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INTERGENERATIONAL EARNINGS MOBILITY AMONG DAUGHTERS AND SONS: EVIDENCE FROM SWEDEN AND A COMPARISON WITH THE UNITED STATES

by

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Intergenerational Earnings Mobility Among Daughters and Sons: Evidence from Sweden and a Comparison with the United States*

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Abstract

This paper adopts Chadwick and Solon's (2002) model by using family earnings in the study of intergenerational earnings mobility with a highlight on the role of assortative mating. I analyze mean and quantile regression coefficients as well as transition matrices to investigate family earnings mobility between parents and daughters, and parents and sons from Swedish register data. My findings indicate that Sweden has a higher degree of mobility compared to the U.S., and that assortative mating also plays an important role as a channel through which income status is transmitted across generations in Sweden. However, the difference in intergenerational mobility patterns between the two countries does not, inherently, depend on factors that affect the marriage match. Swedish daughters and sons exhibit a rather similar scheme of intergenerational earnings transmission. Daughters tend to be slightly more mobile than sons and the difference between their elasticity estimates is small but statistically significant. The quantile regression approach reveals that parents' family earnings are less important as explanatory variable at the upper end of the children's earnings distribution than it is at the bottom while transition matrices show substantial earnings persistence in the top earnings class.

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1 Introduction

The intergenerational earnings mobility between parents and children has been widely examined over the past fifteen years. However, most of the studies focus on the relationship between fathers and sons.[1] A possible source of this disproportionality is an unconscious discrimination which follows the old tradition of studying only male prototypes also in natural sciences, for instance, testing new medications only on men to study their effects on people, even on women. It is, however, motivated in the empirical context, where researchers have resorted to omitting mothers due to the discontinuous labour force behaviour of a large share of women during the 1960s. The lower rate of married women's labour force participation compared to men's, raises the frequency of non-observed earnings in the estimation, and complicates any analysis of intergenerational relationship involving mothers and daughters. Even in the field of sociology, researchers have long had difficulty in assigning women to their appropriate social class. The uncertainty concerning their economic status fueled the growth of studies which use the occupation of the women's husbands, instead of their own, as the criterion of their social classification. This, in its turn, has been a source of discord in the sociological literature (see Erikson, 2005 for a review).

Studies in intergenerational earnings mobility, which include daughters and mothers are still sparse.[2] Österberg (2000) uses Swedish tax data files from 1978 to 1992 to estimate the intergenerational income mobility between pairs of mother-daughter, mother-son and pairs of father-daughter, father-son. She found high intergenerational income mobility between fathers and sons compared to the U.S., and that mothers' earnings correlate more strongly with daughters' earnings than with sons', though they have less influence on children's earnings compared to those of the fathers.

[1] See for example a survey in Solon (2002).

[2] Several studies originated from U.S. data, among others, Peters (1992), Mazumder (2001) and Chadwick and Solon (2002); and another from British data is Dearden *et al.* (1997).

Since intergenerational earnings mobility is characterized by the transference of economic status from parents to children, family structure, and thus, marriage match plays an important role as background in evaluating the degree of association between their economic achievements in terms of family income. The fact that people tend to marry within their own socio-economic class, i.e, marriage homogamy, is of interest as pooling economic (dis)advantages makes society more closed and immobile, and leads to an intergenerational reproduction of inequality (Blossfeld and Timm, 2003). Assortative mating clearly influences the correlation between parents' and children's family earnings, although its link to the intergenerational mobility pattern has not been discussed much in the economic literature. An important exception is, however, a study by Chadwick and Solon (2002), which examines the intergenerational income mobility among daughters with a highlight on assortative mating.[3] It also suggests a way to get around the problem of observing the income of women who do not participate or participate only intermittently in the labour force, by using family income as a measure of economic status. Chadwick and Solon (2002), (henceforth C&S), use the Panel Study of Income Dynamics (PSID) data on daughters and sons born between 1951 and 1966. They find smaller, though substantial, income elasticity estimates for daughters compared to sons, and that assortative mating plays a key role in the income transmission process in the United States. According to their results, the earnings of the spouses are as elastic as the offspring's own earnings with respect to the parents' income.

In this paper, I adopt the same approach by using such a broader measure of income as family income in the analysis of daughters' intergenerational earnings mobility in Sweden. I also focus on the role of assortative mating as one of the possible channels through which economic status is passed on from one generation to an-

[3] Other studies which consider the role of assortative mating in the intergenerational earnings mobility are Lam and Schoeni (1993, 1994) and Ermisch *et al.* (2006).

other. The United States and Sweden are long known to represent extreme cases in a comparison of income inequality among developed countries. It is, thus, interesting to investigate how such countries relate to each other in terms of the intergenerational transmission of family income and assortative mating. Therefore, I first follow C&S's empirical outline closely to be able to compare my main results with those they found for the United States. The second aim of the paper is to conduct a parallel study for sons, in order to compare patterns of the intergenerational mobility between daughters and sons in Sweden, and then extend the analysis by exploring possible nonlinearity. Furthermore, like C&S, I examine the role of assortative mating in the transmission of economic status across generations, but in addition, I also investigate whether similarities and differences exist between married couples and those who are merely registered as cohabitants with joint children. My contributions are mainly the consideration of the role of assortative mating in intergenerational earnings mobility, an issue which has been given scant attention in this field. The large and representative sample of Swedish data promises better precision compared to the PSID-based U.S. estimates, and allows the use of quantile regression as well as an exploration of mobility patterns in the different parts of the daughters' and sons' income distribution.

The rest of this paper proceeds as follows. Section II presents the theory and econometric framework, section III describes the data used, and section IV contains the empirical results of the Sweden-U.S. comparison. In section V, the Swedish results from quantile regressions and transition matrices for both daughters and sons are presented as well as a sensitivity analysis. The last section concludes and summarizes my findings.

2 Theory and econometric framework

2.1 Assortative mating and intergenerational mobility

Intergenerational earnings mobility is the extent of the earnings transmission across generations. A society where the children's earnings distribution is completely independent of their parents can be defined as having a complete intergenerational mobility. Assortative mating is the "mating of individuals having more traits in common than likely in random mating".[4] The process of "who mates with whom" can shape the persistence of a family's position in the earnings distribution from parents to children, and consequently affects the perpetuation of earnings inequality through generations.

An elementary version of the model developed by Lam and Schoeni (1993, 1994) illustrates the role of assortative mating in intergenerational earnings mobility.[5] For simplicity, assume that all daughters marry and participate in the labour force. The intergenerational determination of the daughters' earnings can be expressed with the regression equation:

$$\log E_{wi} = \alpha_w + \beta_w y_{0i} + \varepsilon_{wi} \tag{1}$$

where $\log E_{wi}$ denotes the permanent component of log earnings for a daughter from family i, y_{0i} denotes the permanent component of her parents' log family income. The error term ϵ_{wi} reflects the combined effects on the daughter's earnings of factors orthogonal to parental income, and β_w is the intergenerational elasticity of the daughter's long-run earnings with respect to her parents' long-run income, which is positive if daughters tend to inhabit the same economic position as her parents.

[4] Definition from WordNet 2.0, 2003 Princeton University.

[5] This section follows closely Chadwick & Solon (2002) as well as Lam & Schoeni (1993, 1994).

Assume, as Lam and Schoeni do, that assortative mating can be summarized by a correlation γ between the daughter's log earnings and her husband's log earnings:

$$\gamma = Corr\left(\log E_{wi}, \log E_{hi}\right) \tag{2}$$

where $\log E_{hi}$ is the permanent component of the husband's log earnings. The model does not take into consideration the family labour-supply behaviour which explains the frequency with which married women do not participate in the labour force. Despite its simplicity, it is practical for the empirical analysis and it presents some important aspects of the role of assortative mating in the persistence of income inequality across generations.

First, Lam and Schoeni (1994) state that the regression of the daughter's husband's log earnings on her parents' log income can be written as:

$$\log E_{hi} = \alpha_h + \beta_h y_{0i} + \varepsilon_{hi} \tag{3}$$

where β_h is the elasticity of the daughter's husband's earnings with respect to her parents' income

$$\beta_h = \beta_w \gamma \sqrt{\frac{Var\left(\log E_h\right)}{Var\left(\log E_w\right)}} \tag{4}$$

If individuals' mating is completely random and not conditional on earnings, i.e. $\gamma = 0$, then β_h would be zero. But in the case of a positive assortative mating on earnings, the elasticity β_h would be positive.

Lam and Schoeni (1993) affirm that it is possible for husbands' income to be more correlated with their wives' family backgrounds than with their own family backgrounds. The husband's earnings may thus be as elastic as the daughter's own earnings with respect to her parents' economic status. According to (4), this holds if there is a high degree of assortative mating and if the husbands' earnings exhibit a larger variance than those of their wives.

Second, this model illustrates the relationship between the daughter's family income and that of her parents. Assume that the daughter's family income consists only of her own earnings and her husband's, as is the case in my data, and let S denote her husband's share of their combined earnings. Then the elasticity of the daughter's family income with respect to that of her parents is

$$\beta = S\beta_h + (1 - S)\,\beta_w \tag{5}$$

the share-weighted average of the separate elasticities of the daughter's own earnings and her husband's. If there is no assortative mating on earnings so that $\beta_h = 0$ and if the husband's earnings are greater than the wife's, then the daughter's family income is much less elastic with respect to her parents' income than her own earnings are. But if there is a high degree of assortative mating and β_h is just as large as βw, then the association between the daughter's family income and that of her parents is mainly due to her husband's earnings in the typical family where S is much more than half.

