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A COMPARISON OF UPWARD AND DOWNWARD INTERGENERATIONAL MOBILITY IN CANADA, SWEDEN AND THE UNITED STATES

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A Comparison of Upward and Downward Intergenerational Mobility in Canada, Sweden and the United States[♣]

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Abstract

We use new estimators of directional rank mobility developed by Bhattacharya and Mazumder (2011) to compare rates of upward and downward intergenerational mobility across three countries: Canada, Sweden and the United States. These measures overcome some of the limitations of traditional measures of intergenerational mobility such as the intergenerational elasticity, which are not well suited for analyzing directional movements or for examining differences in mobility across the income distribution. Data for each country include highly comparable, administrative data sources containing sufficiently long time spans of earnings. Our most basic measures of directional mobility, which simply compare whether sons moved up or down in the earnings distribution relative to their fathers, do not differ much across the countries. However, we do find that there are clear differences in the *extent* of the movement. We find larger cross-country differences in downward mobility from the top of the distribution than upward mobility from the bottom. Canada has the most downward mobility while the U.S. has the least, with Sweden in the middle. We find some differences in upward mobility but these are somewhat smaller in magnitude. An important caveat is that our analysis may be sensitive to the concept of income we use and broader measures such as family income could lead to different conclusions. Also, small differences in rank mobility translate into rather large differences in absolute mobility measured in dollars, due to large differences in income inequality across countries.

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1. Introduction

A question of long standing interest among social scientists is the degree to which an individual's status in society is determined by the position of one's parents in the prior generation. This line of inquiry has been primarily motivated by an interest in understanding the degree of equality of opportunity in a society. The sharp rise in inequality in recent decades in some industrialized countries has brought this issue to the forefront as it is sometimes argued that rising inequality may be tolerable from a societal perspective, if there is ample room for families to move up and down the income distribution across generations.

A vast literature has emerged in recent years that has used various measures of intergenerational mobility to try to quantify the persistence of economic advantage or disadvantage across generations. We contribute to a strand of the literature that has attempted to compare rates of intergenerational mobility across countries. Our primary contribution is that we provide a rich set of estimates concerning directional rank mobility using large samples from highly comparable sources of administrative earnings data to study mobility in Canada, Sweden and the United States. The analysis of these three countries may be of particular interest since they cover the scale of welfare state policies from low (United States) to moderate (Canada) to large (Sweden).

Economists have focused primarily on the intergenerational elasticity (IGE) in earnings or income between fathers and sons. Previous surveys of the literature (e.g. Solon, 2002; Corak, 2006; Björklund and Jäntti, 2009; Black and Devereux, 2010) report similar results concerning the IGE in Canada, Sweden and the U.S. Canada and Sweden appear to have the same level of relatively high income mobility, while mobility in the U.S. by this measure is significantly lower.

While the IGE is useful for summarizing intergenerational mobility in a single parameter, it has some drawbacks. First, it does not differentiate between upward mobility and downward mobility. In the U.S., for example, much of the popular interest in intergenerational mobility has been motivated by concerns about the potential for upward mobility from the bottom. Indeed, the concern about equality of opportunity is really about the opportunity to move up. Second, the IGE is not informative about nonlinearities in mobility. For example, it could be the case that mobility is high in certain parts of the income distribution but not others. Third, the IGE is known to be sensitive to the length of time averages used and the age at which income is measured in each generation. Some have also raised concerns about selection rules concerning instances of non-positive income given the reliance on the log-log specification.[1] Lastly, estimates of the IGE rely on the marginal distributions of fathers' and sons' earnings. Since these distributions vary greatly over time and across countries one may be interested in mobility comparisons that are less influenced by them.

In this paper, we use a set of measures that are designed to measure mobility by simply comparing the relative ranks of fathers and sons in the income distribution of each respective generation. We refer to these as measures of "directional rank mobility" (DRM). For example, if the child's percentile in the distribution is higher than the parents' percentile in the prior generation then this could be classified as upward mobility.[2] We believe that these measures correspond much more closely to what a typical person thinks of as upward mobility compared to the IGE. Simple statistics that calculate the percent of individuals who experience upward or downward mobility at various points of the income distribution in each country can easily be calculated. Bhattacharya and Mazumder (2011) introduced these measures and discuss some of their key properties along with applying them to U.S. data from the NLSY. Mazumder (2011) also uses these methods and find that they can be useful in characterizing interracial differences in intergenerational mobility in the U.S.

As far as we are aware, no previous study has utilized the directional rank mobility measures on data outside of the United States. The study closest to ours is by Jäntti et al. (2006) who in addition to examining differences in the IGE, also examine four specific transition probabilities using data from the United States, the United Kingdom, Denmark, Finland, Norway and Sweden. They find significantly lower rates of upward mobility from the bottom of the distribution in the United States compared to the

[1] The IGE is also poorly suited for studying group differences in intergenerational mobility (e.g. immigrants vs. natives) because it is only informative about rates of persistence *within* groups as opposed to differences relative to the entire distribution. However, this is not relevant for our study since we look only at aggregate rates at the national level.

[2] These measures are similar to transition probabilities that have been used in prior studies of mobility to measure movements across particular quantiles of the distribution, except rather than using arbitrarily chosen quantiles, comparisons are made between the actual ranks of the parent and the child.

Nordic countries. They also find slightly lower rates of long-distance downward mobility in the United States relative to those in the Nordic countries.[3] But these differences are much less dramatic. They generally found the United Kingdom to fall somewhere between the United States and the Nordic countries.[4]

We utilize administrative data on earnings of fathers and sons for all three countries, including the United States. This provides us with a degree of consistency in both the concept of income we are using and arguably with the reliability of the data that is not typically seen in this literature. Nevertheless, we fully acknowledge that some differences in the data remain that could present issues. For instance, the U.S. data set is relatively small compared to the Canadian and Swedish data sets and the number of years across which we can average fathers' earnings ranges from 5 years in Canada to 30 years in Sweden. To assess the potential importance of such differences, we run a series of robustness checks using Swedish data that has been "worsened" in order to look more like the U.S. data.

Our most basic measures of directional mobility that simply compare whether sons moved or up or down relative to their fathers at different points in the distribution, are similar across the countries. There are however, notable differences in the *amount* of movement. We find larger cross-country differences in downward mobility from the top of the distribution than upward mobility from the bottom. Canada has the most downward mobility while the U.S. has the least, with Sweden in the middle. We find some differences in upward mobility but these are somewhat smaller in magnitude. An important caveat is that our analysis may be sensitive to the concept of income we use (taxable earnings) and that broader measures such as family income could lead to different conclusions. Also, small differences in rank mobility translate into rather large differences in absolute mobility measured in dollars, since there exist large differences in income inequality across countries.

[3] Long distance downward mobility means that the father is in the uppermost quintile, while the son ends up in the lowest quintile.

[4] In a companion paper to Jäntti et al. (2006), Bratsberg et al. (2007) present non-linear estimates of the IGE in the same set of countries (excluding Sweden). They find larger cross-country differences in estimates of the IGE in the bottom of the income distribution than in the middle and the top. This implies that cross-country comparisons based on linear estimates of the IGE may be misleading.

2. Measures

Transition Probabilities

Before describing the new measures of directional rank mobility, we first define transition probabilities. These serve as a useful base for comparison for the new measures as well as to earlier studies. The upward transition probability (hereafter "UTP") is the probability that the child's income percentile (Y_1) exceeds a given percentile *s*, in the child's income distribution by an amount τ, conditional on the parent's income percentile (Y_0) being at or below *s* in the parent's income distribution.[5]

$$(1)\quad UTP_{\tau,s} = \Pr(Y_1 > s + \tau \mid Y_0 \leq s)$$

For example, in a simple case where $\tau = 0$ and $s = 0.2$, the upward transition probability ($UTP_{0,s}$) would represent the probability that the child exceeded the bottom quintile in the child's generation, conditional on parent income being in the bottom quintile of the parent generation.[6] The empirical analysis of upward transition probabilities will vary *s* in increments of 5 percentiles throughout the bottom half of the distribution (i.e. 5, 10,…,50). Using this approach implies that the samples will overlap as progressively more families are added to the sample as *s* increases. We will also show results that use non overlapping percentile *intervals* of the parent income distribution (e.g. *s* <= 5th percentile, 5th percentile > *s* <= 10th percentile,..., 45th percentile > *s* <= 50th percentile).

It is straightforward to see that this estimator can be modified to measure downward transition probabilities by altering the inequality signs:

$$(2)\quad DTP_{\tau,s} = \Pr(Y_1 <= s + \tau \mid Y_0 > s)$$

In this case we vary *s* from 50 to 95. We also consider intervals such as the 95th percentile < *s* <=100th percentile, 90th percentile < *s* <=95th percentile,…, 50th percentile < *s* <=55th percentile.

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5 Bhattacharya and Mazumder (2011) use a more general notation that allows for a less restricted set of transition probabilities. For example, transition probabilities can be estimated conditional on parent income lying within any specific percentile interval.

6 If one were to set up a traditional transition matrix using quintiles of the income distribution this example would measure 1 minus the probability of remaining in the bottom quintile. The introduction of τ is useful to parallel variations on the UP estimator that are introduced later.

Directional Rank Mobility (DRM)

Following Bhattacharya and Mazumder (2011), we use a new measure of upward directional rank mobility ("UP") which estimates the likelihood that an individual will surpass their parent's place in the distribution by a given amount, conditional on their parents being at or below a given percentile.

$$(3)\quad UP_{\tau,s} = \Pr(Y_1 - Y_0 > \tau \mid Y_0 \le s)$$

In the simple case where $\tau = 0$, this is simply the probability that the child exceeds the parents place in the distribution. As with the TP measure, positive values of τ enable one to measure the *amount* of the gain in percentiles across generations. Results will be shown for a range of values for τ and also as s is progressively increased.[7] Similarly one can construct a measure of downward mobility ("DOWN") using an analogous approach:

$$(4)\quad DOWN_{\tau,s} = \Pr(Y_0 - Y_1 > \tau \mid Y_0 \ge s)$$

Bhattacharya and Mazumder (2011) develop the distribution theory for both transition probabilities and the directional rank mobility estimators and justify why the bootstrap can be used to calculate standard errors.

Finally, we also consider a set of more continuous measures that avoids having to specify a specific value for τ. We will also show values of the mean percentile gain for each of our samples conditional on the son's percentile being higher than the fathers' and an analogously defined measure of the mean loss conditional on sons' being below their fathers.[8]

$$(5)\quad MN\_GAIN_s = \frac{1}{N}\sum (Y_1 - Y_0) \mid Y_1 - Y_0 > 0, Y_0 \ge s)$$

$$(6)\quad MN\_LOSS_s = \frac{1}{N}\sum (Y_0 - Y_1) \mid Y_0 - Y_1 > 0, Y_0 \ge s)$$

[7] Bhattacharya and Mazumder (2011) show that the UP measure can also be calculated conditional on continuous covariates and nonparametric regressions can be used to estimate the effects of changing a covariate on upward mobility.

[8] We have also calculated these measures "unconditional" and these are available from the authors. The general cross-country patterns in the data are not altered by whether we look at these unconditionally or not.

Comparison of transition probabilities and directional rank mobility

Since there are an infinite number of possible transition probabilities, depending on the specific quantiles that are chosen, a criticism of transition probabilities is that they require using arbitrarily chosen yardsticks. In contrast, the DRM measures simply compare the child's rank to the parent's rank rather than to an arbitrarily chosen quantile. When making comparisons between population subgroups this is an unambiguous advantage to using the DRM. However, when using the full sample (i.e. pooling all subgroups), the DRM measures are only meaningful if there is some cutoff, *s* used to condition the sample. The choice of *s* of course, is likely to be arbitrary. Even in this case, however, children's ranks are still directly compared to their parents' rank as opposed to an arbitrary yardstick.

