of education, both in quantity and quality, is viewed as contributing to inequality in labor market earnings, and as a key factor in the intergenerational transmission of inequality”. This view coincides with the belief that education is a significant pathway by which earnings are transmitted across generations.

6.1 The transmission of earnings through education

Most researchers who have theoretically addressed the determinants of intergenerational mobility have employed human capital acquisition models similar to that laid out by Becker and Tomes (1979). Becker and Tomes model private investments in the human capital of children as a function of parents’ earnings and the value parents place on their children’s consumption, relative to their own. In one of the most recent papers of this genre, Solon (2003) models human capital attainment as a function of investments made by parents and government and an individual specific level of human capital endowment. Solon shows the intergenerational elasticity in a particular society at a point in time to be a function of the return to human capital, the productivity of investments made to human capital, the progressivity of public investment in human capital, and the heritability of human capital endowment. A number of papers have used the framework described by Solon to make international comparisons of the
transmission of earnings and consider the underlying processes that may be behind cross-country differences, including Esping-Andersen (2004), Corak (2006), and d’Addio (2007).

I present a considerably simplified version of Solon’s model to investigate the impact of the progressivity of human capital attainment and the return to human capital on the intergenerational transmission of earnings. The following equation models a son’s level of human capital attainment as a function of parental investments \(I_{0i}\), government investments \(G_{0i}\), and an inherited human capital endowment \(e_{1i}\):

\[
(8) \quad h_{ui} = F(I_{0i} + G_{0i}) + e_{ui}.
\]

We may expect that both parental investments in human capital and the inherited endowment of human capital will be increasing in fathers’ earnings. It is unclear whether government investments are increasing with fathers’ earnings and especially whether the marginal impact of government investments would be greater for sons of richer or poorer fathers (especially if the investment transformation function is concave). The relative progressivity (with respect to fathers’ earnings) of parental and government investment, the investment transformation function \(F\), and the progressivity of inherited human capital endowment determine the progressivity of human capital attainment, or in other words, the intergenerational transmission of human capital. In the empirical analysis of this paper, I assume no functional form for the transformation of investments to human capital, and instead examine human capital attainment (not investments) in the empirical analysis.

The following equation models a son’s lifetime log earnings as equal to a constant term plus his level of human capital multiplied by the return to human capital \(p\):

\[
(9) \quad y^L_{ui} = \mu + ph_{ui}.
\]

If the return to human capital decreases, while holding the variance of this return constant, each son’s earnings will depend to a greater extent on the constant term, and cross-sectional inequality of earnings will be reduced. An increase in the return to human capital would create greater dispersion in sons’ earnings and would thus be expected to increase the estimated intergenerational earnings elasticity. The partial derivative of sons’ log earnings with respect to fathers’ log earnings (or the intergenerational earnings elasticity) will equal the return to human capital multiplied by the partial derivative of sons’ human capital attainment with respect to fathers’ earnings:

\[
(10) \quad \partial y^L_{ui} / \partial y^L_{ui} = p^* (\partial h_{ui} / \partial y^L_{ui}).
\]
Differences in intergenerational mobility across countries, regions within a country, or across time may therefore be seen as a result of differences in the return to human capital, and the intergenerational transmission of human capital.

6.2 Estimation methods

Using completed years of education as a proxy for human capital, I estimate both the return to education and the intergenerational transmission of education as measures by which to evaluate the model presented above. These variables are estimated for each group within the samples of individuals used in the analysis of changes in intergenerational earnings transmission across time presented in Section 5 of this paper.

I estimate the return to education through a standard regression of log earnings on a linear education term and controls for age:

$$y_i = \alpha + \phi_1 \text{educ}_i + \phi_2 \text{age}_i + \phi_3 \text{age}_i^2 + \epsilon_i.$$ 

The estimated $\hat{\phi}_1$ coefficient is the linear return to education.

As a summary measure of the intergenerational transmission of education, I use the slope coefficient obtained by a regression of sons’ education on fathers’ education:

$$\text{educ}_i = \delta + \gamma_1 \text{educ}_{i-1} + \nu_i.$$ 

An example of this estimate is the 0.88 slope coefficient estimated for all 40-44 year-olds in 1996.