Unlike the simple model in this section, my empirical analysis also considers individuals who, in addition, are not married and those who do not participate in the labour force.

2.2 Model and econometric framework

Let y_{1i} denote the permanent component of log family income for a daughter from family i and y_{0i} for her parents. The transmission of family income across generations can be expressed with the regression equation

$$y_{1i} = \alpha + \rho y_{0i} + \varepsilon_i \tag{6}$$

where the slope coefficient ρ is the intergenerational elasticity of long-run income. The elasticity indicates what percentage above the average the offspring's earnings are predicted to be in their own generation if their parents' earnings are one percent above the average, a generation prior. If the logarithmic earnings variables in the parents' and offspring's generations are of approximately equal variance, then the elasticity will also be the correlation between log earnings in the two generations.[6] Ideally, permanent income should be used in the estimation, but often, researchers have resorted to using a measure of income in a given year, because datasets usually do not pursue either offspring or their parents long enough to enable direct measurement of permanent income. The daughter's log family income in year t is thus modelled as

$$y_{1it} = y_{1i} + \delta_1 + \gamma_1 A_{1it} + \lambda_1 A_{1it}^2 + \upsilon_{1it} \tag{7}$$

where A_{1it} is the age of the daughter from family i in year t, and υ_{1it} is a transitory fluctuation around her long-run income-age profile due to both actual transitory movement and random measurement error. Similarly, the parents' log family income in year s can be modelled as

$$y_{0is} = y_{0i} + \delta_0 + \gamma_0 A_{0is} + \lambda_0 A_{0is}^2 + \upsilon_{0is} \tag{8}$$

[6] Note that whereas intergenerational correlation is a measure of positional mobility and is insensitive to changes in inequality, elasticity measures how much economic differences across generations persist over time. Thus, elasticity incorporates changes in inequality (Aaronson and Mazumder, 2005).

A_{0is} is the age of the biological father in the year s. The relationship between the daughter's log income in year t and the parents' log income in year s is

$$y_{1it} = (\alpha + \delta_1 - \rho\delta_0) + \rho y_{0is} + \gamma_1 A_{1it} + \lambda_1 A_{1it}^2 - \rho\gamma_0 A_{0is} - \rho\lambda_0 A_{0is}^2 + \varepsilon_i + \upsilon_{1it} - \rho\upsilon_{ois} \quad (9)$$

Since υ_{0is} absorbs heterogeneity due to different life-cycle profiles, the equation incorporates the age and age squared of both parents and children in order to correct for the fact that they are not observed at the same point in their life. A least-squares estimation on this regression of the daughter's log income in year t on the parents' log income in year s and age controls for both generations, would give rise to a correlation between the key regressor y_{0is} and the error term υ_{0is}. This results in an errors-in-variables problem leading the estimated coefficient to differ from the true coefficient of the intergenerational elasticity ρ.That is, $\hat{\rho}$ would suffer from the classical errors-in-variables inconsistency, particularly if the error components are uncorrelated with each other.

$$plim\hat{\rho} = \frac{\rho\sigma_y^2}{\left(\sigma_y^2 + \sigma_\nu^2\right)} \langle \rho \quad (10)$$

where σ_y^2 denotes the population variance in parents' permanent income y_{0i} and σ_ν^2 is the variance of the measurement noise υ_{0is}. To reduce this error-in-variables bias, an average of parental log income will be used instead of a single year income. The least squares estimation is applied to the regression

$$y_{1it} = (\alpha + \delta_1 - \rho\delta_0) + \rho\bar{y}_{0is} + \gamma_1 A_{1it} + \lambda_1 A_{1it}^2 - \rho\gamma_0 \bar{A}_{0is} - \rho\gamma_0 \bar{A}_{0is}^2 + \varepsilon_i + \nu_{1it} - \rho\bar{\nu}_{ois} \quad (11)$$

where $\bar{y}_{0i}$ is the average of the sum of the parents' log income. $\bar{A}_{0i}$ is the average age of the father over those years, $\bar{A}_{0i}^2$ the average of his squared age, and $\bar{\nu}_{oi}$ averages the measurement noise over those years.

Now $\hat{\rho}$ has the same probability limit as above aside from the fact that the averaged noise variance $\bar{\nu}_{oi}$ replaces the single-year one σ_{ν}^2 . This variance of the averaged noise is smaller under a broad range of assumptions.[7]

After the estimation of the intergenerational income elasticity with the above method, I examine the sample of married daughters thoroughly by redefining family earnings in equation (11) as the log of the sum of the daughter's earnings (E_{wit}) and her husband's earnings (E_{hit}). As shown before, the elasticity of a couple's combined earnings with respect to the daughter's parents' income can be written as $\beta = S\beta_h + (1 - S)\,\beta_w$ where β_h is the elasticity of the daughter's husband's earnings with respect to her parents' income, β_w is the elasticity of her own earnings and $S = \frac{E_h}{(E_w+E_h)}$ is the share of her husband's earnings in combined earnings. The log of the couple's combined earnings is

$$\log (E_{wit} + E_{hit}) = \log (E_{hit}) - \log (S_{it}) \qquad (12)$$

where S_{it} is the share of the husband's earnings in couple i's combined earnings in year t.

In addition to estimating β with $\log (E_{wit} + E_{hit})$ as the dependent variable, I also reestimate the equation with $\log (E_{hit})$ respective $\log (S_{it})$ as the dependent variable. The difference between the coefficient vectors in these last two regressions is equal to the coefficient vector in the regression with $\log (E_{wit} + E_{hit})$ as the dependent variable.

An estimate of β_h, the elasticity of the husband's earnings with respect to the daughter's parents' income stem from using $\log (E_{hit})$ as the dependent variable.

[7] However, the use of a multi-year average of current income does not solve entirely the inconsistency problem in estimating the intergenerational elasticity. See for example Haider and Solon (2006) and Böhlmark and Lindquist (2006).

Similarly, estimating the regression with $\log(S_{it})$ as the dependent variable produces an estimate of β_S , the elasticity of the husband's share with respect to the daughter's parents' income. If $\beta_S = (1 - S)(\beta_h - \beta_w)$ is close to zero, then $\beta_w \cong \beta_h$, i.e., the elasticities of the daughter's earnings and her husband's earnings with respect to her parents' income are nearly the same.

3 Data

I use high-quality Swedish data, which stem from population registers gathered by Statistics Sweden (SCB). One advantage of this dataset is the possibility to identify both biological and nonbiological parents of offspring. Another clear advantage over the data used by C&S is the large size of the dataset which promises very precise estimates. Further, unlike the PSID data, it is a dataset of individuals rather than of households, although it gives information about the spouse of married persons and cohabitants with joint children. This gives an opportunity to study separately the sample of jointly taxed couples and permits a comparison between them and married couples.

The data set consists of a 20 percent random sample of the Swedish population born in Sweden between 1962 and 1965.[8] The multigenerational nature of the register helps link each of these individuals to either their own biological parents or the parents they live together with, in the case of adoption, by merging the individual data together with parental data. I use information about the biological parents to identify mothers and fathers.

The total sample size consists of 86,145 individuals with 44,093 females and 42,052 males. The sample is divided into four categories each for both daughters and sons.

[8] Note that the random sample consists only of Sweden-born individuals, thus immigrants are not included in the analysis.

The first three categories are the full sample, the married sample and married whose spouses have a positive income. The variable describing an individual's marital status is defined in two ways: those who are married and those with joint children. The fourth category, which offers a way to further explore the existence and magnitude of assortative mating, is a sample of cohabiting couples with joint children, who are not registered as married but are presented, in the data, as jointly taxed.[9]

The data regarding income and earnings are taken from tax-register data (*Utdrag från Inkomst och Förmögenhetregistret*) for the years 1970 and 1975 for the parents and 1999 for the offspring. Since it has been shown that observing individuals early in their careers tends to underestimate the intergenerational elasticity of income, the children's earnings are measured in 1999 when they are 34 to 37 years old. Their income at this age should reflect well their long-run income, at least for the sons. Although this might not be the case for daughters, the use of the husband's earnings to measure the daughter's economic status should resolve the conspicuous bias due to gender difference at these ages.[10] Haider and Solon (2006) have shown that the strong life-cycle pattern in the correlation between current and lifetime earnings causes intergenerational earnings elasticities to be highly sensitive to the age at which offspring's earnings are observed. Also Böhlmark and Lindquist (2006) found empirical evidence that the age at which current earnings are likely to most closely proxy lifetime earnings can vary by factors such as gender, cohort and country.[11]

There are two measures of earnings suitable for the purpose of this study: labour earnings and total income. The income and earnings concepts are defined as follows. Earnings include income from work, wages and salaries; these cover self-employment, sickness benefits and parents' allowance. Total income consists of earnings and tax-

[9] Jointly taxed cohabitants are stated as *samtaxerade* in the Swedish tax register.

[10] Note that maternity allowance is comprised in the labour earnings.

