Trends in Intergenerational Earnings Mobility

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Abstract

This paper examines the trend in intergenerational earnings mobility by estimating ordinary least squares, quantile regression, and transition matrix coefficients using five cohorts from the Panel Study of Income Dynamics, observed between 1968 and 1993. The results indicate that mobility increased for sons with respect to fathers and remained constant for sons and daughters with respect to mothers. Moreover, the findings from the father-son sample suggest that the difference between the mobility levels of the rich and the poor narrowed over this period. The estimated pattern of changing mobility is consistent with an increasing rate of regression to the mean.

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1 Introduction

Are children destined to have the same socioeconomic status as their parents? The measurement of the *level* of intergenerational earnings mobility provides an answer to this fundamental question of equality of opportunity. The literature on this subject from the last decade has provided a widely accepted estimate of this level (or at least a range of estimates) for one cohort of fathers and sons (Solon, 1992; Zimmerman, 1992; and see Solon (1999) for a review). However, a second related and equally important question also must be addressed and thus is the subject of this study. Is this level of mobility measured from one cohort generalizable to other cohorts? That is, is this level of mobility *constant over time*? Moreover, this question is of particular significance in light of growing earnings inequality over the last several decades. The implications of growing inequality, as well as the set of possible policy prescriptions, are quite different in the case of inequality growth with falling mobility as opposed to the case with stable or rising mobility.

As an illustration, imagine two societies, A and B, which both initially have a sustained period of unchanging inequality and some stable level of intergenerational earnings mobility. A change occurs in Society A such that access to opportunities is more limited for the poor causing overall mobility to fall. If all else remains the same, we would expect to see increasing inequality in Society A as the poor get poorer and the rich get richer. At the same time, Society B experiences an increase in earnings variation due to factors independent of parents' earnings, such as a shift to higher job turnover in some industries. In this case, intergenerational mobility might remain stable or even increase as inequality grows. In Society A, these changes might stimulate the enactment of policies aimed at increasing the availability of opportunities for the underprivileged. On the other hand, as long as the proportion of the population in poverty does not rise, Society B might not be concerned at all with growing inequality given its source. Hence, by examining whether mobility has changed over time, we not only can consider the applicability of the mobility level estimate for all cohorts, but also can determine whether any changes in mobility contributed to the observed changes in inequality.

To address these issues, I investigate mobility levels across cohorts that span a nine-year period which coincides with inequality growth. In particular, I use as a starting point a cohort of parents and children similar to that examined in Solon (1992) which generated a highly referenced mobility estimate of 0.4:[1] the adult children between the ages of 21 and 40 in 1985 of parents in the core Panel Study of Income Dynamics (PSID) sample observed between 1968 and 1972. I measure the trend in mobility using several successive, comparable cohorts. In addition to the standard ordinary least squares (OLS) analysis, I also examine the trend in mobility using two other techniques – quantile regression and transition matrices – to identify any differential changes across earnings groups. The key differences between the approach used in this paper and the literature are that I allow for some comparison to the mobility level research, I analyze the trends by earnings groups, and I examine the trends involving female members of the family as well.

The main findings are that the mobility between fathers and sons increased over time, indicating that it is inappropriate to assume that the mobility level experienced by one

[1]This 'mobility estimate' is technically the estimated elasticity of the son's earnings with respect to the father's earnings where a value near one indicates limited mobility, i.e., the son's and the father's earnings were highly correlated; and a value near zero indicates high mobility, i.e., the father's earnings did not systematically influence the son's earnings.

cohort applies to other cohorts. Moreover, as mobility was not found to have declined over this period, mobility could not have contributed to growing inequality. That is, over the period in which inequality rose, the variation in earnings became more dependent on other factors and less dependent on father's earnings. In addition, the quantile regression estimates reveal that the mobility of sons with respect to fathers is lower at the bottom of the son's conditional earnings distribution than at the top, but that over time, this gap narrows. The transition matrices suggest that sons of fathers in the highest quintiles of the earnings distribution became less likely to achieve at least their fathers' quintile. At the same time, sons of fathers in the lowest quintiles became more likely to surpass their fathers' quintile. These findings are consistent with an increasing rate of regression to the mean with respect to father's earnings.

The remainder of this paper is organized as follows. I begin in Section 2 by reviewing the literature measuring the levels of intergenerational mobility as well as a few studies examining the changes in mobility over this period. Section 3 describes the data. Section 4 presents the econometric models used in this study. Section 5 provides the results and some interpretations. Section 6 provides concluding remarks and offers areas of future research. An Appendix provides some technical details regarding the use of quantile regression.

2 Background

The Solon and Zimmerman papers from 1992 produced the now well-known mobility estimate of 0.4 and are two of the most cited papers in this literature.[2] However, before these studies,

[2]Many studies following the publication of these papers have generated a variety of estimates in an attempt to measure mobility with slightly different samples and methods. In a survey by Solon (1999), ten studies using the PSID are listed with mobility estimates ranging from 0.13 to 0.53.

the extent of intergenerational earnings mobility between sons and fathers was believed to be 0.2 or less, implying that society was highly mobile (Sewell & Hauser, 1975; Bielby & Hauser, 1977; Behrman & Taubman, 1985; and Becker & Tomes, 1986). Because this earlier wave of studies involved data limitations which produced biases in the results from measurement error and homogeneous samples (e.g., white male twin samples, or high school graduates from Wisconsin) (Atkinson, Maynard, & Trinder, 1983; and Solon, 1989, 1992), the more recent estimates – which addressed these problems – are regarded as more generalizable.

Most of the research has employed simple OLS to measure the mobility level at the mean of the son's conditional earnings distribution. However, quantile regression has been applied (Eide & Showalter, 1999) and transition matrices have been constructed (Peters, 1992; Zimmerman, 1992) to determine the cross-sectional mobility levels across earnings groups. By examining various quantiles, Eide and Showalter (1999) find that mobility is lowest for the lowest quantiles. Through transition matrices, Peters (1992) shows that mobility is lowest for those whose parents are in the lowest and the highest income quartiles, and Zimmerman (1992) demonstrates that there is somewhat more upward mobility from the bottom than downward mobility from the top.

Most mobility level studies have concentrated on fathers and sons since the labor market behavior of women varies more than men in terms of hours and periods of non-employment making relationships difficult to discern. However, the exceptions include Behrman and Taubman (1985), Peters (1992), Altonji and Dunn (1991), and Chadwick and Solon (2000). Behrman and Taubman (1985) found intergenerational earnings correlation of sons and daughters with respect to the father to be 0.07. Peters (1992) estimated the correlation for parents and daughters to be 0.28. Altonji and Dunn (1991) found earnings correlations of 0.22 for father-son pairs, 0.21 for father-daughter pairs, 0.14 for mothers and sons, and 0.16 for mothers and daughters. Chadwick and Solon (2000) estimate that the elasticity of daughter's family income to parents' family income is 0.43.