Measurement issues

A focal point of research on intergenerational mobility has concerned measurement. In particular, studies have emphasized the importance of having many years of data to better capture "permanent income" (Solon 1992, Zimmerman 1992, Mazumder 2005) and to measure income at an age at which bias due to heterogeneous lifecycle profiles is minimized (Jenkins 1987, Reville 1995, Grawe 2006, Haider & Solon 2006). Some studies have also addressed the issue of how to handle years of zero earnings given the log-log specification (Couch and Lillard 1998, Mazumder 2005). Unlike the regression context, where familiar analytical formulas can be derived to demonstrate how transitory fluctuations or measurement error can affect estimates, it is unclear how the DRM estimates are affected.[9] In practice, we generally find that these issues do not appear to have much of an effect on our findings. This may be due to the fact that we are using sufficiently long time averages and appropriate ages so as to minimize the scope for such bias. However, we leave it to future research to address this issue more thoroughly.[10]

[9] O'Neill et al (2007) consider the effect of classical measurement error on transition probabilities and show through simulations that classical measurement error can lead transition probabilities to overstate mobility as in the regression context.

[10] Note that if lifelong income trajectories cross only once (as in Figure 1 in Haider and Solon 2006), then current rank reflects lifetime rank as long as you observe this rank after the single crossing occurs. Although this is an

3. Data

Canada

The Canadian data are based upon administrative information on individual income tax returns that have been grouped into families. Canadians file their income tax returns (officially referred to as T1 Forms) on an individual basis, and Statistics Canada has grouped these into families using a variety of matching strategies that are described in Harris and Lucaciu (1994). The resulting file is the basic building block for the creation of an inter-generationally linked set of T1 Forms for a series of cohorts of young men and women, and their mothers and fathers. This represents not quite four million individuals and their parents, and in particular 1.9 million men who are the starting point for our research. These individuals are linked to their fathers—not necessarily their biological fathers—if they filed an income tax return between 1982 and 1986 while still living at home. This is required to ensure that a parent-child match is made, and also that the child has an observed Social Insurance Number (SIN), a unique individual identifier that can then be used to link all subsequent T1 Forms which contain information on earnings. These T1 Forms are available for all years between 1978 and 1996.[11]

Our analysis is based on young men who were 33 to 36 years of age in 1999, the most recent year of data that was available at the time we began our research. Fathers' earnings are defined as a five-year average in the period during the early 1980s when the son was 15 to 19 years of age. To be included in the sample fathers had to have positive earnings in each of these five years, and also to be born between 1920 and 1950 (ranging in age from 30 to 60 in 1980 when the sons were 14 to 17).[12] Corak and Heisz (1999) compare the estimates of the intergenerational elasticity calculated from these data with horizons of 1 to 5

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oversimplified case, it does strengthen our intuition that directional rank mobility should suffer less from lifecycle bias than estimates of the intergenerational earnings elasticity.

[11] The algorithm used to create the data leads to an under-representation of children from lower income backgrounds, and from the major metropolitan areas: Montreal, Toronto, and Vancouver. Corak and Heisz (1999), Oreopoulos (2003), and Oreopoulos, Page and Stevens (2008) all explore the nature of this under-reporting and find that it does not play a role in biasing their analytical results. We note that weights based upon Census data have been created to account for the under-reporting, and our analysis uses them throughout even though they make no difference to the results.

[12] Strictly speaking not all of these fathers are biological fathers, and further should be thought of as the male household head. The age restrictions are in part imposed to minimize the possibility that grandfathers or older siblings are captured as part of this category, but also motivated by the need to capture earnings at an appropriate stage in the life cycle.

years for the averaging of annual earnings to account or measurement error. They find that the estimates do not change much once four or five years of averaging are used. Sons' earnings are defined as the average over three years 1997, 1998, and 1999 and had to be greater than one in each of these years. The 33 to 36 year olds we focus upon are a bit older than the age group used in much of the Canadian literature, and is motivated by the availability of slightly more data but mostly to make this analytical sample as closely comparable to what is used in the two other countries.

Sweden

The Swedish data are based on a 25 percent random sample of sons born between 1960 and 1967. This sample was drawn from Statistic Sweden's multigenerational register. The identification rate of fathers for these cohorts of sons is approximately 98 percent. The multigenerational register also includes information on the year of birth and death (when applicable) of each individual as well as information concerning immigration and emigration. The sample of sons was then matched with data from the official Swedish tax register. We use data on pre-tax, labor market income, which is available from 1974 to 2007 to construct our earnings measure for fathers and sons.[13]

For our fathers, Böhlmark and Lindquist (2006) suggest that income measured after age 33 may act as a good proxy of permanent income. For sons born in 1950, they tell us to look at a specific age, namely age 34. But since our sons are born between 1960 and 1967 and have (on average) more education than those studied by Böhlmark and Lindquist (2006), we choose to shift this age upwards by one year to age 35.

Our proxy for permanent earnings of sons is calculated as follows. We use 11 years of earnings data for each son centered on age 35, i.e. from age 30 to age 40. Nominal earnings are deflated using the Swedish consumer price index. We use the natural logarithm of an average of real earnings taken across these ages. We require that sons have at least 10 non-missing observations of earnings. A similar

[13] This measure of earnings includes all taxable labor market insurance benefits such as sickness insurance, parental leave benefits and unemployment insurance.

procedure is used to calculate the permanent earnings of fathers. The only difference is that fathers earnings are measured between age 30 and 60. For fathers, we require at least 20 years of non-missing earnings data.

United States

The sample for the United States is based on pooling the 1984, 1990, 1991, 1992 and 1993 panels of the Survey of Income and Program Participation ("SIPP") matched to administrative earnings records maintained by the Social Security Administration (SSA).[14] The Census Bureau attempted to collect the social security numbers (SSN) of all individuals in the surveys and they were subsequently matched to SSA administrative data bases of Summary Earnings Records (SER) and Detailed Earnings Records (DER). Mazumder (2005) shows that the match rate between the 1984 SIPP and the SER data is extremely high and that selection does not appear to be a serious concern.[15] The SER data covers annual earnings over the period from 1951 to 2007, while the DER data is only available since 1978.

There are two aspects to using SER records that raise potential issues. The first is that some individuals who are working are not covered by the social security system and their earnings will be recorded as zero. Second, earnings in the SER data are censored at the maximum level of earnings subject to the social security tax. While in principle the DER data is not subject to either of these problems the DER data used in this paper only covers labor market earnings reported on W-2 form and not self-employment earnings. Therefore, we use data beginning in 1978 and combine information from both the SER and DER by taking the maximum value of earnings from the two sources in order to use earnings

[14] This data source is not publicly available. Researchers must apply to obtain the data through the Center for Economic Studies at the US Census Bureau (http://www.ces.census.gov/)
[15] Mazumder (2005) only had access to the SER data and focused on children in the 1984 SIPP who were between the ages of 15 and 20, the vast majority of whom had social security numbers. We find similar match rates to Mazumder (2005) between the SIPP and the DER.

data from both labor market earnings and self-employment.[16] The SER data is first imputed based on CPS data from each year starting in 1978.[17]

We start with a sample of males who were living with their parents at the time of the SIPP and who were no older than 20 years old. We require that the adult earnings of these men are observed when they are at least 28 years old. Sons' average earnings are taken over the five years spanning 2003 through 2007. Years of zero earnings are included in the average, however, sons must have positive income in at least two years to be included. Fathers' must have positive earnings in all 9 years between 1978 and 1986 and the average earnings over this span are used to construct a measure of permanent income. Fathers also must have been between the ages of 30 and 60 to be included. This produces a sample of 3251 men who could have been born anytime between 1964 and 1975 and who are observed as adults between the ages of 28 and 43.

Comparison of Samples

Summary statistics for each sample are shown in Table 1. Our samples are reasonably comparable along several dimensions. For example, the mean age of sons in the data ranges from 34 to 35. Similarly fathers' mean age is in a relatively small range of between 40 and 49. One notable difference is that we use just a five year average of fathers' earnings in Canada, a nine year average in the U.S. and a 20-31 year average in Sweden. Another large difference is that we have virtually the universe of observations for Canada, a very large intergenerational sample for Sweden and a small sample for the U.S.

[16] For a small set of self-employed individuals whose earnings were above the taxable maximum, this approach understates their true earnings. To address this, we obtained the full DER data (including the non-topcoded self-employed earnings) and redid all of the analysis in the paper. We found that using the full DER data has an imperceptible effect on the results (typically only changing estimates at the third decimal place). Since there are procedural difficulties in releasing a second set of statistical results through the Census Bureau disclosure avoidance review process in cases where revised estimates lead the sample size to change by just 1 or 2 individuals, and since the current results are virtually identical to the corrected ones, we have opted to show the current results that combines both the SER and DER data.

[17] This is done in the following manner. First the March CPS data is itself adjusted for topcoding based on the cell means by race and sex reported in Tables 3 and 7 of Larrimore et al (2008) who used the internal version of the CPS files. After making this adjustment, then mean values of CPS earnings of those above the SER topcode are calculated and are used to impute the SER data by cells based on race and education level (less than 16 years, 16 years, greater than 16 years) for individuals between the ages of 30 and 55.

Sensitivity Sample for Sweden

One of the important contributions of this paper is that we compare mobility measures using earnings data from official tax registers in all three countries. That is, we have access to high quality, comparable data. For each country, we have used all of the available data in order to do the best job possible to minimize bias due to measurement error. As discussed above, there are, however, significant differences in the size of each data set, in the number of years used to calculate permanent income, and in the average age of fathers when we observe their income.

An alternative approach that is sometimes used in this literature (see e.g. Jäntti et al. 2006) is to assume that different types of measurement error are the same across countries and then "worsen" the data in all countries so that they are made similar along a vector of lowest common denominators. As a robustness check, we also report results from a series of sensitivity analysis using Swedish data that has been worsened in order to emulate the data from the United States. The descriptive statistics for this sensitivity sample are reported in Table 1. Results from these sensitivity analyses are reported in Appendix Table A and discussed as needed in the text below.

4. Aggregate Mobility Results

Aggregate Estimates of Intergenerational Mobility

We begin this section by presenting estimates of the commonly used intergenerational elasticity (IGE) in earnings that are produced using our samples. For Canada, our estimate is 0.26.[18] This is a bit higher than the results reported by Corak and Heisz (1999), but the difference reflects differences in selection rules between the two samples. When we use the earnings of sons between 30 and 33, as they do, the estimated elasticity is 0.22. Our estimate for Sweden is 0.25, which can be compared with Björklund and Chadwick's (2003) estimate of 0.24 and Jäntti et al.'s (2006) estimate of 0.26.[19] For the U.S., our estimate

[18] Corak (2006) reports 7 estimates which range from 0.13 to 0.26. The preferred estimate is 0.19.
[19] Corak (2006) reports a preferred estimate of 0.27, a lower bound estimate of 0.23, and an upper bound estimate of 0.30.

of the IGE is 0.40.[20] Although our estimate is similar to the estimates in landmark studies by Solon (1992) and Zimmerman (1992), it is probably a bit lower than what might be expected given the 9 year time average and the use of the SIPP-SSA data. For example, Mazumder (2005) reports estimates of 0.50 to 0.55 when using a 9 year average of fathers' earnings.[21]

The IGE is affected by the degree of income inequality experienced by the two generations. Because of this, and since changes in the distribution of earnings over time may vary across countries, we also report the intergenerational correlation (IGC) in earnings. As opposed to the IGE, the IGC is robust to changes in the marginal distribution of earnings across generations. Our estimate of the IGC for Canada is equal to 0.23. For Sweden, the estimate is 0.21 and for the U.S. it is 0.26. According to the IGC, the U.S. is still the country with the highest degree of earnings persistence, but the differences between the three countries are now much smaller.