[11] However, neither Haider and Solon (2006) nor Böhlmark and Lindquist (2006) use family income in their studies.

able transfers but also includes capital income. Both measures of income are used in the estimation of intergenerational elasticity between parents and children. The log family income, which consists of the sum of the mother's and father's average of labour respective total income measured in 1970 and 1975, is used for a better proxy of permanent income. Since married women's earnings often are a poor indicator of their position in the earnings distribution, like C&S, I use the wife's share of a couple's combined earnings to predict women's earnings.[12]

Descriptive statistics for daughters and sons, using labour earnings, are shown in Table 1. The full sample contains 37,044 daughters and 38,674 sons. The mean age of both the daughters and sons is 35.43.[13] The mean of log family earnings in 1999 for the daughters is 12.49 implying a mean of 266,000 SEK for the level of family labour earnings. For the sample of sons, the mean of log family earnings is 12.51, that is roughly 271,000 SEK. In the daughters' families of origin, the father's mean age in 1970 is 36.63 and her parents' average of 1970 and 1975 log family earnings is 10.61. the corresponding figures for the sample of sons are almost the same.

4 Sweden and United States comparison

The first part of the empirical analyses applies a least squares estimation mainly on equation (11). The baseline specification is a regression of the log of daughter's (son's) family earnings in 1999 on the log of parents' family earnings averaged over the years 1970 and 1975, controlling for the age of both parents and offspring.[14] Thereafter, the specifications will vary with the use of different dependent variables and the results

[12] But unlike the PSID- variable they use in their study, the definition of "family income" in my data does not include income from other family unit members.

[13] In C&S, the mean age at which daughter's income is observed is 33.57.

[14] Quadratic specifications for the age profiles may seem too restrictive, I use year of birth dummies to control for the daughters' and sons' year of birth instead.

alter from one sample to another. Table 2 shows the estimated intergenerational elasticities for daughters, using labour earnings. The right side of the table reports the equivalent estimates from C&S as a means of comparison, though one has to be careful in comparing between studies, by keeping in mind the very different data sources used.

The estimation process starts with the full sample of 37,044 daughters. The elasticity of a daughter's family earnings with respect to her parents' family earnings is 0.249. The Swedish estimate is lower than the 0.429 C&S have found for the United States and the standard deviation is 82 percent lower than theirs. This result is, though, consistent with previous studies which established that intergenerational earnings mobility, in general, is greater in Sweden than in the United States (Björklund and Jäntti (1997), Österberg (2000)). This also lends support to the notion that the impact of family background on economic status is not as strong in Sweden as in the United States. For instance, Björklund *et al.* (2002) found that brother correlation in long-run earnings is around 0.25 for Sweden while it is about 0.40 for the U.S. Since brother correlation is a more expansive measure of the influence of family and community background than the child-parents earnings correlation, this can partly explain why the U.S. elasticity estimate exceeds the Swedish one.

The next step is to explore the extent to which assortative mating plays a role in intergenerational mobility with a focus on the sample of married daughters.[15] When estimating the intergenerational elasticity in family earnings for the 17,455 married daughters, the estimate increases marginally to 0.250.[16]

The third sample consists of married daughters whose husbands have positive

[15] A parallel estimation for the subsample of 8061 unmarried daughters produces an estimate of 0.194 with the standard error 0.015. Note that cohabitants are not included in the married sample.

[16] Since C&S have two different dependent variables, family income and couple's combined earnings, they reestimate the intergenerational elasticity with $\log(E_{wit} + E_{hit})$, i.e., the sum of a couple's earnings as the dependent variable, and find that the elasticity falls further from 0.429 to 0.387.

earnings. The 340 cases where the husbands' earnings are either missing or nonpositive are eliminated and 17,115 married daughters remain for the rest of the analysis. The elasticity estimates decline from 0.250 to 0.240 when using family earnings as the dependent variable. Pursuing the econometric setup presented in Section 3, I decompose the last estimate into the parts associated with the daughter's earnings and her husband's earnings.

First, I begin with the estimation of the elasticity of the daughter's husband's earnings with respect to her parents' earnings and get a smaller estimate of 0.231. C&S, however, found that the estimate of a daughter's husband's earnings with respect to her parents' income is very close to what they got when using the log of a couple's combined earnings as dependent variable, mainly 0.35 versus 0.36. Second, I estimate the elasticity of a daughter's husband's share of their combined earnings with respect to her parents' earnings. According to equation (5) in the econometric framework, the elasticity of the couple's combined earnings with respect to the daughter's parents' earnings is a weighted average of the elasticity of her earnings and her husband's earnings with respect to her parents' earnings.

The last estimate reported in Table 2 reveals that $\beta_h = \beta_w$, that is, these two elasticities are nearly equal since the two numbers averaged together are about the same size. The daughter's earnings are, thus, almost as elastic with respect to her parents' earnings as her husband's earnings are. This is confirmed by the small, and not significantly different from zero, discrepancy of -0.009. However, since the weight of the husband's elasticity is his share of the couple's combined earnings, the elasticity of the husband's combined earnings seems to contribute more heavily in the sum. This can be explained by the fact that, in the typical couple, the husband's earnings constitute a large part of the couple's combined earnings. C&S get the same result in their analysis but with a positive statistically insignificant, discrepancy of 0.01.

The difference between β_S in my results and in C&S is primarily due to difference in S, the husband's share of couple's combined earnings. This, in its turn, can be a reflection of unequal rate of female labour force participation in the two countries. The husband's share of couple's combined earnings is, presumably, large when women do not enter the labour market and small in the case of higher rate of female labour force participation.

The results of a parallel analysis for sons are displayed in Table 3. The intergenerational income elasticity of Swedish sons with respect to their parents is 0.296 for the full sample of 38,674 sons. The estimate for sons is larger than that of daughters 0.249. The Chi2 statistic for the contrast between these estimates is 8.34 with a probability value of 0.004, so the difference is statistically significant. According to previous studies, the Swedish estimates for intergenerational earnings elasticity between fathers and sons range from 0.13 to 0.28 (see Björklund *et al.* (2005) and Jäntti *et al.* (2006) for a survey). These figures are slightly lower compared to the 0.296 I find here, for sons. However, other literature on this topic reveals that sons exhibit larger elasticity estimates when the parents' family earnings is the measure of parental status (see Solon,1992).

Although statistically significant, the difference in the size of the estimates for daughter's and the son's elasticity is not substantial. However, the results suggest that daughters tend to have greater mobility compared to sons. This lends support to the previous finding of Österberg (2000), which reports rather low elasticity estimates for fathers and daughters ranging from 0.062 to 0.083 depending on different sample selections, and corresponding estimates of 0.125-0.185 for fathers and sons. Moreover, a more recent study of Jäntti *et al.* (2006) shows a higher intergenerational elasticity coefficient of 0.258 between fathers and sons and 0.191 for fathers and daughters. C&S also get a higher estimate for sons, 0.54 compared to 0.43 for daughters. However, the contrast between these estimates is not statistically significant in their analysis.

As for the sample of 15,069 married sons, the elasticity of the son's family earnings with respect to his parents' family earnings is a little higher, 0.258. In order to estimate the intergenerational elasticity for sons with positive earnings, 235 cases had to be dropped. The resulting estimate is almost the same, 0.257, when using family income as the dependent variable. When decomposing this estimate further, a slightly different pattern emerges for sons and daughters. The elasticity of the son's own earnings with respect to his parents' earnings is 0.297. Whereas the discrepancy between this estimate and the 0.257 estimate of a couple's combined earnings is slightly larger and statistically significant for sons with 0.040, it is both negative and not significant for daughters with -0.009. This indicates that the elasticity for the son's own earnings and the spouse's earnings are not definitely of the same magnitude unlike the case for the daughters' sample. One factor that may account for this difference is that own earnings make up a smaller fraction of total family earnings for daughters than for sons.

C&S end up with the same result for both daughters and sons in their analysis. They found that the son's elasticity exhibits a much higher estimate in the range of 0.508-0.535, and the discrepancy is -0.030 with 0.046 in standard error, thus, statistically insignificant. Moreover, C&S show that though assortative mating is playing a role in the transmission of economic status across generations for both daughters and sons, it is less important for sons than for daughters.

In the light of the above results, assortative mating appears to be a channel through which economic status is passed on from one generation to another in Sweden. Assortative mating seems to play more of a role for Swedish daughters than for sons given that β_S is not statistically significant for daughters while it is significantly different from zero for sons. These findings also infer that the difference in the daughters' and sons' intergenerational mobility patterns between the two countries does not, inherently, depend on factors that affect the marriage match. In other words, the difference in assortative mating γ is not the cause of disparity rather than a difference in the labour market structure and earnings determination process. The coefficients of β_h and β_w are quite similar for Sweden and the U.S. though of different size. They are larger in the U.S. results compared to the Swedish ones reflecting the underlying lower level of cross-sectional income inequality and higher intergenerational mobility in Sweden.

To magnify the role of assortative mating for intergenerational income mobility, a similar exercise as above is conducted, this time with the fourth sample, composed of couples who are not registered as married in the data set but are reported as jointly taxed. The results of a parallel study of this sample are displayed in Table 4 and 5 below. In order not to confuse the results with those of the married couples discussed previously, it is worth emphasizing that "samtaxerade" or jointly taxed individuals are formally defined as either married or unmarried but having children together. In this section, the observed individuals are not married but they have children together and might, presumably, be long-term cohabitants. Although some of them might not specifically live together in the same household, having children together qualifies them among jointly taxed individuals. The intergenerational elasticity estimates of the jointly taxed daughters and sons sample is overall, smaller than those of the married daughters and sons, hence even lower compared to the U.S. estimates for married couples. The OLS estimate for the jointly taxed daughter's sample of 25,516 is slightly lower than the previous elasticity for the married daughter's sample, 0.250. The elasticity of jointly taxed daughters whose cohabitants have positive earnings is marginally lower than the corresponding figure for the married daughter sample, 0.230 compared to 0.240, when family labour earnings is the dependent variable.