There are at least three papers which address trends in mobility in the literature with findings that vary considerably. Using the PSID, Mayer and Lopoo (2001) find that sons who are age 30 in the mid-1980s have significantly lower mobility than sons who are 30 in the mid-1990s. Using data from the Occupational Changes in a Generation Surveys, the Survey of Income and Program Participations, the the General Social Surveys, Hauser (1998) uses father's income proxied by the mean income of his occupation and finds no trend in mobility between 1972 and 1996 for non-black men between the ages of 25 and 34. Finally, using the National Longitudinal Survey of Labor Market Experience of Young Men and Youth, Levine (1999) argues that the effect of family background increased between sons aged 24 to 32 in 1976 and sons of those ages in 1989. His analysis involves comparing across the two cohorts the coefficients on log parents' income and the change in R^2 when family background variables are controlled. He finds that the coefficient and the change in R^2 are significantly higher in the later cohort implying that the importance of family rose.

Given that these findings are so varied, it is clear that additional work is required in the area of mobility trends. My findings are consistent with those of Mayer and Lopoo (2001), mostly likely because our data and approach are similar. The key differences in our approaches are the assignment of sons to cohorts and their focus on income mobility compared with my examination of earnings mobility. On the other hand, the findings are in contrast to both the Hauser (1998) and the Levine (1999) papers. This is not entirely surprising given that these studies involved different data sets, the construction of income proxies in Hauser's case, and a strikingly different perspective about the measurement of the importance of family background in the case of Levine. In addition to supporting the evidence on rising mobility between sons and fathers at the mean, the analysis presented here also examines changes in mobility of daughters and with respect to mothers as well as investigates changes in mobility by earnings groups.

3 Data and Sample

The data used in this study come from the PSID. Since the PSID continues to interview children who have moved out of their parents' household, it is well-suited for intergenerational analysis. However, for an analysis of a trend, it is not a long panel so defining a cohort structure is not a trivial undertaking. One approach to the measurement of the trend in mobility would be to use data on children born in different years whose earnings were observed at a common age. This is how Mayer and Lopoo (2001) tackle this question. However, in the mobility literature, mobility is never measured for one age group at a time. It is measured using a sample with children's ages ranging from their 20s to age 40 or younger generally. In light of this, the strategy for assigning children to cohorts pursued here reflects an attempt to measure mobility over time in a way that is comparable to the mobility level research. That is, the cohorts are constructed such that the years in which the adult children are observed varies by cohort but the range of ages and the average age when the adult children are observed are the same across cohorts.

I extract five cohorts of matched parents and children.[3] The first cohort of parent-child pairs is comparable in many ways to the Solon (1992) study. The parent's earnings are taken from the 1968 through the 1972 interviews and the child's earnings are taken from the 1985 through the 1989 interviews.[4] Every subsequent cohort is created by dropping the earliest year of observation used in the previous cohort and adding a later year, keeping the number of years of observation constant. The fifth, and final, cohort takes the parent's earnings from the 1972-76 interviews and the child's earnings from the 1989-93 interviews. In all cohorts, 17 years separate the parent's initial observation of earnings from the child's.[5]

I estimate the mobility level for each cohort separately so that comparisons to the literature can be made, but, to measure the trend, I pool the cohorts. One consequence of this cohort structure is that the cohorts overlap considerably. That is, most of the children in cohort t are in cohort $t+1$ as well. This characteristic is of particular concern when the cohorts are pooled as the autocorrelation implies greater variance when OLS is applied. Because of this issue, when I pool the cohorts, I only include one observation per individual from a randomly selected cohort.[6] This strategy ensures that changes across cohorts are captured separately from any changes across the life-cycle.

The sample extraction criteria for each cohort is identical. All observations are selected

[3]Throughout this paper, *parent-child* mobility should be understood to refer to the mobility between any of the following four combinations: father-son, father-daughter, mother-son, and mother-daughter.

[4]Solon (1992) only uses the child's earnings from the 1985 interview.

[5]Given the length of this panel data, the cumulative effects of even low annual attrition rates could potentially have a large impact on this exercise. However, in an analysis of the impacts of sample attrition in the PSID, Fitzgerald, Gottschalk, and Moffitt (1998) did not find evidence of attrition bias in the intergenerational earnings relationship. Thus, I do not use attrition weights.

[6]The sample characteristics of the non-overlapping cohorts are similar to those of the overlapping cohorts reported later in Table 1 with one important exception. The non-overlapping cohorts are slightly negatively correlated with average observation ages. Thus, the later cohorts have a lower average age. This characteristic tends to bias the trend downward as intergenerational earnings mobility decreases with the age at which the son's earnings are observed (Reville, 1995). To remedy this issue, when the cohorts are pooled, I control for the interaction effect of observation age and parent's earnings.

from the core sample. Parents in the sample are under 70 years of age and have earnings of zero or higher in at least three of the five observed years, i.e., he/she can have missing data in at most two of the five years.[7] The inclusion of zero-earnings observations has been avoided in the intergenerational earnings mobility literature by convention.[8] However, omitting individuals with periods of unemployment or non-employment presents a limited picture of mobility. The 'three years out of five' restriction is imposed to maximize the sample size while still obtaining a reasonable number of earnings observations from which to compute a proxy for permanent earnings. Additionally, in the non-missing years, employment status cannot be reported as retired, disabled, a student, or other, since the earnings of these individuals are not representative of the market return to skills or ability.[9]

Each child in the sample lives in their parent's household in the first year I observe the parent's earnings. Children are at most 23 years old while living with their parents. This restriction excludes those who leave home at late ages as we expect their labor market behavior to be atypical, yet still includes some college-educated children who remain members of the parent's household while in school.[10] Additionally, each child has been out of school for at least three years when I observe his/her earnings, has earnings of zero or higher in all

[7]Earnings are defined as all wages and salaries including overtime, tips, commissions, bonuses, and any other form of payment for labor services. Any observations which have relevant variables imputed by 'major assignment' are excluded from the sample.

[8]See Couch and Lillard (1998) for an evaluation of the effect of including zero-earnings observations.

[9]The employment status of wives was not recorded until 1975 hence I do not restrict mothers by employment status in any of the cohorts.