Lastly, we would like to present an alternative aggregate measure of intergenerational mobility, namely the intergenerational correlation in percentile rankings in earnings, which is simply the father-son Spearman rank correlation. For Canada, the rank correlation is 0.24. For Sweden it is 0.30 and for the U.S. it is 0.30. The most striking difference between these three aggregate mobility measures arises when comparing results between the U.S. and Sweden. The commonly used IGE shows large mobility differences between these two countries, while the father-son percentile rank correlation for the two countries is identical.

[20] Corak (2006) reports 41 estimates which range from 0.09 to 0.61 with a preferred estimate of 0.47. Jäntti et al.'s (2006) estimate is 0.52.

[21] One important difference between the data used here and that used by Mazumder (2005) is the availability of the non-topcoded DER data based on W-2 records. Mazumder (2005) relied on only the topcoded SER data and imputed topcoded earnings based on observable characteristics. When Mazumder (2001) drops fathers with *any* years of topcoded data and uses a 9 year average the estimate is 0.45. A second important difference is that Mazumder (2005) only used the 1984 SIPP whereas we have added samples with fewer of the older cohorts who have reached the age of 40 by 2007. In any case, if we use our sample and estimate the IGE using longer time averages such as 16 years, we find estimates similar to those reported in Mazumder (2005).

Robustness of Aggregate Estimates of Intergenerational Mobility

As noted earlier, The U.S. sample is relatively small compared to the other samples and the Swedish sample contains earnings covering a longer period of time. If we re-estimate the aggregate numbers for Sweden after first worsening the Swedish data so that it looks more like the U.S. data, then we actually see larger differences between the two countries along all three measures. The U.S. and Swedish IGEs are now 0.4 and 0.24, respectively. The U.S. and Swedish IGCs are now 0.26 and 0.16, respectively. Lastly, the father-son percentile rank correlations are 0.30 for the U.S. and 0.26 for Sweden. This implies that the U.S. numbers most likely suffer from a downward bias due to the small sample size and to measurement error and that it is this bias that is partially responsible for generating similar rank correlations for Sweden and the U.S. The father-son percentile correlation now ranks Canada as the most mobile country, the U.S. as the least mobile country, with Sweden in between.

Why Are Intergenerational Correlations Different from Intergenerational Rank Correlations?

The Pearson correlation (the IGC) is intended to measure the strength of a linear association between two normally distributed variables. Importantly, it makes use of the information that it is transmitted via an interval scale. That is, it uses information concerning the marginal distributions of the two variables. The scale used here is a monetary one and differences along this scale reflect differences in earnings inequality. The Spearman correlation (the father-son percentile rank correlation), on the other hand, makes no assumptions about the distributions of the data, nor does it require linearity to be correctly specified (only monotonicity). It does not use information concerning the marginal distributions of the two variables.

When the association in the data is approximately linear and the two variables are normal, these correlations will be similar. However, when there are outliers, or if the data is skewed, or has fat tails, i.e. if there are significant amounts of income inequality in the data, then the two measures can produce quite different correlations. Furthermore, if there are important nonlinearities in the association between fathers' and sons earnings, then these two correlations will also differ.[22] Thus, even if the Spearman correlation provides an accurate summary of aggregate movement across percentile rankings, it may tell us little about equality of opportunity, since it has been decoupled from all of the information concerning earnings inequality that can be gleaned from the actual distribution of earning in the data. The same degree of mobility in terms of percentile ranks may translate into very different changes in financial resources and wellbeing if income distributions vary widely across countries.

5. Upward Mobility Using Transition Probabilities and Rank Directional Mobility

We present our main estimates of upward mobility using cumulative samples in Table 2. Several measures are presented for each country. The first column shows the transition probability out of the fathers' percentile range. So for example, we find that the transition probability out of the bottom quintile is 69 percent in Canada and 68 percent in both Sweden and the U.S. It is worth noting that this particular statistic is equal to 1 minus the probability of staying in the bottom quintile, which is commonly presented as an entry in a transition matrix (defined by quintiles). In Figure 1 we show how the upward transition probabilities differ across the countries along with 95 percent confidence bands.[23] We find almost no differences in upward mobility between Canada, Sweden and the U.S.

This pattern of results is somewhat surprising given the previous literature and the fact that we find large differences in the IGE, but less surprising given the cross-country similarities in the father-son percentile rank correlation. Our reading of the literature suggests that this is mainly driven by the fact that we find higher rates of upward transition probabilities for the U.S. than previous studies. Specifically, a few previous studies using survey data like the PSID and NLSY (e.g. Isaacs et al., 2008; Jäntti et al, 2006) have found greater stickiness in the bottom quintile in the U.S. with around 60 percent of individuals

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[22] For example, if x =1, 2, 3,…, 100 and $y = exp(x)$, then the Spearman correlation between x and y will be 1, but the Pearson correlation between x and y will be about 0.25.

[23] We don't present confidence bands for Canada since we have virtually the population.

transitioning out of the bottom.[24] We have done some extensive experimentation with our U.S. data and believe that much of the greater observed mobility out of the bottom quintile in the U.S. is due to a difference in the concept of income being used.[25] On the one hand, this suggests that the larger differences in cross-country upward mobility observed in prior studies may be somewhat sensitive to the concept of income being used. Put differently, it may be that we are underestimating the cross-country differences that would be observed if one were to use family income. In addition, it might be the case that US survey data may better capture income at the low end of the income distribution than administrative tax data.[26] In any event, this suggests that some caution must be exercised in drawing conclusions from any one dataset or set of measures.

In the next set of columns we present our DRM measures for values of tau equal to 0, 10 and 20. Not surprisingly, we find that very large fractions of sons who start at the very bottom of the distribution surpass their fathers even if they do not surpass their parents' percentile range.[27] Our estimates range from 93 to 94 percent for those who start in percentiles 1 through 5. As we successively cumulate the sample by adding more 5 percentile groups, this fraction gradually falls as fewer sons surpass their fathers. In Figure 2, we plot the UP-0 series for each of the three countries along with 95 percent confidence bands for Sweden and the U.S. using the same scaling as in Figure 1. What is surprising is how similar the rates of upward mobility are across the three countries by using this measure. For all three countries, roughly

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[24] In Table 7 of Jäntti et al. (2006), they report transition probabilities of 0.62 for the U.S. and 0.73 for Sweden. This is the largest substantive difference between their set of results and our own. Using our sensitivity sample for Sweden we find a transition probability of 0.70 (see Appendix Table A), which is only slightly higher than the transition probability (0.68) reported in Table 2.

[25] Most previous studies have used family income as the outcome in either one or both generations. Although we cannot measure the family income of the sons with the SSA data, we can try to better capture family income in the parent generation by including mothers' earnings when available. This also alters the selection of our sample to include many children from single mother families. Making these changes significantly lowers our estimated transition probability. Unfortunately we cannot consistently use family income across the three countries

[26] A forthcoming working paper by Chris Bollinger, Charles Hokayem and James Ziliak entitled "Earnings Nonresponse and Earnings Inequality" shows that the use of DER earnings may do a poor job of reflecting the low end of the U.S. income distribution compared to survey data. This could explain the higher than expected rates of upward mobility from the bottom in the U.S.

[27] For example, a case where the father is at the 2nd percentile and the son is at the 4th percentile will have a value of UP-0=1 even though the son did not surpass the 5the percentile. In this case the transition probability indicator will be 0.

40 percent of those who start in the bottom half of the income distribution will move to the top half of the distribution.

Figure 3 plots the patterns of the UP-20 measure that shows the probability that a son will exceed his father by at least 20 percentiles. By this measure we now see a noticeably lower rate of upward mobility for the U.S. For example, 54 percent of sons in the U.S. who start in percentiles 1 to 15 surpass their parents by 20 or more percentiles compared to 58 percent in Canada. This suggests that while the likelihood of surpassing one's parents is similar across the countries the extent of mobility may differ. This is perhaps a bit clearer in Figure 4, where we plot differences in the average percentile gains across the three countries. The chart illustrates that conditional on surpassing their fathers, sons in the U.S. rise by 2 to 3 percentiles less than those in Canada. The gains of Swedish sons are only slightly lower than those in Canada.

We find broadly similar patterns if we use interval samples. The raw results are shown in Table 3. However, since the samples for the U.S. are relatively small, the estimates bounce around quite a bit, so we chose to plot the results using the cumulative samples.

In Appendix Table A, we replicate the results for Sweden shown in Table 2 using our sensitivity sample, i.e. using our sample of Swedish data that has been "worsened" in order to look like the U.S. data. Looking at Table A, we see that this increases the probability of moving up from the bottom by between 1 and 4 percentage points. For example, the transition probability of moving out of the bottom 5 percentiles rises from 88 to 92 percent, while the probability of rising out of the bottom quintile increases from 68 to 70 percent. Thus, it appears likely that the U.S. numbers may suffer from a small, positive bias of around 2 to 4 percentage points. There may be slightly more stickiness at the bottom than what we can see with this small U.S. data set.

Downward Mobility Using Transition Probabilities and Rank Directional Mobility

In this section, we turn to comparisons of downward mobility across the three countries. Tables 4 and 5 present the full set of results using cumulative and interval samples. In Figure 5, we plot the differences in the downward transition probabilities. Unlike what we saw in Figure 1, there is a more striking cross-country pattern that is evident with Canada exhibiting the highest rates of downward mobility from the top. The U.S. and Sweden in contrast, have virtually identical rates of downward mobility. For example, among Canadian men who start in the top quintile, 67 percent will fall below the top quintile. This compares to about 62 percent in the U.S. and 60 percent in Sweden.[28]

Using the simplest DRM measure of downward mobility, DN-0, we again see little difference across the countries. This is shown in Figure 6. However, we again find more striking differences when we shift to the DN-20 measure that looks at the rate at which sons fall 20 percentiles or more below their fathers. Figure 7 illustrates that downward mobility in earnings is particularly large in Canada at the very top of the distribution (96th percentile and higher) where 55 percent fall 20 percentiles below their fathers. The comparable estimate is 46 percent for Sweden and 44 percent for the U.S. This metric also appears to show the most consistent ordering across the three countries with Canada having the highest degree of downward mobility followed by Sweden and then the U.S. We find that this point generalizes beyond just setting tau equal to 20. In Figure 8, we look at the mean percentile loss among those whose rank falls below their fathers and find a similar pattern. Indeed comparing Figure 8 to Figure 4, it appears that the cross-country differences are larger with respect to downward mobility than with upward mobility.

In Appendix Table A, we replicate the results for Sweden shown in Table 4 using our sensitivity sample. This increases the probability of moving down from the top by 1 to 4 percentage points. For example, the transition probability of moving out of the top 5 percentiles rises from 79 to 83 percent, while the probability of falling out of the top quintile increases from 60 to 64 percent. Once again, this implies that there may be more stickiness at the top and the bottom of the U.S. distribution than what our sample allows us to uncover.

[28] Jäntti et al. (2006) report a transition probability of 0.63 for both the U.S. and Sweden. See their Table 7. Using our sensitivity sample, we calculate a transition probability of 0.64 for Sweden (see Appendix Table A). Previous estimates for Canada and the U.S. using similar data report transition rates out of the top quintile of 74 percent for Canada (Corak and Heisz 1999) and 66 percent for the U.S. (Mazumder 2005).

Absolute Mobility: What Does This Mean in Terms of U.S. Dollars and Cents?