6.3 Explaining changes in earnings transmission over time

Brazil has seen rapid expansion of schooling institutions and significant growth in completed education in the past forty years (see Lam (1999)). The growth in schooling is apparent in the gap in education between sons and their fathers. In 1996, 20-64 year old male heads of household reported a mean value for their fathers’ education of just 2.43 years of completed schooling. The sons themselves had mean schooling of 5.86 years, well over twice as much. More recent advances in schooling can be seen through the comparison of 30-34 year-old males from 1976 through 2002, as shown in Figure 7. This figure plots, for 1976, 1982, 1988, 1996, and 2002, the percent of the population who had attained each grade or higher. Continual significant advances in the educational attainment of each grade through grade eleven (the completion of secondary school) can be seen throughout this time period (the lack of advancement in attainment of college and post-graduate schooling after 1982 is, however, quite startling). While in 1976 just over half of males 30-39 had attained at least four years of schooling (the typical grade at which lower primary schooling is completed), nearly 80% of
individuals had in 2002, 26 years later. Similarly, while under 20% of individuals in 1976 had completed upper primary schooling (with eight or more years of education), nearly half of all individuals in 2002 had. Finally, the percent of individuals completing secondary schooling (at grade eleven) has grown from 12% in 1976 to over 30% in 2002.

Figure 7: Educational Attainment across Time

While the growth in educational attainment has been rapid, the relationship between fathers’ and sons’ education is remarkably stable across time. Figure 8 shows the mean value of the education of sons (age 30-49) for each of the six reported levels of fathers’ education in 1982, 1988, and 1996. This concave curve has remained relatively stable across this period of growth in mean education, though the mapping appears slightly more progressive in the 1988 and 1996 data than in that of 1982. The ‘pluses’ on Figure 8 mark the mean values of sons’ and fathers’ education in each year (with increasing values across time). In the 14 years between 1982 and 1996, the mean education of sons 30-49 increased from 4.4 years to 6.2 years, while that of their fathers increased from 1.6 years to 2.6 years. Increases in mean educational attainment across time can be largely explained by increases in parental education. As the 45° line helps to indicate, an amazing pattern is shown in which sons complete, on average, one level of schooling greater than what their fathers did. That is, fathers with no schooling tend to have sons who complete lower primary (4 years), who have sons who complete upper primary (8 years), who have sons who complete secondary school (11 years), whose sons complete two years of college.
The stability of the relationship between fathers’ and sons’ earnings may appear to indicate that the transmission of education is not changing across time, which is true in a sense. On the other hand, however, the concavity of this relationship means that the slope of the relationship differs at different points along the curve. If fathers’ mean education is changing over time (as is indeed the case), then the marginal increase in sons’ education for a given increase in fathers’ education (the slope of sons’ education with respect to fathers’ education) will decrease over time. If the return to each year of education is approximately equal (which is also the case) then smaller differences in sons’ education will translate directly into smaller differences in sons’ log earnings (and, all else equal, decreases in earnings elasticity). For this reason, the slope coefficient of sons’ education regressed on fathers’ education is the measure I choose to represent the intergenerational transmission of education.

Table 7 reports the estimated levels of intergenerational education transmission (the slope of sons’ education regressed on fathers’ education) for 20-64 year-olds in 1982, 1988, and 1996. The full sample of sons 20-64 years-old observed in these three PNAD surveys consists of 178,422 individuals, which I divide into 27 groups, by year of observation and five-year age clusters. Looking at individuals 40-44, for example, shows an estimated slope coefficient for the
regression of sons’ education on fathers’ education of 0.95 in 1982, 0.93 in 1988, and 0.88 in 1996. Table 7 also shows that the level of education transmission remains relatively constant as any particular birth cohort ages. Interestingly, the intergenerational education transmission slope is shown to decrease both between 1982 and 1988 and between 1988 and 1996. As Figure 8 showed, the relationship between fathers’ and sons’ education remained stable between 1988 and 1996. This pattern indicates that the change in education transmission over the 1988 to 1996 period was the sole result of movement along the education transmission curve and not due to a shift in it.

Table 7: Variation in Education Transmission and Return across Time

<table>
<thead>
<tr>
<th>Age range</th>
<th>Education Transmission</th>
<th>Return to Education</th>
</tr>
</thead>
<tbody>
<tr>
<td>20-24</td>
<td>0.75</td>
<td>0.63</td>
</tr>
<tr>
<td>25-29</td>
<td>0.85</td>
<td>0.75</td>
</tr>
<tr>
<td>30-34</td>
<td>0.94</td>
<td>0.84</td>
</tr>
<tr>
<td>35-39</td>
<td>0.99</td>
<td>0.91</td>
</tr>
<tr>
<td>40-44</td>
<td>0.95</td>
<td>0.93</td>
</tr>
<tr>
<td>45-49</td>
<td>0.94</td>
<td>0.90</td>
</tr>
<tr>
<td>50-54</td>
<td>0.91</td>
<td>0.86</td>
</tr>
<tr>
<td>55-59</td>
<td>0.87</td>
<td>0.92</td>
</tr>
<tr>
<td>60-64</td>
<td>0.92</td>
<td>0.90</td>
</tr>
<tr>
<td>Combined</td>
<td>0.93</td>
<td>0.87</td>
</tr>
</tbody>
</table>