[10]In accordance with the finding that intergenerational earnings mobility decreases with son's age (Reville, 1995), I find that the consequence of lowering the upper limit on the child's age from 23 to 17 years old when the parent's earnings are first observed using this data is higher mobility. The fact that the earnings of older sons exhibit less mobility than the earnings of younger sons could imply that the younger sons have not yet reached an earnings level representative of their permanent earnings. Unfortunately, there are trade-offs in observing the sons at older ages using the PSID which prevent further improvements along this line. For the daughter samples, the elasticity is inversely related to the average age of the daughter probably because older daughters are more likely to have children and stay at home or work part-time. Thus, their earnings are most representative of the market return to their ability and skills when they are younger.

five of the observed years, and does not report their employment status as retired, disabled, a student, or other in the relevant years. The no-school requirement ensures that, regardless of education level, the children have gained a minimal level of potential labor market experience before their earnings are observed. Unlike other work (Solon, 1992) which only use one year of the son's earnings, I require five years. The rationale is that at this state in the lifecycle, one year of earnings, or even 3 years as I allow in the parent's case, is unlikely to be a good representation of their typical earnings. For all of the children that satisfy these restrictions, if any siblings remain, all younger children within a family are dropped.[11] This procedure serves to retain the child whose adult earnings are most likely to reflect their permanent earnings while preserving independence across observations.[12]

Table 1 provides some summary statistics on two of the five overlapping cohorts. Cohorts 2 through 4 and the father-daughter and mother-son samples are omitted for compactness. The limited statistics provided here are sufficient to reflect the trends and the parent-child differences.

By construction, the ages of the parents and children are comparable over all cohorts. Sons are on average about 32 years old when I first observe their earnings and daughters average about a year younger than sons in all cohorts. Fathers are on average about 43 years old when I first observe them. Mothers are two to three years younger on average than fathers. This differential is explained by women's relatively early age of marriage and age at first birth.

[11]When I pool the cohorts, if siblings appeared in different cohorts, I keep only one randomly selected sibling.

[12]When younger siblings who satisfy the sample extraction criteria are included, mobility appears higher, most likely due to the fact that the average age of the sample falls when the younger siblings are included.

Table 1: Sample Summary Statistics

Parent-Child Pair:	Father-Son		Mother-Daughter	
Cohort:	'68-'85	'72-'89	'68-'85	'72-'89
Mean Child's Age	31.6	31.8	30.3	30.9
Min	21	21	18	21
Max	40	40	40	40
Mean Parent's Age	43.2	43.3	39.6	40.3
Min	23	23	19	22
Max	68	68	65	63
Mean Earnings*				
Child	26,878	27,823	11,267	12,391
# Unemployed**	47	50	60	60
# Housewives***	1	3	186	167
Max	232,420	318,210	51,380	124,120
Parent	27,511	29,763	4,671	5,384
# Unemployed**	18	22	-	-
# Housewives***	10	7	-	-
# Zeros****	-	-	363	319
# Heads*****	-	-	47	52
Max	239,900	191,550	44,038	41,710
Sample Size	407	389	498	469

*All nominal figures are deflated using the CPI and presented in 1984 dollars.
**Number of observations whose employment status was unemployed in at least one year.
***Number of observations whose employment status was housewife in at least one year.
****Number of observations whose earnings were zero in at least one year.
*****Number of mothers who were listed as head of the household.

As the U.S. experienced real earnings growth over this period, I expect and see that real earnings increased over time for all types of earners. The table also indicates that the average earnings of both fathers and sons are substantially higher than mothers and daughters, although the father-mother gap is much larger than the son-daughter gap. There are two primary reasons for this earnings differential: the male-female wage differential, and the difference in the proportion of men compared to women who work in the market for a wage. The relative size of the gender earnings gaps between the parents and the children can be explained by the shrinkage of both types of gaps over time, as well as by the fact that the male-female wage differential increases over the life-cycle.

4 Econometric Models

4.1 OLS

The model derived here is a modified version of the estimation strategy developed by Solon (1992). Let W_i^c and W_i^p be the long-run, permanent component of earnings for the child and parent, respectfully, of family i.[13]

$$\ln(W_i^c) = \alpha + \rho \ln(W_i^p) + \varepsilon_i, \tag{1}$$

where it is assumed that $E(\varepsilon_i \mid x_i) = 0$. By applying least squares to regression equation (1), we could estimate ρ, the elasticity of the child's earnings with respect to the parent's earnings.[14] However, permanent earnings are not directly observable, and thus, must be proxied. The approach used here is similar to that done in the literature, namely to use an average of several annual earnings observations for both the child and the parent.[15] Additionally, controls for age are necessary for comparability since the child is observed at a different point in the life-cycle than his/her parent. Thus, the following relationship is used to extract an estimate of permanent earnings.

$$\begin{aligned} \frac{1}{T}\sum_{t=1}^{T}\ln(W_{it}^g) &= \ln(W_i^g) + \beta_1^g A_i^g + \beta_2^g (A_i^g)^2 + \eta_i^g, \qquad (2) \\ g &\in \{c, p\}, \end{aligned}$$

[13]In general, the superscript c refers to the child of the family while the superscript p refers to the parent of the family.

[14]If the variance of the parents' and the children's samples are equal, this elasticity is also the *correlation* between the parents' and children's earnings.

[15]Solon (1992) only averages the annual earnings of the parents.

where $\ln(W_i^g)$ represents the age-adjusted, permanent component of earnings, and A_i is the median age when the T earnings are observed. The permanent earnings of parents and children are estimated separately to allow the age-earnings profiles to vary by generation.[16] I rearrange equation (3) to solve out for $\ln(W_i^g)$ which I then subsitute into equation (1) to get:

$$\frac{1}{T}\sum_{t=1}^{T}\ln(W_{it}^c) = \alpha + \rho\frac{1}{T}\sum_{t=1}^{T}\ln(W_{it}^p) + A_i\beta' + u_i, \tag{3}$$

where $\beta' = [-\rho\beta_1^p, -\rho\beta_2^p, \beta_1^c, \beta_2^c]$, $A_i = [A_i^p, (A_i^p)^2, A_i^c, (A_i^c)^2]$, and $u_i = \varepsilon_i + \eta_i^c - \rho\eta_i^p$. As in equation (1), ρ represents the elasticity of the child's earnings with respect to the parent's earnings.