In terms of upward mobility, we find surprising similarities between Canada, Sweden, and the United States. We did, however, find that Canada had more downward mobility than the U.S. and Sweden. But what do these findings mean in terms of absolute mobility and changes in living standards across generations? What does this mean in terms of U.S. dollars and cents?

Figure 9 displays the distribution of fathers' and sons' earnings in the U.S., Canada and Sweden expressed in 2007 U.S. Dollars.[29] Sweden has by far the most compressed earnings distribution, while the U.S. has the most unequal, particularly at the top. Canadian sons with earnings in the bottom half of the distribution earn more than their U.S. counterparts, while U.S. sons at P70 or above earn more than Canadian sons. Figure 9 clearly shows us that moving the same distance in terms of percentile rankings does not necessarily imply equal changes in earnings.

Figure 10 translates the mean percentile gains reported in Figure 4 into U.S. Dollars. The small differences in percentile gains observed in Figure 4 translate into modest, but not trivial, differences in absolute mobility. Sons whose fathers were in the bottom 5 percentiles of the earnings distribution gain (compared to their fathers) approximately $17,000 in the U.S., $19,000 in Sweden and $24,000 in Canada. U.S. sons make the smallest absolute gains over their fathers and they would have taken large losses if they had not moved up in the earnings distribution, since earnings in the low end of the distribution in the U.S. have fallen significantly across the two generations (see Figure 9). The largest absolute difference observed in Figure 10 is for those sons with fathers in the P1 to P15 range. Here we see that Canadian sons gain approximately $8,000 more than U.S. sons, which is roughly 20 percent of the median income of U.S. sons.

We also found that Canada had somewhat more downward mobility than Sweden and the U.S. Figure 11 translates the mean percentile losses reported in Figure 8 into U.S. Dollars. In Figure 11, we see that small differences in mean percentile losses translate into large differences in terms of absolute

[29] The different currencies were first expressed in 2007 country-specific prices and then translated into US dollars using the OECD's measures of purchasing power parity for actual individual consumption measures (PPPP41) for 2007.

mobility (i.e. dollars lost relative to one's father). The U.S. clearly has the highest level of absolute downward mobility, followed by Canada, and then Sweden. For both the U.S. and Canada, the magnitudes of these losses are much larger than the magnitudes of the gains made by those in the bottom end of the distribution. For Sweden, however, the losses seen in Figure 11 are of roughly the same magnitude as the gains seen in Figure 10.

6. Discussion and Conclusion

The current literature on cross-country differences in intergenerational mobility has noted the large difference in the intergenerational elasticity between the U.S. on the one hand and most other industrialized countries. Our approach potentially can add more richness to comparisons of this one summary statistic. By using recently developed measures of directional rank mobility we are able to examine differences in upward vs. downward mobility and look for differences at different points of the distribution. Rather than describing the rate at which earnings regress to the mean over generations we are able to describe the likelihood of a son surpassing his father's rank in the earnings distribution. In that way, our measures are arguably more easily understood by the general public.

Our findings show only moderately sized differences in rates of mobility across the distribution between Canada, Sweden and the United States. There appears to be a clear ordering in the amount of downward earnings mobility from the top of the income distribution, with Canada having the greatest declines in percentiles across generations followed by Sweden and then the U.S. Interestingly, we find almost no differences when we look at upward mobility from the bottom despite the well known concern that that perhaps there are poorer prospects for upward mobility in the U.S. An important caveat to our analysis is that by using only fathers' earnings and by relying exclusively on administrative earnings data that we may be overstating upward mobility in the U.S. relative to what would be found using sons from single parent families and combining all sources of family income using survey data. Nevertheless, we think our analysis is at least a useful first step in adding a little more nuance and richness to cross-country comparisons.

A more fundamental question is whether these measures of rank movement and the amount of rank movement mean the same thing in all three countries. It may be the case that moving 10 percentiles from the bottom of the earnings distribution is significantly more meaningful in the U.S. in terms of living standards than a comparable move in Sweden. For example, we find that upward mobility plays a much larger role in the U.S. in terms of keeping an individual out of poverty than in Canada and Sweden.

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Table 1: Summary Statistics for Intergenerational Samples

Country	Variable	Mean	S.D.	Minimum	Maximum
Canada					
	Sons' Age (1999)	34,7	1,1	33	36
	Fathers' Age (1980)	45,6	6,0	30	60
	Sons' earnings	10,5	0,6	3,4	15,2
	Fathers' Earnings	10,6	0,5	8,4	15
	N	199983			
Sweden					
	Sons' Age	35,0	0,0	30,0	40,0
	Fathers' Age	47,8	1,8	30,0	60,0
	Sons' Earnings	12,2	0,8	2,6	15,5
	Fathers' Earnings	12,1	0,6	0,9	15,1
	N	58532			
United States					
	Sons' Age (2005)	34,1	3,4	28	43
	Fathers' Age (1982)	39,9	6,3	30	60
	Sons' earnings	10,6	0,8	--	--
	Fathers' Earnings	10,9	0,6	--	--
	N	3251			
Sweden - Sensitivity Sample					
	Sons' Age (2005)	35,8	3,4	30	41
	Fathers' Age (1982)	42,3	6,5	32	60
	Sons' earnings	12,3	0,8	4,5	14,4
	Fathers' Earnings	12,2	0,5	7,8	14
	N	3251			

Table 2: Upward Mobility Using Cumulative Samples

	Canada					*Sweden*					*United States*				
Father's Pctile Range	Trans. Prob.	Directional Rank Mobility			Mean gain if UP	Trans. Prob.	Directional Rank Mobility			Mean gain if UP	Trans. Prob.	Directional Rank Mobility			Mean gain if UP
		UP-0	UP-10	UP-20			UP-0	UP-10	UP-20			UP-0	UP-10	UP-20	
1 to 5	87,4	92,9	73,5	59,7	37,5	87,6	93,0	73,7	59,8	36,2	91,4	93,8	75,9	58,6	34,4
						(0,6)	(0,5)	(0,8)	(1,0)	(0,5)	(2,2)	(1,6)	(3,4)	(3,8)	(2,1)
1 to 10	80,9	89,7	72,5	58,8	37,4	79,3	88,9	72,1	58,9	36,6	79,7	90,2	72,3	57,5	35,9
						(0,6)	(0,4)	(0,6)	(0,7)	(0,4)	(3,8)	(1,7)	(2,3)	(2,7)	(1,5)
1 to 15	75	87	70,9	57,5	37,3	73,1	85,6	70,2	57,4	36,4	74,5	87,7	69,8	54,2	34,4
						(0,5)	(0,4)	(0,5)	(0,6)	(0,3)	(3,7)	(1,6)	(2,0)	(2,3)	(1,1)
1 to 20	69,4	84,2	68,9	55,8	36,9	67,6	82,8	68,6	56,2	36,2	67,8	85,2	69,1	54,5	34,3
						(0,4)	(0,4)	(0,4)	(0,4)	(0,2)	(3,7)	(1,5)	(1,6)	(1,8)	(1,0)
1 to 25	63,8	81,6	67	54,3	36,5	62,8	80,7	66,9	54,5	35,6	64,4	83,6	68,3	53,2	34,1
						(0,4)	(0,3)	(0,4)	(0,4)	(0,2)	(3,6)	(1,1)	(1,4)	(1,6)	(0,9)
1 to 30	58,8	79,1	65	52,7	36	58,0	78,2	65,0	52,6	34,9	59,0	81,0	66,7	52,1	33,8
						(0,4)	(0,3)	(0,4)	(0,4)	(0,2)	(3,3)	(1,2)	(1,2)	(1,3)	(0,7)
1 to 35	53,9	76,7	63	50,9	35,4	53,2	75,9	62,9	50,8	34,2	54,4	78,4	64,6	50,6	33,4
						(0,3)	(0,3)	(0,4)	(0,3)	(0,2)	(2,0)	(1,0)	(1,3)	(1,2)	(0,7)
1 to 40	49,5	74,5	61,1	49,2	34,8	48,9	74,0	61,1	49,0	33,4	48,9	75,4	62,3	48,8	33,3
						(0,3)	(0,3)	(0,3)	(0,3)	(0,2)	(2,5)	(1,0)	(1,2)	(1,2)	(0,6)
1 to 45	45,3	72,4	59,3	47,5	34,1	44,3	71,8	59,2	47,1	32,7	43,4	72,3	59,2	46,4	32,6
						(0,3)	(0,3)	(0,3)	(0,3)	(0,1)	(2,8)	(0,9)	(1,1)	(1,1)	(0,6)
1 to 50	41	70,2	57,3	45,7	33,4	39,8	69,8	57,3	45,2	32,0	39,4	70,5	57,6	45,0	32,0
						(0,3)	(0,2)	(0,3)	(0,3)	(0,1)	(2,9)	(0,8)	(0,9)	(1,1)	(0,6)

Standard errors in parentheses.

Table 3: Upward Mobility Using Interval Samples

Father's Pctile Range	*Canada* Trans. Prob.	Directional Rank Mobility *UP-0*	*UP-10*	*UP-20*	Mean gain if UP	*Sweden* Trans. Prob.	Directional Rank Mobility *UP-0*	*UP-10*	*UP-20*	Mean gain if UP	*United States* Trans. Prob.	Directional Rank Mobility *UP-0*	*UP-10*	*UP-20*	Mean gain if UP
1 to 5	87,4	92,9	73,5	59,7		87,6	93,0	73,7	59,8	36,2	91,4	93,8	75,9	58,6	34,4
						(0,6)	(0,4)	(0,8)	(1,0)	(0,6)	(2,2)	(1,6)	(3,4)	(3,8)	(2,1)
6 to 10	83,6	86,5	71,5	57,9		81,3	84,7	70,5	58,0	37,0	78,5	86,5	68,7	56,4	37,6
						(0,7)	(0,6)	(0,8)	(1,0)	(0,5)	(3,8)	(2,9)	(3,6)	(4,3)	(2,5)
11 to 15	78,6	81,5	67,8	54,9		76,1	79,1	66,3	54,4	36,1	79,0	82,7	64,8	47,5	31,1
						(0,8)	(0,8)	(0,9)	(0,9)	(0,5)	(3,7)	(3,5)	(3,7)	(4,7)	(2,3)
16 to 20	73,3	76	62,9	50,9		71,9	74,5	63,8	52,6	35,2	74,8	77,9	66,9	55,2	34,0
						(0,8)	(0,9)	(0,9)	(0,9)	(0,5)	(3,7)	(3,7)	(3,6)	(4,0)	(2,1)
21 to 25	68,5	71,1	59,2	48,2		69,1	72,0	60,2	47,6	33,0	74,7	77,2	65,4	48,1	33,0
						(0,8)	(0,9)	(0,9)	(1,0)	(0,5)	(3,6)	(3,6)	(3,9)	(3,9)	(1,9)
26 to 30	64,5	66,8	55,3	44,6		64,2	66,1	55,5	43,3	30,9	64,4	68,1	58,3	46,6	32,2
						(0,8)	(0,9)	(0,9)	(0,9)	(0,5)	(3,3)	(3,6)	(3,8)	(3,7)	(2,0)
31 to 35	60	62,3	51	40		59,5	62,2	50,1	39,8	28,7	60,5	62,3	51,9	41,4	30,3
						(1,0)	(1,0)	(0,9)	(1,0)	(0,4)	(3,2)	(4,1)	(4,5)	(4,1)	(1,7)
36 to 40	56,9	59,1	48	37,4		57,8	60,4	48,9	36,7	26,7	52,8	54,6	46,6	36,8	32,3
						(0,9)	(0,9)	(0,9)	(0,9)	(0,4)	(3,9)	(4,4)	(4,5)	(4,1)	(2,2)
41 to 45	53,1	55,4	44,5	33,7		51,4	54,2	43,5	31,7	25,1	45,7	47,5	34,6	26,5	23,8
						(0,9)	(1,0)	(0,9)	(0,9)	(0,4)	(3,7)	(3,9)	(4,0)	(3,5)	(1,9)
46 to 50	48,4	50,7	39,7	28,9		48,9	51,7	40,8	28,2	23,1	52,8	54,0	42,9	32,5	25,3
						(1,0)	(0,9)	(0,9)	(0,8)	(0,4)	(3,9)	(4,2)	(4,5)	(3,9)	(1,7)

Standard errors in parentheses.