Following the same procedure described in equation (5), the estimate declines when the log of "husband's" earnings is used as the dependent variable. In the case of jointly taxed sons, the corresponding estimate rises slightly from 0.238 to 0.282. As for the sign and magnitude of the discrepancy, it is very similar to what was found before for married sons and daughters.

Jointly taxed couples seem to be more intergenerationally mobile than married ones. This can be explained by the fact that married individuals are likely to be more traditional than cohabitants. This in turn would mean that individuals who are cohabiting tend to live together with individuals who might necessarily not belong to their own socio-economic class. However, assortative mating is also at work for the merely jointly taxed daughters and sons. Hence, the general results do not change appreciably depending on the definition of married sample. Whether individuals are married or merely jointly taxed, the intergenerational earnings transmission and the effect of assortative mating are the same.

5 Swedish sons and daughters comparison

5.1 Quantile regression results

We now leave the comparison of the intergenerational income mobility between Sweden and the United States, and instead extend the analysis by a comparison between the Swedish sons and daughters by using a quantile regression approach and taking the possibility of nonlinearities into account.

The mean regression coefficients show that although statistically significant, the difference in the size of the estimates for daughter's and the son's elasticity is quite small. However, is it possible that the explanatory power of the parents' earnings is different for the daughter (son) ending up at the top of the daughter's (son's) earnings distribution, than it is for the daughter (son) at the bottom of the distribution?

Mean square error measures the effect of the explanatory variables on the conditional mean of the dependent variable. Quantile regression as introduced by Koenker and Bassett (1978), on the other hand, estimate the conditional quantile functions, models in which quantiles of the conditional distribution of the response variable are expressed as functions of observed covariates. Just as the sample mean can be defined as the solution to the problem of minimizing a sum of squared residuals, the median can be defined as the solution to the problem of minimizing a sum of absolute residuals as in the following equation

$$Min_{\beta \in \mathbb{R}^K} \sum_{i \in \{i: y_i \geq x_i \beta\}} \theta \left| y_i - x_i \beta \right| + \sum_{i \in \{i: y_i \prec x_i \beta\}} (1 - \theta) \left| y_i - x_i \beta \right| \tag{13}$$

where y_i is the dependent variable, which is the log of son's and daughter's family earnings in 1999, x_i is the k by 1 vector of explanatory variables, the log of parents' family earnings averaged over the years 1970 and 1975, with the first element equal to unity. The coefficient vector is β and θ is the quantile to be estimated. The coefficient β will differ depending on the particular quantile being estimated.

Quantile regression estimates the marginal effect of an explanatory variable at an arbitrary point in the conditional distribution of the dependent variable. It is a well-suited method to answer questions concerning the tails of the distribution rather than the mean and to address the issue of the difference between individuals who lie at the top of the distribution and those at the bottom.

To gain further understanding about the sons' and daughters' earnings mobility, I proceed by using quantile regression to uncover possible patterns at the tails of their conditional earnings distribution. The same specification as in the mean regression above is used, that is regressing the log of daughter's (son's) family earnings in 1999 on the log of parents' family earnings averaged over the years 1970 and 1975, controlling for ages of both parents and offspring. The results are displayed in Table 6 and 7.[17] At first sight, the median estimate seems lower overall compared to the OLS estimate. The uppermost of both tables shows that the estimates gradually decline from the lowest quantile toward the 0.25 quantile, rise then drop again at the 0.75 quantile to finally increase toward the top. This W-pattern is apparent for both the full samples of daughters and sons. Another common pattern is the large size of the estimates at the bottom and the top quantiles, however, they are of higher magnitude at the 0.05 quantile with 0.350 respective 0.266 for the daughter's sample, and with 0.454 compared to 0.278 for the son's sample.

For the full sample and the married sample of daughters, the estimates are greater at the bottom quantile though both the bottom and the top display larger figures than those in between. The reverse is true for the sample of married daughters whose husbands have positive earnings, the elasticity is greater at the top than at the bottom quantile, with 0.235 versus 0.257, but this is only the case when using family labour earnings as the dependent variable. The discrepancy between the elasticity of the daughters' family labour earnings and the elasticity of her husband's earnings with respect to her parents'earnings, is less negative the higher the quantile is, from -0.024 to -0.031. Here, a word of caution is in order. The restriction imposed on the estimates does not hold when using quantile regression instead of least-squares. This means that the elasticity of couple's combined earnings and the elasticity of the husband's share of couple's combined earnings with respect to the daughter's parents' family earnings do not add up as described in equation (5). Consequently, one should abstain from drawing any conclusions about the role of assortative mating in the earnings transmission process.

[17] Heteroskedasticity-consistent standard errors are calculated for the OLS regressions and bootstrap standard errors are reported for the quantile regressions. For more details, see Efron (1982) and Wu (1986).

As discussed in Koenker and Bassett (1982), the test for equality of coefficients across quantiles is based on the asymptotic normality of the estimated parameters. A standard Wald test is formed using a bootstrapped estimate of the covariance matrix. Formal tests of the null hypothesis of equality of parents' earnings coefficients across the 0.05-0.95 ranges are rejected with zero p-values for all three samples and different specifications.

The same general structure in the daughters' results appears for the sons except that the size of the estimate of the parents' family labour earnings is largest at the 0.10 quantile instead of the 0.05 quantile, for the married sample. The estimate at the bottom is the largest, overall, despite both the top and the bottom quantiles displaying larger estimates than the middle ones. Nonetheless, it is worth noting that the 0.05 quantile coefficient estimate of the elasticity of the sons' earnings with respect to his parents' earnings, falls by almost a half in the full sample, from 0.454 to 0.241 at the 0.25 quantile. For the married son's sample, the estimates drop from 0.433 at the bottom quantile to 0.209 at the 0.25 quantile, which is a decrease of about 52 percent, when using the son's earnings as the dependent variable. Although one cannot say much about its meaning, it is, however, interesting to observe that the discrepancy falls from 0.078 at the bottom quantile to -0.008 at the top, thus reaching its minimum at the 0.95 quantile. The equality of the parents' family earnings coefficients across all quantile ranges also is rejected with zero p-value for all three samples of sons and for the various specifications.

In this analysis, the quantile regression results are highlighting that parents' family earnings is a less important explanatory variable at the upper end of the children's earnings distribution than it is at the bottom tail of the distribution. These findings seem to convey that both the daughters and sons exhibit a similar pattern of higher intergenerational earnings elasticity at the top of the income distribution than at the bottom. Eide and Showalter (1999) also found, when using quantile regression on the PSID and High School and Beyond (HSB) data, that the intergenerational earnings correlation between fathers and sons is greater at the bottom of the son's conditional earnings distribution than at the top. They even found that estimating only the mean effect of the father's earnings by least squares is restrictive. This also applies here because the variation between the observed effect of the parents' earnings on the children's earnings at the different quantile would have been concealed had one only used the least squares method. Estimating solely the mean effect of the parents' family earnings would indeed have been restrictive. Interestingly, the daughters' and sons' intergenerational earnings mobility features seem to exhibit more resemblance than difference, and the use of a quantile regression method somehow confirms the previous results from the least-squares estimation.

5.2 The transition matrix approach

So far, the least squares method and the quantile regression approach applied in the estimation of intergenerational elasticity have shown a rather small contrast in patterns of mobility for the Swedish daughters and sons.

According to Hertz (2005), two components constitute intergenerational mobility: the conditional expectations of income given parents' income and the degree of variation around this expectation. The first component is captured by the intergenerational regression equation while the other one is not. Expected mobility may also be estimated about the conditional median instead of mean by using least absolute deviations, a quantile regression at the median, instead of least squares. Although elasticity measures how much the economic differences between families is expected to persist over time, it does not say anything about the probability of unexpected outcomes, that is, the probability of the proverbial rags-to-riches transition. Since elasticity is much more a measure of intergenerational persistence than mobility, there is a risk that considering solely the regression coefficients might conceal important difference in mobility patterns between daughters and sons. Mobility matrices, on the other side, magnify the likelihood that an adult son or daughter moves in the earnings distribution relative to his or her parents' place a generation prior. Like the quantile regression, mobility matrice has the advantage of allowing for asymmetric patterns, for instance, more mobility at the top of the distribution than at the bottom or vice versa. But the difference between quantile regression and transition matrices is that the later offers a possibility to estimate the observed probability of moving from and to any point in the earnings distribution, which is the function of both the expected and unexpected components of mobility. The quantile transition matrix approach gives further information about the nature, direction of mobility, and movement across the earnings distribution. Thus, the construction of transition matrices is complementary to the use of autoregressive models estimated above.

Previous researchers in this field have used transition matrices to illustrate the differences across the distribution of the child's earnings compared to that of the parents. Peters (1992) and Dearden *et al.* (1997) construct quartile transition matrices, and in both studies, about one-third of sons born to fathers in the bottom quartile rose to the top half of the income distribution. They also find that there is less mobility at the top and bottom of the distribution, and that sons born to fathers at the two extremes of the income distribution are more likely to occupy the same position as adults, compared to sons born to fathers with incomes in the second and third quartiles. Jäntti *et al.* (2006) examine earnings mobility among pairs of fathers and sons, and fathers and daughters across the U.S., the U.K. and the Nordic countries with the help of mobility matrices. They find that persistence is greatest in the tails of the distribution though it tends to be high at the upper ends.