Note that $\hat{\rho}$ is biased as a result of the error in the measurement of W_i^p. Assuming that the errors are serially uncorrelated, $\hat{\rho}$ has the probability limit,

$$\text{plim } \hat{\rho} = \rho\left(\frac{\sigma_{W^p}^2}{\sigma_{W^p}^2 + \frac{\sigma_{\eta^p}^2}{T}}\right),$$

where $\sigma_{W^p}^2$ is the variance of the permanent component of the parent's earnings, $\sigma_{\eta^p}^2$ is the variance of the transitory part of the parent's earnings, and T is the number of annual earn-

[16] To test the effect of the assumption that the parents' and children's age-earnings profiles are different, I use the following approach involving residuals. I first apply least squares to the following variation on equation (3) (no constant term):

$$\frac{1}{T}\sum_{t=1}^{T}\ln(W_{it}^g) = \beta_1^g A_i^g + \beta_2^g (A_i^g)^2 + \eta_i^g.$$

I then compute the residuals from this equation when $g = c$ and $g = p$, which I call $\widehat{\ln(W_i^c)}$ and $\widehat{\ln(W_i^p)}$, and estimate ρ using the following equation.

$$\widehat{\ln(W_i^c)} = \alpha + \rho\widehat{\ln(W_i^p)} + \varepsilon_i$$

For comparison, I pool the parents and children and estimate a single age-earnings profile for each cohort. From this, I compute residuals and estimate ρ again. The differences between the coefficients estimated under these two assumptions are not significant indicating that the differences between the age-earnings profiles of the parents and children are not driving the results discussed in later sections.

ings observations entered in the parent's average computation.[17] Fortunately, the magnitude of the bias shrinks as T increases. Zimmerman (1992) found that averaging parent's earnings renders the bias from errors-in-variables negligible.

4.2 Quantile Regression

The quantile regression technique (Koenker & Bassett, 1978) can be applied to the specification detailed above to examine the degree of intergenerational mobility at several distinct points on the conditional distribution of the children's earnings for each cohort. Again, let W_i be the long-run, permanent component of earnings for a member of family i. In the previous subsection, least squares applied to equation (1) produced $\hat{\rho}$, the estimated elasticity of the child's earnings with respect to the parent's earnings at the *mean* of the child's conditional earnings distribution. Here, the quantile regression method can be applied to equation (4) to obtain $\hat{\rho_\theta}$, the estimated elasticity at the θth quantile of the child's conditional earnings distribution.

$$\ln(W_i^c) = \alpha_\theta + \rho_\theta \ln(W_i^p) + \varepsilon_{i,\theta}, \tag{4}$$

where

$$Quant_\theta(\ln(W_i^c) \mid \ln(W_i^p)) = \alpha_\theta + \rho_\theta \ln(W_i^p).$$

In this case, the relationships among permanent earnings, annual earnings, and age are allowed to vary across the conditional earnings distribution so that:

$$\frac{1}{T}\sum_{t=1}^{T} \ln(W_{it}^g) = \ln(W_i^g)_\theta + \beta_{1,\theta}^g A_i^g + \beta_{2,\theta}^g (A_i^g)^2 + \eta_{i,\theta}^g, \tag{5}$$

[17] The fact that the parent's permanent earnings are estimated using an average of three, four, or five years of earnings may introduce heteroskedasticity due to the relationship between the degree of measurement error and the number of years included in the average described above. Therefore, I compute heteroskedasticity-robust standard errors using the Eicker-White estimator.

$$g \in \{c, p\}.$$

$\ln(W_i^g)_\theta$ is plugged in for $\ln(W_i^g)$ in equation (4), resulting in the following re-specification of the model.[18]

$$\frac{1}{T}\sum_{t=1}^{T}\ln(W_{it}^c) \quad = \quad \alpha_\theta + \rho_\theta \frac{1}{T}\sum_{t=1}^{T}\ln(W_{it}^p) + A_i\beta_\theta' + u_{i,\theta} \tag{6}$$

where $\beta_\theta' = [-\rho_\theta\beta_{1,\theta}^p, -\rho_\theta\beta_{2,\theta}^p, \beta_{1,\theta}^c, \beta_{2,\theta}^c]$, $A_i = [A_i^p, (A_i^p)^2, A_i^c, (A_i^c)^2]$, and $u_{i,\theta} = \varepsilon_{i,\theta} + \eta_{i,\theta}^c - \rho_\theta\eta_{i,\theta}^p$.

4.3 Transition Matrices

Both the OLS and quantile regression approaches to measuring mobility capture all absolute movements in earnings. Transition matrices supplement our understanding of the movements observed by allowing us to determine *who* moves *where* in the earnings distribution. Each element, p_{kj}, of the matrix provides an estimate of a child's conditional probability of being in quintile k given that the child's parent was in quintile j. The diagonal elements of the matrix are similar to the quantile regression coefficients on parent's earnings in that they indicate to what degree a child 'stays' in his/her parent's relative region of the earnings distribution. The off-diagonal elements of the transition matrix offer insight into the destination of the children who move away from their parent's quintile.

I employ the multinomial probit model to obtain the conditional probabilities of transition from the parent's quintile to the child's. Let d_{ki} be a dummy variable which indicates whether an individual i is in quintile k. That is, $d_{1i} = 1$ if child i is in the highest quintile; otherwise, $d_{1i} = 0$.

[18] For technical details regarding the estimation of this model, the standard errors, and a test for equality of the slope coefficients, see the Appendix.

The conditional transition probabilities for child i given that the child's parent was in quintile j are:

$$
\begin{aligned}
P_{j1i} &= \Pr(d_{1i} = 1 \mid d_{ji} = 1; x_i), \\
&\vdots \\
P_{j5i} &= \Pr(d_{5i} = 1 \mid d_{ji} = 1; x_i),
\end{aligned} \tag{7}
$$

where x_i represents the same vector of regressors found in equation (3). The estimate reported in each element, p_{jk}, of the transition matrix is evaluated at the mean log earnings and ages among those in quintile j.[19]

I also present a summary measure of mobility, the average jump, based on all elements of the transition matrix. An average jump can be computed for each matrix by the following algorithm:

$$AJ = \frac{\sum_{j=1}^{5} \sum_{k=1}^{5} |j-k| p_{jk}/5}{AJ^*}, \tag{8}$$

where AJ^* is the maximum possible value for the numerator.[20] AJ takes values between 0 and 1 such that at its minimum, there is no mobility, i.e. $P_{jj} = 1, \forall j$.

5 Results

5.1 OLS and Quantile Regression

Tables 2 through 5 present the OLS (mean) and quantile regression findings. The result in the top left-hand corner of Table 2 corresponds to the Solon (1992) and Zimmerman (1992)

[19] Under the usual regularity conditions, the maximum likelihood estimator is consistent and asymptotically efficient with variance I^{-1}, where $I = -\left[E \frac{\partial^2 \log l}{\partial \beta \partial \beta'}\right]$. The standard errors for each element of the transition matrix are computed using the delta method.

[20] For a 5X5 transition matrix, $AJ^* = 2\frac{2}{3}$.

finding in terms of cohort and gender. The coefficient presented here is larger than their finding of approximately 0.4 as a result of my inclusion of zero-earnings observations and employment status restrictions.[21] Likewise, the quantile regression coefficients for the first cohort presented here are larger than the estimates obtained by Eide and Showalter (1999) in every quantile. However, I still find, as they did, that intergenerational earnings mobility is lowest at the lowest quantile of the sons' conditional earnings distribution for this cohort. The implication of the findings for the cross-section presented in this row is that mobility between fathers and sons, at the mean and across all quantiles, is lower when the sample includes zero-earners than otherwise.