Table 4: Downward Mobility Using Cumulative Samples

	Canada					*Sweden*					*United States*				
Father's Pctile Range	Trans. Prob.	Directional Rank Mobility			Mean loss if DN	Trans. Prob.	Directional Rank Mobility			Mean loss if DN	Trans. Prob.	Directional Rank Mobility			Mean loss if DN
		DN-0	DN-10	DN-20			*DN-0*	*DN-10*	*DN-20*			*DN-0*	*DN-10*	*DN-20*	
96 to 100	82,2	89,2	67,8	54,9	36,1	78,8	87,9	60,8	45,7	32,8	81,0	86,5	59,5	44,2	33,7
						(0,8)	(0,6)	(0,9)	(0,9)	(0,6)	(3,1)	(2,6)	(3,8)	(4,1)	(2,4)
91 to 100	76,8	86,9	68,5	55,5	37	70,5	84,3	61,7	48,0	34,7	71,5	85,3	60,7	44,2	33,3
						(0,6)	(0,5)	(0,6)	(0,7)	(0,4)	(3,4)	(2,0)	(2,5)	(2,4)	(1,7)
86 to 100	71,9	84,6	67,8	55	37,1	64,6	81,4	62,0	48,4	35,1	65,8	83,4	63,1	45,7	34,3
						(0,5)	(0,4)	(0,5)	(0,6)	(0,4)	(4,1)	(1,6)	(1,9)	(2,2)	(1,3)
81 to 100	67,1	82,3	66,5	54,1	36,9	59,9	78,8	61,0	48,1	35,2	62,2	81,4	63,0	47,5	35,1
						(0,4)	(0,4)	(0,4)	(0,5)	(0,3)	(4,0)	(1,4)	(1,7)	(1,8)	(1,1)
76 to 100	62,3	80,1	65,2	53,1	36,6	56,2	76,9	60,5	48,0	35,2	57,3	79,8	62,1	47,5	34,5
						(0,4)	(0,4)	(0,4)	(0,4)	(0,3)	(3,7)	(1,2)	(1,4)	(1,5)	(0,9)
71 to 100	57,8	78	63,7	51,7	36,1	52,9	75,2	59,8	47,6	34,9	52,8	77,6	60,8	46,3	33,7
						(0,4)	(0,3)	(0,4)	(0,4)	(0,2)	(3,3)	(1,1)	(1,3)	(1,4)	(0,8)
66 to 100	53,3	75,8	61,9	50,2	35,6	49,7	73,5	58,9	46,9	34,5	50,5	76,6	60,5	46,5	33,2
						(0,4)	(0,3)	(0,3)	(0,3)	(0,2)	(2,4)	(1,1)	(1,3)	(1,3)	(0,7)
61 to 100	49,2	73,7	60,2	48,6	34,9	46,7	71,9	57,8	46,0	34,0	47,3	75,2	58,8	45,3	32,4
						(0,3)	(0,3)	(0,3)	(0,3)	(0,2)	(2,5)	(1,1)	(1,3)	(1,2)	(0,7)
56 to 100	45,2	71,7	58,5	46,9	34,3	43,4	70,4	56,4	44,6	33,2	43,7	73,5	57,6	44,3	32,0
						(0,3)	(0,3)	(0,3)	(0,3)	(0,2)	(2,5)	(1,0)	(1,1)	(1,2)	(0,7)
51 to 100	41	69,6	56,7	45,3	33,7	39,8	68,6	54,9	43,2	32,5	39,4	70,5	55,7	42,7	31,7
						(0,3)	(0,3)	(0,3)	(0,3)	(0,2)	(2,6)	(0,9)	(1,0)	(1,0)	(0,5)

Standard errors in parentheses.

Table 5: Downward Mobility Using Interval Samples

	Canada					*Sweden*					*United States*				
Father's Pctile Range	Trans. Prob.	Directional Rank Mobility			Mean loss if DN	Trans. Prob.	Directional Rank Mobility			Mean loss if DN	Trans. Prob.	Directional Rank Mobility			Mean loss if DN
		DN-0	DN-10	DN-20			*DN-0*	*DN-10*	*DN-20*			*DN-0*	*DN-10*	*DN-20*	
96 to 100	82,2	89,2	67,8	54,9		78,8	87,9	60,8	45,7	32,8	81,0	86,5	59,5	44,2	33,7
						(0,7)	(0,6)	(0,9)	(1,0)	(0,5)	(3,1)	(2,7)	(3,8)	(4,2)	(2,4)
91 to 95	81,1	84,5	69,3	56,1		76,1	80,7	62,6	50,3	36,8	76,7	84,0	62,0	44,2	32,9
						(0,8)	(0,7)	(0,9)	(0,9)	(0,6)	(3,4)	(3,3)	(4,3)	(3,8)	(2,3)
86 to 90	77,1	80	66,2	54,1		72,6	75,6	62,5	49,3	35,9	75,9	79,6	67,9	48,8	36,5
						(0,8)	(0,7)	(0,9)	(0,9)	(0,5)	(4,1)	(4,0)	(3,9)	(4,1)	(2,4)
81 to 85	72,9	75,6	62,7	51,4		67,7	70,9	57,9	46,9	35,6	71,8	75,5	62,6	52,8	37,8
						(0,9)	(0,9)	(1,0)	(1,0)	(0,5)	(4,0)	(3,4)	(3,9)	(3,9)	(2,3)
76 to 80	68,8	71,4	59,9	48,7		66,7	69,4	58,6	47,5	35,1	67,3	73,5	58,6	47,5	31,7
						(0,8)	(0,9)	(0,9)	(0,9)	(0,5)	(3,7)	(3,7)	(4,2)	(4,0)	(2,3)
71 to 75	64,8	67,2	55,9	44,8		64,5	66,8	56,5	45,7	33,4	60,7	66,3	54,0	40,5	28,6
						(0,9)	(0,9)	(0,9)	(0,9)	(0,5)	(3,3)	(3,7)	(4,4)	(4,1)	(2,0)
66 to 70	60,3	62,5	51,7	41,5		60,6	63,5	53,5	43,0	31,6	69,1	71,0	58,6	47,5	30,5
						(0,9)	(1,0)	(1,0)	(0,9)	(0,4)	(3,8)	(3,8)	(4,0)	(4,3)	(1,8)
61 to 65	57,1	59,3	48,2	37,3		58,4	60,6	49,5	39,4	29,0	59,5	65,6	47,2	37,4	25,9
						(0,9)	(0,9)	(0,9)	(1,0)	(0,4)	(3,7)	(4,7)	(4,4)	(4,1)	(2,0)
56 to 60	53,2	55,3	44,5	33,6		55,3	58,1	46,0	33,8	25,9	56,2	59,3	48,1	35,8	27,5
						(0,9)	(0,9)	(1,0)	(0,9)	(0,4)	(3,6)	(4,8)	(4,4)	(4,1)	(1,8)
51 to 100	48,8	50,9	40,1	30,1		49,7	52,0	41,4	29,8	24,4	42,3	43,6	38,7	28,8	26,9
						(0,9)	(0,9)	(1,0)	(0,8)	(0,4)	(3,8)	(3,9)	(4,2)	(3,5)	(1,6)

Standard errors in parentheses.

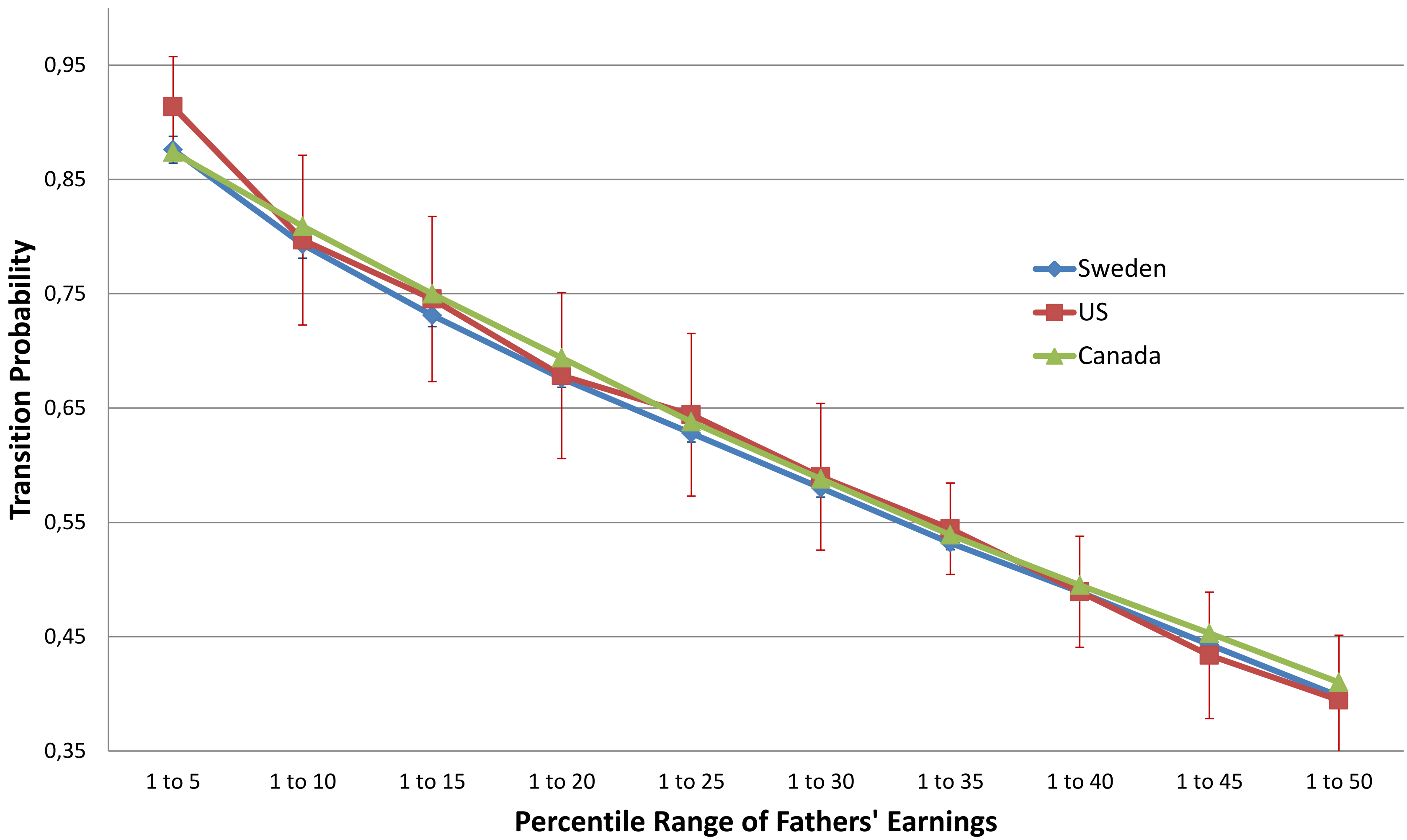


Figure 1: Upward Transition Probability Using Cumulative Samples (Tau=0)