I, now, turn to the analysis of a decile transition matrix relating the daughter's (son's) position in the earnings distribution to their parent's position. This consists of dividing the population into ten equal sized categories, ranked in order of earnings, and presenting the distribution of parents and children across these categories. The extreme cases of mobility can be detected as follows in a transition matrix. If the parental earnings distribution is not relevant in determining the child's distribution, then all elements of the matrix, i.e. the probability, will not differ from 0.10. In the opposite case of complete immobility where the child's current position in the earnings distribution is absolutely shaped by the position that his or her parents had in their generation, everyone stays on the leading diagonal of the matrix. In other words, the diagonals will all contain a one and the rest, a zero. The advantage of a decile transition matrix over a quartile one is that it offers a more detailed depiction and a finer desegregation of intergenerational mobility. However, a possible disadvantage of the use of a transition matrix is that nonlinear pattern could partly reflect ceilings and floors at the top and bottom of the matrix, since an upward mobility is not possible for those born at the top and a downward mobility for those born at the bottom. Hence, the degree of immobility at the top and bottom might be exaggerated. In that case, the use of regression models, which is not subject to this limitation might be preferable.

Table 8 and 9 display the transition matrices by deciles of labour earnings, for the sons and daughters full sample. At first sight, a striking fact is the notably large figures for the top deciles of both daughters and sons, suggesting that the least amount of mobility exists for those whose parents are found in the highest decile group. According to Table 8, if the parents belong to the highest decile group, there is a 24 percent probability that the daughter will also end up in the highest decile group of the earnings distribution. The corresponding probability is 14 percent for those whose parents are found in the bottom decile group. It seems that chances of falling one decile for those on top are larger than chances of rising one decile for those born at the bottom.

In the case of the relationship between parents and sons, about 27 percent of sons born to parents in the top decile group also have earnings in the top decile group, while only 16 percent of those whose parents belong to the bottom decile group, end up in the bottom of the earnings distribution as adults. Similar patterns occur for both daughters and sons, given that the most dominant signs of immobility are apparent in the top earnings class. This can also be seen when looking at the leading diagonal of the matrices, the biggest proportion of daughters and sons who remain in the same decile group as their parents is at the top, i.e., those who belong to the highest family earnings decile group. The proportion though is a little higher for sons than for daughters, reinforcing the above findings when using regression models, that daughters tend to be somewhat more mobile than sons.

Kendall's tau-b statistic is a measure of the degree of association in the transition matrices, it is constrained to lie between -1 and +1. This statistic is 0.116 for the daughter's full sample and 0.153 for the son's full sample. Though the statistic shows a positive and rather weak relationship, it points to the fact that the linkage between the son's economic status and that of his parents is more important than the association between the daughter's and her parents' earnings. [18]

Given the parent's earnings decile group, the probability that married daughters and sons end up in a certain decile group is reported in Table 10 and 11. If the parents are in the top earnings group, there is a 27 percent chance for a married daughter to be in the same group. The equivalent probability for a married son is slightly higher, 29 percent. The same pattern as above clearly emerges when considering the sample

[18] According to Peters (1992), the tau-b statistic falls slightly when deciles are used though the pattern of results is not sensitive to whether earnings are grouped by quartiles, quintiles or deciles.

of married daughters and sons, the least amount of mobility still exists for those whose parents are found in the highest earnings decile. Nonetheless, some distinctions can be worth mentioning. Kendall's tau-b statistic is higher for the married sample, 0.207 for the sons and 0.182 for daughters. This can be interpreted as a positive sign of assortative mating, the degree of association in earnings between the married daughters (sons) and their parents and in-laws seems somewhat stronger. Moreover, the probability for married sons whose parents belong to the top decile group, to end up in the middle and lower decile group is rather small compared to the full sons' sample. The same tendency can even be noticed for married daughters. About four percent of daughters born to parents in the top decile group have earnings in the fifth decile group, and only four percent of married sons from the top decile group end up in the second decile group as adults.

The results shown in the transition matrices suggest substantial mobility, especially when looking at the probabilities in the middle of the earnings distribution which are around 0.10. However, there is an asymmetric pattern, the immobility of earnings across the generations is more important at the extreme ends of the earnings distribution for both daughters and sons, though virtually more at the top than at the bottom. More immobility at the top than at the bottom means, in general, that children of rich parents are less likely to end up poor whereas those of poor parents tend to end up rich or at least belonging to the middle class. The higher probabilities for those who stay at both the top and bottom of the parents' earnings distribution denote an underlying non-linearity and can be an indication that ceilings and floors are likely to exist at the top and the bottom of the transition matrices. The nonlinear pattern is due to the fact that those at the top are limited from further upward mobility and those at the bottom are restricted from moving downward. Corak and Heisz (1999) also show non-linearities in the association of income across generations when using mobility matrices and nonparametric techniques to analyze data on Canadian men. They find that intergenerational income mobility between fathers and sons is much greater at the lower end of the income distribution than at the upper end.

Österberg (2000) found some evidence of non-linearities in her analysis, and that, in general, father's earnings correlate more weakly with the daughter's earnings than with those of the son. However, she discerned the most dominant signs of immobility in the middle income classes. This probably depends on her use of a quartile instead of a decile matrix and the fact that the lack of mobility in the highest classes is not visible because of the broader definition of the income classes in her analysis. On the other hand, Peters (1992) and Dearden *et al.* (1997), when using transition matrices to investigate intergenerational income mobility, have found that sons are more mobile with respect to their parent's income, in comparison to daughters.

As Dearden *et al.* (1997), I use three rankings indices and ranking systems in order to compare the pattern of earnings mobility between daughters and sons.[19] For the first index, as with the measure of elasticity, the smaller the sum of the elements of the leading diagonal and the adjacent cells is, the higher the mobility. A large value of both the Bartholomew and the Shorrocks index indicates a high sign of mobility. According to the ranking indices in Table 12, the daughters are clearly more mobile, i.e., more independent of their parents' position in earnings distribution compared to the sons. The difference in magnitude between the daughter's and the son's index is quite small. Whereas the index of the diagonal is larger for the married sample than the full sample, both the Bartholomew and the Shorrocks index are smaller. The larger value of the index for married sons compared to married daughters gives an

[19] The rankings indices are (i) a simple summation of the elements of the leading diagonal and the adjacent cells where the larger the index size, the higher the mobility; (ii) a weighted mobility index suggested by Bartholomew (1982) which, if a_{ij} is the proportion of daughters or sons in quantile j whose parents were in quantile i, is defined by $\sum_i \sum_j a_{ij} \, |i-j|$; (iii)an index which satisfies the mobility axioms, defined by Shorrocks (1978), for a matrix A as $(n - traceA) / (n-1)$.

insight that married daughters are slightly more mobile than married sons.

5.2.1 Sensitivity analyses

Since the transition matrices gave a hint about possible nonlinearity in the data, I tried a number of sensitivity analyses using different specifications in order to test the robustness of the results of the linear model estimated previously. First, I used both quadratic terms and year of birth dummies to account for the offspring's age when estimating the earnings transmission across generations with OLS and quantile regression. I also changed the constraint on the offspring's age to include only daughters and sons born in 1962 and 1963. The same general pattern of results remains and is present across the quantiles despite those various specifications. I use total income as well in the estimation, the basic results are the same as those from labour earnings and are presented in the Appendix.

Moreover, I tried to mimic the analysis in Österberg (2000) by dividing my original sample into mother-daughter, mother-son pairs and father-daughter, father-son pairs, using the earnings measures corrected for the difference in age between the generations, to see whether intergenerational elasticities would get about as low as what she found, mainly between 0.053 and 0.030 compared to 0.071 and 0.131. Although I get smaller coefficient estimates in the results when using individual earnings corrected for age, the magnitude of the elasticities does not belong to the small range stated above. One important reason for this divergence in the results is the different data used. Another reason is the different time period which plays a rather critical role in the measurement of the mothers' earnings. Österberg (2000) observes mothers under a three-year period, from 1978 to 1980, while I have only data for mothers' earnings for an earlier period of 1970 and 1975. As a result, 43 percent of mothers in my study have zero earnings for at least one year compared to only 18 percent of mothers in her analysis. Regardless, my main results confirm those she found in her study, namely that daughters are more mobile than sons and that Sweden does have a higher degree of mobility compared to the U.S. Moreover, this study offers a potential solution to the difficulty she was confronted with, mainly a more reliable indicator of mothers' status by using family income as a measure of their economic status. Further, the mean age of 53 at which fathers are observed in her empirical study, can partly explain the rather low elasticity estimates in her results. Grawe (2006), when examining several studies from different countries, pointed out that there is a significant negative relationship between the father's age and the estimated intergenerational earnings persistence. According to Grawe (2006), observing fathers late in the lifecycle, for instance, at the age of 53 as opposed to age 34, tends to reduce earnings persistence estimates by 0.18.[20] This is mainly due to a lifecycle bias which follows from the rise in the variance of permanent earnings over the lifecycle.

6 Conclusions

This paper examines the extent of intergenerational earnings mobility among daughters and sons in Sweden. Using high-quality data from population registers gathered by Statistics Sweden (SCB) and a broader measure of income status, family earnings, I obtained estimates that range from 0.231 to 0.250 for daughters and 0.257 to 0.297 for sons. These figures are smaller than those found for the U.S. though my using of family income as a measure of economic status yields somewhat larger elasticities than those previously estimated in Sweden. My results also confirm the fact that the impact of family background on economic status is not as strong in Sweden as in the United States.