The quantile regression estimates allow us to distinguish between the mobility levels of different types of children. Since the quantiles are points along the earnings distribution *conditional* on fathers' earnings (rather than along a population earnings distribution), I argue that the differences that are distinguishable are varying abilities. To illustrate, consider a son on the bottom tail of the earnings distribution for sons whose fathers earned x. I assume that this son is at this point on the conditional earnings distribution because he is low ability in his chosen line of work. The lowest quantile estimate of 0.671(0.123) suggests that the mobility of this son is low. Since x can be high or low, this finding suggests that there is an intergenerational persistence of low earnings, but also that a low-ability son can be helped along by his father's influence or resources. Now consider a son on the top tail of the earnings

[21] If all zero-earners are omitted from the sample and no employment restrictions are imposed, as in Solon (1992), the father-son intergenerational elasticity is 0.398 (0.059) with a sample size of 380; Solon (1992) finds 0.413 (0.093) with a sample size of 290. If zero-earnings are included but no employment restrictions are imposed, as in Couch and Lillard (1998), the father-son intergenerational elasticity is 0.166 (0.068) with a sample size of 438; Couch and Lillard (1998) find 0.011 (0.036) with a sample size of 206. My sample sizes are larger because my selection criteria is less restrictive for the parents.

Table 2: Father-Son OLS and Quantile Regression Results
Elasticity of Son's Earnings with respect to Father's Earnings
Dependent Variable: 5-Year Average of Log Son's Earnings

	Mean	.10 Qnt.	.25 Qnt.	.50 Qnt.	.75 Qnt.	.90 Qnt.
'68-'85 Cohort	**0.500**	**0.671**	**0.596**	**0.462**	**0.316**	**0.224**
[407], {13,806}	**(0.070)**	**(0.123)**	**(0.094)**	**(0.066)**	**(0.063)**	**(0.087)**
'69-'86 Cohort	**0.370**	**0.588**	**0.443**	**0.354**	**0.316**	**0.283**
[391], {4,483}	**(0.094)**	**(0.236)**	**(0.083)**	**(0.073)**	**(0.061)**	**(0.093)**
'70-'87 Cohort	**0.342**	**0.549**	**0.490**	**0.379**	**0.276**	**0.234**
[391], {6,062}	**(0.086)**	**(0.165)**	**(0.096)**	**(0.092)**	**(0.060)**	**(0.066)**
'71-'88 Cohort	**0.252**	**0.462**	**0.425**	**0.299**	0.139	0.151
[389], {6,170}	**(0.069)**	**(0.209)**	**(0.093)**	**(0.088)**	(0.078)	(0.078)
'72-'89 Cohort	**0.217**	0.478	**0.348**	**0.259**	**0.125**	**0.119**
[389], {6,307}	**(0.072)**	(0.255)	**(0.079)**	**(0.083)**	**(0.053)**	**(0.048)**
All Cohorts	0.232	0.239	0.546	0.237	0.130	0.014
[536], {$1.5X10^4$}	(0.219)	(0.424)	(0.290)	(0.242)	(0.187)	(0.122)
Cohort	**0.938**	1.691	**1.144**	0.601	0.467	0.166
	(0.316)	(0.935)	**(0.499)**	(0.441)	(0.336)	(0.253)
Cohort Interaction	**-0.092**	-0.169	**-0.111**	-0.058	-0.046	-0.016
	(0.032)	(0.092)	**(0.050)**	(0.044)	(0.033)	(0.025)

Note: The number in square brackets is the sample size and the number in curly brackets is the χ^2 statistic testing the equality of the quantile slope coefficients. In the mean regression column, the number in parentheses is the heteroskedasticity-robust standard error. In the quantile columns, the number in parentheses is the bootstrapped standard error. Bold represents significance at the 5% level. In the top panel, the specification includes child's age, parent's age, their respective squared terms, and a constant term. In the bottom panel, the specification also includes a variable indicating cohort, an interaction between the cohort and the parent's earnings, and an interaction between the observation age and the parent's earnings.

distribution for sons whose fathers earned x. The findings in this row imply that high ability sons do not depend nearly as much on their father's earnings, whether high or low.

The first column of this table allows us to address whether intergenerational earnings mobility at the mean has changed over time. The top panel displays $\hat{\rho}$ estimated by applying equation (3) (or equation (6) in the quantile regression cases) to each cohort. The estimates in the bottom panel are based on pooling all five cohorts, dropping multiple observations of individuals and any siblings, and including a *cohort* variable, an interaction between $\ln(W_i^p)$ and the cohort, and an interaction between $\ln(W_i^p)$ and the observation age.[22] The coefficients in the bottom panel indicate that average mobility between fathers and sons increased by $-0.092(0.032)$ per cohort. The coefficients in the top panel indicate that mobility fell such that the intergenerational elasticity in the fifth cohort was less than half than that in the first cohort.

The five following columns allow us to determine who experienced the most change in mobility. For fathers and sons, the magnitudes of the coefficients fell over time for all quantiles, although only significantly for the 0.25 quantile. In addition, the difference among the quantiles diminished over time. In other words, mobility increased for all sons, but the rate of change appears to be slightly higher for lower ability sons.

Table 3 presents the OLS and quantile regression results for the father-daughter sample. In the first cohort, the elasticity of daughter's earnings with respect to father's earnings estimated by mean regression is similar in scale to the father-son elasticity in the first cohort, but the standard error is three times larger. The greater variance is likely due to the fact

[22] The coefficients on the observation age interaction are not shown. This variable is included because there is a small correlation between cohort and observation age in this pooled, non-overlapping cohorts sample.

that a large number of daughters, at some point during the five observed years, did not participate in the labor market. After the first cohort, few of the coefficients from either the mean or the quantile regressions are significantly different from zero. The OLS and quantile coefficients on the cohort interaction term from the pooled cohorts sample indicate that the difference in the coefficients across the cohorts is not significant at the mean or in any quantile.

Table 4 reports the mean and quantile regression estimates for the mother-son sample. The elasticity of son's earnings with respect to mother's earnings is positive for the first cohort, but smaller in magnitude by a factor of almost twenty compared to the father-son elasticity for this cohort. The size of the coefficient is derived from the fact that many mothers did not work in the market for a wage, and if they did, their wage was relatively low compared to what their sons earn in adulthood. The coefficient is also driven down by the fact that a 'stay-at-home mom' can be an indicator of a high-wage father. Few of the quantile coefficients are significant. The coefficients on the cohort interaction term from the pooled regressions suggest no significant change in mobility between mothers and sons over time.

Finally, Table 5 presents the mother-daughter mobility measures from the OLS and quantile regressions. The elasticities of the daughter's earnings with respect to the mother's earnings from both the mean and the quantile regressions were not significantly different from zero in any cohort, nor when the sample was pooled.