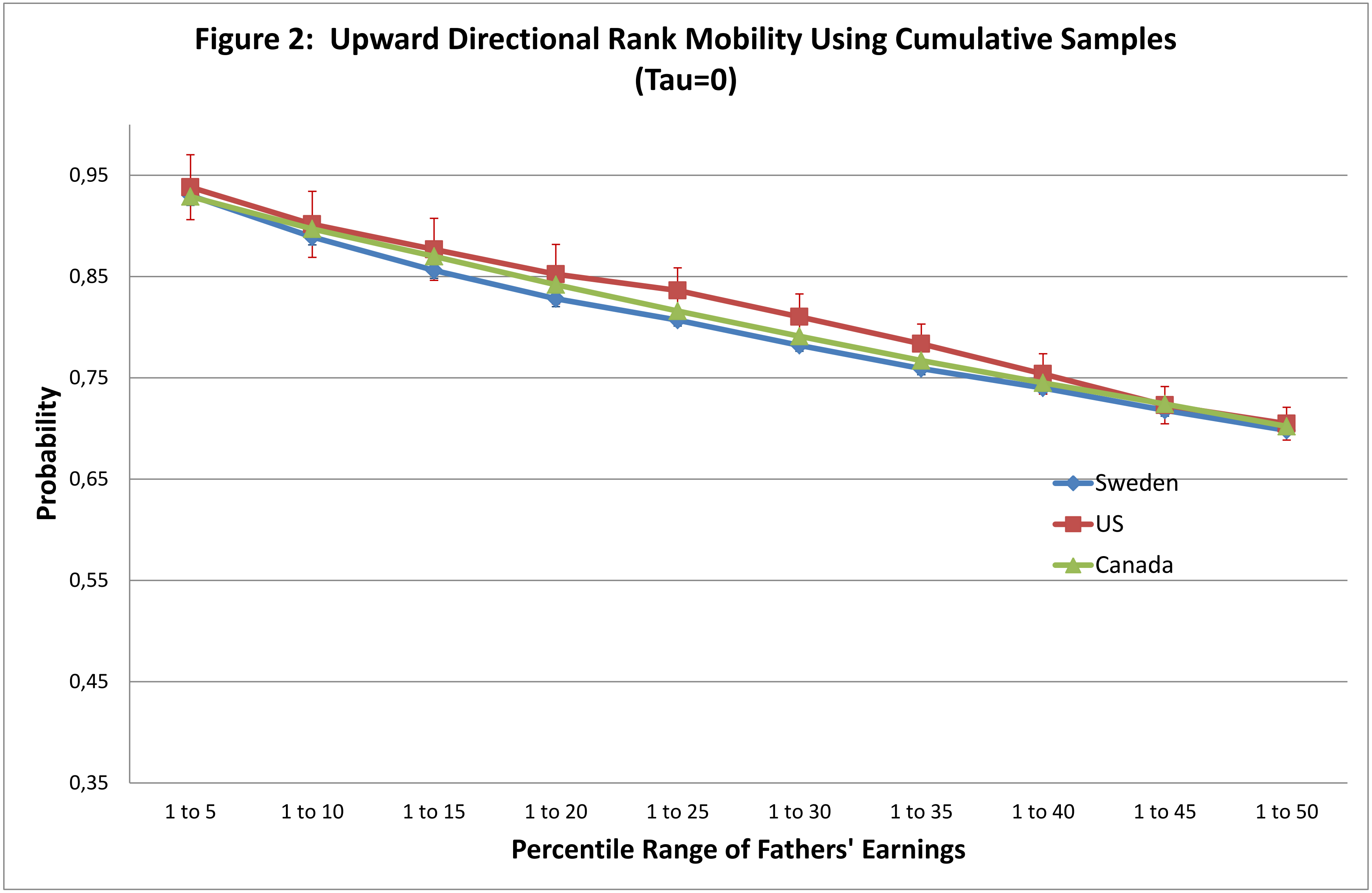


Figure 2: Upward Directional Rank Mobility Using Cumulative Samples
(Tau=0)
Probability
0,95
0,85
0,75
0,65
0,55
0,45
0,35
1 to 5
1 to 10
1 to 15
1 to 20
1 to 25
1 to 30
1 to 35
1 to 40
1 to 45
1 to 50
Percentile Range of Fathers' Earnings
Sweden
US
Canada

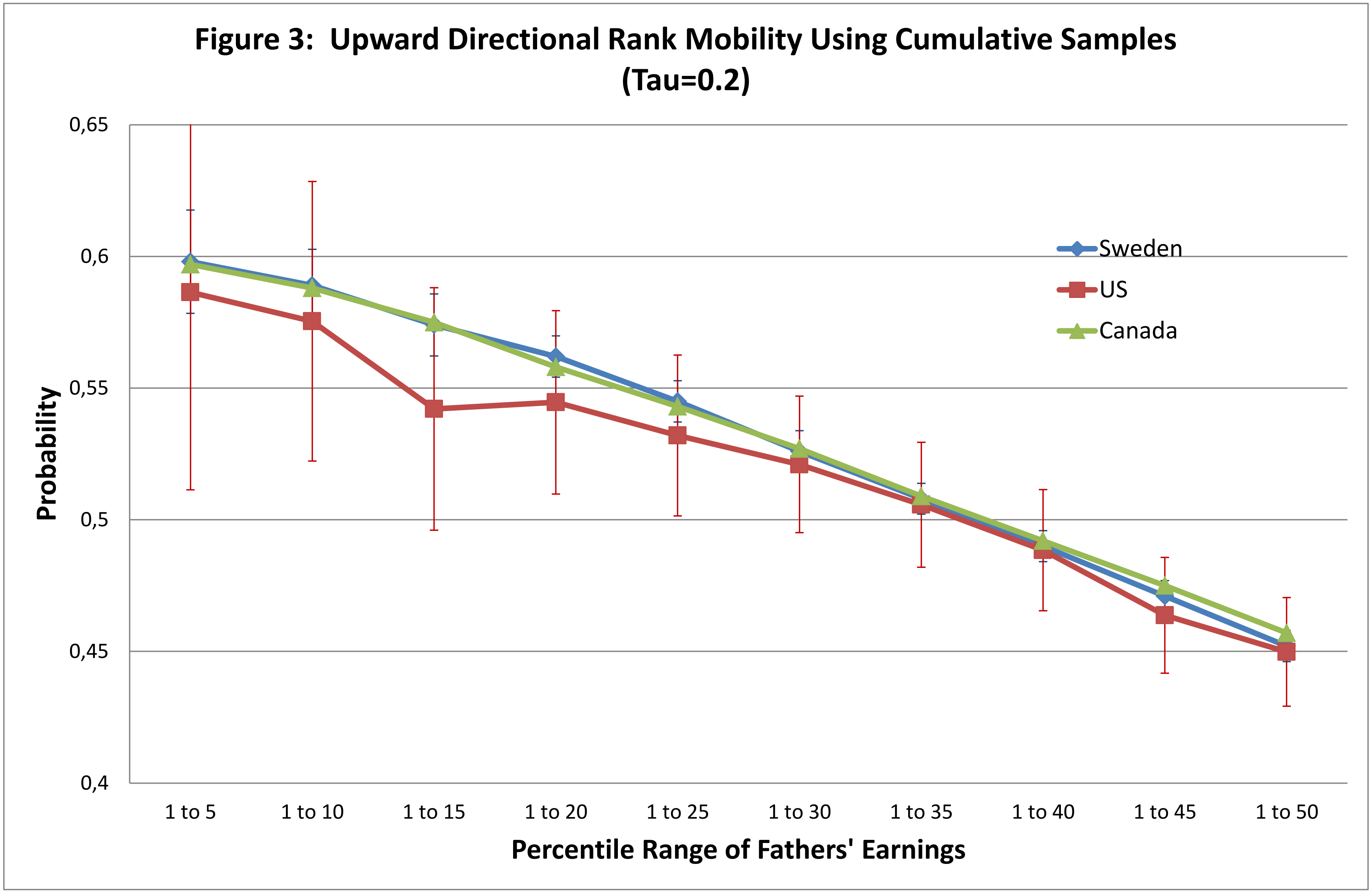


Figure 3: Upward Directional Rank Mobility Using Cumulative Samples
(Tau=0.2)
0,65
0,6
0,55
0,5
0,45
0,4
Probability
Sweden
US
Canada
1 to 5
1 to 10
1 to 15
1 to 20
1 to 25
1 to 30
1 to 35
1 to 40
1 to 45
1 to 50
Percentile Range of Fathers' Earnings

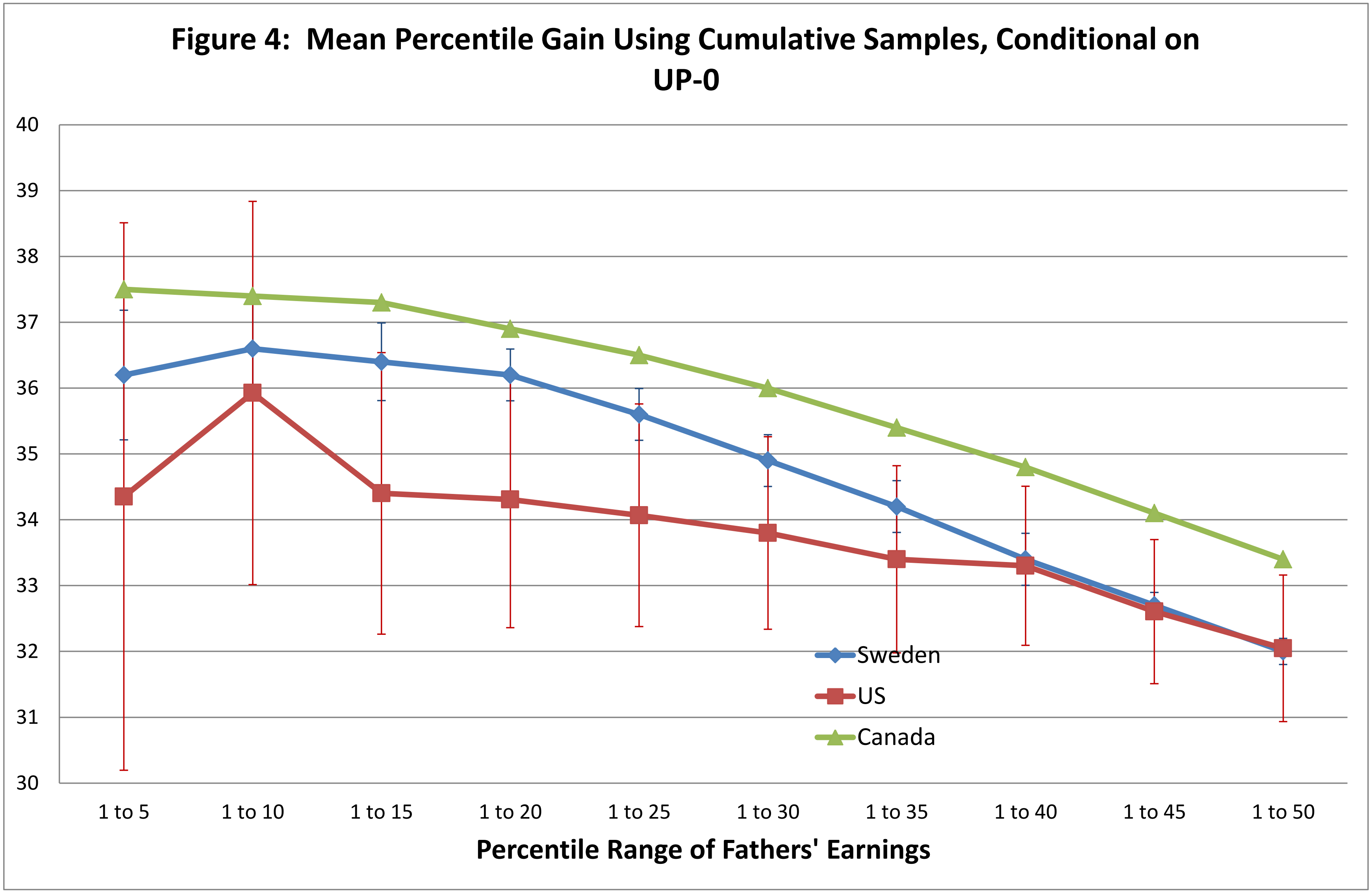


Figure 4: Mean Percentile Gain Using Cumulative Samples, Conditional on UP-0
40
39
38
37
36
35
34
33
32
31
30
Sweden
US
Canada
1 to 5
1 to 10
1 to 15
1 to 20
1 to 25
1 to 30
1 to 35
1 to 40
1 to 45
1 to 50
Percentile Range of Fathers' Earnings