[20] The mean age at which the fathers' earnings are observed in my analysis is 36.63 for daughters and 36.62 for sons.

A comparison between Swedish daughters and sons suggests that daughters tend to have greater mobility compared to sons. Assortative mating appears to affect the intergenerational earnings transference for both daughters and sons in this study. The elasticity for the son's own earnings and the spouse's earnings are of the same magnitude, unlike the case for daughters. Assortative mating seems to play more of a role in the transmission of economic position for daughters than for sons. My findings show that the difference in the daughters' and sons' intergenerational mobility between Sweden and the United States does not, inherently, depend on factors that affect the marriage match, but rather on the difference in the labour market structure, policies and earnings determination process. The degree of assortative mating is somewhat larger in the U.S. results compared to the Swedish ones, probably because of the underlying lower level of cross-sectional income inequality and higher intergenerational mobility in Sweden.

A separate analysis of jointly taxed couples exposes that they tend to be somewhat mobile than married ones. Assortative mating is also at work for the merely jointly taxed daughters and sons. It is still less important for daughters than for sons, so the general results do not change appreciably depending on the definition of married sample. Regardless of whether individuals are married, cohabitants, or merely jointly taxed, the pattern of intergenerational earnings transmission and the effect of assortative mating are the same.

When using the quantile regression approach, the parents' family earnings are revealed to be less important in explaining the children's earnings distribution at the upper end of the distribution than at the bottom tail. These findings convey that both daughters and sons exhibit a similar pattern of higher intergenerational earnings elasticity at the top of the income distribution than at the bottom. This variation between the observed effect of the parents' earnings on the children's earnings at the different quantile would have been concealed had one only used the least squares method. On the whole, the daughters' and sons' intergenerational earnings mobility features exhibit more similarity than difference, and the use of a quantile regression method confirms the previous results from the least squares estimation.

Similar patterns occur for both daughters and sons, given that the most dominant signs of immobility are apparent in the top earnings class when using a quantile transition matrix method. Looking at the leading diagonal of the matrices, the biggest proportion of daughters and sons who remain in the same decile as their parents is those who belong to the highest family earnings decile. The proportion is higher for sons than for daughters, reinforcing the above findings when using regression models, that daughters tend to be more mobile than sons. The general results shown in the transition matrices suggest considerable mobility, despite an asymmetric pattern, immobility of earnings across generations is more important at the extreme ends of the earnings distribution for both daughters and sons, though virtually more at the top than at the bottom. Children of rich parents are less likely to end up poor whereas those of poor parents tend to end up rich or at least belonging to the middle class.

The ranking indices attest that daughters are more independent of their parents' position in the earnings distribution compared to sons. Married daughters, also, show more mobility than married sons, an indication that assortative mating affects sons more than daughters, and a further confirmation of the results from the mean and the quantile regression analysis.

The higher probabilities for those who stay at both top and bottom of the parents' earnings distribution denote an underlying non-linearity and imply a presence of ceilings and floors at the top and bottom of the transition matrices. Poverty traps can also arise from institutions that govern economic interactions and market failures, which contribute to the persistence of inequality among families and lower the level of mobility (see for example Bowles and Gintis, 2002). This can primarily affect the lowest strata of the earnings distribution. Further empirical studies are required in order to determine and interpret the pattern and degree of nonlinearities in the Swedish intergenerational earnings mobility.

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Table 1: Descriptive Statistics.

	Daughters				Sons			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Age in 1999	35.43	1.11	34.00	37.00	35.43	1.11	34.00	37.00
Log family earnings 1999	12.49	0.92	3.13	16.39	12.51	0.86	3.97	16.39
Father's age in 1970	36.63	6.93	22.00	77.00	36.62	6.93	20.00	76.00
Parents' average of 1970 1975 log family earnings	10.61	0.44	6.45	12.87	10.61	0.44	6.06	12.88
Sample Size	37044				38674			

Table 2: Intergenerational Elasticities for Daughters

	Sweden[a]			United States[b]		
	Full Sample	Married Sample	Whose Husbands Have Positive Earnings	Full Sample	Married Sample	Whose Husbands Have Positive Earnings
Dep. Variable						
Log Family	0.249	0.250	0.240	0.429	0.408	0.387
Income	(0.011)	(0.009)	(0.008)	(0.063)	(0.055)	(0.055)
Log $(E_w + E_h)$		0.250	0.240		0.386	0.348
		(0.009)	(0.008)		(0.065)	(0.063)
Log (E_h)			0.231			0.360
			(0.013)			(0.079)
Log S			-0.009			0.012
			(0.009)			(0.052)
Sample Size	37044	17455	17115	533	372	365

a) The independent variable is daugters' family labour earnings.

b) The U.S. results are from Chadwick and Solon (2002)

Table 3: Intergenerational Elasticities for Sons

	Sweden[a]			United States[b]		
	Full Sample	Married Sample	Married With Positive Earnings	Full Sample	Married Sample	Married With Positive Earnings
Dep. Variable						
Log Family	0.296	0.258	0.257	0.535	0.541	0.508
Income	(0.010)	(0.010)	(0.009)	(0.059)	(0.062)	(0.058)
Log $(E_w + E_h)$		0.258	0.257		0.585	0.552
		(0.010)	(0.009)		(0.067)	(0.063)
Log (E_h)			0.297			0.523
			(0.013)			(0.077)
Log S			0.040			-0.030
			(0.009)			(0.046)
Sample Size	38674	15069	14834	501	340	338

a) The independent variable is sons' family labour earnings.

b) The U.S. results are from Chadwick and Solon (2002)

Table 4: Intergenerational Elasticities for Jointly Taxed Daughters

	Sweden[a]	
	Jointly Taxed Sample	Whose Cohabitants Have Positive Earnings
Dep. Variable		
Log Family Earnings	0.239	0.230
	(0.008)	(0.007)
Log $(E_w + E_h)$	0.239	0.230
	(0.008)	(0.007)
Log (E_h)		0.219
		(0.011)
Log S		-0.011
		(0.007)
Sample Size	25516	24967

a) Labour earnings are used for the Swedish data.

Table 5: Estimated Intergenerational Elasticities for Jointly Taxed Sons

	Sweden[a]	
	Jointly Taxed Sample	Jointly Taxed With Positive Earnings
Dep. Variable		
Log Family Earnings	0.248	0.238
	(0.008)	(0.007)
Log $(E_w + E_h)$	0.248	0.238
	(0.008)	(0.007)
Log (E_h)		0.282
		(0.011)
Log S		0.043
		(0.007)
Sample Size	23192	22822

a) Labour earnings are used for the Swedish data.

Table 6: Quantile Regression Results for Daughters

Full Sample								
		Quantile[a]						
	OLS[b]	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Dep. Variable								
Log Family	0.249	0.350	0.245	0.190	0.218	0.210	0.258	0.266
Labour Earnings	(0.011)	(0.044)	(0.026)	(0.012)	(0.011)	(0.007)	(0.011)	(0.010)
Sample Size	37044							
Married Sample								
Log Family	0.250	0.270	0.217	0.205	0.204	0.247	0.262	0.258
Labour Earnings	(0.009)	(0.033)	(0.021)	(0.014)	(0.008)	(0.008)	(0.009)	(0.018)
Sample Size	17455							
Whose Husbands have Positive Earnings[c]								
Log Family	0.240	0.235	0.198	0.201	0.206	0.247	0.263	0.257
Labour Earnings	(0.008)	(0.026)	(0.018)	(0.015)	(0.010)	(0.011)	(0.007)	(0.015)
Log (E_h)	0.231	0.298	0.203	0.122	0.166	0.255	0.264	0.275
	(0.013)	(0.056)	(0.035)	(0.014)	(0.009)	(0.012)	(0.015)	(0.021)
Log S	-0.009	-0.024	-0.040	-0.021	-0.009	-0.007	-0.024	-0.031
	(0.009)	(0.045)	(0.014)	(0.007)	(0.005)	(0.006)	(0.010)	(0.005)
Sample Size	17115							

a) Bootstrapped standard errors for quantile regressions in parentheses.

b) Heteroskedasticity-robust standard errors are used for the OLS regressions.

c) Note that $\beta = S\beta_h + (1 - S)\,\beta_w$ does not hold when using quantile regression.

Table 7: Quantile Regression Results for Sons

Full Sample								
		Quantile[a]						
	OLS[b]	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Dep. Variable								
Log Family	0.296	0.454	0.374	0.241	0.281	0.248	0.272	0.278
Labour Earnings	(0.010)	(0.053)	(0.025)	(0.010)	(0.008)	(0.007)	(0.010)	(0.009)
Sample Size	38674							
Married Sample								
Log Family	0.258	0.290	0.295	0.249	0.230	0.271	0.276	0.276
Labour Earnings	(0.010)	(0.029)	(0.024)	(0.013)	(0.009)	(0.009)	(0.011)	(0.014)
Sample Size	15069							
Married Sons with Positive Earnings[c]								
Log Family	0.257	0.300	0.282	0.242	0.228	0.270	0.274	0.278
Labour Earnings	(0.009)	(0.027)	(0.026)	(0.012)	(0.008)	(0.010)	(0.011)	(0.020)
Log (E_h)	0.297	0.433	0.368	0.209	0.252	0.305	0.324	0.308
	(0.013)	(0.092)	(0.040)	(0.013)	(0.007)	(0.009)	(0.010)	(0.015)
Log S	0.040	0.078	0.035	0.030	0.038	0.038	-0.006	-0.008
	(0.009)	(0.029)	(0.014)	(0.007)	(0.006)	(0.006)	(0.009)	(0.004)
Sample Size	14834							

a) Bootstrapped standard errors for quantile regressions in parentheses.

b) Heteroskedasticity-robust standard errors are used for the OLS regressions.

c) Note that $\beta = S\beta_h + (1-S)\beta_w$ does not hold when using quantile regression.