Table 3: Father-Daughter OLS and Quantile Regression Results
Elasticity of Daughter's Earnings with respect to Father's Earnings
Dependent Variable: 5-Year Average of Log Daughter's Earnings

	Mean	.10 Qnt.	.25 Qnt.	.50 Qnt.	.75 Qnt.	.90 Qnt.
'68-'85 Cohort	**0.455**	0.299	0.848	0.419	**0.333**	0.135
[441], {6,222}	**(0.207)**	(0.310)	(0.301)	(0.389)	**(0.137)**	(0.100)
'69-'86 Cohort	0.153	0.117	0.188	0.074	**0.250**	**0.203**
[434], {10,973}	(0.216)	(0.421)	(0.462)	(0.267)	**(0.081)**	**(0.060)**
'70-'87 Cohort	-0.008	-0.669	-0.225	0.165	**0.226**	**0.158**
[430], {8,823}	(0.162)	(0.576)	(0.342)	(0.164)	**(0.094)**	**(0.063)**
'71-'88 Cohort	-0.044	**-0.696**	-0.159	0.105	0.142	0.099
[408], {9,443}	(0.122)	**(0.350)**	(0.362)	(0.148)	(0.087)	(0.071)
'72-'89 Cohort	0.068	-0.431	0.382	0.132	0.082	0.113
[410], {10,923}	(0.166)	(0.423)	(0.538)	(0.200)	(0.072)	(0.067)
All Cohorts	**1.522**	0.551	**1.656**	**1.641**	**0.695**	**0.603**
[562], {$1.3X10^4$}	**(0.442)**	(1.042)	**(0.800)**	**(0.767)**	**(0.311)**	**(0.279)**
Cohort	1.210	0.983	1.177	0.545	0.345	0.383
	(0.859)	(1.994)	(1.864)	(1.256)	(0.673)	(0.474)
Cohort	-0.125	-0.111	-0.133	-0.057	-0.035	-0.043
Interaction	(0.087)	(0.207)	(0.189)	(0.124)	(0.067)	(0.047)

Note: The number in square brackets is the sample size and the number in curly brackets is the χ^2 statistic testing the equality of the quantile slope coefficients. In the mean regression column, the number in parentheses is the heteroskedasticity-robust standard error. In the quantile columns, the number in parentheses is the bootstrapped standard error. Bold represents significance at the 5% level. In the top panel, the specification includes child's age, parent's age, their respective squared terms, and a constant term. In the bottom panel, the specification also includes a variable indicating cohort, an interaction between the cohort and the parent's earnings, and an interaction between the observation age and the parent's earnings.

Table 4: Mother-Son OLS and Quantile Regression Results
Elasticity of Son's Earnings with respect to Mother's Earnings
Dependent Variable: 5-Year Average of Log Son's Earnings

	Mean	.10 Qnt.	.25 Qnt.	.50 Qnt.	.75 Qnt.	.90 Qnt.
'68-'85 Cohort	**0.029**	0.052	**0.027**	0.016	0.007	0.013
[462], {9,428}	**(0.014)**	(0.046)	**(0.013)**	(0.010)	(0.011)	(0.011)
'69-'86 Cohort	**0.045**	0.091	0.025	0.018	-0.004	0.010
[456], {7,377}	**(0.015)**	(0.049)	(0.017)	(0.010)	(0.012)	(0.013)
'70-'87 Cohort	**0.043**	0.094	0.019	**0.025**	0.001	0.016
[463], {6,688}	**(0.015)**	(0.048)	(0.018)	**(0.012)**	(0.012)	(0.015)
'71-'88 Cohort	0.010	0.009	0.012	0.005	-0.005	0.002
[454], {4,008}	(0.011)	(0.036)	(0.020)	(0.014)	(0.010)	(0.015)
'72-'89 Cohort	0.018	0.019	0.008	0.014	-0.000	0.011
[447], {4,407}	(0.012)	(0.037)	(0.017)	(0.010)	(0.012)	(0.015)
All Cohorts	0.018	0.081	0.035	-0.042	-0.005	0.027
[589], {$1.6X10^4$}	(0.043)	(0.086)	(0.048)	(0.035)	(0.037)	(0.029)
Cohort	0.059	-0.029	0.055	-0.015	0.085	0.041
	(0.062)	(0.197)	(0.066)	(0.044)	(0.051)	(0.034)
Cohort	-0.006	-0.005	-0.010	0.006	-0.007	0.000
Interaction	(0.009)	(0.026)	(0.009)	(0.007)	(0.008)	(0.008)

Note: The number in square brackets is the sample size and the number in curly brackets is the χ^2 statistic testing the equality of the quantile slope coefficients. In the mean regression column, the number in parentheses is the heteroskedasticity-robust standard error. In the quantile columns, the number in parentheses is the bootstrapped standard error. Bold represents significance at the 5% level. In the top panel, the specification includes child's age, parent's age, their respective squared terms, and a constant term. In the bottom panel, the specification also includes a variable indicating cohort, an interaction between the cohort and the parent's earnings, and an interaction between the observation age and the parent's earnings.

Table 5: Mother-Daughter OLS and Quantile Regression Results
Elasticity of Daughter's Earnings with respect to Mother's Earnings
Dependent Variable: 5-Year Average of Log Daughter's Earnings

	Mean	.10 Qnt.	.25 Qnt.	.50 Qnt.	.75 Qnt.	.90 Qnt.
'68-'85 Cohort	-0.027	-0.028	-0.105	-0.007	-0.019	-0.028
[498], {9,276}	(0.045)	(0.126)	(0.138)	(0.042)	(0.018)	(0.012)
'69-'86 Cohort	-0.021	-0.056	-0.025	0.016	-0.017	-0.022
[495], {9,913}	(0.046)	(0.154)	(0.125)	(0.041)	(0.021)	(0.011)
'70-'87 Cohort	0.007	0.044	0.023	0.018	0.018	-0.015
[495], {5,180}	(0.046)	(0.136)	(0.128)	(0.042)	(0.023)	(0.011)
'71-'88 Cohort	0.004	-0.186	0.014	0.006	0.010	-0.013
[473], {8,821}	(0.045)	(0.107)	(0.146)	(0.038)	(0.021)	(0.012)
'72-'89 Cohort	0.010	-0.168	0.028	0.006	-0.006	-0.018
[469], {5,270}	(0.044)	(0.156)	(0.120)	(0.040)	(0.017)	(0.015)
All Cohorts	0.021	-0.065	0.217	0.149	0.054	0.005
[621], {$1.5X10^4$}	(0.123)	(0.314)	(0.299)	(0.117)	(0.045)	(0.042)
Cohort	0.138	0.300	0.245	0.272	0.032	0.012
	(0.159)	(0.473)	(0.448)	(0.153)	(0.068)	(0.063)
Cohort	-0.014	-0.042	-0.014	-0.039	-0.002	-0.002
Interaction	(0.028)	(0.071)	(0.078)	(0.026)	(0.011)	(0.010)

Note: The number in square brackets is the sample size and the number in curly brackets is the χ^2 statistic testing the equality of the quantile slope coefficients. In the mean regression column, the number in parentheses is the heteroskedasticity-robust standard error. In the quantile columns, the number in parentheses is the bootstrapped standard error. Bold represents significance at the 5% level. In the top panel, the specification includes child's age, parent's age, their respective squared terms, and a constant term. In the bottom panel, the specification also includes a variable indicating cohort, an interaction between the cohort and the parent's earnings, and an interaction between the observation age and the parent's earnings.