It should be noted that these levels of educational transmission are extraordinarily high by international standards. Lam (1999) has compared the intergenerational transmission of education in Brazil and South Africa, two countries with nearly the highest level of cross-sectional inequality in the world. He finds that there exists a much steeper slope for the relationship between mother’s education and children’s education in Brazil than in South Africa. For South Africa, Lam finds the mean years of schooling of 17-year-olds of mothers with no schooling to be 7.7 years, while the mean schooling of children of mothers with 15 or more years of schooling was 10.7 years, 39% higher. In contrast, the mean schooling of 17-year-olds of mothers with no schooling in Brazil is 3.8 years, while that of children of mothers with 15 or more years of schooling is 9.4 years, a full 147% higher. Lam goes on to note (1999, p. 17) that, “the much stronger relationship between parent’s education and children’s education in Brazil is potentially an important factor in the intergenerational transmission of inequality”. 
I now estimate the intergenerational earnings elasticity, by TSIV, of the 27
groups of individuals whose education elasticities are displayed in Table 7. The
sample sizes and resulting intergenerational elasticity estimates of each group are
presented in Table 8. As was shown in Section 5, significant reductions in
earnings elasticity are observed across time, while the effect of age of earnings
observation on elasticity estimates continues to be present.

Table 8: Variation in Intergenerational Earnings Elasticity across Time

<table>
<thead>
<tr>
<th>Age range</th>
<th>Sample Size</th>
<th>Elasticity Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>20-24</td>
<td>5,581</td>
<td>2,790</td>
</tr>
<tr>
<td>25-29</td>
<td>11,213</td>
<td>5,939</td>
</tr>
<tr>
<td>30-34</td>
<td>12,430</td>
<td>7,019</td>
</tr>
<tr>
<td>35-39</td>
<td>10,583</td>
<td>6,731</td>
</tr>
<tr>
<td>40-44</td>
<td>9,432</td>
<td>5,627</td>
</tr>
<tr>
<td>45-49</td>
<td>7,391</td>
<td>4,434</td>
</tr>
<tr>
<td>50-54</td>
<td>6,287</td>
<td>3,599</td>
</tr>
<tr>
<td>55-59</td>
<td>4,413</td>
<td>2,657</td>
</tr>
<tr>
<td>60-64</td>
<td>2,743</td>
<td>1,827</td>
</tr>
<tr>
<td>Combined</td>
<td>70,073</td>
<td>40,623</td>
</tr>
</tbody>
</table>

The relationships between the intergenerational earnings transmission,
intergenerational education transmission, and return to education can be used to
establish the association between the intergenerational transmission of lifetime
earnings and the intergenerational transmission of education. Using a single
observation for each of the 27 year-by-age groups made of 20-64 year-olds in
1982, 1988, and 1996 presented in Tables 7 and 8, I regress estimated
intergenerational earnings elasticity on linear education transmission and return to
education terms. The results of this regression are shown under the heading
Regression 1 in Table 9. The estimated coefficients on return to education and
the intergenerational education slope are both significant at the 1% level. The $R^2$
value of this regression is a very high 0.96, indicating that variation in
intergenerational mobility across age and time is almost fully explained by
variation in these two determinants.
The estimated coefficients on education transmission and return are quite large. A change of one unit of education transmission results in a 0.74 unit change in elasticity. This implies that a change in the intergenerational education slope of 0.38 units, the difference observed between the 1935 and 1975 birth cohorts, is estimated to increase earnings elasticity by 0.28 units, the change in elasticity observed across these cohorts. The estimated coefficient of 3.91 for the return to education is also quantitatively significant. Each 0.02 unit increase in the return to education, the difference observed between 30 and 50-year-old males, is found to increase the intergenerational earnings elasticity by 0.08, the increase observed between using earnings at age 30 and 50.

As was apparent from Table 9, education transmission changes significantly across cohorts, while return to education varies across age. The return to education therefore explains why estimated levels of earnings elasticity change significantly across sons’ ages, while education transmission explains changes in the transmission of lifetime earnings across cohorts. While the analysis of Section 4 was concerned with the measurement of elasticity across age, the analysis of this section is concerned with the relationship between the intergenerational transmission of lifetime earnings and the intergenerational
transmission of education. It may therefore be of use to modify Regression 1 to better control for changes across age. The addition of controls for the age of individuals, through a set of eight dummy variables, tests the possibility that the significance of education transmission is due to correlation with other age-specific unobservables that drive earnings elasticity. The results of this regression are indicated as Regression 2 in Table 9.