Table 8: Parents-Daughter Family Labour Earnings Transition Matrices (Full Sample)

Parents' Decile	Daughter's Decile									
	Top	9^{th}	8^{th}	7^{th}	6^{th}	5^{th}	4^{th}	3^{rd}	2^{nd}	Bottom
Top	0.244	0.142	0.092	0.057	0.071	0.076	0.092	0.081	0.062	0.081
9^{th}	0.163	0.121	0.104	0.088	0.079	0.088	0.101	0.093	0.078	0.083
8^{th}	0.117	0.122	0.110	0.105	0.085	0.091	0.101	0.100	0.082	0.086
7^{th}	0.095	0.107	0.114	0.102	0.100	0.100	0.101	0.095	0.095	0.090
6^{th}	0.087	0.108	0.111	0.108	0.110	0.103	0.091	0.092	0.104	0.085
5^{th}	0.081	0.105	0.108	0.105	0.105	0.101	0.103	0.097	0.105	0.090
4^{th}	0.075	0.085	0.103	0.115	0.105	0.111	0.101	0.111	0.101	0.093
3^{rd}	0.064	0.082	0.109	0.115	0.120	0.108	0.103	0.098	0.104	0.095
2^{nd}	0.045	0.079	0.086	0.114	0.122	0.104	0.105	0.112	0.118	0.115
Bottom	0.046	0.069	0.080	0.096	0.112	0.114	0.103	0.111	0.130	0.138

Sample Size: 37044 Kendall's tau-b: 0.116, Asymptotic Standard Error: 0.004

Table 9: Parents-Son Family Labour Earnings Transition Matrices (Full Sample)

Parents' Decile	Son's Decile									
	Top	9^{th}	8^{th}	7^{th}	6^{th}	5^{th}	4^{th}	3^{rd}	2^{nd}	Bottom
Top	0.266	0.143	0.097	0.078	0.073	0.082	0.066	0.059	0.060	0.075
9^{th}	0.171	0.132	0.101	0.0.93	0.091	0.097	0.079	0.083	0.071	0.081
8^{th}	0.124	0.120	0.111	0.103	0.095	0.101	0.091	0.090	0.084	0.082
7^{th}	0.096	0.117	0.108	0.107	0.104	0.104	0.101	0.093	0.083	0.085
6^{th}	0.087	0.111	0.116	0.092	0.109	0.103	0.099	0.100	0.095	0.088
5^{th}	0.068	0.099	0.113	0.113	0.099	0.103	0.111	0.110	0.090	0.093
4^{th}	0.067	0.082	0.100	0.118	0.107	0.107	0.112	0.106	0.113	0.088
3^{rd}	0.051	0.085	0.093	0.104	0.111	0.100	0.119	0.122	0.117	0.097
2^{nd}	0.044	0.074	0.091	0.101	0.115	0.110	0.112	0.115	0.128	0.111
Bottom	0.039	0.059	0.082	0.097	0.099	0.098	0.108	0.120	0.141	0.156

Sample Size: 38674. Kendall's tau-b: 0.153, Asymptotic Standard Error: 0.004

Table 10: Parents-Son Family Labour Earnings Transition Matrices (Married Sample)

Parents' Decile	Son's Decile									
	Top	9^{th}	8^{th}	7^{th}	6^{th}	5^{th}	4^{th}	3^{rd}	2^{nd}	Bottom
Top	0.286	0.178	0.119	0.100	0.058	0.055	0.053	0.055	0.045	0.051
9^{th}	0.181	0.157	0.135	0.097	0.095	0.072	0.064	0.068	0.067	0.073
8^{th}	0.135	0.125	0.115	0.105	0.111	0.083	0.084	0.093	0.076	0.078
7^{th}	0.090	0.101	0.128	0.120	0.109	0.109	0.087	0.099	0.093	0.077
6^{th}	0.075	0.101	0.109	0.119	0.108	0.107	0.107	0.097	0.093	0.089
5^{th}	0.058	0.085	0.105	0.117	0.099	0.102	0.123	0.097	0.100	0.096
4^{th}	0.056	0.083	0.075	0.095	0.116	0.121	0.119	0.117	0.114	0.103
3^{rd}	0.045	0.073	0.079	0.097	0.117	0.118	0.125	0.114	0.128	0.120
2^{nd}	0.048	0.058	0.087	0.097	0.105	0.115	0.108	0.122	0.128	0.130
Bottom	0.037	0.053	0.068	0.069	0.085	0.118	0.124	0.130	0.136	0.154

Sample Size: 15069. Kendall's tau-b: 0.207, Asymptotic Standard Error: 0.006

Table 11: Parents-Daughter Family Labour Earnings Transition Matrices (Married Sample)

Parents' Decile	Daughter's Decile									
	Top	9^{th}	8^{th}	7^{th}	6^{th}	5^{th}	4^{th}	3^{rd}	2^{nd}	Bottom
Top	0.272	0.171	0.121	0.078	0.070	0.045	0.052	0.060	0.062	0.069
9^{th}	0.174	0.138	0.125	0.103	0.105	0.073	0.070	0.072	0.065	0.075
8^{th}	0.120	0.126	0.117	0.112	0.104	0.097	0.080	0.073	0.091	0.079
7^{th}	0.091	0.116	0.105	0.108	0.107	0.102	0.106	0.087	0.100	0.082
6^{th}	0.083	0.097	0.099	0.116	0.109	0.106	0.115	0.102	0.083	0.091
5^{th}	0.067	0.091	0.111	0.116	0.090	0.101	0.113	0.114	0.104	0.092
4^{th}	0.069	0.081	0.094	0.104	0.107	0.116	0.104	0.114	0.109	0.102
3^{rd}	0.053	0.081	0.080	0.096	0.112	0.120	0.115	0.119	0.112	0.112
2^{nd}	0.036	0.058	0.084	0.096	0.108	0.105	0.129	0.114	0.132	0.127
Bottom	0.043	0.053	0.076	0.086	0.087	0.124	0.119	0.128	0.140	0.144

Sample Size: 17455. Kendall's tau-b: 0.182, Asymptotic Standard Error: 0.006

Table 12: Mobility Rankings

Mobility Rankings	Shorrocks Index	Sum of Leading Diagonal and Adjacent Cells	Bartholomew Index
Full Sample			
Parents-daughter	0.973 (1)	3.298 (1)	29.641 (1)
Parents-son	0.961 (2)	3.417 (2)	28.517 (2)
Married Sample			
Parents-daughter	0.962 (1)	3.527 (1)	27.641 (1)
Parents-son	0.955 (2)	3.691 (2)	26.843 (2)

Index with rank in parentheses; 1, most mobile

A Appendix

Table A1 to A9 report the estimated intergenerational elasticities for daughters and sons using total income.

Table A1: Descriptive Statistics.

	Daughters				Sons			
Variable	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
Age in 1999	35.43	1.11	34.00	37.00	35.43	1.11	34.00	37.00
Log family earnings 1999	12.62	0.75	2.30	17.94	12.61	0.74	0.70	16.62
Father's age in 1970	36.63	6.93	22.00	77.00	36.62	6.93	20.00	76.00
Parents' average of 1970-1975 log family earnings	10.63	0.42	6.45	13.21	10.64	0.42	7.36	13.58
Sample Size	38209				40099			

Table A2: Intergenerational Elasticities for Daughters

	Sweden[a]			United States[b]		
	Full Sample	Married Sample	Whose Husbands Have Positive Earnings	Full Sample	Married Sample	Whose Husbands Have Positive Earnings
Dep. Variable						
Log Family	0.225	0.238	0.237	0.429	0.408	0.387
Income	(0.009)	(0.008)	(0.008)	(0.063)	(0.055)	(0.055)
Log $(E_w + E_h)$		0.238	0.237		0.386	0.348
		(0.008)	(0.008)		(0.065)	(0.063)
Log (E_h)			0.224			0.360
			(0.012)			(0.079)
Log S			-0.013			0.012
			(0.007)			(0.052)
Sample Size	38209	17529	17410	533	372	365

a) The independent variable is daugters' family total income.

b) The U.S. results are from Chadwick and Solon (2002)

c) Note that $\beta = S\beta_h + (1 - S)\,\beta_w$ does not hold when using quantile regression.