5.2 Transition Matrices

Table 6 presents the transition matrices for the first cohort of each of the parent-child combinations. The top left-hand element of the first matrix indicates that a son whose father was in the top twenty percent of fathers in terms of earnings, with mean characteristics for his father's quintile, had a 46 percent conditional probability of ending up in the top twenty percent of sons in terms of earnings. Thus, the diagonal elements of each matrix represent the conditional probabilities of a child staying in the same quintile as their parent. Elements in the lower triangle of the matrix represent the conditional probabilities of a child ending up in a lower quintile than their parent, and elements in the upper triangle represent the conditional probabilities of a child achieving a higher quintile than their parent.[23]

The transition matrices for the sons have several distinct features which the daughters' transition matrices do not exhibit. First, in any of the parents' quintiles, the daughters' conditional probabilities are concentrated in the third and fourth quintiles, where the sons' conditional probabilities are clustered in the highest and lowest quintiles. Second, there is very little difference, and no discernible pattern, in the spread of conditional probabilities across the columns for daughters, where the sons' conditional probabilities are concentrated to some degree along the diagonal. Both of these differences are due to the relatively high proportion of housewives included in the daughter samples.[24]

Figures 1 through 6 display the trend, by the parent's quintile, of the conditional probabilities of a child sharing, exceeding, and falling short of his/her parent's quintile for the father-son and father-daughter samples.[25] The trend in the 'staying' probabilities of the

[23]Note that an observation with an average earnings of zero would be in the lowest quintile.

[24]Tests run indicated that the pattern observed for sons holds for positive-earnings daughters.

[25]The figures describing the mother-son transition matrices are not shown here as all of the features of the

Table 6: Transition Matrices ('68-'85 Cohort)
Conditional Probabilities of Child's Quintile
Given Parent's Quintile

1. Father-Son

	Father → H	2	3	4	L
H	46	41	36	28	15
	(0.5)	(0.5)	(0.5)	(0.4)	(0.3)
2	11	11	11	10	8
	(0.0)	(0.0)	(0.0)	(0.1)	(0.1)
3	11	12	12	12	10
	(0.1)	(0.0)	(0.0)	(0.0)	(0.1)
4	13	13	14	15	15
	(0.1)	(0.1)	(0.1)	(0.0)	(0.1)
L	19	22	27	34	52
	(0.4)	(0.4)	(0.4)	(0.5)	(0.6)
	100	100	100	100	100

2. Father-Daughter

	Father → H	2	3	4	L
H	3	5	2	7	1
	(0.1)	(0.1)	(0.1)	(0.2)	(0.0)
2	5	8	4	10	2
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
3	38	44	35	47	25
	(0.3)	(0.2)	(0.3)	(0.2)	(0.3)
4	55	43	60	36	72
	(0.5)	(0.5)	(0.5)	(0.5)	(0.4)
L	0	0	0	0	0
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
	100	100	100	100	100

3. Mother-Son

	Mother → H	2	3	4	L
H	36	36	31	36	23
	(0.4)	(0.5)	(0.4)	(0.4)	(0.4)
2	11	11	11	11	10
	(0.0)	(0.0)	(0.0)	(0.0)	(0.1)
3	12	12	12	12	12
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
4	14	14	15	14	15
	(0.1)	(0.1)	(0.0)	(0.0)	(0.0)
L	27	27	32	27	40
	(0.4)	(0.4)	(0.4)	(0.4)	(0.5)
	100	100	100	100	100

4. Mother-Daughter

	Mother → H	2	3	4	L
H	3	4	3	3	3
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
2	6	7	5	6	6
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
3	36	38	35	36	36
	(0.3)	(0.2)	(0.3)	(0.3)	(0.3)
4	56	52	57	55	56
	(0.4)	(0.4)	(0.4)	(0.4)	(0.5)
L	0	0	0	0	0
	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)
	100	100	100	100	100

Note: The numbers in parentheses are standard errors.

Figure 1: Son's Probability of Same Quintile as Father by Father's Quintile

Figure 2: Son's Probability of Higher Quintile than Father by Father's Quintile

Figure 3: Son's Probability of Lower Quintile than Father by Father's Quintile

Figure 4: Daughter's Probability of Same Quintile as Father by Father's Quintile

Figure 5: Daughter's Probability of Higher Quintile than Father by Father's Quintile

Figure 6: Daughter's Probability of Lower Quintile than Father by Father's Quintile

highest and the lowest quintiles for sons displayed in Figure 1 is slightly downward. This is consistent with the OLS and quantile regression findings that mobility increased. The two lower figures also suggest increased mobility, and the pattern of mobility suggests increasing regression to the mean.[26] That is, from Figure 2, we see that the sons of fathers from the higher quintiles had progressively lower chances of moving up while the sons of fathers from the lowest quintiles had progressively higher chances of moving up. In Figure 3, we see that the sons of parents from the highest quintiles had progressively higher chances of moving down.

In contrast, some daughters appeared to grow less mobile while others did not change at all. Figure 4 suggests lower mobility for daughters of fathers in the fourth quintile. According to Figure 5, over time daughters from fourth quintile fathers traded upward mobility for staying.

Lastly, Figures 7 and 8 summarize the average jump trends of all four parent-child combinations. The average jumps of sons with respect to fathers increased while the average jumps of sons with respect to mothers remained steady. On the other hand, daughters' average jumps declined with respect to fathers and remained the same with respect to mothers. The mobility of sons was higher by this measure than that of daughters. The OLS and quantile regression estimates suggest the opposite. However, since the average jump weighs greater

father-son transition matrices detailed here apply as well. The figures for the mother-daughter transition matrices are not shown as the statistics based on the transition matrices for the mothers and daughters look very similar to those for the fathers and daughters, with the exception that the curves are flat in the mother-daughter case.

[26] In Figures 2, 3, 5 and 6, the position of one quintile trend-line relative to another is not informative. Children of parents in the lowest quintile appear to have the highest probability of upward mobility, and children of parents in the highest quintile appear to have the highest probability of downward mobility merely because, in both cases, those children have the greatest number of possible quintiles in that direction toward which to move.