As is consistent with casual observation of Table 7, the effect of education transmission is robust to the inclusion of age controls. While the coefficient estimate declines slightly to 0.61, it remains statistically different from zero at even the 1% level. The coefficient on return to education declines significantly to 2.07 in Regression 2, a result of its strong correlation with age, though it also keeps statistical significance.

As a further robustness check on the causality of education transmission on earnings transmission, I added dummies for the year of observation in Regression 3. This addition tests for the possibility that exogenous changes over time, correlated with education transmission, drive changes in earnings elasticity. As seen in Table 9, the year dummies are significant neither quantitatively nor statistically, while the coefficient estimate and statistical significance of education transmission does not change. As nearly all variation in education return is captured by the age and year dummies, the linear education return term is no longer significant in Regression 3. The intergenerational transmission of education is therefore highly correlated with the intergenerational transmission of earnings, even when controls for age and year are included in the regression.

While the regression results presented in Table 9 are all consistent with a direct link between education transmission and return and earnings elasticity, the possibility still exists that one or more omitted variables may be driving these results. If an omitted variable were highly correlated with both educational attainment and labor market earnings, then the significant relationships shown in Table 9 could be estimated in the absence of a causal mechanism. As Bowles (1972) suggested, a strong causal effect of social class background (which is left unobserved in the above regressions) could be misinterpreted as a causal effect of education on earnings and thus education transmission on earnings transmission.
7. Concluding Remarks

This paper uses unique large-scale, high-quality data to estimate the intergenerational transmission of earnings in a developing country and to reveal information about the measurement of earnings elasticity. Employing a two-sample instrumental variables method, this paper is able to construct estimates of the intergenerational elasticity of lifetime earnings, which is found to differ substantially from earnings elasticity measured at relatively young ages. Moreover, by incorporating data from multiple survey years, this paper separates cohort effects of changes in earnings transmission from these age measurement effects. Finally, the paper found that education may be the most significant pathway by which earnings are transmitted intergenerationally in Brazil.

Brazil’s high level of cross-sectional inequality, high return to education, and significant intergenerational transmission of education all lead one to expect that Brazil may have among the world’s highest level of earnings transmission. This paper finds that to be the case. Estimates of intergenerational earnings elasticity were made for two samples of individuals of age 25-34, comparable to other studies in this literature. Estimates of earnings mobility were first made by two-sample instrumental variables regressions for all males with reports of their father’s education. This method, which used fathers’ education to instrument for fathers’ earnings, found the elasticity of the earnings of sons of age 25-34 with respect to the earnings of their fathers to be 0.69. Traditional OLS methods of mobility estimation were also conducted for the subset of individuals of this first sample for whom fathers’ earnings were directly observed. This method resulted in an elasticity estimate of 0.53. Both methods of estimation indicate that Brazil has one of the highest levels of intergenerational earnings transmission currently observed.

The paper shows the importance of the age at which earnings are observed for any elasticity estimate. Estimates of mobility formed using sons of relatively young ages are found to significantly underestimate the true intergenerational elasticity in lifetime earnings. This paper outlines two methods by which an improved measure of the intergenerational transmission of lifetime earnings may be obtained. Applying these procedures to the data of Brazil provides an intergenerational lifetime earnings elasticity estimate of 0.85.

This paper examined the earnings elasticities of individuals born over a 58-year span. Using data from the 1982, 1988, and 1996 PNAD surveys, life-cycle measurement effects were separated from changes in the underlying transmission of lifetime earnings across cohorts. Life-cycle measurement effects were shown to produce elasticity estimates for sons of age 20 just 75% of those formed for sons of age 45.

This paper also provided an analysis of the determinants of intergenerational earnings mobility. The significant variability of earnings
transmission across time in Brazil provided the opportunity for a within-country comparison of the transmission of earnings to that of education. The hypothesis that education transmission largely shapes the level of intergenerational lifetime earnings mobility faced by a population was supported.

Taken together, education transmission and education return were found to explain over 90% of the variation in earnings elasticity across age and cohort. The return to education was found to vary with the age at which earnings were observed, while the level of education transmission was found to vary with earnings elasticity changes across cohort. The reductions in Brazil’s level of lifetime earnings transmission seen over the last half-century were found to coincide with reductions in the level of educational transmission.

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Dunn: The Intergenerational Transmission of Lifetime Earnings