Table A3: Intergenerational Elasticities for Sons

	Sweden[a]			United States[b]		
	Full Sample	Married Sample	Married With Positive Earnings	Full Sample	Married Sample	Married With Positive Earnings
Dep. Variable						
Log Family	0.272	0.254	0.254	0.535	0.541	0.508
Income	(0.009)	(0.009)	(0.008)	(0.059)	(0.062)	(0.058)
Log $(E_w + E_h)$		0.254	0.254		0.585	0.552
		(0.009)	(0.008)		(0.067)	(0.063)
Log (E_h)			0.307			0.523
			(0.012)			(0.077)
Log S			0.054			-0.030
			(0.007)			(0.046)
Sample Size	40099	15144	15070	501	340	338

a) The independent variable is sons' family total income.

b) The U.S. results are from Chadwick and Solon (2002)

Table A4: Quantile Regression Results for Daughters

Full Sample								
		Quantile[a]						
	OLS[b]	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Dep. Variable								
Log Family	0.225	0.153	0.164	0.198	0.181	0.224	0.297	0.318
Labour Earnings	(0.011)	(0.035)	(0.014)	(0.010)	(0.006)	(0.008)	(0.010)	(0.010)
Sample Size	38209							
Married Sample								
Log Family	0.238	0.126	0.116	0.147	0.197	0.283	0.320	0.353
Labour Earnings	(0.010)	(0.024)	(0.016)	(0.008)	(0.007)	(0.008)	(0.012)	(0.025)
Sample Size	17529							
Whose Husbands have Positive Earnings[c]								
Log Family	0.237	0.127	0.116	0.149	0.198	0.283	0.323	0.355
Labour Earnings	(0.009)	(0.018)	(0.010)	(0.007)	(0.004)	(0.007)	(0.010)	(0.017)
Log (E_h)	0.224	0.080	0.101	0.119	0.193	0.290	0.314	0.323
	(0.013)	(0.039)	(0.024)	(0.012)	(0.011)	(0.013)	(0.018)	(0.025)
Log S	-0.013	-0.089	-0.053	-0.018	0.006	0.028	0.035	0.038
	(0.009)	(0.012)	(0.009)	(0.005)	(0.005)	(0.005)	(0.006)	(0.010)
Sample Size	17410							

a) Bootstrapped standard errors for quantile regressions in parentheses.

b) Heteroskedasticity-robust standard errors are used for the OLS regressions.

c) Note that $\beta = S\beta_h + (1 - S)\beta_w$ does not hold when using quantile regression.

Table A5: Quantile Regression Results for Sons

Full Sample								
		Quantile[a]						
	OLS[b]	0.05	0.10	0.25	0.50	0.75	0.90	0.95
Dep. Variable								
Log Family	0.272	0.215	0.195	0.243	0.273	0.268	0.327	0.358
Labour Earnings	(0.010)	(0.029)	(0.018)	(0.012)	(0.011)	(0.008)	(0.011)	(0.014)
Sample Size	40099							
Married Sample								
Log Family	0.254	0.166	0.173	0.180	0.228	0.290	0.340	0.333
Labour Earnings	(0.010)	(0.030)	(0.015)	(0.007)	(0.008)	(0.011)	(0.013)	(0.017)
Sample Size	15144							
Married Sons with Positive Earnings[c]								
Log Family	0.254	0.152	0.165	0.180	0.228	0.290	0.340	0.333
Labour Earnings	(0.010)	(0.025)	(0.014)	(0.007)	(0.008)	(0.010)	(0.012)	(0.025)
Log (E_h)	0.307	0.018	0.197	0.212	0.282	0.374	0.403	0.397
	(0.014)	(0.044)	(0.020)	(0.011)	(0.011)	(0.015)	(0.020)	(0.027)
Log S	0.054	-0.011	0.013	0.040	0.062	0.079	0.068	0.063
	(0.008)	(0.034)	(0.010)	(0.007)	(0.005)	(0.005)	(0.008)	(0.010)
Sample Size	15070							

a) Bootstrapped standard errors for quantile regressions in parentheses.

b) Heteroskedasticity-robust standard errors are used for the OLS regressions.

c) Note that $\beta = S\beta_h + (1 - S)\,\beta_w$ does not hold when using quantile regression.

Table A6: Parents-Daughter Family Labour Earnings Transition Matrices (Full Sample)

Parents' Decile	Daughter's Decile									
	Top	9^{th}	8^{th}	7^{th}	6^{th}	5^{th}	4^{th}	3^{rd}	2^{nd}	Bottom
Top	0.257	0.140	0.089	0.060	0.056	0.074	0.096	0.092	0.053	0.081
9^{th}	0.164	0.124	0.098	0.094	0.077	0.081	0.099	0.098	0.078	0.087
8^{th}	0.122	0.118	0.113	0.104	0.096	0.083	0.099	0.100	0.088	0.077
7^{th}	0.086	0.109	0.109	0.102	0.104	0.089	0.111	0.105	0.097	0.087
6^{th}	0.090	0.105	0.109	0.112	0.104	0.100	0.092	0.094	0.104	0.091
5^{th}	0.076	0.104	0.109	0.104	0.110	0.105	0.099	0.096	0.108	0.089
4^{th}	0.070	0.089	0.108	0.108	0.107	0.120	0.097	0.101	0.104	0.097
3^{rd}	0.062	0.083	0.104	0.109	0.122	0.124	0.101	0.094	0.101	0.100
2^{nd}	0.048	0.078	0.094	0.112	0.121	0.112	0.101	0.107	0.118	0.109
Bottom	0.046	0.063	0.087	0.101	0.111	0.113	0.107	0.106	0.126	0.140

Sample Size: 38209 Kendall's tau-b: 0.115, Asymptotic Standard Error: 0.004

Table A7: Parents-Son Family Labour Earnings Transition Matrices (Full Sample)

Parents' Decile	Son's Decile									
	Top	9^{th}	8^{th}	7^{th}	6^{th}	5^{th}	4^{th}	3^{rd}	2^{nd}	Bottom
Top	0.285	0.149	0.095	0.067	0.059	0.079	0.073	0.059	0.053	0.081
9^{th}	0.179	0.134	0.097	0.093	0.084	0.086	0.096	0.079	0.069	0.082
8^{th}	0.122	0.122	0.116	0.095	0.094	0.103	0.088	0.086	0.088	0.086
7^{th}	0.091	0.118	0.110	0.107	0.101	0.098	0.112	0.092	0.088	0.082
6^{th}	0.078	0.110	0.120	0.106	0.101	0.106	0.100	0.101	0.099	0.079
5^{th}	0.061	0.098	0.114	0.105	0.114	0.101	0.101	0.117	0.098	0.091
4^{th}	0.063	0.080	0.104	0.120	0.115	0.101	0.110	0.106	0.110	0.091
3^{rd}	0.055	0.083	0.089	0.109	0.123	0.101	0.108	0.118	0.115	0.098
2^{nd}	0.047	0.067	0.087	0.107	0.120	0.111	0.111	0.118	0.124	0.108
Bottom	0.038	0.060	0.082	0.097	0.098	0.115	0.100	0.118	0.140	0.150

Sample Size: 40099. Kendall's tau-b: 0.153, Asymptotic Standard Error: 0.004

Table A8: Parents-Daughter Family Labour Earnings Transition Matrices (Married Sample)

Parents' Decile	Daughter's Decile									
	Top	9^{th}	8^{th}	7^{th}	6^{th}	5^{th}	4^{th}	3^{rd}	2^{nd}	Bottom
Top	0.286	0.169	0.112	0.083	0.067	0.047	0.045	0.045	0.060	0.085
9^{th}	0.177	0.143	0.134	0.112	0.080	0.095	0.064	0.057	0.065	0.073
8^{th}	0.100	0.111	0.121	0.135	0.109	0.092	0.088	0.083	0.079	0.082
7^{th}	0.090	0.107	0.114	0.108	0.109	0.102	0.094	0.105	0.88	0.081
6^{th}	0.076	0.098	0.090	0.106	0.111	0.112	0.109	0.106	0.092	0.100
5^{th}	0.070	0.096	0.098	0.114	0.109	0.098	0.112	0.105	0.102	0.101
4^{th}	0.064	0.078	0.096	0.100	0.112	0.108	0.108	0.119	0.113	0.101
3^{rd}	0.053	0.077	0.082	0.094	0.110	0.109	0.128	0.119	0.128	0.100
2^{nd}	0.039	0.062	0.088	0.090	0.099	0.125	0.132	0.123	0.119	0.123
Bottom	0.043	0.057	0.071	0.086	0.106	0.108	0.120	0.129	0.140	0.141

Sample Size: 17529. Kendall's tau-b: 0.182, Asymptotic Standard Error: 0.006

Table A9: Parents-Son Family Labour Earnings Transition Matrices (Married Sample)

Parents' Decile	Son's Decile									
	Top	9^{th}	8^{th}	7^{th}	6^{th}	5^{th}	4^{th}	3^{rd}	2^{nd}	Bottom
Top	0.304	0.189	0.114	0.095	0.071	0.044	0.044	0.038	0.044	0.057
9^{th}	0.180	0.166	0.139	0.104	0.076	0.066	0.066	0.058	0.064	0.081
8^{th}	0.132	0.127	0.121	0.098	0.104	0.089	0.089	0.075	0.090	0.074
7^{th}	0.090	0.096	0.126	0.111	0.113	0.100	0.089	0.093	0.100	0.082
6^{th}	0.076	0.095	0.105	0.127	0.109	0.111	0.100	0.087	0.099	0.090
5^{th}	0.056	0.080	0.096	0.108	0.115	0.128	0.099	0.127	0.092	0.098
4^{th}	0.047	0.076	0.086	0.090	0.118	0.120	0.126	0.118	0.116	0.101
3^{rd}	0.046	0.070	0.084	0.095	0.109	0.110	0.117	0.145	0.107	0.115
2^{nd}	0.042	0.057	0.083	0.099	0.101	0.113	0.129	0.137	0.125	0.112
Bottom	0.034	0.059	0.062	0.080	0.089	0.126	0.134	0.114	0.150	0.152

Sample Size: 15144. Kendall's tau-b: 0.216, Asymptotic Standard Error: 0.006