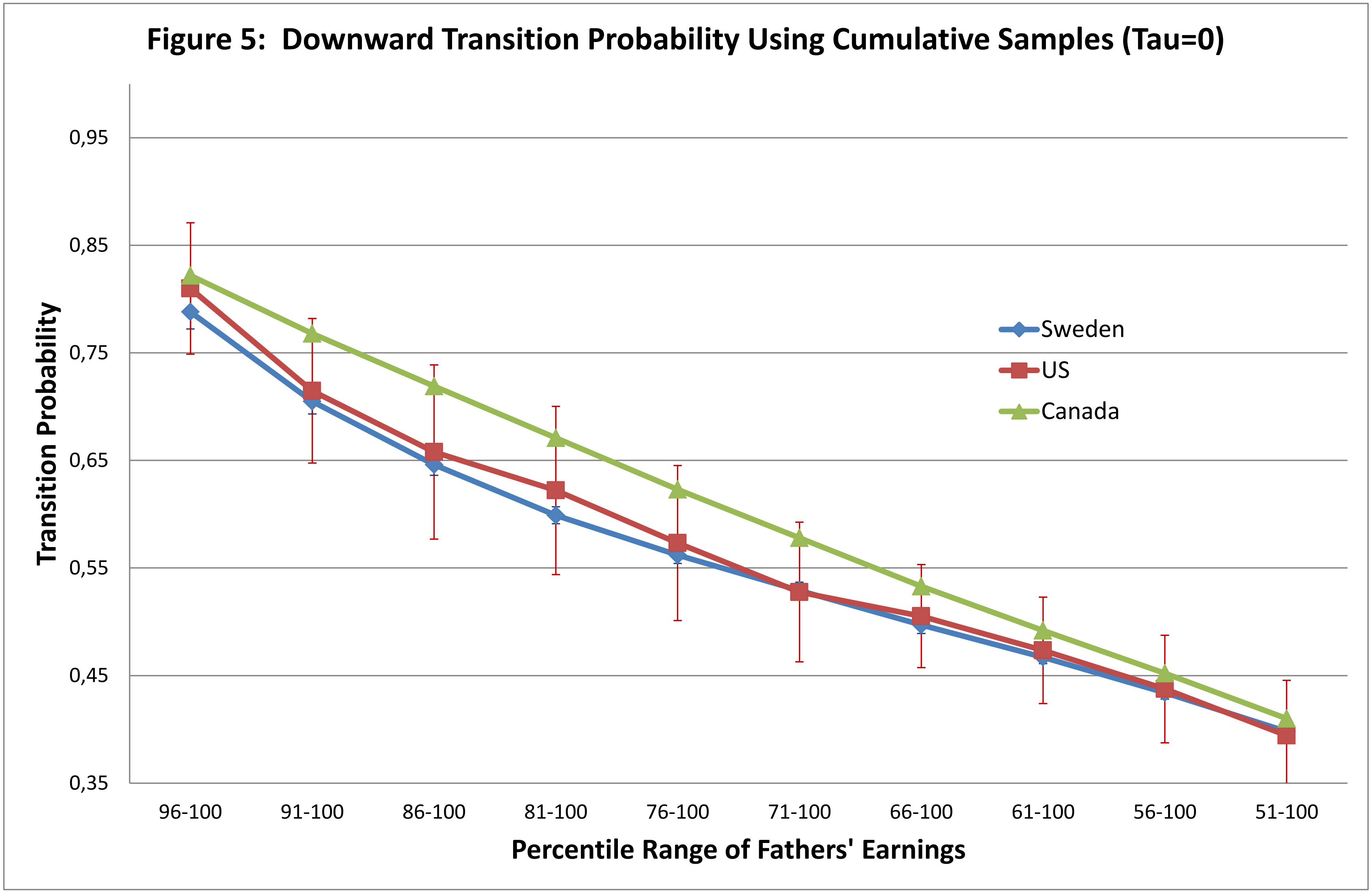


Figure 5: Downward Transition Probability Using Cumulative Samples (Tau=0)
Transition Probability
0,95
0,85
0,75
0,65
0,55
0,45
0,35
Sweden
US
Canada
96-100
91-100
86-100
81-100
76-100
71-100
66-100
61-100
56-100
51-100
Percentile Range of Fathers' Earnings

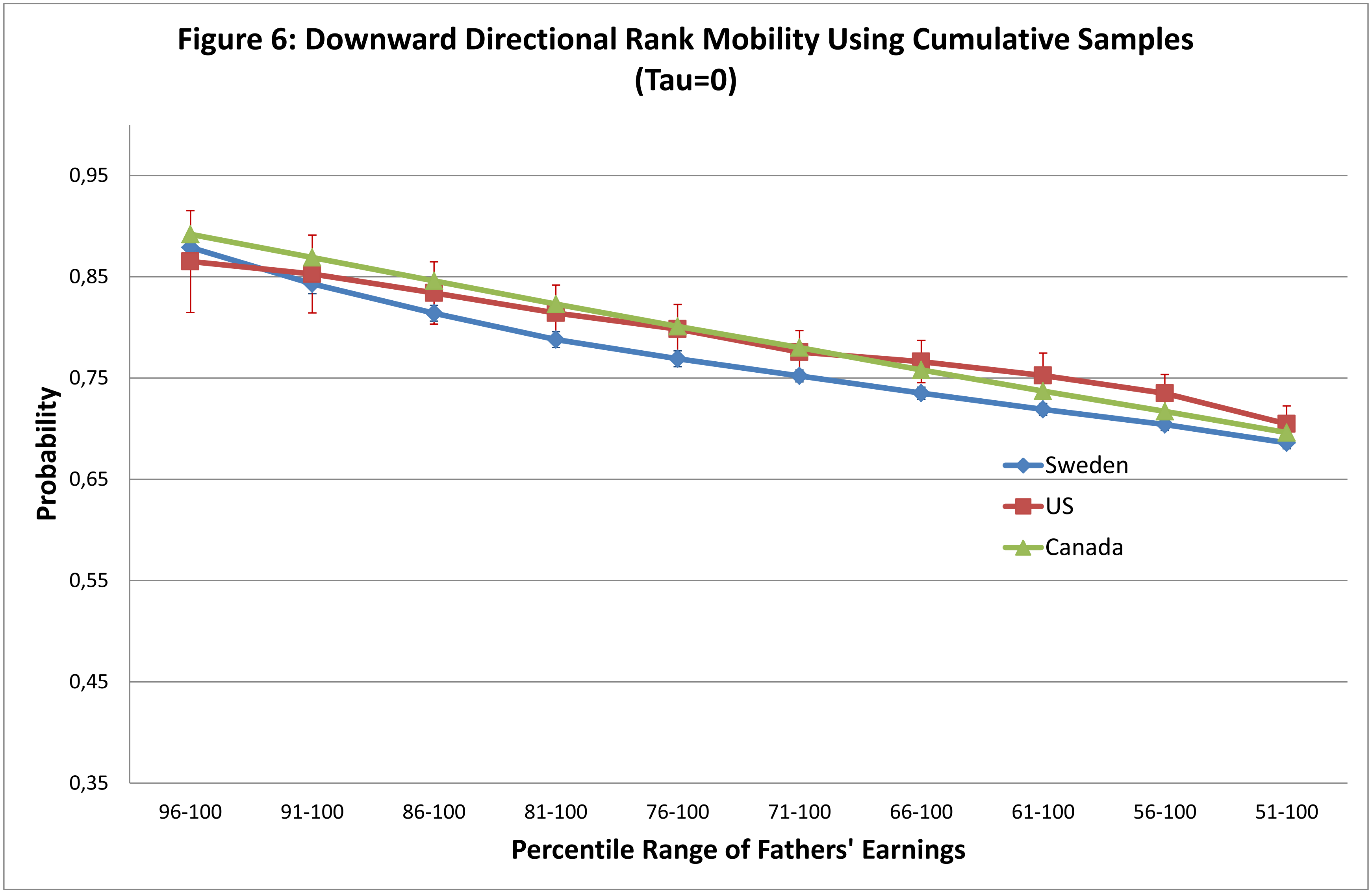


Figure 6: Downward Directional Rank Mobility Using Cumulative Samples
(Tau=0)
Probability
0,95
0,85
0,75
0,65
0,55
0,45
0,35
96-100
91-100
86-100
81-100
76-100
71-100
66-100
61-100
56-100
51-100
Percentile Range of Fathers' Earnings
Sweden
US
Canada