Figure 7: Average Jump of Son

Figure 8: Average Jump of Daughter

moves more heavily than smaller moves, sons may be less likely to move at all compared with daughters, but when a move is made, sons must move a greater distance from the parent's earnings.

6 Summary and Conclusion

Whether the degree of intergenerational earnings mobility has changed over time, particularly given the growth in inequality of recent decades, is of interest for two reasons. First, if mobility has changed, it would not be appropriate to assume that an estimate based on one cohort is an applicable measure of the degree of equality of opportunity for all recent cohorts. Second, the implications and policy prescriptions of inequality growth depend on whether mobility fell over this period or not. To address these issues, I use five cohorts from the PSID to analyze intergenerational earnings mobility patterns between parents and children over time.

It is clear from the results that intergenerational earnings mobility between fathers and sons rose over this period, while the mobility between mothers and sons and mothers and daughters remained high throughout. The quantile regressions reveal that the difference in mobility between the rich and the poor narrowed. In addition, the transition matrices for fathers and sons indicate increasing regression to the mean. The results for the fathers and daughters are more mixed. The OLS and quantile estimates on fathers and daughters suggest no change in mobility, where the transition matrices suggest a decrease over time. Overall, these findings imply that an estimate of mobility from one cohort is not necessarily applicable to other cohorts and that the changing mobility, given the direction of change, could not have contributed to growing inequality over this period.

The findings of this study raise several issues which can be addressed in further research. First, the analysis involving mothers and daughters does not produce many statistically significant relationships. However, strong statistical correlations between a mother and her child or a parent and a daughter may exist, but are merely hidden by the variation in the labor market behavior of women.

Second, the causes of the trend in father-son earnings mobility need to be explored. The optimistic interpretation is that access to opportunities were better for the later cohorts. A less optimistic perspective is that the later cohorts faced a more risky market and adjusted their behavior accordingly. Other potential explanations of the trend might include business cycles, the increasing return to education, or changes in family structure in the U.S. The questions addressed here need to be re-evaluated with consideration of these possibilities.

Appendix

Quantile Regression Estimation

Let the following hold.

$$\begin{aligned} w_i &= x_i'\gamma_\theta + \epsilon_\theta, \\ \text{where } Quant_\theta(w_i \mid x_i') &= x_i'\gamma_\theta. \end{aligned}$$

According to Koenker and Bassett (1978), γ_θ is estimated by minimizing the following equation.

$$\min_{\gamma_\theta} \frac{1}{n}\left[\sum_{i:w_i \geq x_i'\gamma_\theta} \theta \mid w_i - x_i'\gamma_\theta \mid + \sum_{i:w_i < x_i'\gamma_\theta} (1-\theta) \mid w_i - x_i'\gamma_\theta \mid\right].$$

Thus,

$$\begin{aligned} \widehat{\gamma}_\theta &= \arg\min_{\gamma_\theta} \frac{1}{n}\sum_{i=1}^{n} \left(\theta - I(w_i - x_i'\gamma_\theta < 0)\right)(w_i - x_i'\gamma_\theta) \\ &= \arg\min_{\gamma_\theta} \frac{1}{n}\sum_{i=1}^{n} \left(\theta - \frac{1}{2} + \frac{1}{2}sgn(w_i - x_i'\gamma_\theta)\right)(w_i - x_i'\gamma_\theta). \end{aligned}$$

The first order condition given below is equivalent to a moment condition and therefore, the General Method of Moments (GMM) can be used to solve for the estimators (Powell, 1984, 1986).

$$\begin{aligned} \frac{1}{n}\sum_{i=1}^{n} \left(\theta - \frac{1}{2} + \frac{1}{2}sgn(w_i - x_i'\gamma_\theta)\right) x_i' &= 0, \\ E(\Psi(x_i, w_i, \gamma_\theta)) &= 0. \end{aligned}$$

Design-Matrix Bootstrapped Standard Errors

Under regularity conditions (Huber, 1967) , and assuming, in our case, that T is sufficiently large, we have

$$\sqrt{n}\left(\widehat{\gamma}_\theta - \gamma_\theta\right) \xrightarrow{d} N(0, \Lambda_\theta)$$

where

$$\Lambda_\theta = \theta(1-\theta)(E[f_{\epsilon_\theta}(0 \mid x_i)x_i x_i'])^{-1}E[x_i x_i'](E[f_{\epsilon_\theta}(0 \mid x_i)x_i x_i'])^{-1}.$$

It is not assumed that the error term, ϵ_θ, evaluated at zero is independent of x, i.e. $f_{\epsilon_\theta}(0 \mid x_i)$ is left unconstrained. Therefore, I obtain a consistent estimator of the asymptotic covariance matrix using the design matrix bootstrap technique (Buchinsky, 1995). This estimator is found by randomly drawing (x_i^*, w_i^*) from the data sample with replacement to create B bootstrapped samples of $w^* = (w_1^*, ..., w_n^*)'$ and $X^* = (x_1^*, ..., x_n^*)'$, and obtaining bootstrapped estimates, $\widehat{\gamma}_\theta^*$, for each of these samples from the quantile regression of w^* on X^*. Then,

$$\widehat{\Lambda}_\theta = \frac{n}{B}\sum_{i=1}^{B}(\widehat{\gamma}_{\theta,i}^* - \overline{\gamma}_\theta^*)(\widehat{\gamma}_{\theta,i}^* - \overline{\gamma}_\theta^*)',$$

where $\overline{\gamma}_\theta^* = \frac{1}{B}\sum_{j=1}^{B}\widehat{\gamma}_{\theta,j}^*$.

Testing for Equality of the Slope Coefficients

I also test for equality of the slope coefficients as evidence that the elasticities do in fact vary by quantile. The following test statistic is χ^2 distributed.

$$\widehat{\gamma}^R = \left(R'\widehat{\Lambda}^{-1}R\right)^{-1} R'\widehat{\Lambda}^{-1}\widehat{\gamma}_{\theta,S},$$

where $\widehat{\gamma}_{\theta,S}$ is the stacked vector of all unrestricted quantile estimates, $\widehat{\Lambda}$ is a consistent estimator for the asymptotic covariance matrix of all of the unrestricted quantile estimates, and $R' = (R_1, ..., R_p)$, where p is the number of quantiles estimated, and

$$R_j = \begin{pmatrix} e_j & 0_{q_1} \\ 0_{q_2} & I_{k-1} \end{pmatrix},$$

where e_j is a vector of zeros with the value one in the jth position, k is the number of regressors, 0_{q_1} is a $pX(k-1)$ matrix of zeros, and 0_{q_2} is a $(k-1)X1$ vector of zeros.

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