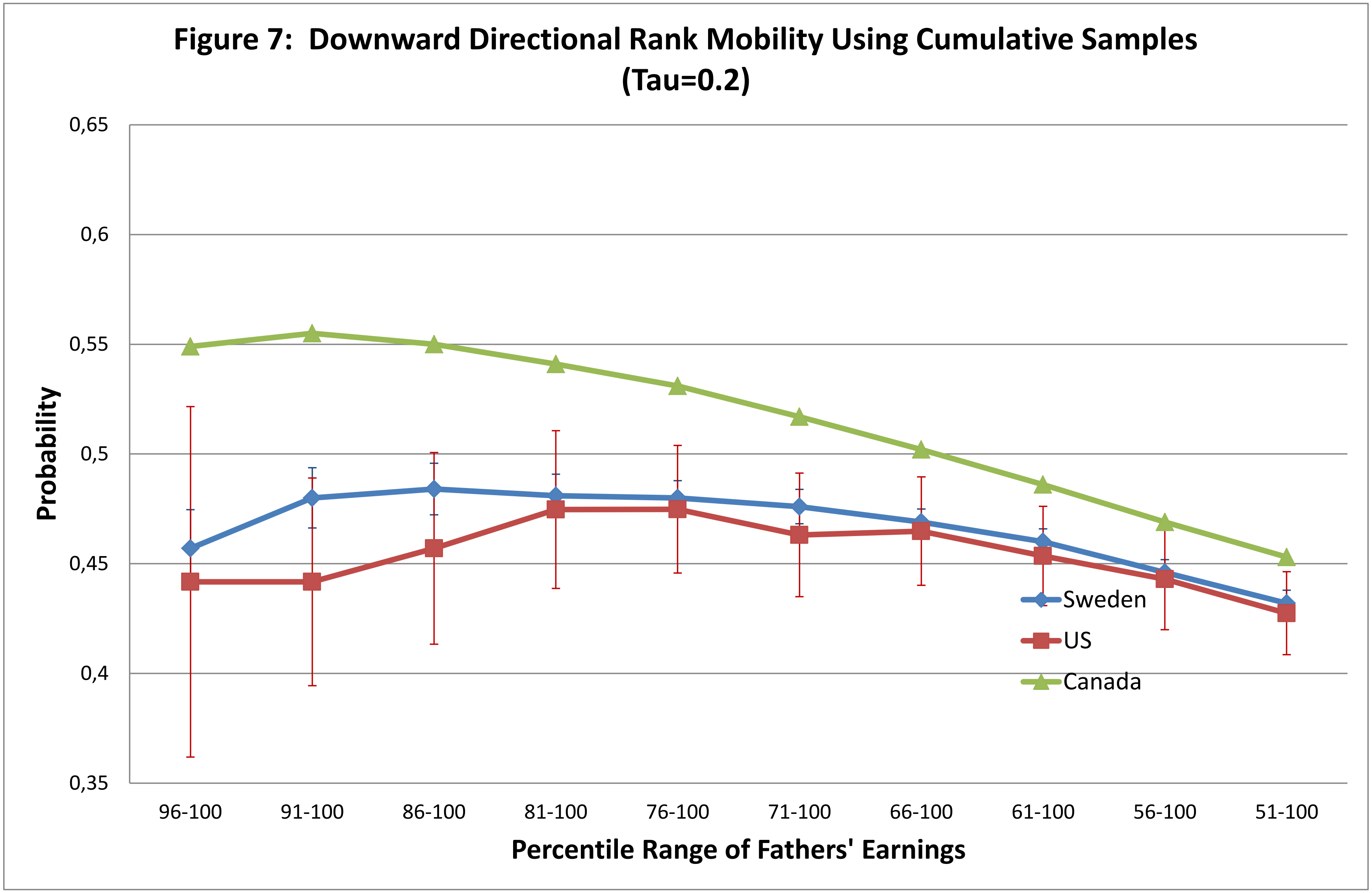


Figure 7: Downward Directional Rank Mobility Using Cumulative Samples
(Tau=0.2)
Probability
0,65
0,6
0,55
0,5
0,45
0,4
0,35
96-100
91-100
86-100
81-100
76-100
71-100
66-100
61-100
56-100
51-100
Percentile Range of Fathers' Earnings
Sweden
US
Canada

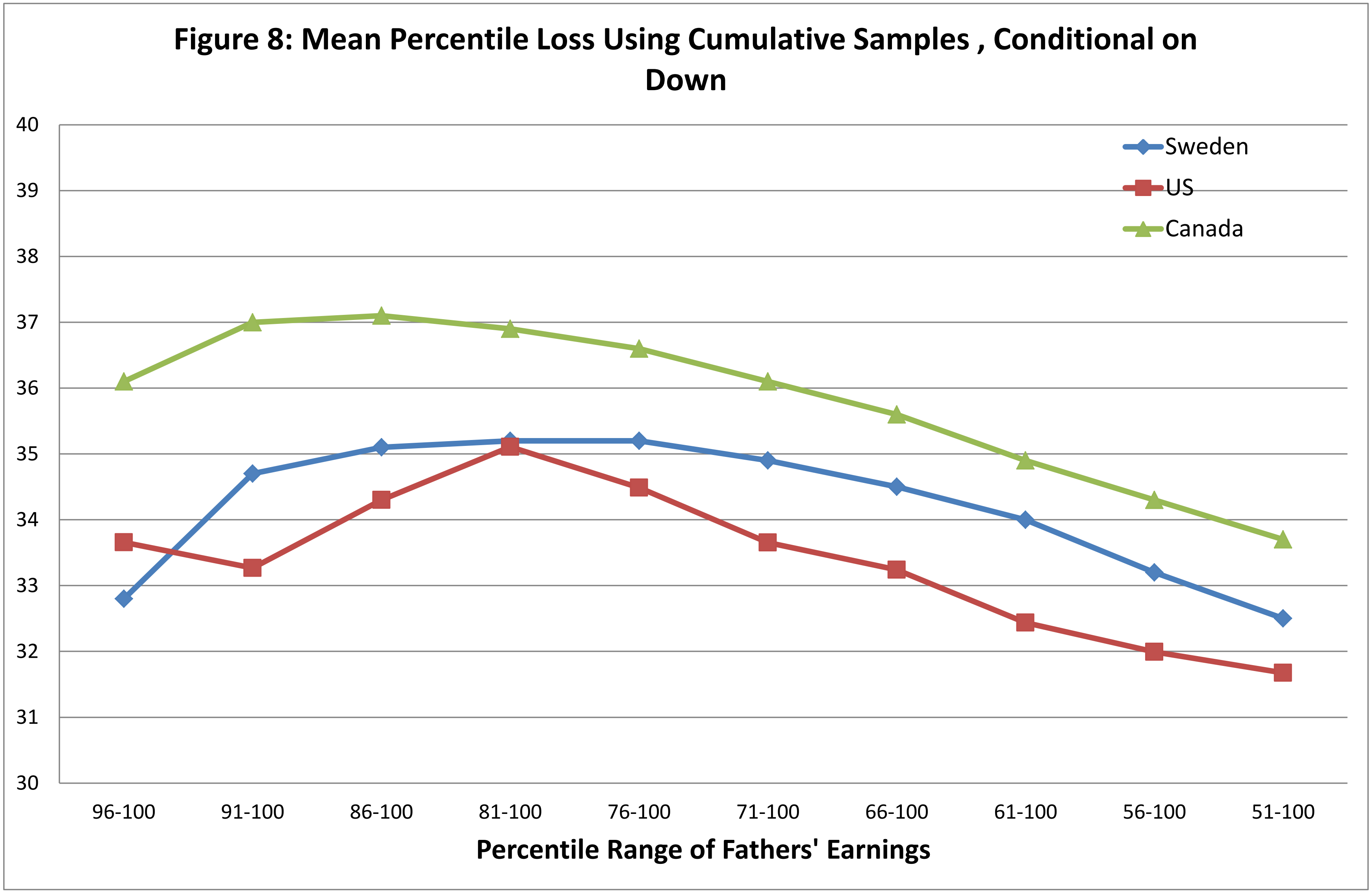
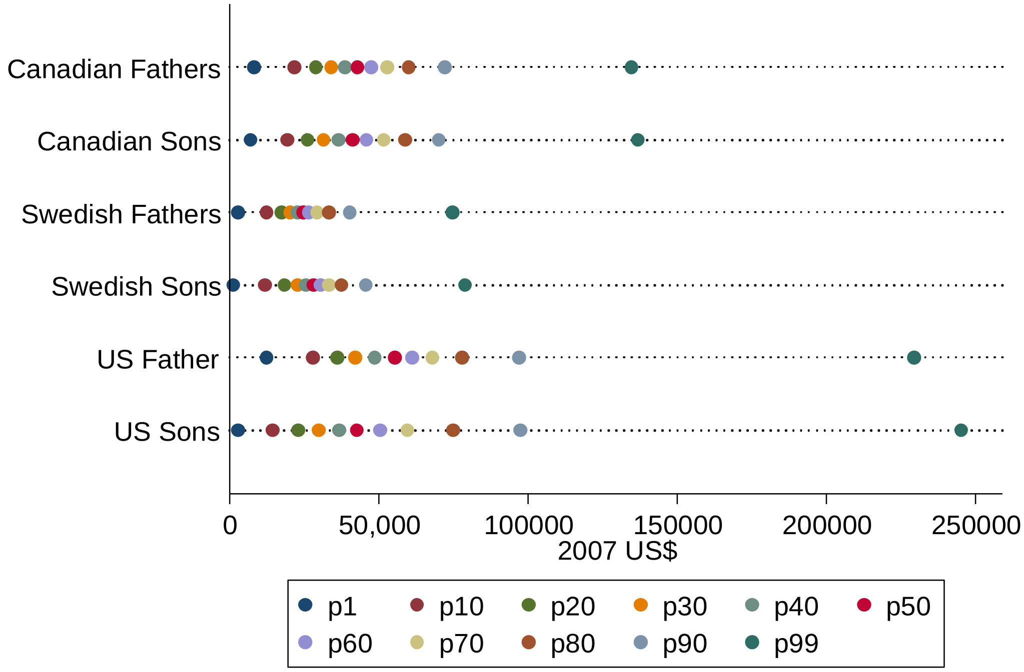


Figure 8: Mean Percentile Loss Using Cumulative Samples , Conditional on Down
40
39
38
37
36
35
34
33
32
31
30
Sweden
US
Canada
96-100
91-100
86-100
81-100
76-100
71-100
66-100
61-100
56-100
51-100
Percentile Range of Fathers' Earnings

Figure 9: Earnings Percentiles Expressed in US Dollars



Appendix Table A: Upward and Downward Mobility Using the Sensitivity Sample for Sweden, Cumulative Samples

Father's Pctile Range	Trans. Prob.	Directional Rank Mobility UP-0	UP-10	UP-20	Mean gain if UP	Father's Pctile Range	Trans. Prob.	Directional Rank Mobility DN-0	DN-10	DN-20	Mean gain if DN
1 to 5	92,0	95,1	77,9	62,6	37,4	96 to 100	82,7	88,3	67,3	52,5	37,3
	(2,2)	(1,7)	(3,1)	(4,0)	(2,1)		(3,2)	(2,6)	(3,8)	(4,0)	(2,4)
1 to 10	81,3	90,5	74,8	59,2	37,0	91 to 100	73,8	84,0	64,6	50,8	37,5
	(2,1)	(1,6)	(2,5)	(2,7)	(1,7)		(2,3)	(2,0)	(2,6)	(2,8)	(1,8)
1 to 15	76,0	88,1	73,8	58,8	38,0	86 to 100	66,5	81,3	63,0	51,3	37,6
	(2,0)	(1,5)	(2,0)	(2,4)	(1,2)		(2,2)	(1,8)	(2,1)	(2,4)	(1,5)
1 to 20	69,7	84,8	72,7	58,4	38,5	81 to 100	63,5	80,3	63,5	51,4	37,1
	(1,9)	(1,4)	(1,8)	(2,0)	(1,1)		(1,6)	(1,5)	(1,9)	(2,1)	(1,2)
1 to 25	64,8	81,5	70,1	56,1	37,4	76 to 100	57,9	78,2	62,3	50,1	36,4
	(1,6)	(1,3)	(1,5)	(1,7)	(1,0)		(1,7)	(1,4)	(1,6)	(1,7)	(1,0)
1 to 30	59,7	79,1	67,4	53,3	36,2	71 to 100	56,1	77,3	62,2	50,5	36,3
	(1,5)	(1,3)	(1,6)	(1,6)	(0,8)		(1,6)	(1,3)	(1,7)	(1,5)	(0,9)
1 to 35	53,4	75,7	64,1	50,4	35,1	66 to 100	52,3	75,5	60,7	48,9	35,6
	(1,4)	(1,1)	(1,4)	(1,5)	(0,8)		(1,6)	(1,3)	(1,4)	(1,5)	(0,8)
1 to 40	48,9	73,5	61,9	48,0	34,2	61 to 100	48,8	73,5	59,3	47,2	34,9
	(1,4)	(1,1)	(1,4)	(1,4)	(0,7)		(1,5)	(1,2)	(1,3)	(1,4)	(0,7)
1 to 45	44,6	71,9	60,5	46,5	33,4	56 to 100	44,8	71,3	57,5	45,4	34,1
	(1,3)	(1,3)	(1,2)	(1,2)	(0,7)		(1,4)	(1,3)	(1,4)	(1,3)	(0,8)
1 to 50	41,1	70,0	58,8	45,0	32,8	51 to 100	41,2	69,0	55,9	43,3	33,4
	(1,3)	(1,1)	(1,2)	(1,3)	(0,7)		(1,3)	(1,3)	(1,1)	(1,3)	(0,7)

Standard errors in parentheses.